Assessing the seismic AVA detectability of CO\textsubscript{2} storage sites using novel time-lapse attributes

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ABSTRACT: Monitoring of stored carbon dioxide (CO₂) in subsurface reservoirs is fundamental to operation and management of the storage site, and is a requirement of some national and international legislation. As a consequence, effectiveness of monitorability (the ability to observe the evolving location of subsurface CO₂) for any given level of investment in monitoring technology is a significant investment uncertainty that must be assessed along other components of the storage-site selection criteria (e.g. capacity, injectivity and storage economies). We develop a workflow to assess the time-lapse seismic detectability of changes in subsurface aquifer reservoirs by analysing expected changes in seismic amplitude variation with angle (AVA) in the field. Laboratory measurements are used to calculate the seismic response of the reservoir at different saturations and pressures. We include the scattering effect of material above and below the reservoir by using a finite-difference, full-waveform modelling approach AVA analysis then assimilates local site effects into the detectability assessment. We show that performing waveform modelling which includes local geological heterogeneities above and below the reservoir interval is essential to assess the storage site monitorability. In order to quantify expected time-lapse changes in the seismic response, we introduce a new set of robust time-lapse attributes based on time–frequency decomposition. The attributes effectively separate amplitude and phase changes (time-shifts) of time-lapse seismic records, and allow us to quantify their repeatability against the background noise. Furthermore, the frequency-dependent nature of the attributes provides a quantification of the frequency–domain effects of time-lapse changes. The approach is employed to assess the detectability of supercritical CO₂ in two analogue storage sites in the near-shore UK North Sea. Analysis of laboratory measurements and AVA responses indicate the contrasting monitorability of the two sites, which helps decision making about further site investigation and development. Application of the approach to hydrocarbon reservoir monitoring is straightforward.

INTRODUCTION

The process of capturing carbon dioxide (CO₂) and injecting it into deep subsurface saline aquifers or depleted hydrocarbon reservoirs is a potentially important method to reduce atmospheric emissions of CO₂ from large point-source emitters such as power stations (e.g. van der Meer 1993; Bachu et al. 1994; Law & Bachu 1996; Bachu 2000; Haszeldine 2009; Scott et al. 2012). Generally, hydrocarbon reservoirs appear to offer lower-risk storage sites than saline aquifers owing to the existence of relatively higher-quality and more abundant pre-existing data, and to the availability of a known seal provided by geological caprock proved by having trapped hydrocarbon for millions of years. Also, CO₂ has been injected into reservoirs successfully within the oil industry for many years for the purpose of enhanced oil recovery (EOR). The disadvantages of hydrocarbon reservoirs are that drilled wells and the production itself may have created leakage pathways, and they also usually have relatively small storage volume compared to saline aquifers. So, despite the higher uncertainty associated with saline aquifers, due to their size they are becoming increasingly attractive targets for CO₂ storage (e.g. Haszeldine 2009).

Targeting saline aquifers for CO₂ storage makes it essential that high-quality methods of site evaluation exist (e.g. Ringrose & Simone 2009), and the ability to detect and track post-injection changes to reduce uncertainties is essential. Assessing the monitorability of the storage site is a part of any site selection process (e.g. White et al. 2005; Vanorio et al. 2010; Jafargandomi & Curtis 2011a, b, 2012). The principle aim of monitoring is to be able to observe and track major changes in the three-dimensional (3D) distribution of CO₂ during the injection phase, post-injection site management, and during post-closure stewardship. Jafargandomi & Curtis (2011a) defined a storage site to be monitorable if: (1) geophysical monitoring is possible within existing practical and financial constraints; (2) the spatial resolution is sufficient to image the spatial position of injected CO₂ to within the desired level of location uncertainty;
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(3) changes in geophysically measurable signals due to CO2 injection are detectable above measurable noise; and (4) there is sufficient petrophysical resolution and uncertainty-reduction for petrophysical and fluid parameter estimates to fulfill the monitoring objectives. Neglecting practicality and cost for now, detectability of petrophysical changes in storage reservoir rocks due to fluid injection/production is the minimum requirement for a site to be monitorable: the geophysical monitoring techniques employed should be able to detect where some minimum threshold volume or saturation of CO2 has been exceeded within any specified spatial subvolume of a subsurface reservoir, or after leakage into the overburden. However, existing definitions of monitorability require that saturations of CO2 can also be estimated (e.g. JafarGandomi & Curtis 2012). In this paper, we develop a workflow to quantify the detectability of changes at potential storage sites.

Seismic reflection amplitude variations with source-to-receiver offset (AVO) or equivalent with the angle between incident and reflected rays at the reflector (AVA) have been used extensively in the hydrocarbon industry to detect and identify reservoir fluids (e.g. Castagna & Smith 1994; Castagna et al. 1998), and to monitor changes in reservoir parameters (Tura & Lumley 1999; Landro 2001; Veire et al. 2006). We develop an approach based on the AVA technique to assess the site monitorability using limited available data (specifically, sonic well-logs together with rock samples taken from analogue outcrops or drilled boreholes). Under such situations, prediction of the AVA response of the reservoir–caprock interface using the Zoeppritz equations provides valuable information about the detectability of possible changes. Further, we apply full-waveform forward modelling of common midpoint (CMP) gathers in order to include local site geology (i.e. heterogeneity both above and below the reservoir) in the AVA analysis.

Although, such modelling presents a more realistic estimate of the AVA response, methods to quantify time-lapse changes by analysing different attributes of resulting waveforms are far from standardized, and, indeed, the application of technique or use of one attribute over another can lead to a degree of subjectivity (attribute-dependences) in the conclusions about time-lapse detectability. One of the main causes of such subjectivity is that changes in amplitude and changes in phase of seismic waveforms become confounded in existing methods and attributes (e.g. Ghaderi et al. 2010). To overcome this, we propose to quantify time-lapse changes using a set of robust time-lapse attributes based on the time–frequency decomposition of seismic records; this optimally separates the amplitude and phase changes in waveforms, thus removing concurrent subjectivity in waveform analysis.

In the following section we introduce the monitorability assessment workflow. Then we employ the workflow to assess the monitorability of two analogue CO2 storage sites in the nearshore UK North Sea. These are not sites at which CO2 will actually be injected but, rather, have been studied in detail as analogues for potential offshore aquifer storage reservoirs (Smith et al. 2011). Finally, we discuss results of the assessment and implications for the future application of the novel time-lapse attributes introduced herein.

DETECTABILITY ASSESSMENT WORKFLOW OVERVIEW

We consider a situation where detectability of changes at the site has to be assessed based on limited pre-existing data (likely to be the case for most aquifer storage sites in the UK North Sea). The data assumed to be available from site survey and preliminary research include specific laboratory measurements on core plugs from the selected caprock and reservoir rock samples. At earlier stages of site investigation, when no samples from a borehole are available, samples of geological analogues, meaning accessible rock outcrops that are expected to match the properties of the subsurface caprock and reservoir, may be used to assess the geophysical response of the reservoir. Use of analogous would, of course, increase uncertainty on parameter estimates owing to mismatch between analogue and reservoir geologies, and to pressure-related differences due to the reservoir’s overburden.

Figure 1 illustrates the workflow used to assess the detectability of changes at prospective sites. The laboratory experiments test the direct impact on observable geophysical parameters (e.g. P- and S-wave velocities and density) of injecting supercritical CO2 into the rock pore-space. These data are used to calibrate the petrophysical model (the relationship between P- and S-wave velocities fluid saturations at different pressures) that is required to predict geophysical parameters of the reservoir rocks under different injection scenarios. Sonic-log data are used to construct a velocity model that spans above, throughout and below the reservoir; this will be used to investigate the impact of local site geological heterogeneity on site monitorability.

A primary goal of much industrial geophysical monitoring is to discriminate between different saturating fluids in pore spaces. AVO/AVA analysis has proven to be effective for this purpose in the hydrocarbons industry when discrimination is typically required between oil, gas and brine. Several theoretical relationships have been proposed to predict the amplitude variation of reflected seismic waves from subsurface interfaces (Knott 1899; Zoeppritz 1919; Aki & Richards 1980; Waters 1981). Recently, there have been efforts to include overburden effects (Skopintseva & Stovas 2010) and frequency-dependence (Liu et al. 2011) in AVA analysis.

Modelling of full-waveform common mid-point (CMP) gathers is routinely used in the hydrocarbon industry and includes all of these effects. Further, it may also include the effect of seismic attenuation. Synthetic CMP gathers may be generated for a 1D (vertically-varying) medium by using analytical or semi-analytical wavefield modelling methods such as so-called reflectivity modelling (e.g. Kennett & Clarke 1983). However, using a large number of layers to incorporate scattering and velocity-gradient effects renders these approaches inefficient. To calculate synthetic CMPs we use the finite-difference time-domain (FDTD) scheme developed by JafarGandomi & Takenaka (2007, 2013). The algorithm uses staggered-grid finite-difference operators in time and space. The advantages of this scheme are that it generates synthetic wavefields in the r–p (plane-wave) domain that propagates in 3D space through a velocity model that varies in 1D, it is highly efficient due to the employed 1D approximation of the 3D Earth model, and it can incorporate any frequency-dependent attenuation model (described by 1/Q where Q is the quality factor). We generate synthetic CMP gathers in the r–p domain by gathering synthetic traces for a range of incident angles.

A petrophysical model that relates rock and pore-fluid properties to geophysically observable properties is essential in order to predict geophysical observations of the reservoir under different injection scenarios. In partially saturated rocks, the bulk modulus depends not only on the degree of saturation but also on the mesoscopic and microscopic characterisation of saturation. JafarGandomi & Curtis (2012) proposed an approach to account for the impact of mesoscopic and microscopic characteristics of saturation on seismic waves based on a combination of available rock physics models. They combine the White (1975) model, which accounts for the mesoscopic effects, with the
An assessment of the repeatability of any time-lapse survey is a requirement for successful site monitoring, which is the last stage of the detectability assessment workflow (Fig. 1). Changes between surveys in the acquisition system, and in both natural and instrumental noise cause changes in recordings regardless of whether any changes in the reservoir occurred (Lumley, 2001). Either of the individual baseline or monitor surveys may also be affected by source noises owing to the short time-intervals between successive shots, and the inaccuracy in the timing system (Landro 2008). These effects reduce the signal-to-noise ratio (Jacovitti & Scarano 1993). Therefore, any changes in the reservoir occurred (Lumley, 2001). The resulting 4D anomalies may be manifest as amplitude changes and/or time-shifts (phase changes) on the seismic records. Each of these attributes carries information about different types of changes in the subsurface reservoir: while an amplitude change might indicate a variation in saturation of the reservoir, a time-shift is an important indicator of changes in the reservoir pressure and compaction, or changes in the overburden (e.g. Landro & Stammeijer 2004; Fucik et al. 2009). In most cases, separation of amplitude and phase change are desirable but difference cross-sections and maps do not discriminate sufficiently between them. Cross-correlation is often used to estimate the time-shift between repeated arriving waves. However, such estimates are not robust for short time-windows (Ursenbach & Bancroft 2001) and their accuracy does not improve with increasing signal-to-noise ratio (Jacovitti & Scarano 1993).

Here, we describe an approach based on time–frequency decomposition to separate the amplitude and phase differences between two or more vintages of time-lapse records. We follow a similar approach to that developed by Kristekova et al. (2006) for quantitative comparison of earthquake seismograms. Any signal in the time domain $s(t)$ can be represented by its time–frequency decomposition $W(t,f)$ calculated by applying a continuous wavelet transform (CWT) to the signal (see the Appendix). Recently, it has been shown that non-parametric time–frequency distributions, such as the spectrogram (SP) and Wigner–Ville distribution (WVD), provide better trade-off between time and frequency resolution than the CWT (Wang 2010; Liu & Fomel 2012). Here, we build on a SP representation that is the short-time quadratic integral measure of the energy distribution of $s(t)$:

$$W(t,f) = \left[ \int_{\tau=t}^{\tau=t+\Delta t} s(\tau) h(\tau-\tau) e^{-2\pi i \tau} d\tau \right]$$

where $h(t)$ is a localizing window function such as a Box car function. We will also show comparisons to the alternative CWT method. Following Kristekova et al. (2006), a change in the signal amplitude is estimated by calculating the non-normalized envelope difference ($\delta E$):

$$\delta E(t,f) = \left| W_2(t,f) - W_1(t,f) \right|$$

where $W_1(t,f)$ and $W_2(t,f)$ are the time–frequency representations of the baseline record and the monitor (repeated) record, respectively. Changes in the signal phase are estimated by calculating the non-normalized phase difference ($\delta \theta$):

$$\delta \theta(t,f) = \left[ \text{Arg}[W_2(t,f)] - \text{Arg}[W_1(t,f)] \right] \pi$$

where $\text{Arg} \left[ \right]$ indicates the phase angle $\theta$ (in radians) of the function to which it is applied. Including the envelope $W_1(t,f)$ in equation (3) imposes the shape of the baseline signal on the phase difference; this equalizes the spatial resolution of envelope and phase difference estimates in equations (2) and (3), respectively. Finally, the time–frequency envelope $\delta E$ and phase differences $\delta \theta$ are the result of normalizing by the global maximum values for the baseline signal:

$$\delta E(t,f) = \frac{\delta E(t,f)}{\max \left| W_1(t,f) \right|}$$

$$\delta \theta(t,f) = \frac{\delta \theta(t,f)}{\max \left| \text{Arg}[W_1(t,f)] \right|}$$
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\[ \delta E(t,f) = \frac{\delta \overline{E}(t,f)}{\max \{ |\mathcal{W}(t,f)| \} } \]  

(5)

\( \delta E \) then varies with the relative amplitude values, whereas \( \delta \theta \) varies with the phase differences.

It is possible to normalize \( \delta E \) and \( \delta \theta \) locally with respect to \( |\mathcal{W}(t,f)| \) instead of by its global maximum value but such normalization creates spiky \( \delta E \) and \( \delta \theta \) distribution due to divisions by near-zero values. This effect is especially significant for signals contaminated with noise. If we wish to estimate the detectability of changes against the background noise level, \( \delta E \) and \( \delta \theta \) may alternatively be normalized by the maximum noise amplitude.

It is possible to estimate the amplitude and phase changes as a function either of time or frequency alone by integrating \( \delta E \) and \( \delta \theta \) over frequency or time, respectively. The time-projected counterparts of \( \delta E(t,f) \) and \( \delta \theta(t,f) \), respectively, are:

\[ \delta E(t) = \frac{\int_{f_{\text{min}}}^{f_{\text{max}}} \delta E(t,f) df}{\max \left( \int_{f_{\text{min}}}^{f_{\text{max}}} |\mathcal{W}(t,f)| df \right)} \]  

(6)

\[ \delta \theta(t) = \frac{\int_{f_{\text{min}}}^{f_{\text{max}}} \delta \theta(t,f) df}{\max \left( \int_{f_{\text{min}}}^{f_{\text{max}}} |\mathcal{W}(t,f)| df \right)} . \]  

(7)

Similarly the frequency-projected counterparts of \( \delta E(t,f) \) and \( \delta \theta(t,f) \) are:

\[ \delta E(f) = \frac{\int_{t_{\text{min}}}^{t_{\text{max}}} \delta E(t,f) dt}{\max \left( \int_{t_{\text{min}}}^{t_{\text{max}}} |\mathcal{W}(t,f)| dt \right)} \]  

(8)

\[ \delta \theta(f) = \frac{\int_{t_{\text{min}}}^{t_{\text{max}}} \delta \theta(t,f) dt}{\max \left( \int_{t_{\text{min}}}^{t_{\text{max}}} |\mathcal{W}(t,f)| dt \right)} \]  

(9)

In equations (6)–(9), \( f_{\text{max}}, f_{\text{min}}, t_{\text{max}} \) and \( t_{\text{min}} \) indicate the upper and lower bounds of the frequency and time windows of interest. Notice that the arguments following \( \delta E \) and \( \delta \theta \) on the left of equations (4)–(9) define the domain in which each function or attribute is defined. It is also useful to describe the total average envelope and phase differences of the baseline, and monitor signals with single-valued measures:

\[ \delta E = \frac{\int_{f_{\text{min}}}^{f_{\text{max}}} \int_{t_{\text{min}}}^{t_{\text{max}}} |\delta \overline{E}(t,f)|^2 df \, dt}{\int_{f_{\text{min}}}^{f_{\text{max}}} \int_{t_{\text{min}}}^{t_{\text{max}}} |\mathcal{W}(t,f)|^2 df \, dt} \]  

(10)

\[ \delta \theta = \frac{\int_{f_{\text{min}}}^{f_{\text{max}}} \int_{t_{\text{min}}}^{t_{\text{max}}} \left[ \delta \overline{E}(t,f) \right]^2 df \, dt}{\int_{f_{\text{min}}}^{f_{\text{max}}} \int_{t_{\text{min}}}^{t_{\text{max}}} \mathcal{W}(t,f)^2 df \, dt} \]  

(11)

which may be used to assess the repeatability of the time-lapse surveys as whole. From hereon, we approximate the integrals in equations (6)–(11) numerically with summation operators.

The following example demonstrates the quantification of amplitude and phase changes in a synthetic signal that includes three seismic events \( e1, e2 \) and \( e3 \) in Fig. 2, each one a Gabor wavelet with a dominant frequency of 30Hz. We modify the three events of the original (baseline) signal to create an altered (monitoring) signal as follows:

- amplitude of \( e1 \) is reduced by 20% but its phase is unchanged;
- amplitude of \( e2 \) is unchanged but its phase is reduced by 20%;
- amplitude and phase of \( e3 \) are both reduced, by 20 and 40%, respectively.

For comparison we estimate amplitude and phase changes using both SP and CWT for time–frequency decomposition (Figs 2 and 3, respectively). Figure 2a shows the original and modified signals by dashed and solid lines, respectively, while Figure 2b, c shows the amplitude and phase changes of the modified signal with respect to the original signal, as estimated using the SP method. The calculated \( \delta E(t,f) \) shows the maximum value of 20% for \( e1 \) and \( e3 \), and no value for \( e2 \), which corresponds exactly to the changes applied. The calculated \( \delta \theta(t,f) \) shows the maximum values of 20 and 40% for \( e2 \) and \( e3 \), respectively, and no value for \( e1 \), which again matches exactly the applied changes. The projected amplitude and phase differences are also shown with respect to time and frequency, which present concise information about changes that occurred compared to the baseline signal. Figure 3 indicates that using CWT for time–frequency decomposition provides the same accuracy as using SP (Fig. 1), except that the time–resolution of the estimated attributes using CWT is lower than that provided by SP for lower frequencies but is higher than SP for higher frequencies. It is worth mentioning that a constant time-shift in the monitor signal causes both phase and envelope differences.

We compare the SP- and CWT-based estimates of the phase–shift with that of the commonly used cross-correlation approach in Figure 4. The same window-length is used for both of the cross-correlation and SP-based estimates. The estimated phase changes \( \delta \theta \) are converted to the corresponding time-shifts \( \Delta t \) using:

\[ \Delta t[s] = \frac{\delta \theta[\text{radians}]}{2\pi f_c} \]  

(12)

where \( f_c \) is the dominant frequency of the wavelet. The true time-shift values for \( e2 \) and \( e3 \) are 3.3 and 6.6 ms, respectively. Figure 4 indicates the higher accuracy and resolution of the SP- and CWT-based estimates of the time–shift compared with that of the cross-correlation. From hereon we therefore use the SP method to calculate all time–frequency decompositions.
We now illustrate for real sites both the performance of the new attributes and the detectability assessment method by assessing the AVA detectability of the CASSEM (CO2 Aquifer Storage Site Evaluation and Monitoring) project analogue storage sites (Smith et al. 2011). In the CASSEM project, two sites were selected as analogues of UK offshore fields. They were studied in detail to develop storage-site evaluation and monitoring methodologies (no CO2 will actually be injected at these analogue sites). The two sites are in the near-shore and on-shore UK North Sea, at the Firth of Forth region and the York–Lincolnshire region, which from hereon we refer to as the Forth site and the Lincs site, respectively.

The target aquifer for the Lincs site is in the Triassic Sherwood Sandstone Group (SSG). In previous studies, this formation has been observed to have a relatively uniform thickness of 300 m. The postulated injection point for this site lies at a depth of 1200 m. The seal is the Mercia Mudstone Group (MMG), and the underlying formation is the Roxby Formation (gypsum and mudstone). The target aquifer for the Forth site is in the Kinnesswood and Knox Pulpit Formations (K&K), and the caprock is the Ballagan Formation (BGN). The thickness of the potential reservoir is about 300 m, and the main aquifer/seal levels are at an interpreted depth range of 2000–2500 m. The geological interpretation and modelling of these two sites are described in Monaghan et al. (2009).

A range of laboratory experiments have been carried out to measure the ultrasonic properties of the reservoir sandstones of the CASSEM analogue storage sites, while saturating the samples with a range of different proportions of brine v. supercritical CO2, and under a range of stress conditions (Fisher et al. 2010). These experiments are conducted on four sandstone samples: two from the Clashach Quarry, which is considered to be geologically analogous to the reservoir formation at the Forth site, and two samples from the Sherwood Sandstone Formation, which is the actual reservoir formation at the Lincs site (which outcrops some distance from the potential reservoir). Two samples from the Merica Mudstone and Ballagan Formation representing caprocks at the Lincs and Forth sites were also examined for their geophysical properties at different pressures. For the caprock samples of the Lincs site, the measurements were conducted under dry conditions and we use the Gassmann equations to correct for saturation (Smith et al. 2003). The P- and S-wave velocities are measured at 1 and 0.6 MHz frequencies, respectively. A summary of the laboratory measurements on Clashach Quarry (CL1) and Sherwood Sandstone (SSK) samples is given in Table 1, and more details about these measurements can be found in the CASSEM project report (Fisher et al. 2010). For further investigations, we used samples CL1 with a porosity of 22.6% and SSK with porosity of 20% as representative of the two aquifers.

Figure 5 shows the measured P- and S-wave velocities and best-fit petrophysical models for samples CL1 with a porosity of 22.6% and SSK with porosity of 20% as representative of the two aquifers.
for both samples that, while S-wave velocity does not change significantly with $S_{CO_2}$, there are more than 200 and 300 m s$^{-1}$ drops in the P-wave velocities of samples CL1 and SSK, respectively, when the samples are fully saturated with CO$_2$ when compared with brine-filled samples.

An increase of pore-fluid pressure is a direct consequence of injecting CO$_2$ into the saline aquifers. Recent studies show that this increase can be in the range of several MPa (e.g. Birkholzer et al. 2009; Vidal-Gilbert et al. 2009). For this reason, to estimate the impact of CO$_2$ injection on the elastic parameters of the rocks, both saturation and pore-fluid pressure increase (differential pressure decrease) have to be considered, simultaneously. Although increasing $S_{CO_2}$ has different impacts on the P- and S-wave velocities (decreasing the former and increasing the latter), increasing pore-fluid pressure led to a decrease of both P- and S-wave velocities. Figure 6 depicts the trajectories of the P- and S-wave velocity changes due to the combined effects of $S_{CO_2}$ increase and differential pressure decrease. The expected change in P-wave velocity of the reservoir rocks due to CO$_2$ injection is greater when accounting for both $S_{CO_2}$ and pore-pressure increase. However, increasing $S_{CO_2}$ leads to an increase in S-wave velocity, which partially neutralizes the impact of the pore-pressure increase. The combined effects of $S_{CO_2}$ and pore-pressure increase therefore yields smaller overall changes in the S-wave velocity. Figures 5 and 6 imply that accounting for both saturation and differential pressure is necessary to obtain a realistic estimate of the elastic parameter changes expected in the reservoir.

Since the frequency of the laboratory measurements (0.6–1 MHz) is much higher than the frequencies used in the field (30 Hz), we scale the measured velocities to the field frequency using the hybrid White–Pham petrophysical model. The scaling is conducted by best-fitting the hybrid model to the laboratory measurements, then reducing the input frequency to 30 Hz in the model while all the other parameters (Table 2) are fixed. The predicted P- and S-wave velocities and attenuation at 30 Hz are considered to be representative of geophysical parameters that would be estimated from a reflection seismic experiment. Table 3 provides the estimated density, P- and S-wave velocities, and P-wave attenuation ($Q_P^{-1}$) for the reservoir rocks with $S_{CO_2}$ val-
ues of 0 and 60% at 30 and 1 MHz. Expected differential pressures at the aquifer level are approximately 13.8 and 27.6 MPa for the Lincs and Forth sites, respectively, and we assume a 3.4 MPa drop in differential pressures due to CO₂ injection (MacKay et al. 2011). The expected drop in P-wave velocity of sample SSK of about 244 m s⁻¹ at the lower frequency is greater than that of sample CL1 (c. 147 m s⁻¹). The S-wave velocity changes of SSK and CL1 are −13 and +4 m s⁻¹, respectively. The expected changes in density are −38 and −32 kg m⁻³ for the Lincs and Forth sites, respectively. Changing S\textsubscript{CO₂} has also a significant impact on Q\textsuperscript{−1}P. Increasing S\textsubscript{CO₂} from 0 to 60% leads to a 0.02 (1/49) and 0.01 (1/97) increase in Q\textsuperscript{−1}P at 30 Hz for the Lincs and Forth sites, respectively. Table 3 implies that in practice (i.e. at field scale), greater changes in the P-wave velocity of the reservoir rocks may be observed after injecting CO₂ into aquifers, compared with the values obtained in laboratory measurements. For the S-wave velocities, no significant difference between the field and laboratory measurements is expected.

**AVA response**

To distinguish the AVA characteristics of the Lincs and Forth sites we apply the classification method introduced by Rutherford & Williams (1989) that distinguishes three classes of gas-sand AVA anomalies. According to their classification, an AVA anomaly represents Class 1 when the reflection coefficient of a normal-incidence P-wave is strongly positive, and the amplitude decreases with offset. A phase reversal might be expected at far offset for Class 1. In Class 2, the normal-incidence P-wave reflection coefficient is small (either positive or negative), and a large change in AVA is expected. In the case of CO₂ injection, if the normal-incidence reflection coefficient is slightly positive, a phase reversal at near or moderate offsets is expected. Class 3 AVA anomalies present a large negative normal-incidence reflection coefficient. This anomaly becomes stronger with offset, which represents so-called bright spots.

We calculate the AVA response of the interface between aquifer and caprock for the two storage sites at different reservoir CO₂ saturations and corresponding differential pressures using the Zoeppritz equations. Figure 7 shows P-wave and converted P to S-wave AVA anomalies (PP and PS, respectively) for the Lincs and Forth sites. We convert the incident angles to ray parameters (horizontal slownesses) for consistency with later sections. Both sites clearly present Class 2 AVA anomalies; however, the gradient of the Lincs’ AVA anomaly is greater than that of the Forth’s AVA anomaly. Increasing S\textsubscript{CO₂} decreases the P-wave reflection coefficients for both sites towards negative reflection coefficients with a greater rate of decrease for the

### Table 1. Measured P- and S-wave velocities (m s⁻¹), \(V_P\) and \(V_S\) respectively, of the potential reservoir and cap rocks of the Lincs and Forth sites (Fisher et al. 2010)

<table>
<thead>
<tr>
<th></th>
<th>(S_{CO_2}) (%)</th>
<th>(P_d) (MPa)</th>
<th>(V_P) (m s⁻¹)</th>
<th>(V_S) (m s⁻¹)</th>
<th>(S_{CO_2}) (%)</th>
<th>(P_d) (MPa)</th>
<th>(V_P) (m s⁻¹)</th>
<th>(V_S) (m s⁻¹)</th>
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<td>Sherwood Sandstone</td>
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Ballagan Formation (Forth caprock) | 0.0 | 3.5 | 3309 | 2217 |
| Merica Mudstone (Lincs caprock)    | 0.0 | 3.5 | 3379 | 2171 |

at University of Edinburgh on December 28, 2013

http://pg.lyellcollection.org/
Novel time-lapse AVA attributes

Also, greater separation between AVA anomalies at different CO₂ saturations at the Lincs site is particularly valuable in order to detect the CO₂ saturation by time-lapse monitoring. As shown in Table 3, injection of CO₂ in the aquifers has little impact on the S-wave velocity of the reservoir rocks. Figure 7c, d show converted P- to S-wave AVA responses of the aquifer–caprock interfaces for both sites with different CO₂ saturations. The magnitude of the converted S-wave coefficient for the Lincs site is larger than that for the Forth site. Regardless of the magnitude of the reflection coefficients, separation between the S-wave AVA anomalies for different saturations is very small.

Analysis of AVA responses of aquifer–caprock interfaces using the Zoeppritz equations provides valuable information about the monitorability of changes in the aquifers. However, such analysis lacks an assessment of the impact of overall site geology (i.e. overburden/underburden effects) and frequency-dependent effects. The following subsection describes a strategy to incorporate those.

**Synthetic CMP gathers**

We now examine the detectability of changes by generating synthetic common mid-point (CMP) gathers, taking account of...
overburden/underburden. We use the sonic-logs to construct subsurface velocity models for this purpose (Fig. 8). At the Forth site, we combine the sonic-logs obtained from two boreholes: the Firth of Forth-1 borehole, which is close to the potential injection location (Jin et al. 2010) with a total penetration depth of 2040 m; and the BGS Glenrothes borehole located approximately 15 km north of the potential injection location with a total penetration depth of 567 m. The Firth of Forth-1 borehole did not penetrate through the target caprock and aquifer formations (BGN and K&K formations, respectively). However, the BGS Glenrothes borehole penetrates both caprock and aquifer formations since, at the Glenrothes site, the formations are offset to shallow depths by a fault between the two boreholes (Brerton et al. 1988). We use the corresponding caprock and aquifer sonic-log segments from the BGS Glenrothes borehole, corrected for burial depth (Monaghan et al. 2009), at the Firth of Forth-1 borehole location. At the Lincs site, we chose the Slatfleetby-1 borehole with a total penetration depth of 2414 m near the potential injection location (Brerton et al. 1988; Monaghan et al. 2009). Since we have no information about the S-wave velocity and the density, we use empirical relationships from Han et al. (1986) to estimate them from the sonic-logs:

\[
V_P = -0.794849 S_{CO_2} + 0.2041580 \rho
\]

\[
V_S = 0.794V_P - 849
\]

\[
\rho = 0.204V_P + 1580.
\]

In these equations, the units for P- and S-velocities are m s\(^{-1}\) and for density kg m\(^{-3}\). Attenuative implications of subsurface random heterogeneities are quite well understood among seismologists through the scattering effect (e.g. Sato & Fehler 1997). In exploration seismology, the scattering effect of these random heterogeneities is assumed to be negligible with respect to the target impedance contrasts (i.e. major layer boundaries). However, in the case of time-lapse monitoring, small changes in the seismic amplitudes are exactly the sought after signals, and such scattering effects must be taken into account. In the absence of 2D and 3D information about heterogeneities, the sonic well-log is used to quantify the expected impact of 1D random heterogeneities on the propagating seismic waves (Shiomi et al. 1997). The scattering attenuation for a seismic wave propagating through a 1D random subsurface model may be approximated by (Sato 1982):

\[
Q^3(k) = \frac{k}{4} P(2k)
\]
Novel time-lapse AVA attributes

The random functions for each site are obtained by removing the background velocity, which is a smoothed version of the well-log. The estimated attenuation models imply greater seismic energy (amplitude) loss for higher wavenumbers at the Lincs site than the Forth site at the same depth. The Forth site presents greater scattering attenuation for $k < 0.01$ (large-scale heterogeneities). The scattering effect is implicitly included in the FDTD waveform modelling by introducing fine layering (Jafar Gandomi & Takenaka 2013).

In addition to the scattering effect, incorporating the effect of seismic wave attenuation due to fluid flow in the reservoir pore-space is also essential for realistic waveform modelling. Carcione (1998) showed that viscoelastic effective rheologies can be used to represent the poroelastic effect due to wave propagation in porous media. Picotti et al. (2010) indicated that the attenuation due to wave-induced fluid flow at the mesoscopic-scale (e.g. Pride et al. 2003) can be represented with the Zener rheological model. We use a Generalized Zener Body (GZB) model (consisting of five relaxation times) to incorporate the induced attenuation due to the patchiness of the CO$_2$–brine mixture into the FDTD modelling scheme. Figure 9a, b depicts the estimated $Q^{-1}$ models from the hybrid White–Pham petrophysical model for patch sizes of 10 cm, and the best-fit GZB models for the Lincs and Forth sites, respectively. As can be seen in Figure 9, the attenuation predicted from the petrophysical model and the GZB model are in a good agreement. Note that in this case we assume an intrinsic viscoelastic attenuation of $1/60$ due to friction between solid grains.

We consider an off-shore time-lapse monitoring situation in which the seismic survey is conducted before and after CO$_2$ injection. We assume that injecting CO$_2$ into the brine-saturated aquifer creates a 50 m-thick CO$_2$-saturated zone at the top of both aquifers, with a $S_{CO2}$ value of 60%. We calculate synthetic seismograms for incident P-waves with ray parameters of between 0 and 0.14 s/km$^{-1}$ to create CMP gathers. This range of ray parameter is equivalent to incident angle ranges of 0°–30° and 0°–40° for the reservoir–caprock interfaces at the Lincs and Forth sites, respectively. We use the velocity models obtained from the well-logs (Fig. 8) for calculation of the pre-injection gathers and modify the top 50 m of the reservoirs following the expected changes in geophysical parameters given in Table 3 to calculate the post-injection gathers. We assume a constant intrinsic (viscoelastic) attenuation of $Q^{-1}_P = Q^{-1}_S = 1/60$ for all layers at both sites, except for the CO$_2$-saturated zone for which attenuation models in Figure 9 are used. A zero-phase Ricker wavelet with a central frequency of 30 Hz is used as the incident downgoing wave. The positions

Fig. 7. P-wave AVA at different CO$_2$ saturations predicted using the Zoeppritz equations for (a) the Lincs site and (b) the Forth site. Converted P- to S-wave AVA at different CO$_2$ saturations for the Lincs and Forth sites are shown in (c) and (d), respectively.
of both the centre of the initial source wave and the receiver are 100 m above the seabed. The top boundary condition of the finite-difference grid is set as a non-reflecting boundary to avoid water-layer multiples, and hence we assume that free-surface multiples have been removed from the seismic data prior to AVA analysis. Figure 10a, c shows the post-injection synthetic CMP gathers (pre-critical angle) in the $\tau$-p (plane-wave) domain for the Lincs and Forth sites, respectively. The amplitudes of the synthetic seismograms show the divergence of the wavefield, and hence represent data that would be recorded on hydrophones. Corresponding differences between the pre- and post-injection gathers are also shown in Figure 10b, d, respectively. Note that the amplitude of the difference records is amplified to improve the visibility.

Using pairs consisting of pre- and post-injection CMPs for each site, we calculate the time-lapse attributes $\delta E$ and $\delta \theta$ in both time and frequency domains using the SP-based approach for the time–frequency decomposition. Figures 11 and 12 show the calculated time-lapse attributes for the Lincs and Forth CMPs, respectively. In general, negative values of $\delta E(t)$ for the reservoir-caprock interface for the Lincs site (Fig. 11a) are in agreement with the estimated AVA response using the Zoeppritz equations (Fig. 7a). However, that is not the case for the Forth
Novel time-lapse AVA attributes

The low magnitude of $\delta E$ and $\delta \theta$ for both sites is due to normalization by the global maximum of the baseline records, which occurs at the earlier parts of the traces. Such normalization exposes the impact of local site geology including seismic energy loss due to scattering and the attenuative effects of geological formations.

The Lincs CMP shows a strong negative $\delta E(t)$ anomaly (~3%) at the top of the aquifer (0.7–0.75 s) followed in line by a positive anomaly (0.75–0.8 s), which indicates the base of the CO$_2$-saturated zone (Fig. 11a). The presence of the CO$_2$-saturated zone at the top of the aquifer also affects the travel-time and amplitude of later events in the CMP gather (e.g. Ghaderi et al. 2010). $\delta \theta(t)$ values (Fig. 11b) show very small changes for the top reservoir event except at far-offsets, which is as expected. The strong negative $\delta \theta(t)$ anomalies between 0.92 and 1.05 s are due to the increased travel-time of the interbed multiple reflections within the high-velocity evaporite-dominant formations underlyng the aquifer (Fig. 8). We select the event in the time-window shown with the dashed lines in Figure 11a to estimate $\delta E(f)$ and $\delta \theta(f)$. The largest decrease in amplitude occurs at 12–22 Hz, dominantly at 13 Hz and the larger ray parameters (far offsets). At the smaller ray parameters (near offsets), the negative amplitude change is centred around both 30 and 13 Hz, the former being the dominant frequency. The interference between the reverberations within the CO$_2$-saturated zone caused the increased amplitude in 20–25 Hz frequency range.

Fig. 10. Post-injection synthetic CMP gathers in the $\tau$-$p$ (plane-wave) domain calculated for (a) the Lincs site and (c) the Forth site; corresponding differences between the post- and pre-injection gathers are shown in (b) and (d), respectively. Note that the amplitude of the difference records is amplified to improve visibility.
Corresponding estimated time-lapse attributes for the Forth site are shown in Figure 12. Generally, the values of all time-lapse attributes at the Forth site are lower than those for the Lincs site because of its deeper position, which leads to greater seismic energy loss. This implies that the monitorability of the Forth site is poorer (monitoring using AVA will be more difficult) than at the Lincs site. The maximum values of $\delta E_I$ and $\delta \theta_I$ at the Forth site are $-0.6$ and $0.3\%$, respectively. Similar to the Lincs site, the negative $\delta E_I$ associated with the top reservoir ($1.15–1.25\, \text{s}$) at the Forth site is followed by a positive $\delta E_I$ anomaly caused by reflection from the base of the CO$_2$-saturated zone. Lack of information from below the reservoir at the Forth site makes the later parts of $\delta E_I$ and $\delta \theta_I$ (Fig. 12a, b) artificially look cleaner than those for the Lincs site (Fig. 11a, b). There is a phase-reversal at far-offsets (ray parameter $0.1\, \text{skm}^{-1}$) at the reservoir-caprock interface of the Forth site, which is not present on the calculated AVA response from the Zoeppritz relationships (Fig. 7), showing how important it is to perform waveform modelling, including surrounding rock layers, in addition to predicting reflectivity at the top reservoir only.

When the maximum amplitude of the baseline trace is used in the denominator of equations (4)–(9), the magnitude of estimated $\delta E$ and $\delta \theta$, both in the frequency and time domains, is an indication of the detectability of changes in the subsurface parameters given the background geology. Such measures may be used to compare monitorability of different storage sites. However, local normalization of $\delta E$ and $\delta \theta$, both in the frequency and time domains, could also be applied to quantify time-lapse changes of any individual reflection event in a seismic gather (e.g. Fig. 13).

**Repeatability**

In the previous subsection, time-lapse attributes were calculated for the noise-free signals that have exposed the impact of site
geology on the AVA detectability. However, the AVA detectability may also be affected significantly by the signal-to-noise ratio. Here, we assess the repeatability between pre- and post-injection surveys at the two sites by adding random noises to the phase and amplitude of the pre- and post-injection synthetic records:

$$S^*_k = \alpha r S_k | e^{i \alpha \theta}$$  \hspace{1cm} (16)$$

where $S^*_k$ and $S_k$ are the modified and the original traces, subscript $k=1,2$ indicates pre- or post-injection records, respectively, $r$ is the random noise sampled from a Gaussian distribution with zero mean and unit standard deviation, and $\alpha$ is a scale factor representing the strength of the random noise and is defined as a fraction of the global maximum of the pre-injection record. We calculate the single-valued time-lapse attributes (equations 10 and 11) with $\alpha$ values between 0.01 and 0.2 for the zero-offset records at the Lincs and Forth sites (Fig. 13). For comparison, we also calculate corresponding NRMS (Kragh & Christie, 2002) expressed in percentage:

$$\text{NRMS} = \frac{200 \times \text{RMS}[S_k - S_k^*]}{\text{RMS}[S_k] + \text{RMS}[S_k^*]}$$  \hspace{1cm} (17)$$

where

$$\text{RMS}(x) = \sqrt{\sum_{t_{min}}^{t_{max}} x^2 / N}$$  \hspace{1cm} (18)$$

and $N$ is the number of samples in the interval $t_{min} - t_{max}$. Figure 13 shows the calculated single-valued $\delta E$, $\delta \theta$ and
NRMS with respect to the noise strength (α) for the Lincs and Forth sites. The larger than δE and δθ values of NRMS is due to the cumulative effects of envelope and phase differences on the NRMS estimates. Variation of all three parameters of δE, δθ and NRMS with respect to the noise strength α indicates a greater gradient for the Forth site than the Lincs site, which implies greater repeatability of time-lapse measurements for the Lincs site.

**DISCUSSION**

The risk of potential leakage associated with storage sites may be reduced through comprehensive monitoring. Assessing monitorability of a site contributes to the risk plan that is necessary for any storage site to be legal under current European Union legislation. Site detectability assessments based on the analysis of available data and estimated attributes indicate that the two sites considered here demonstrate distinctly different AVA detectabilities: the Lincs site shows greater changes in reservoir rock parameters due to supercritical CO2 injection, greater values of the new time-lapse attributes and, therefore, better detectability than the Forth site. Site-specific characteristics such as greater burial depth and greater velocity fluctuations (Fig. 8) in the overburden, as well as lower sensitivity of P- and S-wave velocities of the reservoir rock to CO2 saturation (Table 2), cause lower detectability of the Forth site.

Although there are some agreements between the estimated AVA responses using the Zoeppritz equations (see the subsection on ‘AVA response’) and the synthetic CMPs (see the subsection on ‘Synthetic CMP gathers’) for the Lincs site, for both sites there are also some expected discrepancies between the results of these two approaches due to the incorporation of local site geology in the latter method. For example, while the Lincs AVA response predicted by the Zoeppritz equations shows a polarity reversal (Fig. 7a), by contrast there is no indication of such a reversal in the modelled wavefield in Figure 11a. The opposite contrast is observed for the Forth site. Such discrepancies highlight the importance of having knowledge of local site geology in the overburden/underburden when upscaling the AVA results obtained from the Zoeppritz equations.

Ideally, the monitorability of each specific storage site would be assessed using a 3D volume, including the volumes above and below the reservoir. However, the quality of such assessments is subject to the reliability of detailed geological and geophysical models, which are usually not available at the earlier stages of site selection. In addition, moving towards 2D and 3D analyses requires significantly increased computational resources and cost. Given these pros and cons, it seems reasonable that a method to assess site detectability based on 1D (depth-dependent) data, and the compilation of information from neighbouring wells and outcrop analogue such as the method described here, provides sufficient information for the initial monitorability assessment of sites from a short-list of potential storage sites.

It is likely that porosity of the reservoir rocks varies after injecting CO2 into brine-saturated aquifers due to both chemical and mechanical effects. This in turn will affect the estimated P- and S-wave velocities. Local mechanical impacts on porosity at the pore-scale are included by introducing pressure into the analysis. Including chemical diagenetic effects, which might be considerable in the long term, would require that the petrophysical model included the impact of chemical reactions (e.g. Vanorio et al. 2008, 2010; Agersborg et al. 2011).

The new attributes proposed in equations (4)–(9) are robust (e.g. Fig. 2) and more informative (frequency-dependent) than the commonly used cross-correlation or Taylor expansion methods (e.g. Zabibi Naeini et al. 2009) to estimate time-lapse changes on seismic records. These attributes might also be used to overcome the difficulties in detection of reservoir pore-pressure (e.g. Kvam & Landro 2005), and estimation of thickness and velocity changes of injected CO2 layers (e.g. Ghaderi & Landro 2009).

Frequency-dependent attenuation (Chapman et al. 2006) is usually ignored during AVA analysis. However, in future, the new time-lapse attributes may offer a significant step towards quantitative assessment of fluid saturation (e.g. CO2 natural gas or oil) in reservoirs using low-frequency seismic methods. Figure 14 shows the impact of fluid-induced attenuation on the estimated attributes at different frequencies and times. In this figure we compare the estimated δE(t) and δE(f) of the zero-offset records at the Lincs and Forth sites with those estimated for viscoelastic conditions in the reservoir using a constant Q0=Q0et=60 (i.e. neglecting fluid-flow effects on the seismic waves). In this case we normalize the envelope differences and the phase differences with the local maximum of the reflection events within a 4T wide time-window (where T is the dominant period of the incident wave) centred at the top-reservoir reflection. Figure 14 indicates that for both sites the incorporation of fluid-flow-induced attenuation decreases the expected amplitude changes. This is because the increased attenuation in the CO2-saturated zone reduces the velocity and, hence, the impedance.
Novel time-lapse AVA attributes

1. The greater change in $\delta E$ (equations 10 and 11) for the Forth site is due to the higher velocity of the reservoir rocks, which leads to a greater velocity reduction due to flow-induced attenuation. Ideally, time-lapse attributes may be inverted to estimate saturation and thickness of the CO$_2$-flooded zone. What is clear is that attenuation is certainly frequency-dependent and the measurement of this by using attribute $\delta E(f)$ may aid this inversion.

2. Although, we use AVA data to assess the site monitorability, the same general approach may be applied to a variety of existing seismic and non-seismic geophysical methods (e.g. JafarGandomi & Curtis 2011a, 2012) and emerging geophysical methods that may be applicable to monitoring CO$_2$ storage reservoirs. Such methods may use more exotic data types or may be used in more heterogeneous reservoir/overburden structures. For example, Zhou et al. (2010) used coda wave interferometry in a down-hole vertical seismic profile (VSP) setting to monitor possible leakage from CO$_2$ stores. Khatiwada et al. (2008) showed that the same interferometry approach may be used to monitor CO$_2$ stored in geologically complicated environments such as layered basalts. In each case, a workflow similar to that in Figure 1 can be created, replacing AVA by the relevant data type.

CONCLUSION

We propose an approach to assess the AVA detectability of subsurface reservoirs as a key component of the overall site monitorability based on the results of laboratory measurements and the use of seismic amplitude variation with offset/angle (AVO/AVA) data. We developed the approach within the framework of assessing the detectability of injected supercritical $S_{CO_2}$, where CO$_2$ is to be stored in saline aquifer reservoirs, as a part of the storage-site selection process. We show that, although laboratory measurements on the reservoir and caprock samples under different saturations and pressures provide valuable information, further site-specific data such as well-logs are necessary in order to represent local site geology and to have a reliable estimate of site monitorability. We introduce a new set of robust time-lapse attributes based on time–frequency decomposition to quantify the changes in the seismic records due to the changes in the reservoir fluids. We apply the proposed approach to assess the detectability of the CASSEM project analogue CO$_2$ storage sites in the near-shore UK North Sea in the Firth of Forth region (Forth site) and the York–Lincolnshire region (Lincs site). This result highlights the importance of performing waveform modelling that includes local geological heterogeneities above and below the reservoir interval rather than using only petrophysical relations to predict reflection amplitudes from the top of the reservoir. The latter approach can give quite misleading results. Overall, expected time-lapse changes using the new time-lapse attributes for CO$_2$-injection scenarios indicate more reliable time-lapse detectability and repeatability for the Lincs site than for the Forth site.

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APPENDIX

Any signal in the time domain \( s(t) \) can be represented by its time–frequency representation \( W(t, f) \), which is calculated by a continuous wavelet transform (CWT):

\[
W(t, f) = \int s(\tau) \overline{\psi}(\tau - t) \exp(-j2\pi f \tau) \, d\tau
\]

where \( \overline{\psi}(\tau) \) is a scaled (by \( a = \omega_0 / 2\pi f \)) and translated (by \( t = b \)) version of some function such as a Morlet wavelet that has zero amplitude at negative frequencies:

\[
\psi(t) = \frac{1}{\sqrt{2\pi}} \exp(-i\omega_0 t) \exp\left(-\frac{t^2}{2}\right).
\]

Here \( t \) and \( f \) represent time and frequency, respectively, the asterisk indicates complex conjugation, and the parameter \( \omega_0 > 5 \) allows a trade-off between time and frequency resolution (e.g. Vetterli & Kovacevic, 1995).

REFERENCES


Novel time-lapse AVA attributes


