Abstract

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Introduction

Addressing climate change requires effective strategies to mitigate greenhouse gas emissions, and geologic CO2 sequestration has emerged as a promising approach. This technique involves injecting CO2 into carefully selected geological formations such as deep saline aquifers or depleted oil and gas fields, ensuring secure and long-term storage. Monitoring and verifying CO2 behavior within the subsurface reservoir are crucial for assessing storage capacity, detecting potential leakage, and evaluating environmental impacts.

Optimal sensor placement and monitoring design play a critical role in achieving accurate and efficient CO2 monitoring in geologic sequestration projects. 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.

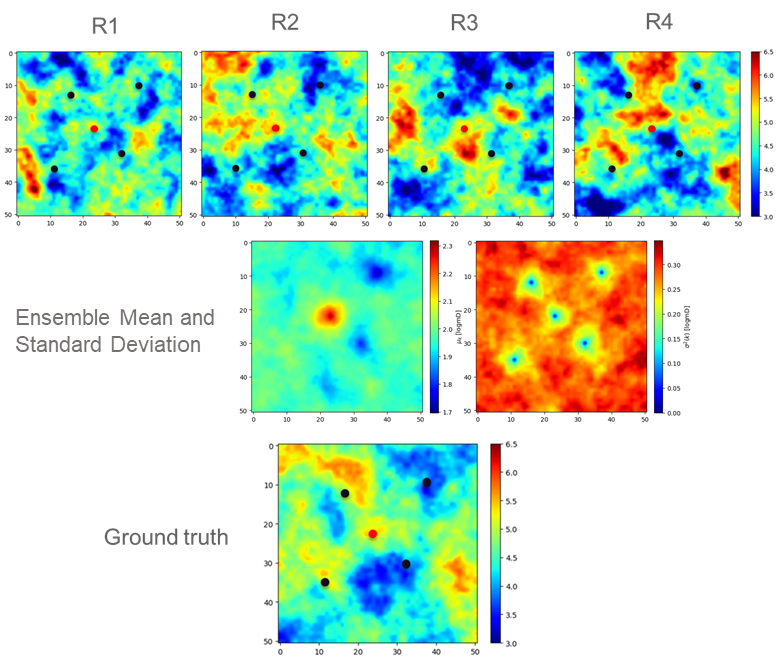
In conclusion, this paper introduces a novel approach for optimal sensor placement and monitoring design in geologic CO2 sequestration. By combining machine learning techniques and uncertainty quantification methods, we aim to enhance the effectiveness and efficiency of monitoring systems, providing 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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Acknowledgement

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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.