Optimal sensor placement and monitoring design in geologic CO2 sequestration: A machine learning and uncertainty quantification approach

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Abstract

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Introduction

Geologic CO2 sequestration (GCS) has emerged as an important technology to reduce anthropogenic greenhouse gas emissions to the atmosphere (Metz, 2005; Michael, et al., 2010). Different types of underground formations have been proposed to store CO2 emissions including oil and gas reservoirs, coal beds and seams, and deep saline aquifers (Placeholder1). The main concern in GCS projects is potential leakage of the CO2 through leakage pathways, such as improperly abandoned wells, faults, and fractures (Placeholder1). Such risks can pose a major threat to overlying resources (e.g., groundwater resources, oil and gas reservoirs, etc.) and human health (Placeholder1). Monitoring and verifying CO2 behavior within the subsurface reservoir are crucial for assessing storage capacity, detecting potential leakage, and evaluating environmental impacts (Placeholder1).

To ensure safe and efficient operations in a large-scale GCS site, risk management techniques are used to minimize and mitigate potential risks during CO2 injection and post-injection periods (Placeholder1). Monitoring is thus an important aspect of CGS risk management. Several monitoring techniques have been developed, including near surface CO2 flux and tracer measurements (Placeholder1), groundwater chemistry monitoring (Placeholder1), seismic surveying (Placeholder1), and pressure monitoring (Placeholder1).

Optimal sensor placement and monitoring design play a critical role in achieving accurate and efficient monitoring in GCS projects. Depending on the reservoir properties and heterogeneity, the placement of monitoring wells can provide a more accurate measurement of the injected CO2 plume and help mitigate potential leakage risks. In common CGS operations, each injection well is paired with one monitoring well, though large-scale projects often incorporate a larger number of monitoring wells. Moreover, the selection of monitoring measurement plays an important role in reducing uncertainties and quantifying risks in GCS operations. Therefore, it is crucial to define an optimal monitoring strategy in terms of both well placement and monitoring measurement type.

Recent advancement in monitoring systems such as smart or intelligent wells are capable of providing large amounts of data in terms of volume, velocity, variety, value, and veracity. Classical techniques in data processing and forecasting are sometimes hindered by big data, therefore machine learning provides a promising approach to enhance data-driven monitoring and quantification of large-scale GCS projects. Machine learning approaches, when combined with reduced-order modeling (ROM) techniques, enable efficient and accurate prediction of key parameters, including pressure distribution, CO2 plume migration, and reservoir behavior. By analyzing extensive datasets, machine learning algorithms can uncover complex latent patterns and relationships that may not be discernible through traditional methods. These insights facilitate the optimization of sensor placement and monitoring strategies, enabling better decision making in GCS projects.

Accurately quantifying uncertainties is vital for the reliability of predictions and optimizing monitoring design under uncertain conditions. Uncertainty quantification is particularly important in GCS due to inherent complexities and variabilities associated with subsurface conditions, fluid flow, and measurement errors. Markov Chain Monte Carlo (MCMC) filter-based approaches provide a robust framework for characterizing uncertainties associated with reservoir properties, operating conditions, and measurement errors. Leveraging MCMC techniques allows for informed risk assessment, ensuring the safety and efficiency of GCS projects.

Numerous research endeavors have been dedicated to addressing monitoring design, sensor placement, and uncertainty quantification in GCS. Previous studies have explored various modeling techniques, simulation frameworks, and optimization algorithms to enhance monitoring strategies and improve forecasting. These investigations have focused on different aspects, such as multi-objective optimization, real-time monitoring, and adaptive sampling strategies. In this paper, we build upon the work of Chen et al. (2018) to systematically design an optimal monitoring placement and measurement strategy for large-scale GCS.

We propose a novel method for optimal sensor placement and monitoring design in GCS, leveraging a ROM-based predictive model and a filter-based data assimilation approach to select the most informative monitoring well location and measurement type in order to reduce uncertainties and CO2 leakage risks. By integrating machine learning techniques, uncertainty quantification methods, and optimization algorithms, we aim to enhance the efficiency, accuracy, and reliability of monitoring systems in GCS projects.

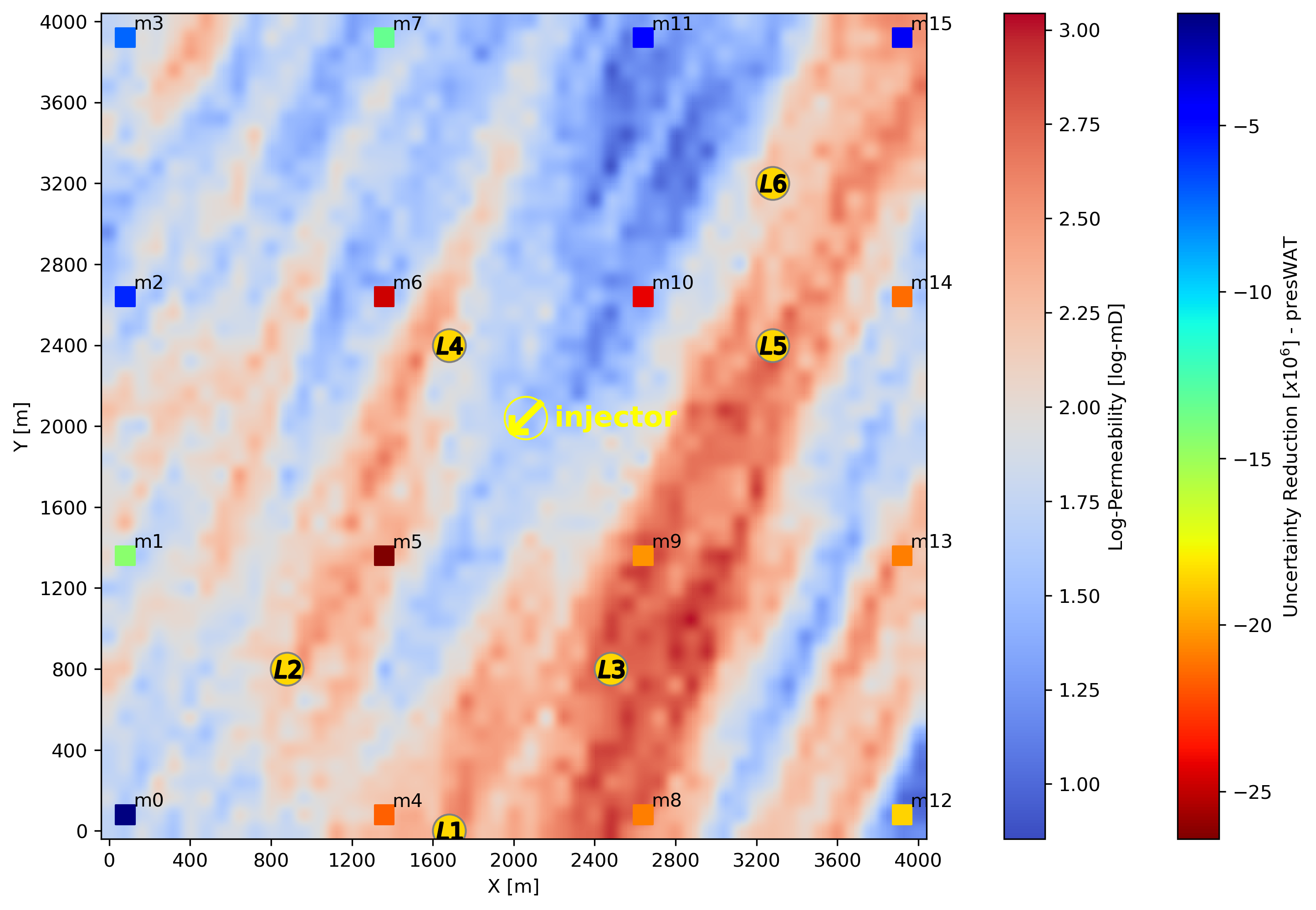
The structure of this paper is as follows: Section 2 present our methodology, Section 3 presents the results of our approach for two synthetic cases, and Section 4 summarizes our findings, discusses their implications, and outlines potential avenues for future research in the field of GCS.

Methodology

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Results

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**Figure 1: Log-permeability distribution for the uppermost layer of the ground truth model and four prior models (R1, R2, R3 and R4). The red dot indicates the location of the injection well. The four black dots are the locations of four monitoring wells.**

Conclusions

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# **References**

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