Assessing Monitorability of CO_2 saturation in subsurface aquifers

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Summary

We investigate the geophysical monitorability of injected supercritical CO_2 stored in subsurface saline aquifers. We use available petrophysical models to predict the effect of supercritical CO_2 on formation density, P- and S-wave velocities and attenuation, and electrical resistivity. We use Shannon's information measure to quantify the information expected to be obtained from different Geophysical monitoring methods. Our results show that expected information is generally nonlinearly related to the level of uncertainty in the geophysical parameters, to the CO_2 saturation, and in the case of seismic measurements to the measurement frequency. We show that seismic attenuation contributes greatly to the overall information obtained, and that adding together information from different geophysical parameters and methods can significantly improve monitorability and accuracy of CO_2 saturation estimates.

Introduction

The process of injecting carbon dioxide (CO_2) into deep subsurface aquifers may be an important method to reduce atmospheric emissions of CO_2. In order to reduce risks associated with the stored CO_2, geophysical monitoring is generally required. Any geophysical monitoring technique employed must be able to detect where a certain minimum threshold volume or saturation of CO_2 has been exceeded in a subsurface reservoir or after leakage into the overburden, but also to monitor the saturation (hence volume) of CO_2 within some predefined or characteristic spatial volume, and with some minimum degree of accuracy. Defining these minimum thresholds is equivalent to defining the term "monitorable", as applied to a particular storage site.

In this paper we investigate the monitorability of changes in petrophysical parameters of aquifer reservoir rocks in order to estimate the CO_2 saturation (S_{CO2}) using a Monte Carlo inversion approach. Sambridge and Mosegaard (2002) reviewed the theory and application of Monte Carlo methods in geophysical inverse problems, and recently Monte Carlo inversion has been widely used for describing hydrocarbon reservoir parameters (e.g., Bosch et al., 2007; Chen et al., 2007; Chen and Dickens, 2009).

Whether or not monitorability requirements can be met depends essentially on the geology and geography of the storage site. The geology dictates the magnitude of signal that is in principle measurable given any injection scenario, while geography limits the range of applicable geophysical methods. The process of estimation of reservoir parameters generally consists of a series of geophysical and petrophysical inversions (Figure 1). In this paper we focus on the petrophysical inversion component.

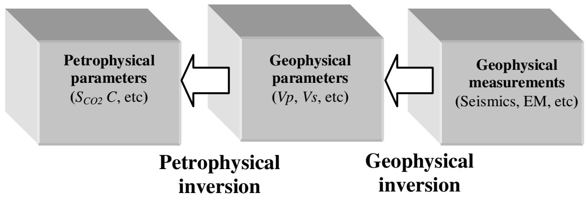

Figure 1: Model parameters and data spaces included in the series of inversions to estimate reservoir saturations.

For a petrophysical parameter to be monitorable we must be able to detect changes in it, and estimate its magnitude. Since detectability of petrophysical changes with geophysical methods is strongly site-dependent, instead of examining a large number of site conditions and reservoir situations, we introduce levels of uncertainties in geophysical parameters to represent the uncertainty due to geophysical measurements and inversions.

We develop methods to estimate expected uncertainties in the inversion for key petrophysical parameters that assist in operational decision-making, given various qualities of Geophysical parameter estimates. This in turn identifies key contributions to uncertainty and allows an appropriate selection of targeted geophysical monitoring technique(s) to reduce overall uncertainty on petrophysical parameters.

Monte Carlo inversion of petrophysical properties

In this section we investigate uncertainty in the estimation of S_{CO2} from Monte Carlo inversion of density, P- and S-wave velocities and attenuation, and electrical resistivity (ρ, V_P, V_S, Q_P, Q_S, and r, respectively). Assumed, typical uncertainties in petrophysical parameters are translated into uncertainties in the inverted reservoir parameters.

We begin by calculating petrophysical parameters corresponding to a reservoir rock with 24.6% porosity and 5% clay content and the material parameters given in Table 1 for a range of S_{CO2} (1%-99%). Bulk modulus, density and viscosity of the supercritical CO_2 correspond to a temperature of 38 ^oC and pressure of 10 MPa which may be considered representative of expected storage aquifers. Brine salinity is chosen to be 50 ppt. To calculate elastic bulk and shear moduli and density we use the model proposed by Carcione et al. (2000) and Pham et al. (2002)

for clay-bearing sandstones; to calculate electrical resistivity we use Pride's (1994) model. From hereon we assume that errors in the petrophysical models are negligible. In this work we have held all petrophysical parameters other than S_{CO2} constant (i.e., we ignore changes in the rock matrix due to CO_2 injection), but this constraint may be relaxed.

Table 1: Material parameters of clay bearing sandstone and the pore fluids it contains.

Sand	Bulk modulus	39 GPa
	Shear modulus	33 GPa
	Density	2650 km/m^3
	Average particle diameter	100 μm
Clay	Bulk modulus	25 GPa
	Shear modulus	9 GPa
	Density	2650 km/m^3
	Average particle diameter	2 μm
Brine	Bulk modulus	2.4 GPa
	Density	1030 kg/m^3
	Viscosity	1.798 cP
CO_2	Bulk modulus	0.057 GPa
	Density	667 kg/m^3
	Viscosity	0.052 cP

In partially saturated rocks the bulk modulus depends not only on the degree of saturation, but also on the microscopic characterization of saturation. Patchy saturation and uniform saturation are considered as extreme cases (Mavko et al., 1998). Whether one should apply patchy or uniform saturation to describe fluid heterogeneity depends on the frequency of interest. Essentially if the wavelength of the seismic wave is much longer than the size of CO_2 patches, the uniform saturation model can be used. We calculate P- and S-wave velocities and attenuation of the reservoir rock for three frequencies of $5\text{x}10^1$ Hz, $5\text{x}10^3$ Hz and $5\text{x}10^5$ Hz, representing seismic, sonic and ultrasonic frequency ranges, respectively.

In a Bayesian framework the solution to an inverse problem is represented by a posterior probability distribution function (*pdf*), $\sigma(\mathbf{m})$, over the model parameter space and is related to the prior pdf $\rho(\mathbf{m})$ through

$$\sigma(\mathbf{m}) = const.L(\mathbf{m})\rho(\mathbf{m}), \tag{1}$$

where $L(\mathbf{m})$ is the likelihood function and is defined to be Gaussian in the difference between observed data d^i_{obs} and calculated (predicted) data $d^i(\mathbf{m})$:

$$L^i(\mathbf{m}) = \frac{1}{\sqrt{2\pi\sigma^i}}\exp\left[-\left(\frac{d^i_{\text{obs}} - d^i(\mathbf{m})}{\sigma^i}\right)^2\right], \tag{2}$$

where σ^i is the standard deviation of uncertainty in observed data.

In equation (2), superscript i=1,…,6 refers to each of the geophysical parameters $\{\rho, V_P, V_S, Q_P, Q_S, r\}$.

To obtain Monte Carlo samples of the posterior pdf we use the Metropolis-Hastings method, a Markov Chain Monte Carlo algorithm with a Gibbs sampler (e.g., Sambridge and Mosegaard, 2002). We assume a uniform prior pdf for S_{CO2} in the range 0%-100%. We randomly sample the prior distribution 5000 times and use the Metropolis-Hastings algorithm to sub-select samples of the posterior distribution.

Information quantification

The state of knowledge about any random or uncertain parameter that is described by a pdf may be quantified by using an information measure (Lindley, 1956). In designing any monitoring strategy we wish to maximize the obtained information about the parameter S_{CO2}. Shannon (1948) introduced a unique, linear measure of information, which is related to the entropy of any p.d.f. *f(x)* by

$$I\{f(\mathbf{x})\} = -Ent(\mathbf{x}) + c = \int_{\mathbf{x}} f(\mathbf{x})\log\{f(\mathbf{x})\}d\mathbf{x} + c\ , \tag{3}$$

Here I is the information measure as defined by Shannon (1948), *Ent* is the entropy function, *f(x)* is the pdf of the random variable **x**, and c is a constant. In a Bayesian inverse problem, information about a parameter is maximised when its pdf constrains its range of values most tightly (Lindley, 1956). Shannon's entropy has been widely used in experimental design theory and applications (e.g., Sebastiani and Henry, 2000; van den Berg et al, 2003; Guest and Curtis, 2009). We assess information in the posterior pdf to assess the quality of information about parameters **m**:

$$I\{\sigma(\mathbf{m})\} \approx -Ent(\mathbf{m}) = \sum \sigma(\mathbf{m})\log\{\sigma(\mathbf{m})\}. \tag{4}$$

To calculate the information we first normalize histograms of the samples of the posterior pdf to have unit volume, whereafter they represent a numerical approximation to the posterior pdf. We use these discrete histogram values to calculate I in equation 4.

Figure 2 shows the posterior histograms of inverted S_{CO2} from *Vp* (top row) at the lowest frequency ($5\text{x}10^1$ Hz) with three values of uncertainties in *Vp* (0.5%, 1%, and 3%) and their corresponding calculated information I (bottom row), both plotted against true S_{CO2}. Increased uncertainty in the geophysical parameter increases the uncertainty, and decreases the information obtained in the posterior pdf, as expected intuitively.

Figure 3 shows the information in the posterior distribution of S_{CO2} inverted individually from *Vp*, *Vs*, *Qp*, and *Qs* estimates at three different frequencies, and for 1% uncertainty in the geophysical parameters. Even though in the case of *Vp* the inversion results give more information with increasing frequency, this increase is not linear. This implies that in any extension of the results of laboratory measurements (high-frequency) to field measurements (low- and intermediate-frequency) the nonlinear effect of frequency scaling must be taken into account.

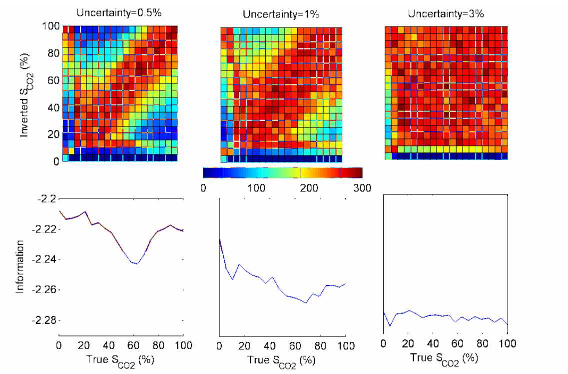

Figure 2: Posterior histograms (top row) and information values (bottom row) for *Vp* as a function of S_{CO2} with 0.5%, 1%, and 3% uncertainty and f=5x10^1 (Hz).

At the intermediate frequency (5x10^3 Hz), *Vp* gives the maximum information over the range of S_{CO2}=30%-80. The information curve from *Qp* has two large peaks at S_{CO2}<15% and S_{CO2}>85%. The information curves from *Vs* show little sensitivity to frequency and give more information at the low and high S_{CO2} than at the intermediate S_{CO2}. While at the low frequency *Qs* provides very little information, at the higher frequencies it presents high levels of information. At the intermediate frequency *Qs* produces the maximum information at S_{CO2}>80%. At the high frequency (5x10^5 Hz) there are two clear peaks around S_{CO2}=20% and S_{CO2}=80% on the *Qs* information curve. These patterns are thus rather complicated.

Figure 4 illustrates variation of the P- and S-wave velocities and attenuation against S_{CO2} and frequency that help to explain the information curves in Figure 3. Figure 4 agrees qualitatively with similar plots of Pham et al. (2002) calculated for partial water saturation (i.e., both water and air in pore spaces). The gradient of *Vp* with respect to S_{CO2} increases with increasing frequency, so S_{CO2} can be better discriminated at high frequencies and hence information increases with frequency in Figure 3. However, the gradient of *Vs* with respect to S_{CO2} does not change with frequency, so there is no similar information gain. The position of peaks on the *Qp* and *Qs* information curves in Figure 3 coincide with the position of peaks of the 1000/*Qp* and 1000/*Qs* in Figure 4, respectively.

Figure 3 and 4 imply that in the case of seismic monitoring, the purpose of monitoring has a significant effect on the selection of appropriate monitoring methods. If the purpose of monitoring is to detect the presence of CO_2 in the storage formation, or to detect CO_2 migration or leakage into the surrounding rocks, measuring *Vp* with time-lapse reflection seismics with a low frequency content may be sufficient.

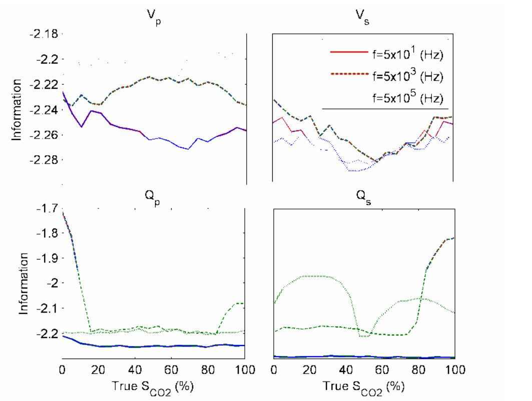

Figure 3: Information values for petrophysical parameters as a function of S_{CO2} at three different frequencies.

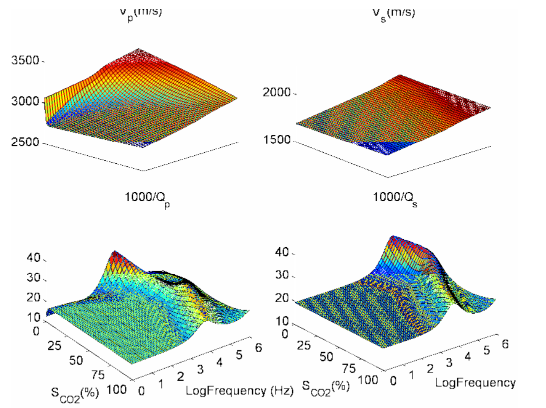

Figure 4: Variation of the P- and S-wave velocities and attenuation against S_{CO2} and frequency for a reservoir rock with properties given in Table 1. All horizontal axes are identical and colors reflect the height of each surface.

However, if the purpose of monitoring is to evaluate S_{CO2} in the brine, measuring only *Vp* with time-lapse reflection seismics is not enough and measuring other parameters such as attenuation (e.g., Chapman et al., 2006) as well as other geophysical methods such as sonic logging or cross-well methods may have to be applied.

Figure 5 shows the posterior histograms of the inverted S_{CO2} from the density and electrical resistivity (top rows) and their calculated information (bottom row), all plotted against the true S_{CO2}. Since localizing density and electrical resistivity changes in the field is difficult, we assume a 3% uncertainty in their values and note that this could be much higher in some cases. The density information curve indicates lower information is obtained at intermediate S_{CO2}. Compared with the other geophysical parameters the information curve from electrical resistivity presents far higher values. This shows that electrical resistivity has potential to aid S_{CO2} monitoring, provided it can be estimated reasonably accurately. The negligible sensitivity of electrical resistivity to the frequency of measurement over the frequency range of interest in geophysics may also be an advantage. Joint inversion of electrical resistivity and elastic parameters may significantly reduce the uncertainty in inversion results and improve monitoring capability.

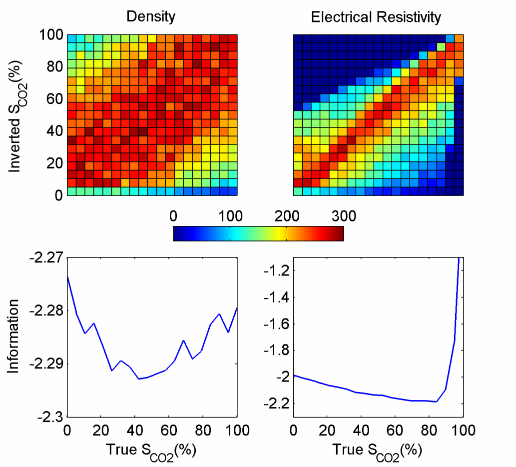

Figure 5: Posterior histograms (top row) and information values (bottom row) for the inversion of density and electrical resistivity with 3% uncertainty, as a function of true S_{CO2}.

In practice, it is common to invert P- and S-wave impedances (IP and IS, respectively). Figure 6 shows the Monte Carlo results for inversion of IP and IS at the low frequency. In this case inversion of IP gives better result than the Vp (Figure 2) and the obtained information at higher S_{CO2} (>50%) is much improved.

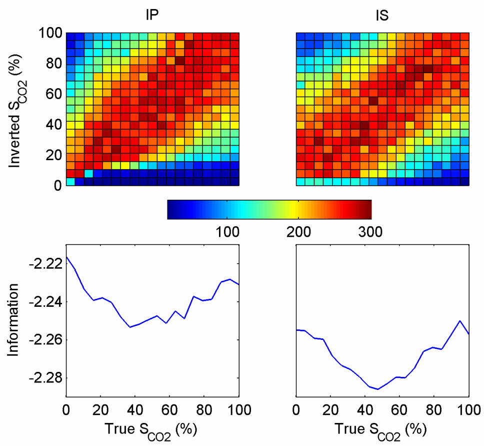

Figure 6: Posterior histograms (top row) and information values (bottom row) for the inversion of IP and IS with 1% uncertainty and f=5X10^1 (Hz), as a function of true S_{CO2}.

Generally, we conclude that Shannon information is a good measure of the expected quality of petrophysical inversions of Geophysical parameters for S_{CO2}. It will allow suites of Geophysical measurements to be selected that maximize information, thus also minimizing uncertainty in S_{CO2}.

Conclusions

We develop a Monte Carlo inversion scheme to assess the monitorability of the changes in the petrophysical parameters of the aquifer reservoirs due to supercritical CO_2 injection. We use Shannon information to quantify the obtained information in the posterior distributions. Our results show that the monitorability of S_{CO2} is strongly dependent on the level of Geophysical uncertainty, and on the true value of S_{CO2}. In the case of seismic measurements it is also dependent on the frequency of measurements. We show that seismic attenuation may contribute significantly to the overall obtained information.

Selecting an appropriate geophysical monitoring method depends on the purpose of monitoring. We indicate that combining different geophysical parameters and methods (seismics and non-seismics) may significantly increase the overall information obtained, improving monitorability and quantification of S_{CO2} in aquifer reservoirs. The Shannon information is a good criterion to select an optimal suite of Geophysical monitoring methods.

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