

Integrating probabilistic seismic inversion with geomodelling at a CO₂ storage site

Introduction

Seismic data is crucial for constructing three-dimensional (3D) digital geomodels of the subsurface. Seismically interpreted horizons and faults are used to constrain the stratigraphy of the model while facies and reservoir properties can be inferred from well logs using e.g. geostatistical or stochastic simulations. The integration between seismic data and facies modelling is a non-trivial task and was already addressed by Doyen et al. (1994) and later in Doyen (2007). Since then, several different methods have been implemented e.g. combining rock properties from seismic inversion with multipoint geostatistics (González et al., 2007), seismic driven probabilistic classification of reservoir facies (Grana et al., 2013) and iterative geo-statistical inversion workflows (Azevedo et al., 2019).

This abstract demonstrates how litho-fluid class predictions from seismic inversion can be used to condition geostatistical simulations of facies. The scope is to show the application to a potential CO₂ storage site in the North Sea. The goal is to integrate a Bayesian seismic inversion method (Kolbjørnsen et al., 2020) quantifying the probability of sand and shale in the reservoir interval with conventional geostatistical simulations. We show how the sand probability cube from the inversion, can guide the modelling between the well locations and create a relatively detailed model in an early phase of a project evaluation. We believe our approach can be easily adapted and be beneficial to other similar sites.

Geological and geophysical setting

The CO₂ storage complex is in the Stord basin west of Bergen and Stavanger. It consists of the Hermod sand, a large turbiditic fan system of late Paleocene age. The system comprises a highly complex network of channels and channelized lobes and pinches out to the east. The Hermod sand is part of the Sele formation between Balder and Lista which predominantly consists of shale. The sand has excellent reservoir properties with high porosity and multi-Darcy permeability.

A pre-stack merge of two multicient surveys, CGG18002 and CGG18M01, was prepared to create seamless and AVO friendly partial angle stacks, covering the inversion area. The angle ranges of the partial angle stacks were 2-11° (Near), 11-20° (Mid) 20-29° (Far) and 29-38° (Ultra Far). The inline and crossline intervals were both 12.5 meters whereas the vertical sampling rate was 4 ms.

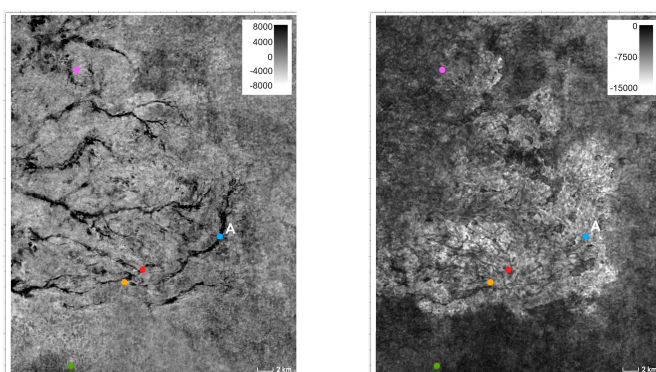


Figure 1 Left: Maximum EEI amplitude at $\text{Chi}=0^\circ$ within a short ($\sim 10\text{ms}$) window inside the reservoir. Right: Minimum EEI amplitude at $\text{Chi}=20^\circ$ between top and bottom of reservoir. Coloured dots indicate well locations.

The turbiditic fan and the stratigraphic pinch out are identified on 3D seismic data. The top of the Hermod sand is classified as an AVO class II or IIp having similar or slightly higher acoustic impedance (AI) and lower V_p/V_s ratio than the overlying Sele shale. Inside the sandy interval a harder sand with higher AI but similar V_p/V_s ratio is sometimes observed. The harder sand is often located in the main sand channels and is classified as an AVO class I. See further details in Figure 1 showing maps of

extended elastic impedance (EEI) of $\text{Chi}=0^\circ$ (intercept) and 20° (AVO), respectively. Both the channel pattern and the turbiditic fan system are clearly visible.

Sand probability cube

The sand probability cube was created by updating a 3D prior probability distribution of litho-fluid classes (lfc) using the Bayesian inversion method that is described in Kolbjørnsen et al. (2020) and Aker et al. (2021). The lfc are modelled as Gaussian distributions of V_p , V_s and density by grouping logged values of the nearby wells into distinct classes that are likely to be resolvable by the seismic. The prior distribution comprises a 3D cube matching the seismic grid and is populated with the initial probabilities for the different lfc. The cube is subdivided into zones using seismically interpreted horizons and a specified depth uncertainty. The lfc are placed into their respective zone(s) with a top of zone probability according to well log observation and geologic knowledge of the area. Furthermore, each lfc is assigned a typical thickness in ms, limiting the number of subsequent cells it can take before another lfc becomes more probable. The 3D cube is finally populated with prior probabilities of the lfc according to a 1D Markov model.

Figure 2 shows the updated sand probability, after inversion, in an east-west cross section through well A crossing a sand channel. A map plotting the maximum probability between the top and bottom reservoir is shown to the right. The thickness of sand in the cross section varies laterally being most thick in the sand channel at the well and further to the west. The structure is dipping upwards and pinching out to the east and patterns of major feeding sand channels are observed to the west. The inversion is clearly improving the sand detectability when comparing the map in Figure 2 with the EEI($\text{Chi}=20^\circ$) map in Figure 1. Since the inversion is not setup to distinguish channelled (harder) and non-channelled (softer) sand the channels seen in the EEI($\text{Chi}=0^\circ$) map of Figure 1 are less visible in Figure 2. We note that the channels are aligned with regions of thicker intervals with non-zero sand probability, as seen at well A, and in the thickness map in Figure 3.

Notice a gradual trend of lower sand probability in the map of Figure 2 towards north-west. This is consistent with lateral changes in geology that are observed in the wells making the seismic response of the sand less pronounced there. Despite the lower probability, sand is equally present and confirmed in the wells in the north-east corner. Instead of adapting the inversion to handle these lateral changes, we remove the trend as described in the next section, before using the cube as a guide in the facies modelling. The trend should not be confused with the dark patches of low probability, seen especially in the south-eastern part in the map. Some of these patches are due to shadowing effect from shallower injectites and the sand quality is more uncertain there.

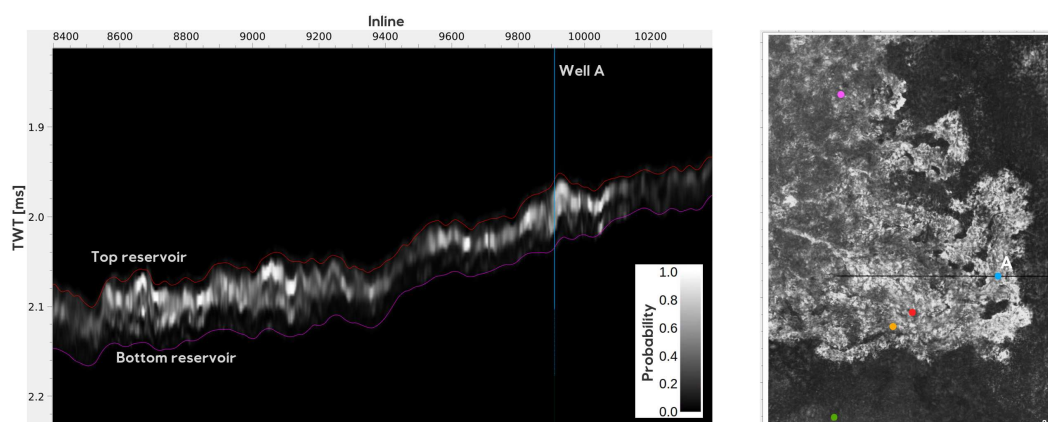


Figure 2 East-west section of sand probability cube (left) and map of maximum sand probability (right) between the top and bottom reservoir horizons. Well path of well A is shown in the section.

Integration with the geomodel

A geomodel of the reservoir interval was created between seismically interpreted top and bottom reservoir horizons using a grid resolution of $100 \times 100 \times 3$ meters. The sand probability cube was time-to-depth converted and resampled to the geomodel grid. The resampled cube enabled the estimation of net sand thickness by taking the vertical sum of sand probabilities times the grid cell thickness. The resultant net thickness map is shown in Figure 3. It is evident that the estimated net is generally less than the observations with increasing deviations towards north-west. To compensate for this the probability cube was multiplied with a ratio map as shown in Figure 3. The ratio map was created by interpolating the ratios at the wells.

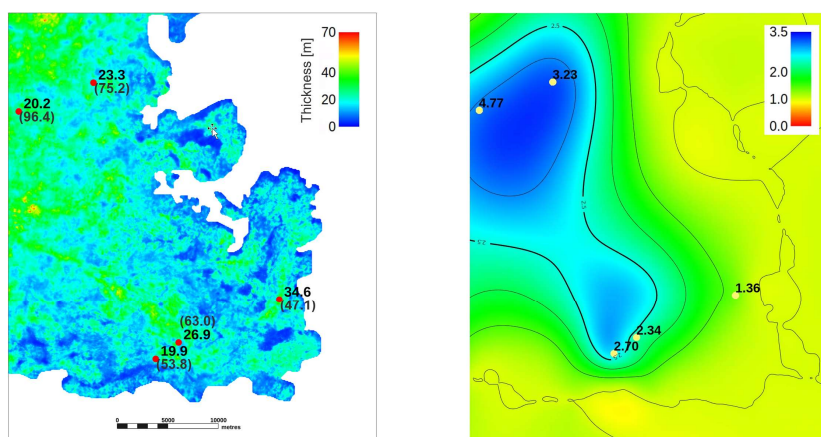


Figure 3 Left: Net thickness from the sand probability cube including values at the well locations. Corresponding values from well facies logs are shown inside parentheses. Right: Interpolated map of ratios between values from the facies logs and the probability cube.

The sand probability cube after multiplication was applied in the facies modelling using co-simulation with a variogram capturing the main sand channels' axes and the facies well logs. A simple sand-shale facies model was applied. An east-west section of the resulting sand facies distribution is shown in Figure 4 with the facies log of well A overlaid. The map to the right shows the sand facies distribution along a layer in the central part of the reservoir. The stochastic simulation was stopped when reaching a pre-defined fraction of sand-facies cells in the model to match the sand facies well logs and ensure reasonable connectivity of sand cells throughout the model.

Comparing the cross sections in Figure 4 and Figure 2, the distribution of the modelled sand facies and the pattern of non-zero sand probability is similar. Especially, notice the pinch out to the east and the region with less sand west of well A before entering a thicker unit. A few sand cells seem to be disconnected from the main body due to the randomness in the simulations. Overall, we think the workflow has resulted in a facies model that honours the observations in the seismic data and allows for a level of detail that would be difficult to obtain otherwise.

Conclusions

We conclude that a sand probability cube can relatively easily be used as guide for facies population in a reservoir model workflow. The workflow has been applied to model the sand distribution in a potential CO₂ storage site in the North Sea. The sand probability cube is created by a probabilistic litho-fluid inversion using pre-stack angle information in the seismic and elastic rock properties of the well logs. By calibrating the sand probability cube to match the sand thickness in the wells, the cube has been used as guide for sand facies modelling. We believe this creates a model that honours the seismic facies predictions, to a level of detail that would otherwise be hard to achieve. It has also served as an efficient approach for building a reservoir model in an early evaluation phase of a CO₂

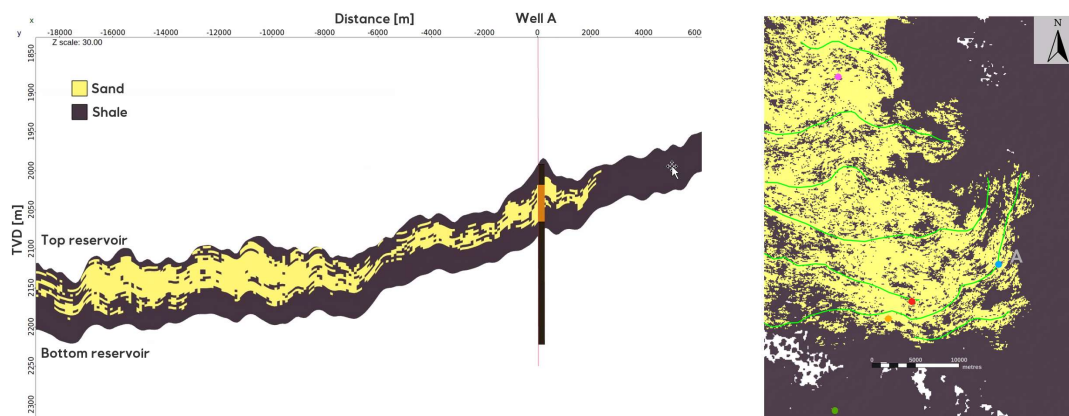


Figure 4 Modelled sand cells (yellow) in background shale (brown). Left: East-west section through well A with sand facies log overlayed. Right: Distribution of sand along a layer in the reservoir model. Green lines indicate main channels axes directions (ref. Figure 1).

storage project. Future efforts should focus on extending the inversion and facies model to distinguish between channelled and non-channelled sand, as well as improving the property modelling by conditioning on porosity distributions obtained from the seismic inversion. It should also be investigated whether simulated subsurface realizations from the inverted probability distributions of the lfcs can be used to define the ensemble variance.

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