Seismic modelling for reservoir studies

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Seismic modelling for reservoir studies: a comparison between convolutional and full-waveform methods for a deep-water turbidite sandstone reservoir

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Abstract

Two seismic modelling approaches, i.e. 2D pre-stack elastic finite-difference and 1D convolution methods are compared in a modelling exercise over the fluid-flow simulation model of a producing deep-water turbidite sandstone reservoir in the West of Shetland Basin. If the appropriate parameterisation for 1D convolution is used, the differences in 3D and 4D seismic responses from the two methods are negligible. The key parameters to ensure an accurate seismic response are a representative wavelet, the distribution of common-depth points and their associated angles of incidence. Conventional seismic images generated by the 1D convolutional model suffer from lack of continuity because it only accounts for vertical resolution. After application of a lateral resolution function, the convolutional and finite-difference seismic images are very similar. While transmission effects, internal multiples and P-to-S conversions are not included in our convolutional modelling, the subtle differences between images from the two methods indicates that such effects are of secondary nature in our study. A quantitative comparison of the (normalised root-mean-square) amplitude attributes and waveform kinematics indicates that the finite-difference approach does not offer any tangible benefit in our target-oriented seismic modelling case study, and the potential errors from 1D convolution modelling are comparatively much smaller than the production-induced time-lapse changes.

Keywords:

Simulator-to-seismic modelling, Time-lapse monitoring, Finite-difference modelling, 1D convolution
1 Introduction
Simulator-to-seismic (Sim2seis) modelling is the process of creating a post-stack seismic response of 2D or 3D static and dynamic reservoir models. As well as an aid for structural interpretations, Sim2seis modelling is a powerful approach for understanding the seismic signature of a heterogeneous distribution of petrophysical properties in multiple facies. From time-lapse perspective, Sim2seis modelling sheds light on the 4D seismic response of overlapping geo-bodies of saturation and pore pressure changes in producing reservoirs. Sim2seis fills the scale gap between the low-resolution band-limited seismic data and the fine-scale heterogeneity embedded in the reservoir models or geological outcrops (Bakke, Gjelberg and Petersen 2008; Bakke et al. 2013; Lecomte et al. 2016). In time-lapse seismic applications, in addition to 4D seismic feasibility (Webb et al. 2019) and quantitative interpretation analysis, Sim2seis modelling is instrumental in seismic history matching workflows where the adjustments to the simulation model are guided by evaluation of the consistency between the Sim2seis results and the observed 4D seismic data. While the choice of the algorithm for seismic modelling is a critical aspect of Sim2seis, it has only been discussed by a handful of studies in the literature. Burns et al. (2002) compared 2D ray tracing with a 2D hybrid method (ray tracing in the overburden and finite-difference (FD) in the reservoir interval) to study the 4D seismic signature of the oil-water contact (OWC) in the Gullfaks Field. It was observed that, whilst the results were similar in broad scale and both were successful in modelling the OWC response, the image from ray tracing was reported to suffer from migration artefacts due to the lack of diffracted waves and poor imaging of the complex geometries close to faults. In an application to a static reservoir model from an African deep offshore reservoir, Thore (2006) reported significant differences between 1D convolution and 2D pre-stack FD images. While he asserted that identifying the origin of the differences between the images was not straightforward, he attributed such differences partly to the inherent smoothness and potential processing artefacts of the FD results. Arts et al. (2007) compared the results of time-lapse 1D convolution and 2D pre-stack FD methods over the Sleipner CO₂ storage project. While both methods provided similar information on the link between the CO₂ layer thickness and the seismic amplitude, the modelling results were significantly different in terms of lateral coherency and resolution, and the FD result appeared to have a better correlation with the observed 4D response. Marvillet et al. (2007) compared the results of a 2D full-waveform modelling with 1D convolution modelling in a 4D seismic feasibility study on the Bu-Hasa Field and reported higher correlation between the full-waveform modelling results and the observed baseline seismic data. In a quantitative comparison, Shahin et al. (2011) assessed the semi-analytical 2D split-step Fourier plane-wave technique versus FD modelling, and investigated the effects of internal multiples and converted waves on the 4D seismic response. These effects were found to be negligible as compared to the production induced 4D seismic signature. Finally, Hill et al. (2017) compared time-lapse 3D FD with 1D convolution model and observed the seismic images to be broadly similar in overall content, but exhibit notable differences in the geometry, magnitude and the polarity of the 4D seismic attributes from the two methods.
Aside from Sim2seis analysis, seismic modelling is used for a number of purposes in time-lapse seismic studies throughout the lifecycle of the reservoir. Seismic modelling can aid the design and execution of the 4D seismic acquisition, processing and imaging by shedding light on the major sources of noise in the 4D seismic data through measuring the impact of non-repeatable acquisition parameters for the baseline and monitor seismic surveys (Lecerf 2019; Svay et al. 2013), the uncertainty in processing and imaging velocities (Bakulin et al. 2007), or the 4D seismic image distortions due to dynamic overburden (Domes 2010). Typically ray-tracing, FD, and to a lesser extent hybrid methods are used to address these challenges. Hybrid methods are specifically designed for 4D seismic applications by using a fast modelling approach in the coarse static overburden and a more sophisticated approach in the dynamic detailed reservoir interval. Lecomte (1996), Hokstad et al. (1998), and Gjøystdal et al. (1998) proposed a hybrid modelling scheme which combines local FD simulation in a complex reservoir zone with ray-tracing techniques in a structurally simpler overburden. In another approach called FD-injection, Robertsson, Levander, and Holliger (1996) and Robertsson and Chapman (2000) followed a procedure very similar to that presented above, however they used FD in both overburden and the reservoir zone. Kirchner and Shapiro (2001) used a Born repeat-modelling technique, which is a combination of FD modelling and perturbation theory. With the advance of computational power in recent years, the implementation of similar FD grids in the overburden and reservoir interval has however become computationally affordable. Also, due to some obstacles to practical implementation of the hybrid methods, they were not widely recognised for Sim2seis applications after being introduced in the literature. The main challenges include different gridding in the overburden and the reservoir interval and coupling of the seismic response along the interface between the overburden and the reservoir zone.

Based on the above mentioned and mostly qualitative comparisons, while similarities in the main features of the seismic images from different methods were observed, the differences were attributed to assumptions behind each modelling technique and their treatment of the wave propagation phenomena (e.g. the source and receiver directivity and the wave propagation effects such as spreading, reflection and transmission in discontinuities, scattering, focusing and defocusing), as well as illumination (Xie, Jin and Wu 2006), processing and imaging effects. While there appears to be a tendency in the literature in favour of full-waveform over convolutional modelling, in automated seismic history matching workflows, the mismatch between the Sim2seis results and the observed 4D seismic responses is evaluated through several hundreds or thousands of iterations. Therefore, it is not practical to implement costly FD seismic modelling. Instead, a quick, yet acceptably accurate seismic modelling approach is preferred. Here, to evaluate the uncertainty in Sim2seis results due to different seismic modelling algorithms, seismic images from 2D pre-stack elastic FD and 1D convolution models were compared quantitatively over a producing deep-water turbidite sandstone reservoir in the West of Shetland Basin.
Figure 1 Static properties for the model, (a) porosity, (b) volume of shale. Dynamic properties for the model after six years of production, (c) saturation changes, and (d) pore pressure changes. Changes in elastic properties (e) P-impedance, (f) S-impedance, and (g) $V_P/V_S$ ratio.

2 Reservoir model description and petro-elastic modelling

A 2D section through a 3D fluid-flow simulation model was chosen for this seismic modelling study. The reservoir thickness varies between 30 m and 100 m and structural complexities such as channels, faults and thin intra-reservoir shale layers are present. Figure 1(a-d) shows the distribution of porosity, volume of shale, water saturation and pore pressure changes after six years of production. The reservoir is produced under water injection to maintain the aquifer support. There is an out-of-plane injector in the vicinity of the lower and upper channel complexes to the right (C1 and C2) which causes an increase in pore pressure of up to 14 MPa. The upper channel system has been partly water-flooded, and in the regions where pore pressure build-up and water sweep co-exist, the softening due to increase in pore pressure and hardening due to replacement of oil by water compete against each other. A calibrated petro-elastic model (PEM) was used to estimate the production-induced changes in the elastic parameters. Gassmann (1951) fluid substitution model parameters are calibrated using pressure-volume-temperature (PVT) analysis and wireline log data (Batzle and Wang 1992; Amini 2018). MacBeth (2004) stress-sensitivity parameters for the West of Shetland sandstones are used to take into account the effect of pore pressure changes on rock frame. The PEM parameterisation is detailed in Appendix A. PEM results are shown in Figure 1(e, f, and g), where the time-lapse elastic response in channels to the right is dominated by softening due to pressure build-up, while in the thin
channel system towards the left the hardening due to saturation changes is dominant. Because this study is tailored towards Sim2seis analysis for seismic history matching purposes, our focus has been on assessment of the seismic response at reservoir level, hence the reservoir grid is embedded in a homogenous background velocity model.

3 2D pre-stack elastic FD seismic modelling

Despite not being computationally cost effective, the same FD grid is applied to the whole model (the overburden and the reservoir) to avoid the previously mentioned complications of the hybrid methods. The following sections detail the settings for the FD parametrisation, seismic survey acquisition, seismic processing and imaging workflows.

3.1 FD modelling parameterisation

The staggered-grid FD scheme (Virieux 1986; Levander 1988) is used to solve the velocity-stress wave equations (2nd order in time and 4th order in space). To increase the accuracy and the computational efficiency of the FD modelling, Holberg’s (1987) differentiators are implemented in our calculations. The Perfectly Matched Layer (PML) method (Berenger 1994) with a layer thickness of 40 grid blocks is implemented on all four sides of the model to minimise the effect of the spurious reflections from the computational boundaries of the model. A compressional point source is initiated at source locations by adding the source wavelet (30-Hz Ricker wavelet) to the coupled diagonal stress components for each time step. To avoid numerical artefacts in the FD calculations, the spatial grid size and the temporal time step are chosen based on the grid dispersion criterion and the stability limit of the staggered grid scheme (Virieux 1986). In this exercise, according to these criteria, the spacing in the x and z direction is set equal to 0.90 m and the time step interval to 0.18 ms. A horizontal interface is added above the reservoir as a reference seismic event. This isolated flat event is used to extract the seismic wavelet for the convolution model, as well as to ensure the correct two-way-time (TWT) alignment between the seismic images from convolution and FD algorithms.

3.2 Corner-point grid to Cartesian grid conversion

The FD algorithm in this study requires an earth model with regular Cartesian cells. However, the fluid-flow simulation model is built using irregular corner-point geometry (CPG). The average size of the cells in the CPG grid is 60 m (lateral) × 3 m (vertical), and in the Cartesian grid is 0.90 m × 0.90 m. An algorithm is designed for extracting pseudo-logs from the CPG grid to perform the grid conversion (Figure 2). The result of the grid conversion is shown in Figure 3. A favourable resemblance between the two grids ensures that the information is preserved during the grid transformation.
Figure 2 Extracting pseudo-logs from the CPG grid with tilted pillars. Firstly, the intersection of the vertical line going through each pseudo-log location (CMP denotes common mid-point) and the faces of the CPG cells were calculated. Then, the reservoir properties within each cell were assigned between the corresponding interfaces. Finally, each vertical pseudo-log was discretised using the desired vertical sampling interval (0.9 m).

Figure 3 (a) CPG to (b) Cartesian grid conversion. Each column in the Cartesian grid represents a pseudo-logs extracted as explained in Figure 2.
Figure 4 Configuration of the FD numerical grid, marine survey geometry and the fold coverage. The dashed box shows the active numerical grid for one of the shot points and its associated receivers. The elastic parameters inside the reservoir are given by PEM. The elastic properties of the overburden and underburden are assigned based on the wireline log data for the background shales ($V_p = 2811 \text{ m/s}, V_S = 1289 \text{ m/s}$, density above the flat surface $\rho = 2300 \text{ kg/m}^3$ and below the flat surface $\rho = 2349 \text{ kg/m}^3$).
Table 1 2D marine seismic survey configuration.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>number of shot points</td>
<td>83</td>
</tr>
<tr>
<td>shot spacing</td>
<td>45 m</td>
</tr>
<tr>
<td>streamer length</td>
<td>2520 m</td>
</tr>
<tr>
<td>number of hydrophones</td>
<td>112</td>
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<tr>
<td>receiver spacing</td>
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<tr>
<td>minimum offset</td>
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<tr>
<td>common-mid point (CMP) spacing</td>
<td>11.25 m</td>
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<td>maximum fold</td>
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</tr>
<tr>
<td>wavelet dominant frequency</td>
<td>30 Hz</td>
</tr>
</tbody>
</table>

3.3 2D seismic survey

A 2D marine survey is designed for pre-stack FD modelling (Figure 4). Table 1 summarises the survey parameters. Note that all the distances are multipliers of the cell size of 0.90 m. A seismic streamer with length of 2.52 km with 112 hydrophones with spacing of 22.5 m recorded the seismic response for 3 s. The minimum and maximum source-receiver offsets are 45 m and 1250 m, respectively. Eighty-three shot points with a spacing of 45 m are located 5 m below the streamer. To account for the acquisition and migration aperture and guarantee full-fold acquisition (maximum fold of 28) over the reservoir zone, the model is extended on both sides. The extended model has 3100×7200 grid cells (2970 m × 6480 m). To decrease the run-time, a dynamic computational grid is adopted in which only the part of the model involved for each shot point (a grid size of 3100×4100) is used for FD calculations. A sample of the raw shot gathers is shown in Figure 6. It is worth noting that our implementation of PML does not fully eliminate the reflections from the edges of the model. Therefore, a relatively weak ghost reflection from the top boundary (i.e. sea surface) could be present in the propagating wavelet.

3.4 Seismic processing and imaging workflow

The same modelling procedure and processing workflow are applied to the baseline and monitor surveys. Figure 5 shows the seismic processing and imaging workflow that includes the following main steps:

**Loading data and geometry** – The SEG-Y file containing 83 shot gathers is imported into the processing software. Each shot gather contains 112 traces of 1500 time samples, with a sampling interval of 2 ms. Survey geometry contains the indices and coordinates of the sources and receivers.

**Amplitude recovery** – In 2D, the amplitude decays with geometrical spreading by $1/\sqrt{\text{distance}}$. Considering the spreading from the source to target followed by the spreading from target back to the receiver, the amplitude decays by $1/\text{distance} = 2/(\text{velocity} \cdot \text{twt})$.

**Trace binning** – The offset gathers are sorted for the migration algorithm.
**Migration** – Pre-stack Kirchhoff time migration algorithm is applied for imaging. Two different scenarios for the choice of migration velocity for the monitor surveys (M) are examined. In the first scenario, the root-mean-square (RMS) velocity of the baseline survey (B) is used for migration of both baseline and monitor seismic images ($BL_{PSTM(B)}$, $M_{PSTM(B)}$), and in the second scenario separate RMS velocities for the baseline and monitor images are used ($BL_{PSTM(B)}$, $M_{PSTM(M)}$). The velocity difference between the baseline and monitor surveys is shown in Figure 7. It should be noted that although the 4D difference in the interval velocity is up to 70 m/s, the difference in the RMS velocities is small (less than 2 m/s). The seismic images (Figure 8) demonstrate that in this exercise with a constant overburden velocity and a moderate reservoir thickness, the image perturbations due to uncertainty in migration velocity of the monitor survey (Figure 8d) are much smaller than the magnitude of the 4D changes (Figure 8c). However, care must be taken in generalising our observation regarding the appropriate velocity for migration of the monitor survey when dealing with a changing overburden or/and thick stacked reservoirs. For example, in a case study in West Africa, Chen *et al.* (2014) observed that an increase in gas saturation in a shallow reservoir led to significant velocity changes between the two seismic surveys. As a consequence large time shifts were induced between the baseline and monitor surveys, causing imaging repeatability problems and uncertainties in the 4D seismic interpretation of the targets beneath the shallow gas accumulations. Migrating the baseline and monitor surveys with the same velocity model was found to be inadequate, hence they incorporated production-induced changes in the migration velocity for the monitor survey.

**Ensemble stacking** – The migrated offset gathers are stacked after migration to generate the final stacked section and are exported as a SEG-Y file. Due to the limited offset range in this study, the effect of wavelet stretch at far-offsets is not notable and no trace mute is applied prior to stacking.

![Seismic processing workflow](image)

*Figure 5 Seismic processing workflow.*

Figure 6 A raw shot gather from FD calculations. The colour‐bar on the image is saturated between (-0.5, +0.5) to enhance all the events. No amplitude correction has been applied on this gather. A trace is extracted to highlight the relative magnitude of the different events. The events are marked as: 1) the direct wave, 2) the remaining spurious boundary reflections from two sides of the computational grid, 3) the P‐wave reflection from the horizontal interface above the reservoir, 4) the P‐wave reflection from the reservoir, 5) the diffractions from sharp edges and discontinuities in the reservoir, and 6) the spurious boundary reflection from the base of the computational grid.
4 1D convolution modelling
Following the application of FD modelling, we create the seismic images using the widely popular 1D convolution approach. Figure 9 shows the key components of this method for generating a post-stack seismic image. The geometry of the seismic grid and the position of the common mid-points (CMPs) are first extracted from the seismic acquisition geometry. Then, for each seismic bin, the vertical pseudo-logs at each CMP location are extracted. To simulate the full-stack seismic response, considering the corresponding range of angles of incidence (assuming a horizontal reflector), the Zoeppritz equations (Aki and Richards 1980) are used to calculate the PP reflectivity coefficients. The average of the reflectivity series for all CMPs in each bin is calculated and assigned to the centre of each bin. The mean reflectivity series in depth is then converted to TWT, and discretised by careful selection of a small enough sampling interval to preserve the reflectivities at all the internal reservoir interfaces. Finally, the wavelet with the same sampling interval is convolved with the mean discretised reflectivity series to generate the full-stack synthetic seismic trace.

The isolated flat event above the reservoir on the full-stack FD seismic section is used to extract the far-field wavelet for the convolution model (Figure 8e). It should be noted that the wavelet at this event is asymmetric and not zero-phase. This is one of the inherent features of FD modelling, where the signature of the propagating wavelet differs from the initiated source wavelet due to application of the derivation operator (Figure 10). The red wavelet is the 30 Hz Ricker wavelet initiated at the source location in the FD calculation. The blue wavelet is the propagating wavelet throughout the media. In practice, the wavelet for convolution-based Sim2seis modelling is either extracted statistically from the observed seismic data, or deterministically by performing seismic well-ties.

4.1 Imaging calibration (migration operator)
Figure 10 shows the seismic section from 1D convolution versus FD modelling for the baseline survey. The main difference between the two sections is the lateral smoothness and coherency of the FD result against the discontinuities in 1D convolution image. Even the boundaries of the simulation model grid cells are clearly visible on the convolutional image. The latter shows all the lateral details of the simulation grid, because the 1D convolution algorithm considers the reflections as being from a point, while in reality – and as is captured by FD modelling – the reflected information come from an area also known as the Fresnel zone. To take the Fresnel zone and the limited lateral seismic resolution into account, the lateral resolution function should be considered. Figure 12 shows the algorithm for creating a migrated post-stack seismic section based on 1D convolution, where the conventional 1D convolution seismic image is convolved with lateral resolution functions.

4.2 The seismic spatial resolution operator
The seismic spatial resolution operator is the seismic image of a single point scatterer in the subsurface. This image depends on the depth of the point scatterers, the background velocity, the seismic survey geometry, the wavelet frequency spectrum, and the migration type (post- or pre-stack). Different
approaches have been proposed to calculate this operator (Toxopeus et al. 2008), including (1) closed-form expression (Chen and Shuster 1999), and (2) angle and band-limitation filter (Lecomte 2008). In this study, we used the first approach by Chen and Shuster (1999) and extended it from single frequency calculations to band-limited wavelet applications. Figure 13a shows the lateral resolution function of a point scatterer at reservoir depth for three selected single frequencies (5, 30, 90 Hz) and for the full wavelet bandwidth. Ideally, the lateral resolution operator should be calculated for each point scatterer in the target zone. However, because the overburden in our case is very simple and the reservoir is not very thick, the resolution filter does not vary significantly vertically across the reservoir zone. The shape of the lateral resolution function also depends on the survey coverage. Figure 13(b and c) show the variations of the lateral resolution function at different CMP locations. The lateral resolution function at the edges with lower fold coverage differs from the resolution function at the full fold area. Figure 13c shows the 1D convolution section after application of the lateral resolution function. The seismic images from adapted convolutional model and FD methods are very similar. More quantitative comparison between the two images are discussed in Section 5. One of the important aspects of Sim2seis modelling is the lateral scale differences between the seismic data and the reservoir model. It should be noted that what is commonly referred to as the seismic bin size is not the true representation of the spatial resolution of the seismic data. For example, while the bin size in this exercise is 11.45 m, the size of the Fresnel zone after migration is around 60 m, which is comparable with the average cell size of the simulation model (50 m).

5 Discussion
The baseline seismic images from both methods are shown in Figure 14. Here, the amplitudes in the difference sections are multiplied by three to highlight the dissimilarities. The major differences belong to structural discontinuities, e.g. at the edges of the model, fault locations, and the boundaries of the grids in the simulation model. As mentioned above, the lateral resolution operator overcomes this shortcoming of the 1D convolution to a large extent. To go beyond visual inspection and perform a more detailed quantitative comparison, the baseline seismic response from 1D convolution is subtracted from the FD seismic image. Normalised root-mean-square (NRMS) attribute between top and base horizons is used to quantify the errors (Figure 14f). The average NRMS amplitude difference between the conventional 1D convolution and FD methods is just above 15% (red curve).

After application of the lateral resolution function, the main differences disappear and the average NRMS difference is decreased to less than 10% (blue curve). Time-lapse sections from both methods are shown in Figure 15. Similar to the baseline comparison, the results from 1D convolution after application of the lateral resolution function and FD modelling are very similar. The NRMS attribute is calculated between top and base horizons (Figure 15f). The difference in the NRMS values between FD and convolutional methods is negligible in comparison
to the production induced effects, and for the majority of traces, the adapted 1D convolution shows closer NRMS values to the FD results. To further inspect the time-lapse seismic signal from each method, the subtle waveform shifts between the baseline and monitor surveys are extracted using a local cross-correlation attribute (Rickett et al. 2007). In a trace-by-trace analysis, using a moving window of 100 ms, the local time-lag associated with maximum correlation between the baseline and monitor images is estimated. The resulting local time-shifts are shown in Figure 16. A positive time-shift value indicates a downward shift of the seismic wiggles in the monitor traces with respect to the baseline trace. Time-shifts are partly driven by travel time changes due to velocity changes. For example, time-shifts in channel systems C1 and C2 appear to be consistent with the expected slowdown of up to 0.8 ms due to pressure build-up. Aside from these intervals, the velocity changes in other regions are negligible and the notable observed waveform shifts are caused by perturbation in the reflectivity series below seismic tuning thickness. Regardless of their cause, the waveform shifts from convolutional and FD methods are very similar with each other. This indicates that the performance of the two methods in representing waveform amplitude and kinematics is very similar.

![Figure 7](a) change in the interval velocity, and (b) change in the RMS velocity between the baseline and monitor surveys.)
Figure 8 FD modelling results, (a) baseline, (b) monitor, (c) time-lapse (monitor-baseline), (d) monitor($V_{PSTM-MON}$)-monitor($V_{PSTM-BL}$) (e) baseline trace at CMP 250. To highlight the differences, the amplitude in the difference sections is multiplied by three.
Figure 9 Key components of 1D convolution algorithm.

Figure 10 Source and propagating wavelets in FD modelling in time and frequency domains.
Figure 11 Baseline seismic section from (a) FD, and (b) 1D convolution model.

Figure 12 Adapted 1D convolution algorithm to simulate a migrated post-stack seismic section. (adapted from Toxopeus, Petersen and Wapenaar (2003))
Figure 13 (a) resolution function at CMP location 220 for 5, 30, 90 Hz frequencies and the full bandwidth post-stack resolution function, (b) lateral variation of the full bandwidth resolution function, and (c) full bandwidth post-stack resolution function at CMP locations 10, 50, 100, and 220.
Figure 14 Seismic images from (a) FD, (b) conventional 1D convolution, (c) adapted 1D convolution after application of the resolution function; (d) difference between (a) and (b), (e) the difference between (a) and (c); (f) NRMS attribute for (d) and (e).
Figure 15 Time-lapse seismic images from (a) FD, (b) conventional 1D convolution, (c) adapted 1D convolution after application of the resolution function; (d) the difference between (a) and (b), (e) the difference between (a) and (c). To highlight the differences, the amplitude in the difference sections (a), (b) and (c) is multiplied by three; (f) the 4D NRMS attribute from (a), (b) and (c).
Figure 16 Waveform shifts between baseline and monitor images for (a) FD, (b) conventional 1D convolution, (c) adapted 1D convolution after application of the resolution function, and (d) the expected travel-time changes due to reduction in velocity.
6 Conclusions

The baseline and time-lapse seismic images from convolution and FD modelling over a producing reservoir interval embedded in a homogenous background velocity model are found to be very similar. In the presence of structural complexities, sub-seismic sand-shale heterogeneity and overlapping time-lapse saturation and pressure changes, the simple convolution model is highly successful in preserving the detailed characteristics of the waveform (amplitude and kinematics). Application of a lateral resolution function is a powerful technique to resolve the discontinuity of the 1D convolution images. The images from adapted convolutional model which take the resolution function into account are found to be very similar to those from FD modelling. It should be noted that our 1D convolution model only considers the primary PP reflectivities using Zoeppritz equations, whereas the pre-stack elastic FD modelling implicitly takes the internal reservoir multiples and mode conversions into account. The highly similar images from both methods indicates that such effects are of secondary nature in our Sim2seis modelling. In our case study with a homogenous overburden velocity and a moderate reservoir thickness (less than 100 m), the image perturbations due to uncertainty in the migration velocity for the monitor survey are found to be negligible. The computation time for 1D convolution modelling is of the order of a few minutes, whereas the total FD modelling computational time is more than 13 days per survey and the seismic processing and migration took an hour per survey. It is worth mentioning that these timings only cover the computational time, and the additional time needed for data preparation, FD modelling setup, processing, and migration parametrisation should also be added in a more realistic evaluation of the cost of the computations. Here, the total FD modelling runtime is reduced to nine hours by distributing the calculations over 16 computational nodes in a computer cluster. The comparison presented here indicates that FD modelling does not offer any tangible benefit for target-oriented Sim2seis application in our case study, and the potential errors from convolution model are comparatively much smaller than the production induced time-lapse changes. However, care must be taken in generalising our findings to other reservoir settings and time-lapse applications. It should be noted that the application of the lateral resolution function after 1D convolution does not address the illumination issue associated with the steeper reflectors. To capture the illumination patterns within an imaging operator, it is recommended to use 2D/3D point-spread functions instead (Lecomte 2008). Convolutional modelling is of limited use in assessing the time-lapse seismic imaging, processing and acquisition footprint where the seismic wave propagation in the whole earth model (particularly the overburden) is of primary concern.

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Appendix A. Petro-elastic model parameters

Gassmann model parameters (Equation A-1 and A-2) are calibrated using wireline log data (Amini 2018) (Table A-1). Nur (1995) Critical Porosity model (Equation A-3 and 4) was used for estimation of rock frame bulk and shear moduli ($k_{frame}$, $\mu_{frame}$). Hill (1963) average was used to calculate the minerals’ effective bulk and shear moduli ($k_0$, $\mu_0$).

\[
k_{\text{sat}} = k_{\text{frame}} + \frac{(1-k_{\text{frame}}/k_0)^2}{\phi/k_{\text{fluid}}+(1-\phi)/k_0-k_{\text{frame}}/k_0^2}
\] (A-1)

\[
\mu_{\text{sat}} = \mu_{\text{frame}}
\] (A-2)

\[
k_{\text{frame}} = k_0 (1 - \phi/\phi_c)
\] (A-3)

\[
\mu_{\text{frame}} = \mu_0 (1 - \phi/\phi_c)
\] (A-4)

where subscript $\text{sat}$ refers to the saturated condition, $\phi$ is porosity, $k_{\text{fluid}}$ is the effective bulk modulus of the fluid mixture using harmonic averaging, and $\phi_c$ is the critical porosity.

To take the effect of pore pressure changes on rock frame into account, MacBeth (2004) rock stress sensitivity equations are used:

\[
k_{\text{frame2}} = k_{\text{frame1}} \frac{1+E_k e^{-CP_{\text{eff1}}/P_k}}{1+E_k e^{-CP_{\text{eff2}}/P_k}}
\] (A-5)

\[
\mu_{\text{frame2}} = \mu_{\text{frame1}} \frac{1+E_\mu e^{-CP_{\text{eff1}}/P_\mu}}{1+E_\mu e^{-CP_{\text{eff2}}/P_\mu}}
\] (A-6)

where $E_k$, $P_k$, $E_\mu$, and $P_\mu$ are the stress sensitivity coefficients and are equal to 1.1277, 5.62 MPa, 1.0833, and 7.97 MPa respectively for the West of Shetland sandstones. Subscripts 1 and 2 in these equations refer to pre- and post-production reservoir states.

In-situ acoustic properties of fluids are calculated using the PVT data (Figure A-1) and the empirical equations by Batzle and Wang (1992) at reservoir temperature ($T$) 57 °C. From PVT measurements the fluid properties are given as gas gravity (Gg) of 0.56, oil API of 25, and brine salinity of 18000 ppm. In-situ density and bulk modulus for gas, oil and brine as a function of pore pressure are shown in Figure A-2.
Table A-1 Calibrated rock properties

<table>
<thead>
<tr>
<th>Bulk modulus (GPa)</th>
<th>Shear modulus (GPa)</th>
<th>Density (gr/cc)</th>
<th>$\phi_c = c_1 + c_2 \phi_c, \phi_c &lt; c_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sand</td>
<td>Wet-clay</td>
<td>2.65</td>
<td>0.054, 1.541, 0.265, 0.383, 0.1823</td>
</tr>
<tr>
<td>Wet-clay</td>
<td>Sand</td>
<td>2.34</td>
<td></td>
</tr>
</tbody>
</table>

Figure A-1 (left) gas-oil-ratio, and (right) oil formation volume factor.

Figure A-2 In-situ acoustic properties for gas, oil and brine.