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Reducing Risk in Basin Scale Sequestration: A Bayesian Model Selection Framework for Improving Detection

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Abstract

Geological CO_2 sequestration is a key technology for mitigating atmospheric greenhouse gas concentrations while providing low carbon energy. Deployment of sequestration at scales necessary for a material contribution to greenhouse gas mitigation poses a number of challenges not encountered in current operations. At the basin scale, injection sites will not be as well characterized as current operations. Predictions of system response to this magnitude of injection are expected to have greater uncertainty and risk. Through an integrated, model based design and assimilation, monitoring provides a platform for mitigating the associated risks. Because footprints of basin scale injection projects are expected to be very large, the high resolution monitoring programs in existing projects are not economically feasible for monitoring at large scales. The acceptable levels of resolution and risk are dependent on the footprint of the network and the monitoring technique employed, which are in turn, constrained by cost of deployment and regulatory requirements.

Network design must make an implicit assumption on the size of the leak that is able to be measured. Leak detection at the surface is complicated by the many natural and anthropogenic sources of CO_2 that can mask a leak or result in the incorrect assessment of whether a leak has occurred. In this paper, we introduce a Bayesian framework for decision support in discriminating between CO_2 detected from a leak and CO_2 measured from background fluctuations. For small leakage concentrations, the signal cannot be distinguished from background fluctuations. When complementary observations are jointly considered, the ability to discriminate between a leakage and background concentrations improves, and the number of samples required for confident detection decreases. Incorporation of Bayesian decision support tools into monitoring programs will assist in reducing risk in geological sequestration in a cost effective manner by providing a framework for efficient integration of complementary observations and enhancing the information content of the network.

Keywords: integrated monitoring, basin scale, leakage detectection, Bayesian model selection

1. Introduction

Rising concentrations of atmospheric CO_2, largely attributed to the combustion of fossil fuels, are a concern because of their potential impact on global climate change. CO_2 sequestration is an attractive option for mitigating

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climate change because it can be deployed immediately and at scale, with little disruption to existing energy production and distribution infrastructure. For geological sequestration to make a meaningful contribution in reducing CO_2 concentrations, injection volumes must be on the order of Gigatonnes per year, corresponding to a hundred fold increase in the scale of existing injection operations. Increasing the magnitude of future operations far beyond our current knowledge base raises concerns of safety and security of geological sequestration.

Monitoring and verification are key components in managing risk. When models representing the physics of sequestration are used to design monitoring programs, an understanding of the uncertainty and potential systems interactions is gained and an appropriate mitigation plan can be formed. Observed data provides information about the system response, which can be used to calibrate models for more accurate prediction of future behavior. Comparison of observed data against simulation models provide confidence that the uncertainty in the system is characterized to a reasonable degree, and that the physics governing complex, nonlinear processes of sequestration are well understood. Assimilation of monitoring data with dynamical models allow for detection of anomalous behavior, serving as an early warning system and providing a mechanism to signal the need for intervention. In the event that a leak does occur, monitoring and verification provide a means for remediation through the ability to locate a leak.

A number of researchers have explored aspects of monitoring design [1-4]. However, issues of detection limits, limits of monitoring methods and what are acceptable rates of leakage have not been thoroughly explored. Moreover, there is no clear guideline on what is the acceptable leakage rate to safeguard the public and protect the environment. Detectable concentrations and the sensitivity of a monitoring network are functions of the monitoring technique, sensor density, frequency of measurement acquisition and cost of deployment [5]. This paper explores the challenges of monitoring at the basin scale and the difficulties encountered in detecting a leak at the surface. We focus on the problem of leak detection at the surface. A framework for detection based on Bayesian model selection theory is presented and applied to the problem of distinguishing whether detected CO_2 is from a leak or from background fluctuations. Cases from a single measurement site and from two simultaneously measured locations are used to demonstrate the power of Bayesian decision tools in assisting leak detection and data integration to improve detection limits.

2. The Need for Integrated Monitoring

Designing an effective scheme for monitoring CO_2 sequestration is not a trivial task. Technical issues such as determining whether a leak can be distinguished from background CO_2 levels, and the type and magnitude of leak that can be detected are intertwined with the cost of monitoring network. Incorporating risk into monitoring design requires a sound understanding the systems interactions, limitations of monitoring methods and instrumentation, and uncertainty in models and parameters employed.

Table 1 lists costs for a number of monitoring technologies. A high cost, high resolution method, such as seismic, is effective at tracking the movement of CO_2 in the subsurface with a relatively high degree of certainty, but the high cost precludes frequent measurements to provide the most up to date view of the state of the system. Low cost, low resolution methods, such as surface deformation, permit more frequent measurements, but have more uncertainty in the location of the CO_2 and whether the anomaly detected is real. The interval between measurements represents the minimum time that an anomaly could be detected. In the Sleipner project, repeat seismic surveys are performed at two year intervals, on average, whereas satellite based geodetic measurements, such as InSAR, can be acquired at bimonthly intervals. The size of the leak and the associated remediation costs would be much larger in the case of a seismic based monitoring program than an InSAR based program.

Designing a monitoring system for basin scale injection presents a number of challenges not encountered in present day operations. The large footprints of injection at the Gigatonne scale are expected to cover a variety of surface and subsurface environments, requiring integration of different monitoring techniques appropriate for each domain of the system, each having different scales of support, to provide a consistent view of the state of the system. Detection limits of a monitoring array are a function of the spatial density of the network. Implicit in the design is the level of uncertainty acceptable in detection. Techniques, such as flux chambers or fluid samples from observation wells, are point measurements which provide a high degree of certainty in the vicinity of measurement, but require a dense spatial sampling array to interpolate between measurements and characterize spatial variability of CO_2 concentrations. Methods, such as eddy covariance towers, have the ability to monitor large areas but provide an integrated measurement of the processes over the footprint area. Installation of permanent sensors may constrain future monitoring configurations later in the life of the project.

Observations from multiple types of complementary information can be jointly assimilated to constrain the solution and increase confidence in detecting a leak. Each type of monitoring data yields information about a particular attribute of the system at that scale. Integration of complementary data provides a more robust assessment of the state of the system, allowing for a more confident assessment of storage security. The task of designing a monitoring program can be recast as an optimization problem where different techniques and deployment configurations are selected to meet the goals of detection and balance the trade-offs between safety, cost and uncertainty.

Table 1: Costs for a selection of monitoring techniques. The small estimate represents the cost for monitoring a Sleipner sized area. The large estimate represents the cost for monitoring a basin scale project. The high resolution, intensive monitoring programs currently applied to existing sequestration projects are not economically feasible at the basin scale.

Technology	**Unit Cost**	**20 km^2 ($MM)**	**1000 km^2 ($MM)**
Seismic	$38,610/km^2 [6]	0.772	38.6
Observation well	$3,000,000/well (including logs) [7]	3	120 1 well/25 km^2)
Fluid sample and analysis	$200/sample [8]	0.000,8 (4 repeat samples/ well)	0.032
InSAR	$2,000-3,000/km^2 [9]	0.04-0.06	2-3
Eddy covariance tower	$25,000/tower [10]	3.9 (2 m tower height, 0.1 km2 flux footprint) 0.03 (30 m tower height, 28 km2 flux footprint)	250 (2 m tower height) 0.89 (30 m tower height)

3. Challenges of Leak Detection

Because of the large number of natural and anthropogenic sources of CO_2 at the surface, distinguishing a leak from background CO_2 concentrations is a challenging task. Natural fluctuations and instrument error result in a noisy signal which may mask the presence of a small leak. Figure 1 shows CO_2 measurements from the Ameriflux Harvard Forest site [11]. Large daily, seasonal and annual fluctuations make small, leak detection challenging. Overprinted on the data is a long term trend, which could be attributed to instrument drift or increasing atmospheric CO_2 concentrations. Well characterized baseline concentrations of CO_2 fluctuations at the site are essential for understanding the causes of variability and identifying anomalous concentrations of CO_2. Tracers co-injected with the CO_2 can remove ambiguity about the source [12], provided they propagate through the system at the same or greater velocity as the injected CO_2. Naturally occurring isotopes and concentrations of associated combustion species, such as CO, can be used to discriminate between atmospheric CO_2 concentration due to fossil fuels and CO_2 due to natural biogenic processes [13].

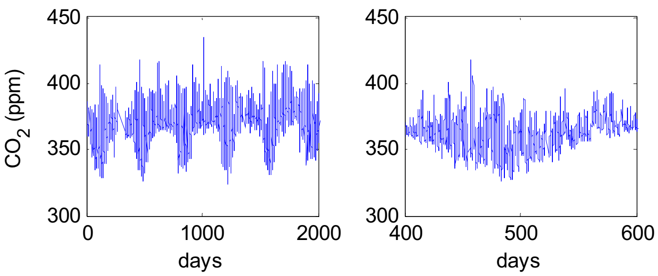

Figure 1: CO_2 measurements taken at the Ameriflux Harvard Forest site. The observed signal is subject to large natural fluctuations, gaps in continuity of measurements, instrument error and anthropogenic influences.

4. Bayesian Model Selection Applied to Leak Detection

Given the uncertainty in the system, if CO_2 fluctuations are well characterized, leak detection is an exercise in detecting a change in the statistics of the population of measurements. The presence of a leak will alter the statistics of the set of observations. Detecting a leak can be viewed as a model selection problem, where we need to choose between two competing theories: the presence of a leak (M_L) and the presence of no leak (M_{NL}), given an observed set of data (D). A schematic of the model selection problem is shown in Figure 2. The task is to select the model that best represents the distribution of observations.

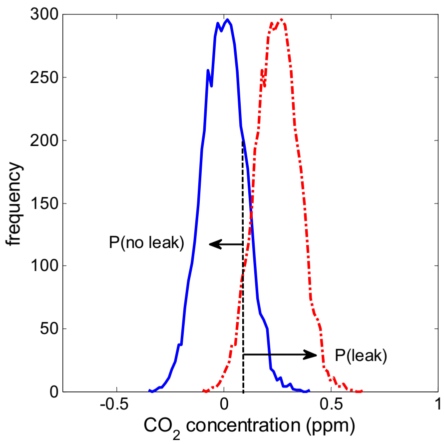

Figure 2: Schematic of the leak detection problem framed as an exercise in model discrimination. For small leakage concentrations, there is large overlap between the distributions and large ambiguity in discriminating which model is best described by the data. For large leakage concentrations, there is little overlap between distributions and less ambiguity regarding the distribution which best represents the observations.

Bayesian model selection provides a framework for determining which model is supported by the data [14]. This technique is widely used to support decision analysis in fields ranging from financial engineering to social science to biostatistics to atmospheric science. In this application, we use the Bayes factor, $B_{L,NL}$, to discriminate between the two models:

$$B_{L,NL} = \frac{P(D \mid M_L)}{P(D \mid M_{NL})} = \frac{\int P(\theta_L \mid M_L) P(D \mid \theta_L, M_L) d\theta_L}{\int P(\theta_{NL} \mid M_{NL}) P(D \mid \theta_{NL}, M_{NL}) d\theta_{NL}}, \tag{1}$$

where θ are the parameters for the respective models. Bayes factors provide a flexible framework for allowing us to combine prior and posterior information into a ratio indicative of evidence in favor of one model versus another. Table 2 summarizes the interpretation of the Bayes factor for decision support.

Table 2: Interpretation of Bayes factors, after Jeffreys [15].

B_{12}	**Strength of evidence**
< 1	Negative, supports M_2
1-3	Slight support for M_1
3-10	Substantial support for M_1
10-30	Strong support for M_1
30-100	Very strong support for M_1
> 100	Decisive support for M_1

Bayesian model comparison has a number of advantages over traditional hypothesis test methods. Because it considers the probability of possible value of parameters of interest, it can explicitly account for uncertainty in the model and parameters, and is not dependent on the parameters used by each model. There are no implicit assumptions on the distribution of the data, allowing flexibility to compare random variables characterized by complex, non-Gaussian distributions. It also guards against the problem of over fitting to the data, if one model has more complexity than the other. A disadvantage to Bayesian comparison is that it may be computationally intensive to obtain likelihoods if they are characterized by complex distributions. Additionally, prior distributions for the parameters for each model must be specified, and these may not be readily available.

4.1. Model Selection Applied to a Single Monitoring Site

The Bayesian selection framework was applied to investigate the ability to distinguish small leaks in a noisy signal. One year of CO_2 concentration data was extracted from the Harvard forest data set. The distributions for synthetic leaks of 0.1, 0.5, 1.0 and 5.0 ppm were created by adding those amounts to the data. Distributions of the models are shown in Figure 3a. Simulating a leak in this manner produces a translation of the probability distribution centered about a higher mean, while the variance remains the same. A set of observations were drawn from each leak concentration distribution and the likelihood of observations resulting from the leakage distribution were compared against the likelihood that the observations was drawn from the distribution representing the no leakage case. Figure 3b summarizes the ability to select the leakage model given observations at a single measurement site, using the Bayesian framework.

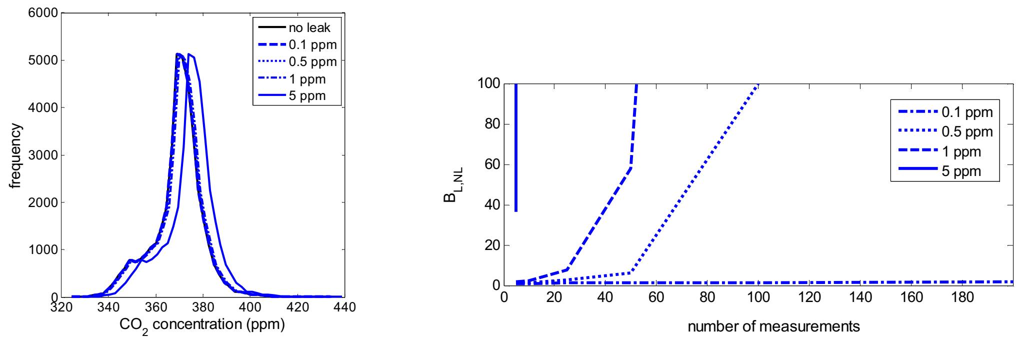

Figure 3: a) Model distributions of the 0.1, 0.5, 1 and 5 ppm leakage models to be compared. Distributions of the small leakage concentrations have a large overlap with the distribution of the background concentration. b) Summary of Bayes factors in support of the M_L. The 5 ppm leak has decisive support of M_L for measurement populations greater than 5.

With the exception of the 0.1 ppm leak, as the number of samples increase, support to determine if a leak is present in a noisy signal increases. Because the overlap between distributions decreases as the imposed leak is increased, there is a higher likelihood that a observations from a leakage signal will sample the distribution of the leakage model. Also, less observations are required to detect a leak for larger leakage signals. In the case of the 0.1 ppm leak, the distributions are very similar and there likelihood of samples representing the leakage distribution is similar to sampling the background signal distribution. Even with a large number of samples, it is not possible to confidently distinguish the model which best supports the observations when a small population is present.

4.2. Model Selection Applied to Two Monitoring Sites

In this section, we investigate the role that additional information and type of information have on the ability to improve model selection. We consider observations from two monitoring sites, which monitor different attributes of the process. A schematic of this scenario is shown in Figure 5. We consider a scenario where there is a known potential leakage pathway, such as an abandoned wellbore or fault located a distance from the injection site. Surface observations were taken 250 m downstream from the leakage location, and measurements of subsurface changes caused by potential CO_2 migration are taken at a location 100 m upstream of the leakage pathway. Estimates of plume thickness between observation wells are obtained through indirect geophysical measurements taken at the surface. These could be obtained through an inversion of the changes in seismic velocity or gravity components. Prior information, such as the direction of background flow in the regional aquifer and alignment of monitoring stations with the direction of flow, allows us to incorporate the physics of the process into the probability model.

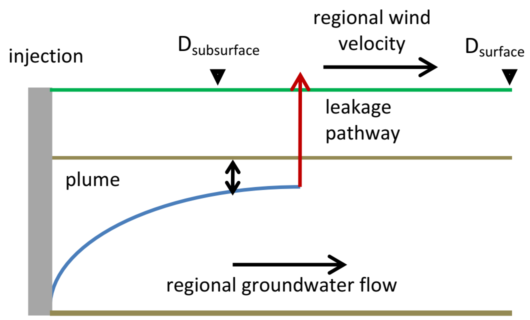

Figure 5: Schematic of two monitoring station case.

Analytical models coupling subsurface flow [16] and surface dispersion of CO_2 [17] were used to estimate joint probability distribution of surface and subsurface observations. The surface dispersion model was used to estimate the leakage rate given the specified downstream distance and distribution of the specified leakage signal to be detected. For the distribution of leakage rates given by the surface model, the subsurface model was used to calculate the distribution of plume thicknesses at the monitoring site. Model parameters for the subsurface and subsurface models are listed in Table A1 of the Appendix. Uncertainty in aquifer thickness and porosity of the subsurface model was also considered.

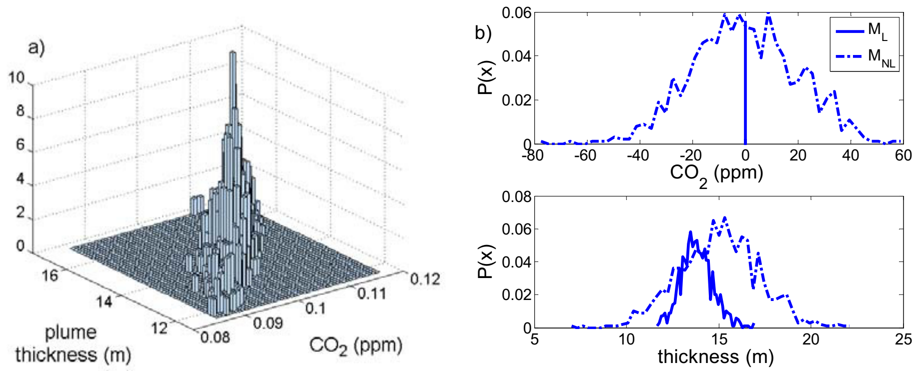

Figure 6: Distributions of surface and subsurface observations: a) Joint distribution for the correlated leakage case, b) Comparison of marginal distributions of concentration and plume thickness for the leakage and no leakage models. The marginal distributions of the leakage rate and plume thickness are obscured by the random noise. The correlated surface and subsurface measurements constrain the joint distribution of observations, providing intrinsic support for M_L.

Distributions for the correlated and uncorrelated models are shown in Figure 6. For case with no leakage, surface and subsurface measurements were assumed uncorrelated. The subsurface set of measurements for the case of no leakage is obtained by applying a Gaussian noise distribution about the mean calculated plume thickness, consistent with the error associated with the monitoring method (standard deviation of high precision field gravimetry: +/- 0.030 mGal [18]). The set of surface concentration observations was constructed from a Gaussian noise model with the same magnitude of standard deviation as the single monitoring station case. Leakage of 0.1 ppm and 0.5 ppm were considered. Bayes factors comparing observations taken at two sites are summarized in Table 4.

When another observation point is considered in the analysis, the number of observations required to support a proposed model is significantly reduced. Even with the overprinting of the noise on the leakage signals, prior knowledge of the correlation between the observed data points provided by the coupled transport model, constrains the distribution of possible observations. This allows for a more confident differentiation of a leak from a noisy signal and with fewer observations. Faster and more confident leak detection will result in a smaller volume of CO_2 released back into the atmosphere, potentially resulting in lower remediation costs to clean up the leak and loss of fewer carbon credits. Earlier detection of a leak also provides value by maintaining a greater number of available options for remediation at earlier stages, which may also be less disruptive. Moreover, the public perception in successfully remediating an anomaly early in the life of a leak will be less harsh than remediation interventions later in the life of a leak. The trade-off between quicker and less ambiguous leak detection must be weighed with the cost of operating the additional monitoring station, and the increased footprint of the monitoring program.

Table 4: Summary of Bayes factors for support of ML incorporating observations from to monitoring sites.

	5 samples	**10 samples**	**25 samples**
0.1 ppm leak	8.7	19.7	23.0
0.5 ppm leak	8.2	24.3	41.9

5. Conclusions

Designing a monitoring network at the basin scale presents challenges not encountered in current injection projects. Because of the large footprint expected of these operations, deployment of high resolution monitoring programs is not economically feasible. Trade-offs between the acceptable level of detection for a specified level of cost and acceptable risk must be made. A determination of the absolute acceptable leakage rate is required to design a monitoring program that safeguards the public and protects the environment.

Detection of a CO_2 at the surface is difficult due to the large variations of CO_2 in the atmosphere due to natural and anthropogenic processes, which can mask the signal of a low concentration leak. Bayes factors provide a powerful tool for assisting decisions of distinguishing whether low concentration leaks can be distinguished from background noise. Incorporation of prior information through an understanding of the underlying correlation between observations constraints the distribution of jointly observed data and improves the decision support for discriminating whether CO_2 measurement are due to background fluctuations or due to a leak. When measurements are integrated with additional observations, detection time can be dramatically reduced and the sensitivity of detection can be increased, allowing faster detection of smaller leakage rates from a noisy signal. Application of complementary data integration, mutual information and decision support tools should be considered when designing a robust monitoring network that reduces risk and ensures safe operation. Incorporating such a framework will allow cost effective integration of complementary methods, combining both high cost and low cost techniques.

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Appendix

Table A1: Summary of parameters used in the surface and subsurface analytical models.

Surface Dispersion Model	
A	0.315
N	1.5×10^{-5} m^2/s
u_*	0.087
K	0.4
M	0.685
Z	0.75 m
z_1	10 m

Subsurface Transport Model	
φ	0.2±0.05
μ_{CO2}	0.05×10^{-3} Pa s
μ_w	0.8×10^{-3} Pa s
ρ_{CO2}	400 kg/m^3
ρ_w	1000 kg/m^3
H	100 ± 5m
L	10 km
S_{gr}	0.3
S_{wc}	0.4
U	1 m/year
k	1×10^{-13} m^2