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An Improved Strategy to Detect CO₂ Leakage for Verification of Geologic Carbon Sequestration

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Introduction

While the purpose of geologic carbon sequestration is to trap CO₂ underground, the potential exists for CO₂ to leak from the storage site along permeable pathways such as well bores or faults and pass from the subsurface to the atmosphere. Although numerous technologies are available to measure near-surface CO₂, leakage detection and storage verification may be challenging due to the large variation in natural background CO₂ fluxes and concentrations, within which a potentially small CO₂ anomaly may be hidden. We present a strategy that integrates near-surface measurements of CO₂ with statistical analysis to enhance properties of the data associated with leakage, while reducing random background contributions [Lewicki et al., 2005]. Using a suite of synthetic CO₂ flux data sets and simulated CO₂ surface leakage, we investigate combinations of sampling and analysis approaches to optimize leakage detection and quantification while minimizing the number of measurements.

Methodology and Results

The algorithm used to detect and quantify leakage consists of a filter that highlights spatial coherence in CO₂ leakage, and temporal averaging that reduces noise from temporally uncorrelated background fluxes [Lewicki et al., 2005]. To highlight spatial coherence, we progressively move a Gaussian weighting function over a regularly spaced grid, and calculate the weighted average of all measured points according to their distance from the specified grid point. To reduce temporally uncorrelated noise, we either (1) average repeated measurements at each sampling location, then apply the Gaussian weighting function, or (2) average flux values at each grid point interpolated using the Gaussian weighting function based on repeated measurements at each sample location.

To test different sampling and processing combinations, we created a suite of synthetic data sets in which surface CO₂ leakage was treated as either a two-dimensional scaled Gaussian distribution or was created with a numerical simulator (TOUGH2/T2CA) as the CO₂ signal associated with leakage along a well bore or a fault. In all cases, background biological noise was added to the surface CO₂ leakage and surrounding area (10⁶ m²) using a lognormal CO₂ flux distribution measured using the accumulation chamber method in central California. These data were adjusted to remove diurnal fluctuations and then the mean, F_B , and standard deviation were calculated (= 8.7 and 6.7 g m⁻² d⁻¹, respectively). Thus, modeled background

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fluxes represent the case in which temporal correlation has been removed. To model re-measurement of fluxes over time, a new realization of the background synthetic data set was repeatedly drawn from the distribution and superimposed on the leakage.

Using synthetic data sets, we explored a range of sampling and processing strategies. In each, we sampled 100 CO₂ fluxes from the underlying synthetic data set. Strategy success was judged based on the fraction misestimation (f_{ME}) of the total CO₂ leakage rate ($= \sqrt{(\text{ImposedLeakageRate} - \text{CalculatedLeakageRate})^2 / \text{ImposedLeakageRate}}$), where the leakage rate is the spatially integrated leakage flux of the synthetic source. In the most successful strategy, fluxes were randomly sampled in space and were re-randomized during each re-sampling, Gaussian filtering was applied to each data set, and fluxes at each interpolated grid point were temporally averaged.

We varied the number of repeat sampling campaigns ($= 10, 50, 100, 200,$ and 360) for scaled Gaussian distributions of leakage with $R/L = 0.01, 0.1,$ and 0.5 ($R =$ Gaussian length scale, $L =$ model domain length in x and y directions $= 1000$ m), while holding F_S/F_B constant ($= 1$, where F_S is maximum surface CO₂ leakage flux) (Figure 1a). These R/L values correspond to ratios of the synthetic leakage signal area (A_S) to the total area of the model domain ($A_T = 10^6$ m²) of $3.14 \times 10^{-4}, 3.14 \times 10^{-2},$ and 0.785 .

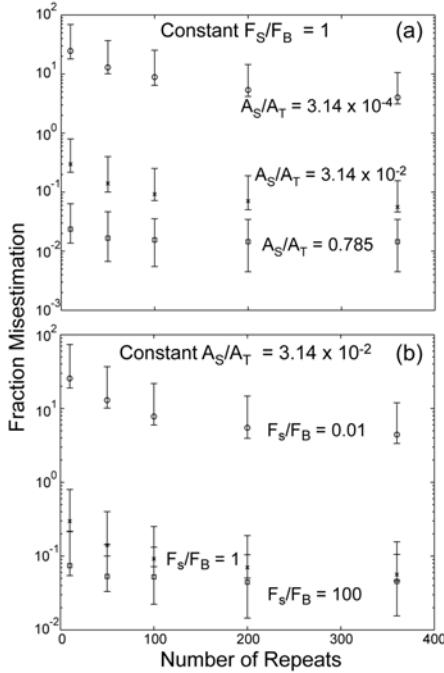


Figure 1. Fraction misestimation (f_{ME}) versus number of repeat sampling campaigns for (a) $A_S/A_T = 3.14 \times 10^{-4}$ (circles), 3.14×10^{-2} (x's), and 0.785 (squares) and constant $F_S/F_B (= 1)$ and (b) $F_S/F_B = 0.01$ (circles), 1 (x's), and 100 (squares) and constant $A_S/A_T (= 3.14 \times 10^{-2})$.

To estimate the distribution of f_{ME} for each case, we performed 100 Monte Carlo realizations of each number of sampling campaigns. The mean and 68% lower and upper bounds of f_{ME} are plotted in Figures 1 and 2.

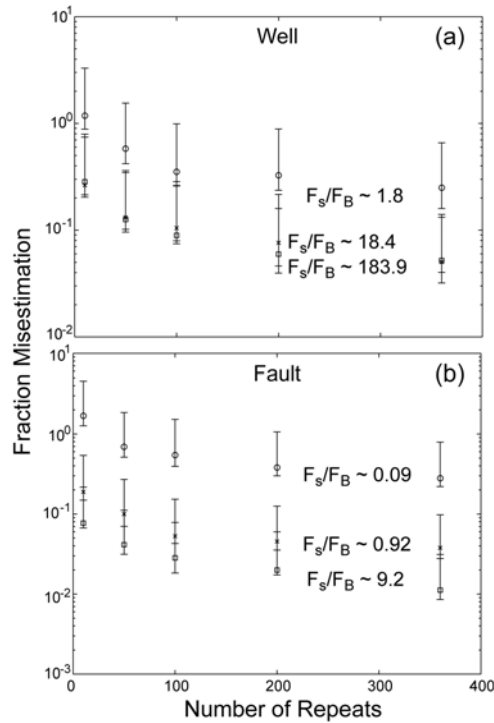


Figure 2. Fraction misestimation (f_{ME}) versus number of repeat sampling campaigns for (a) well scenarios where $F_S/F_B \sim 1.8$ (circles), 18.4 (x's), and 184.9 (squares) and $A_S/A_T \sim 4.34 \times 10^{-2}$ and (b) fault scenarios where $F_S/F_B \sim 0.09$ (circles), 0.92 (x's), and 9.2 (squares) and $A_S/A_T \sim 0.161$.

We modeled two possible leakage scenarios: (1) an abandoned well transports CO₂ from a deep storage reservoir to the vadose zone and (2) a buried fault transports CO₂ to the vadose zone. A CO₂ source was specified in either the fault (linear, 10 x 1000 m) or well (point, 1 x 1 m) geometry at an arbitrary depth of -27.1 m in a three-dimensional vadose zone with surface area = 10⁶ m². Low, medium, and high source leakage fluxes for the well (3.8 x 10⁴, 3.8 x 10⁵, and 3.8 x 10⁶ g m⁻²d⁻¹, respectively) and fault (3.8, 38, and 380 g m⁻²d⁻¹, respectively) scenarios were chosen to generate F_S values over a range of CO₂ fluxes observed in nature, in order to assess a range of f_{ME} values for the two scenarios. The surface leakage fluxes result from upward and lateral CO₂ advection, diffusion, and interaction with vadose zone pore water and are calculated at $t = 100$ y of model time. F_S values corresponding to low, medium, and high leakage fluxes for well simulations are ~16, 160, and 1600 g m⁻²d⁻¹ ($F_S/F_B \sim 1.8, 18.4, 183.9$), and for fault simulations are ~0.8, 8, and 80 g m⁻²d⁻¹ ($F_S/F_B \sim 0.09, 0.92, 9.2$). Results of repeated sampling campaigns are summarized in Figure 2.

Conclusions

For a given number of sampling campaigns, f_{ME} is sensitive to both F_S/F_B and A_S/A_T . If we conservatively assume that f_{ME} values ≤ 0.5 represent leakage anomalies detectable within a reasonable error and values > 0.5 are “undetectable” anomalies, we can make the following statements. (1) Leakage with $F_S/F_B = 1$ is detectable with only 10 sampling campaigns when $A_S/A_T \geq 3.14 \times 10^{-2}$, but for smaller $A_S/A_T = 3.14 \times 10^{-4}$ is undetectable with up to 360 campaigns. (2) Leakage with $A_S/A_T = 3.14 \times 10^{-2}$ is detectable with only 10 sampling campaigns when $F_S/F_B \geq 1$, but for smaller $F_S/F_B = 0.01$ is undetectable with up to 360 campaigns. (3) Simulated surface leakage resulting from CO₂ leakage from an abandoned

well with $A_S/A_T \sim 4.34 \times 10^{-2}$ and $F_S/F_B \geq 18.4$ is detectable with only 10 sampling campaigns; but leakage with smaller $F_S/F_B = 1.8$ requires at least 100 repeats. (4) Simulated surface leakage resulting from CO₂ leakage from a buried fault with $A_S/A_T \sim 0.161$ and $F_S/F_B \geq 0.92$ is detectable with only 10 sampling campaigns; but leakage with smaller $F_S/F_B = 0.09$ requires at least 200 repeats. Due to the relatively high A_S/A_T of simulated leakage anomalies associated with the fault source, it is possible to detect anomalies with low F_S with a reasonable number of samples. This emphasizes the importance of maximizing A_S/A_T in studies where seepage fluxes could have F_S within the background variability of CO₂ flux or could have small A_S (e.g., wells, mostly sealed faults/fractures).

In summary, our strategy provides a simple means to locate and quantify potentially small CO₂ leakage derived from geologic storage reservoirs within natural background variability. If leakage is detected, then further geophysical, geochemical, and reservoir management techniques can be applied to locate and mitigate the leak. Assumptions, limitations, and further implications of our method for verification of geologic carbon sequestration will be discussed.

References

Lewicki J.L., G.E. Hilley, and C.M. Oldenburg, 2005: An improved strategy to detect CO₂ leakage for verification of geologic carbon sequestration. *Geophysical Research Letters*, in press.