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.

*Traditional approaches often rely on intuition or simplified models, leading to suboptimal designs and limited insights into the underlying processes. To overcome these limitations, we propose a novel approach that leverages machine learning techniques and uncertainty quantification methods for optimal sensor placement and monitoring design.*

Machine learning techniques offer the ability to extract patterns and relationships from large datasets, facilitating the identification of informative monitoring locations within the reservoir. By training machine learning models on historical data and incorporating relevant geological and operational features, we can predict optimal sensor placements that capture key CO2 storage dynamics. This data-driven approach enhances our understanding of the subsurface processes and supports more informed decision-making.

Furthermore, uncertainty quantification techniques enable the assessment and management of uncertainties associated with geologic CO2 sequestration. Incorporating uncertainty quantification in sensor placement and monitoring design helps identify areas of high uncertainty, where additional measurements are needed to reduce uncertainties and improve the reliability of predictions. This approach provides a more comprehensive and reliable assessment of CO2 storage and enables the quantification of potential risks associated with leakage or subsurface reactions.

The primary objective of this paper is to present a machine learning and uncertainty quantification-based approach for optimal sensor placement and monitoring design in geologic CO2 sequestration. By integrating these advanced methodologies, we can overcome the limitations of traditional approaches and enhance the effectiveness of monitoring systems. The proposed approach has the potential to provide accurate and robust insights into CO2 storage dynamics, thereby improving our ability to evaluate and optimize geologic sequestration projects.

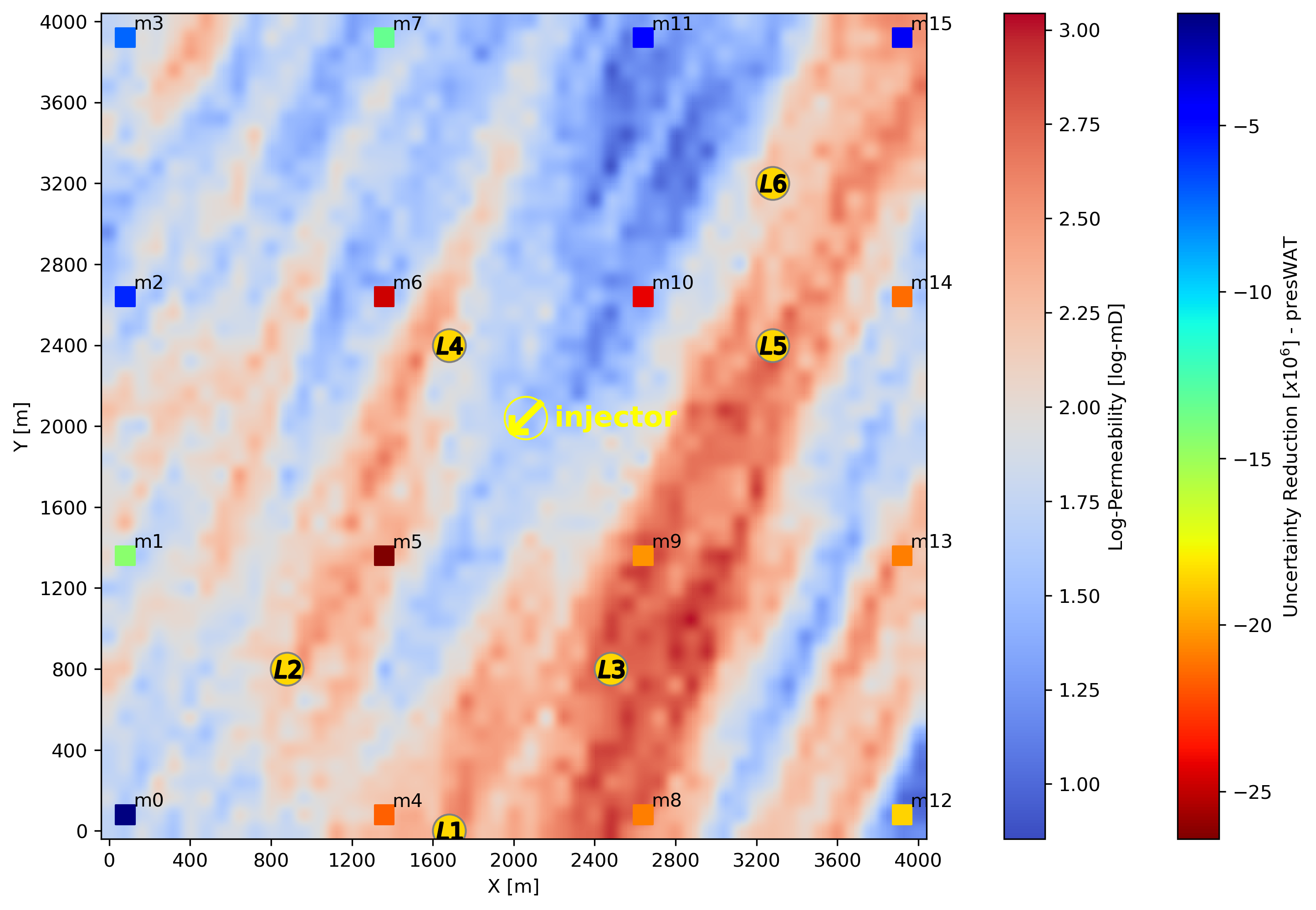
In conclusion, this paper introduces a novel approach for optimal sensor placement and monitoring design in geologic CO2 sequestration. By combining machine learning techniques and uncertainty quantification methods, we aim to enhance the effectiveness and efficiency of monitoring systems, providing robust insights into CO2 storage dynamics and addressing uncertainties associated with subsurface processes. The application of this approach has the potential to advance the field of geologic CO2 sequestration and contribute to sustainable climate change mitigation efforts.

Methodology

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Case Study and 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**

Metz, B. (2005). *Carbon dioxide capture and storage: special report of the intergovernmental panel on climate change.* Cambridge University Press.

Michael, K., Golab, A., Shulakova, V., Ennis-King, J., Allinson, G., Sharma, S., & al., e. (2010). Geological storage of CO2 in saline aquifers - a review of the experience from existing storage operations. *Int J Greenhouse Gas Control*, 4(4):659-67.

**INTRODUCTION V2**

The urgency of mitigating climate change has propelled the development of carbon capture, utilization, and storage (CCUS) techniques, with geologic CO2 sequestration emerging as a promising strategy to reduce atmospheric carbon dioxide levels. However, ensuring the long-term success and safety of CO2 sequestration projects requires robust monitoring systems capable of accurately detecting and quantifying potential leakage risks. To achieve effective monitoring in geologic CO2 sequestration, it is essential to employ optimal sensor placement and monitoring design strategies.

Optimal sensor placement and monitoring design play a pivotal role in detecting CO2 leakage, ensuring reservoir integrity, and minimizing environmental and human health hazards. These strategies involve the selection of sensor locations that can provide the most informative measurements for detecting potential leaks and monitoring the behavior of the CO2 plume. Additionally, designing an efficient monitoring system involves considerations such as the number and type of sensors, their sampling frequency, and the data analysis techniques to be employed.

In recent years, the integration of advanced machine learning techniques and uncertainty quantification methods has emerged as a promising approach to enhance monitoring design in geologic CO2 sequestration. Machine learning approaches, when combined with reduced-order modeling (ROM) techniques, enable efficient and accurate predictions of key parameters, including pressure distribution, CO2 plume movement, and reservoir behavior. By analyzing extensive datasets, machine learning algorithms can uncover complex 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 CO2 sequestration projects.

Accurately quantifying uncertainties is vital for evaluating the reliability of predictions and optimizing monitoring design under uncertain conditions. Uncertainty quantification is particularly important in geologic CO2 sequestration 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 injection rates, reservoir properties, and measurement errors. Leveraging MCMC techniques allows for informed risk assessment, ensuring the safety and efficiency of CO2 sequestration projects.

Numerous research endeavors have been dedicated to addressing optimal sensor placement, monitoring design, and uncertainty quantification in geologic CO2 sequestration. Previous studies have explored various modeling techniques, simulation frameworks, and optimization algorithms to enhance monitoring strategies. 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 existing body of knowledge by providing detailed descriptions and critical evaluations of these previous works. We identify their strengths, weaknesses, and potential avenues for improvement to guide the development of an advanced sensor placement and monitoring design framework.

In this study, we propose a novel method for optimal sensor placement and monitoring design in geologic CO2 sequestration. Our approach leverages a ROM-based optimization strategy to reduce uncertainty associated with 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 CO2 sequestration projects. The ROM-based optimization strategy combines reduced-order models, surrogate modeling, and optimization algorithms to enable rapid and accurate evaluations of sensor placement alternatives. By considering uncertainties through the MCMC filter-based approach, we enhance the robustness of the optimization process and provide quantifiable measures of confidence in the monitoring system design.

The structure of this paper is as follows: Section 2 provides a comprehensive review of previous works, highlighting their strengths, weaknesses, and research gaps. This review serves as the foundation for our proposed approach. Section 3 presents our novel ROM-based optimization strategy, elucidating its underlying principles and discussing the advantages it offers over existing methods. We explain the workflow of the optimization framework, including the generation and selection of reduced-order models, the construction of surrogate models, and the incorporation of uncertainties in the optimization process. In Section 4, we present the results of our approach, showcasing its effectiveness in reducing uncertainty and improving monitoring design in geologic CO2 sequestration. We provide case studies and performance evaluations, demonstrating the benefits of our proposed method. Finally, Section 5 summarizes our findings, discusses their implications, and outlines potential avenues for future research in the field of geologic CO2 sequestration monitoring.

**OUTLINE**

Intro

* CCUS and climate change
* GCS risks and monitoring 🡪 optimal design
* Machine learning 🡪 ROM for predictions
* Uncertainty Quantification
* Previous work detailed description
* Proposed method: a ROM-based optimization strategy to reduce UQ in GCS leakage risk
* Roadmap to paper

Methodology

Results

Conclusion

Data assimilation is also called history matching or inverse modeling in different communities. It has been widely applied to assimilate history data to calibrate model for predictions in petroleum industry, weather forecast, and hydrology community (Oliver et al, 2008; Pu and Kalnay, 2019; Ghorbanidehno, et al., 2020), and has been used extensively in 4D seismic modeling and inversion (Luo et al, 2016, 2020; Oliver, 2022). Data assimilation is also increasingly applied in geologic CO2 sequestration (GCS) community to calibrate the uncertain reservoir parameters (e.g., permeability and porosity) and reduce the uncertainty in predictions (e.g., CO2 plume and CO2/brine leakage risk) (Li et al, 2015). Some of the most relevant and recent research work is introduced below. In general, GCS community deals with higher levels of uncertainty compared to petroleum industry given the lack of appropriate characterization data or financial incentives to collect it.

Under the context of U.S. DOE’s National Risk Assessment Partnership (NRAP), Chen et al. (2020) revealed how uncertainty in predicted risks can be reduced by performing monitoring data assimilation. They developed a workflow based on the ensemble smoother with multiple data assimilation with geometric inflation factors (ES-MDA-GEO) algorithm (Emerick and Reynolds, 2013; Rafiee and Reynolds, 2017) to assimilate the monitoring data into reservoir models and to calibrate models. The updated models were used to predict future risks and reduction in their uncertainties. The effectiveness of this proposed workflow for monitoring data assimilation was demonstrated with multiple examples including a field scale hypothetical case on Rock Springs Uplift storage site in Wyoming, USA. Thereafter, Chen et al. (2022a) developed a novel framework based on iterative risk assessment using data assimilation to effectively quantify the uncertainty reduction in the predicted risk quantities. Their findings indicated that the application of ES-MDA-GEO based data assimilation in conjunction with the NRAP's Open-Source Integrated Assessment Model (NRAP-Open-IAM) was effective in reducing uncertainty in risk-related predictions for GCS.

Later, researchers from U.S. DOE’s SMART Initiative developed machine learning accelerated data assimilation approach for history matching and uncertainty quantification in CO2 sequestration. Tang et al. (2021) leveraged physics in porous media flow behavior and machine learning technique to develop a rapid data assimilation framework. The backend data assimilation approach is ES-MDA, and a deep learning-based proxy model was developed to replace the full-physics simulations which is required in the inverse modeling. Chen et al. (2022b) developed a deep learning accelerated data assimilation approach in GCS. The major difference of this work from the work of Tang et al. (2021) is that Chen et al. (2022b) applied a feature coarsening technique to reduce the model dimension during the training and prediction, that is, the training and prediction processes were performed at the coarse scale. Thereafter, the resolution was further recovered to the fine scale by a piecewise cubic interpolation. This proposed workflow can easily handle data assimilation for large-scale GCS site. Note that the data used for data assimilation in both studies are point measurements from monitoring and injection wells.

At CO2 storage sites the data from monitoring wells are usually very limited given the extremely limited number of monitoring wells. Thus, it is crucial to identify other types of data which can be used for data assimilation and uncertainty reduction quantification in risk predictions. One such type of data that can be used to improve the accuracy of risk predictions is spatial measurements inferred from 4-dimensional seismic surveys (time-dependent, repeat 3-dimensional surveys). In this study, we extend the workflow developed for monitoring data assimilation to spatial data assimilation of seismic data. Instead of directly using the seismic data in our framework, we use multiple CO2 plume interpretations from 4D seismic surveys as inputs for spatial data assimilation.

To the best of our knowledge, this is the first study to perform spatial data assimilation to reduce the prediction of risk quantities at geologic CO2 storage sites. Our framework is integrated into NRAP open-source Integrated Assessment Model (NRAP-Open-IAM) to support the deployment of carbon capture and storage to meet the net-zero emission target by 2050 in the United States.