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Reduced-Order Models for Wellbore Leakage from Depleted Reservoirs

Mohamed Mehana*[1], Bailian Chen[1], Rajesh Pawar[1], 1. Los Alamos National Lab

Abstract

CO_2 has been previously utilized to enhance oil recovery (EOR) in numerous reservoirs. These hydrocarbon-depleted CO_2-filled reservoirs are a ticking time bomb for potential leaks. Accurate leakage estimation is essential to assess the effectiveness of CO_2 sequestration and groundwater protection. We developed reduced-order models to accurately and quickly estimate the CO_2 and oil components (e.g., CH4) leakages from the abandoned wells. We conducted a wellbore leakage analysis for the CO_2-EOR field. We designed a numerical model with an aquifer, caprock, and reservoir components. We used C1, C4, and C10 to represent the light, intermediate and heavy components of crude oil, respectively. We quantified the CO_2/oil components leakage through the wellbore to the aquifer. Then, we performed Monte Carlo simulations to quantify the inherited uncertainty in the model parameters. After that, we developed and compared the performance of a set of reduced-order models (ROMs) to predict CO_2/oil component leakages through an abandoned wellbore. In addition to a large amount of CO_2 leakage, we observed that hydrocarbons leakage through the wellbore poses a potential risk of groundwater contamination. In addition, we observed that CO2 and hydrocarbons leakage profiles are highly sensitive to the wellbore permeability. Moreover, we reported the performance of three ROM development techniques where we found that the Light Gradient Boosting Machine (LGBM) surpasses both the linear regression and Multivariate Adaptive Regression Splines. This is one of the first studies to quantitatively evaluate leakage profiles from CO_2-EOR sites and draws attention to further investigation and analysis.

Introduction

Geological sequestration and utilization of CO_2 is a viable technique to lessen the current emissions levels and provide a solution to the current climate crisis (Yamasaki 2003). Various subsurface systems could be potential storage sites for CO_2, including saline aquifers and depleted oil and gas reservoirs (Benson and Cole 2008). On the other hand, CO_2 could enhance the hydrocarbon recovery from live hydrocarbon reservoirs by providing pressure maintenance or improving hydrocarbon mobility (Mehana et al. 2018). In addition, CO_2 could be utilized to engineer methane production from clathrate hydrate systems.

For either sequestration or utilization, reducing the leakage risk and protecting groundwater resources is imperative (Chen et al. 2018). Depleted hydrocarbon reservoirs especially pose a more alarming alert of hydrocarbon leakage. Although depleted, these reservoirs still possess a significant amount of hydrocarbons that became immobile towards the end of the production. However, the interactions of these residual hydrocarbons with stored CO_2 might result in mobilizing these hydrocarbons again. Consequently, hydrocarbons and CO_2 leakages become a concern for sequestration operations in depleted hydrocarbon reservoirs.

Subsurface systems, especially depleted hydrocarbon reservoirs, are complex and heterogeneous(Li et al. 2006, Mehana et al. 2021). Therefore, it is challenging to identify the leakage pathway and assess its associated risks. Wellbores are one of the commonly accepted leakage pathways (Watson and Bachu 2009). Although properly plugged, these wellbores still provide a possible leakage pathway, given the anticipated degradation of the plugs and the permanent intentions for the sequestration operations. Fortunately, we could assess the leakage potential of various combinations of reservoir properties and operations conditions using numerical simulation (Mehana et al. 2020). However, the computational cost of these simulations, especially compositional ones, is sometimes prohibitive to sufficiently sample the parameter space and quantify the interactions among various controlling parameters. Alternatively, ROMs provide a more computationally efficient approach to predicting the leakages and quantifying the associated risk, promising solutions to overcome the shortcomings of numerical simulations.

ROM development is the focus of various researchers. For instance, Harp et al. (2016) developed ROMs to estimate CO_2 and brine leakage rates along wellbores of abandoned wells at geologic CO_2 storage sites using a Multivariate Adaptive Regression Splines (MARS) algorithm. Recently, Chen et al. (2022) expanded the scope of this work to include hydrocarbon and CO_2 leakages from CO_2-EOR sites. In addition, they quantified the sensitivity of the leakage rates to the key reservoir and wellbore features. On the other hand, Meguerdijian et al. (2022) developed ROMs to study the CO_2 leakage through a fault where they quantified the impact of CO_2 solubility on leakage rates and fault destabilization.

This work aims to develop ROMs based on reservoir simulation results to estimate the CO_2 and hydrocarbon leakages from CO_2-EOR sites. We organized the rest of this paper as follows: we will briefly present the conceptional CO_2 site, the details of the reservoir simulation, and the ROMs methods used in the Methods Section, then we will discuss the results from Linear regression, MARS, and Light gradient boosting algorithm along with the uncertainty associated, after that we will summarize the main findings in the conclusions section.

Methods

In this section, we will present the simulation details along with the techniques used for ROM development.

Simulation details

We created a conceptual model for modeling the CO_2/hydrocarbons flow in the reservoir to study the leakage of CO_2/oil from the wellbore to the aquifer. **Figure** shows the conceptual model containing the reservoir's components, caprock, aquifer, and a wellbore at the center of the model. The grid blocks in the x, y, and z directions are 51, 51, and 20. We used 3, 12, and 5 layers to model the aquifer, caprock, and reservoir in the vertical direction. The assumptions for reservoir modeling and simulation include:

- The oil in the reservoir is well swept (oil saturation is uniformly distributed and under residual oil saturation)
- No injection and production periods and the leakage modeling starts from the end of production.
- We use three oil components, i.e., C1, C4, and C10, to represent the light, intermediate and heavy components of oil, respectively.

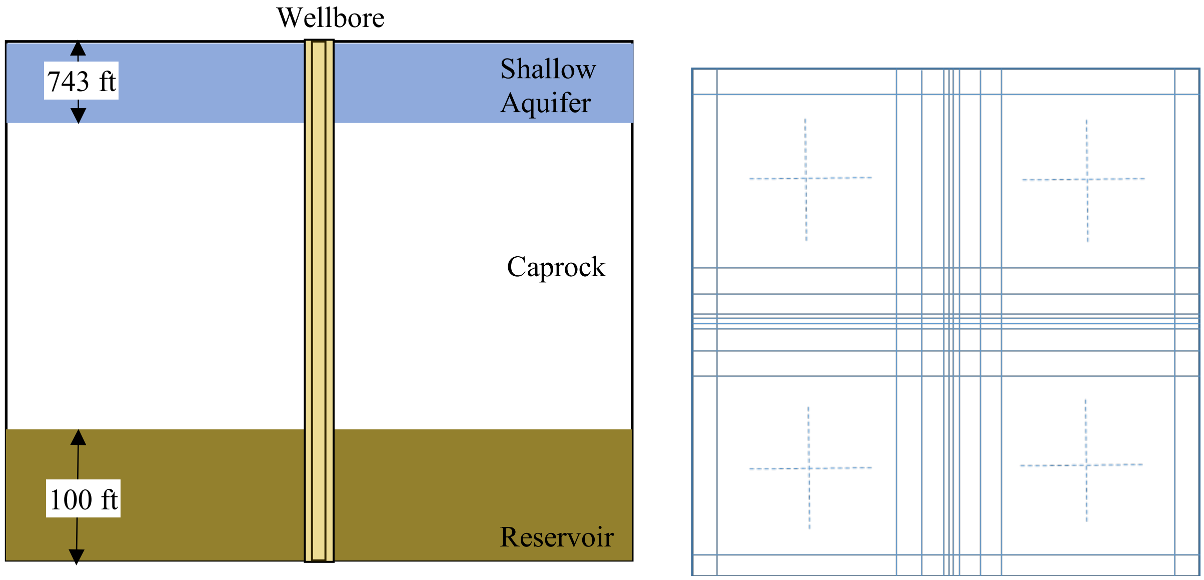

Figure 1. A conceptual model for CO_2/oil leakage analysis (right) and the grid spacing (left).

Reduced-Order Model Development

We examined the performance of three different regressions techniques to develop the ROMs, namely multivariate Linear Regression (LR) (Weisberg 2005), Multivariate Adaptive Regression Splines (MARS) (Friedman 1991), and Light Gradient Boosting Machine (LGBM) (Fan et al. 2019). Multivariate Linear regression is one of the first regression analyses studied and used extensively where the independent and dependent variables are correlated through a linear relationship. On the other hand, MARS is a non-parametric regression technique intended to handle non-linear dependence and input parameter interactions. On the contrary, LGBM is a gradient boosting framework that uses tree-based learning algorithms.

We generated a training database comprising 200 samples using Latin Hypercube sampling (LHS). **Table 1** summarizes the uncertain parameter and its range for the development of the reduced-order model (ROM). All the training simulations were performed by using Eclipse 300.

Table 1: Uncertain parameter and its range for ROM development.

Parameters	Values
Storage reservoir depth	3000~9000 ft
Abandoned reservoir pressure multiplier	1.0~1.2
shallow depth	200~2000 ft
Effective wellbore perm.	0.01~1000 mD
Reservoir permeability	10~100 mD
Net to gross ratio	0.4~1
Residual oil saturation	0.2~0.4
Residual water saturation	0.3
Residual CO_2 saturation	1-So-Sw
Fraction of C1	0.1~0.3
Fraction of C4	0.15~0.45
Fraction of C10	1-fC1-fC10

Results

This section will present the sensitivity analysis' results and performance of linear regression, MARS, and LGBM as ROM development techniques.

Sensitivity analysis

We also quantified the impact of the uncertainty in the input parameters on the leakage profiles using Pearson's correlation (**Figure 2**). We observed that all leakage profiles are highly sensitive and positively correlated to the wellbore permeability. In addition, initial reservoir pressure positively affects all the leakage profiles, but to a lesser degree. On the other hand, the saturation, mole fraction of C1, and mole fraction of C4 are positively correlated with C1 and C4 leakage profiles while negatively correlated with CO_2 and C10.

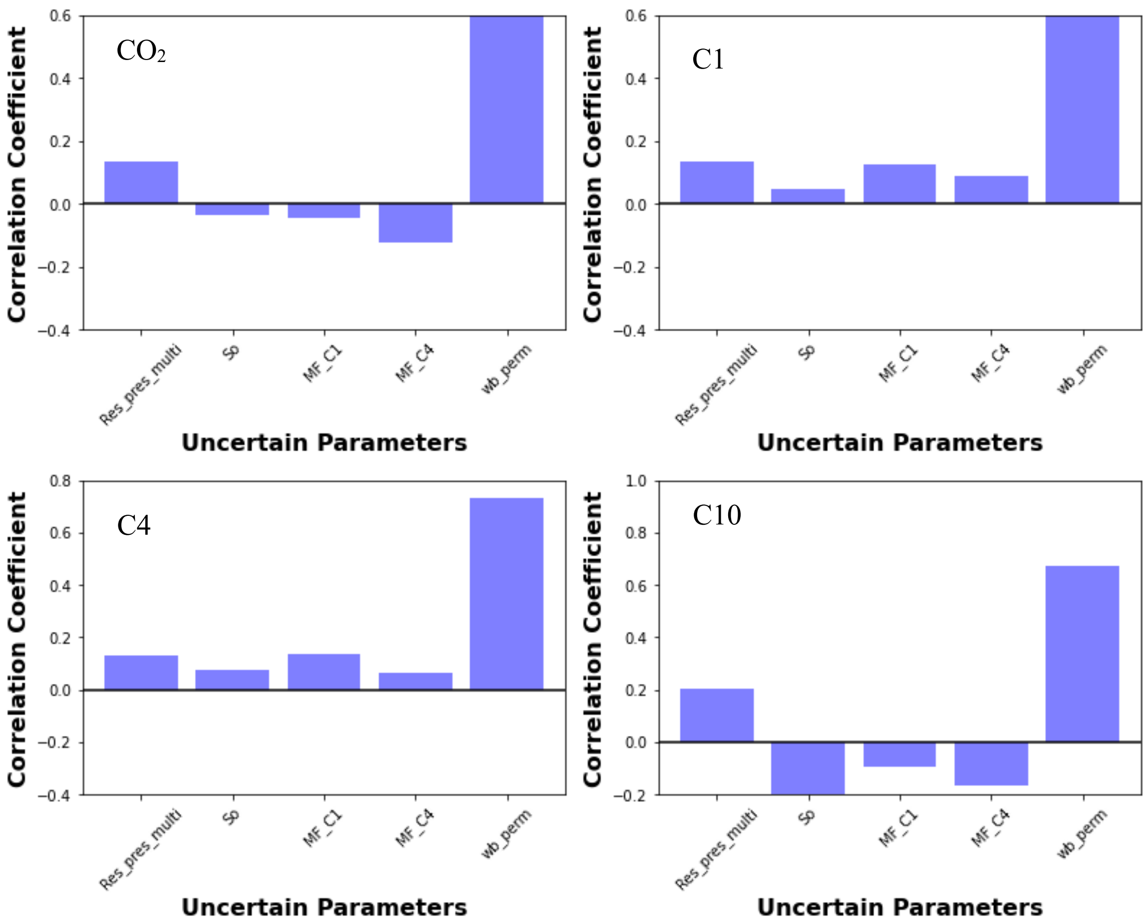

Figure 2. The sensitivity analysis using Pearson's correlation. The uncertain parameters include the reservoir pressure multiplier, oil saturation, mole fraction of C1, mole fraction of C4, and the wellbore permeability.

Linear Regression

Figure 3 shows the correlation coefficients of the CO_2, C1, C4, and C10 leakages rates and their validations cross plots. We observed CO_2 has the best correlation while C1 has the worst. However, all correlations were below 0.8, with the hydrocarbons' correlations around 0.6.

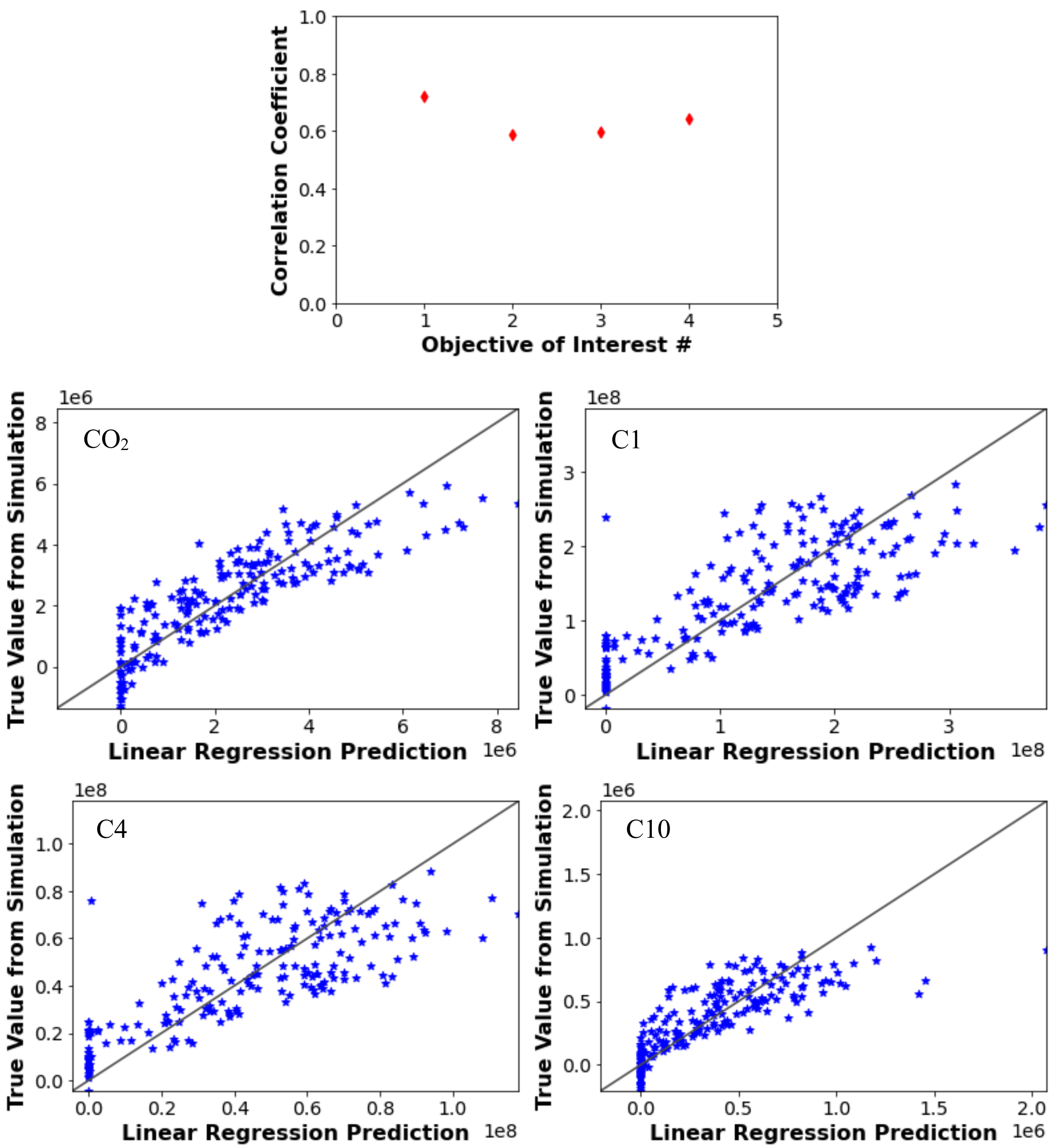

Figure 3. The correlation coefficients of the objective of interest (namely CO_2, C1, C4, and C10 leakage rates) and the cross-validation between the true value from simulation and LR-developed ROMs.

Multivariate Adaptive Regression Splines (MARS)

Figure 4 presents the results from MARS where the correlation coefficients are better than the linear regression. CO_2 has the best correlation coefficients, while C10 has the worst.

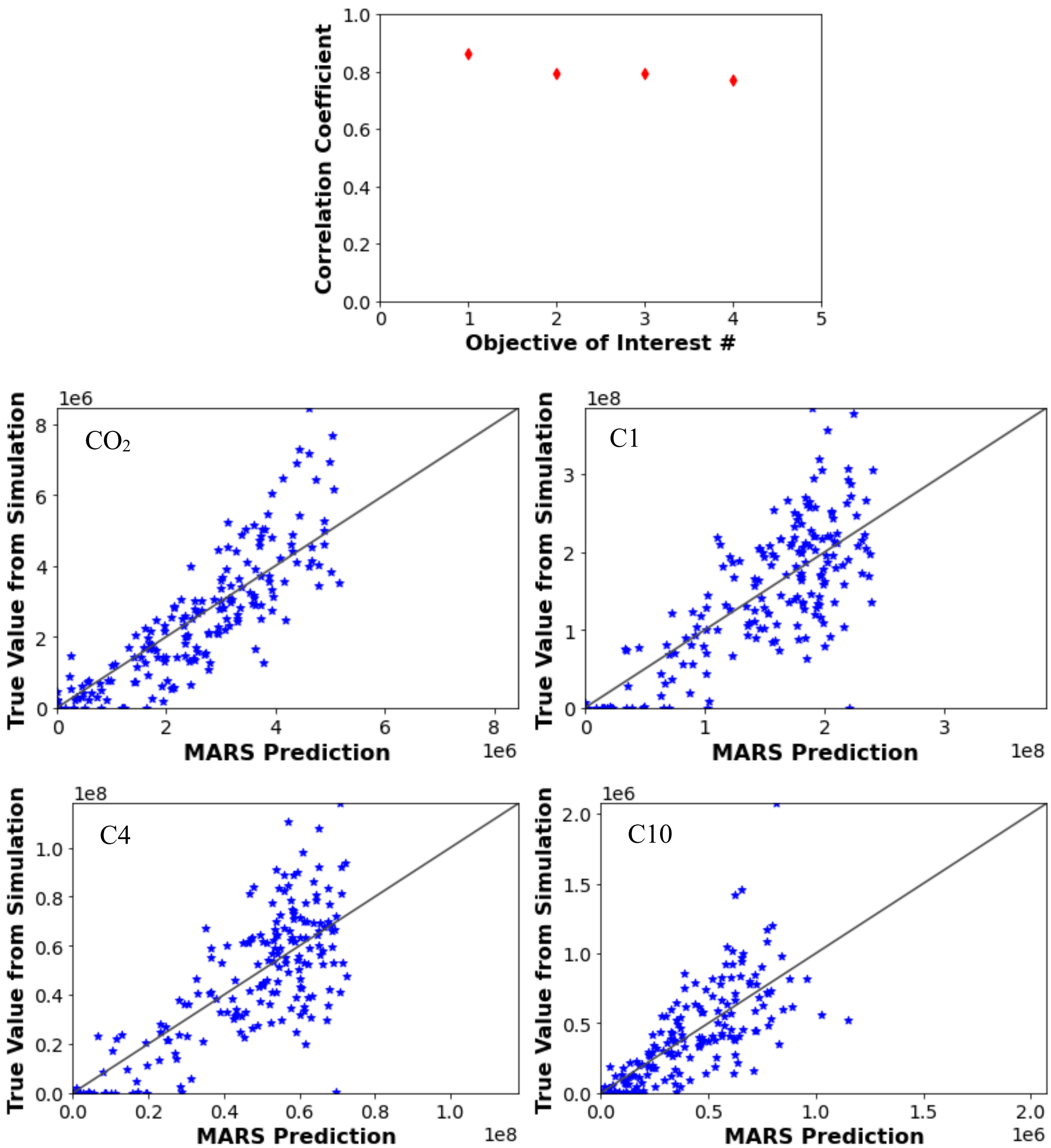

Figure 4. The correlation coefficients of the objective of interest (namely CO_2, C1, C4, and C10 leakage rates) and the cross-validation between the true value from simulation and MARs-developed ROMs.

Light Gradient Boosted Machine (LGBM)

We observed that LGBM yields better results than the previous methods, as shown in **Figure 5**. The correlation coefficient is higher than 0.9 for all the leakage rates.

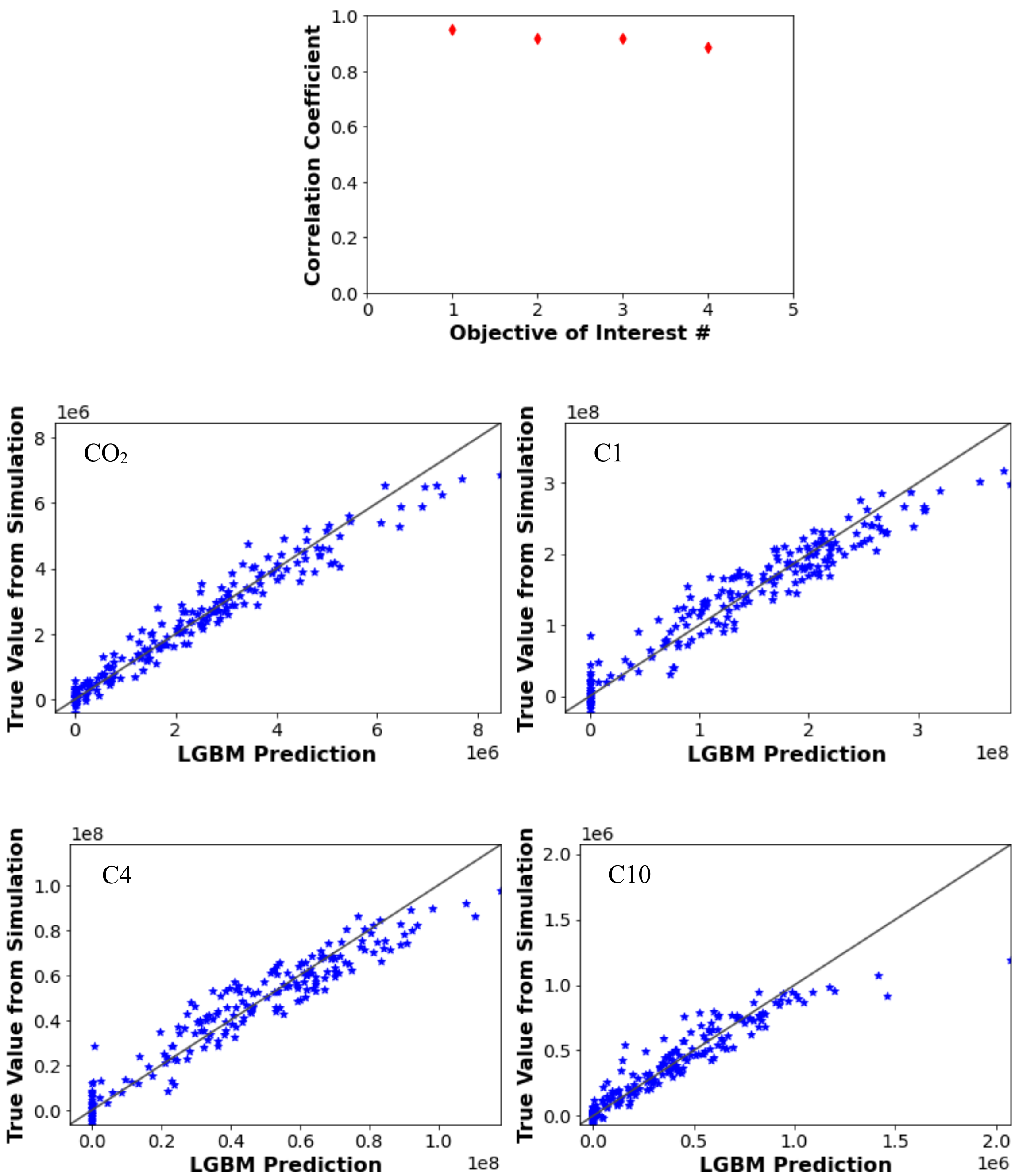

Figure 5. The correlation coefficients of the objective of interest (namely CO_2, C1, C4, and C10 leakage rates) and the cross-validation between the true value from simulation and LGBM-developed ROMs.

Conclusions

In this work, we compared various techniques for ROM development to study the wellbore leakage from the CO_2-EOR fields. We also quantified the impact of the inherited uncertainty on the leakage profiles. The main findings are summarized as follows:

- Hydrocarbons leakages to shallow aquifers pose a potential risk as significant as CO_2 leakage.
- The hydrocarbon and CO2 leakage profiles are highly sensitive to the wellbore permeability, which is positively correlated.
- Out of ROMs development techniques examined, Light Gradient Boosting Machine (LGBM) yielded the best results (with R^2 higher than 0.9 for all the leakage profiles), followed by Multivariate Adaptive Regression Splines (MARS) and finally linear regression.

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References

Benson, Sally M and Cole, David R. 2008. CO2 sequestration in deep sedimentary formations. *Elements* **4** (5): 325-331.

Chen, Bailian, Harp, Dylan R, Lin, Youzuo et al. 2018. Geologic CO2 sequestration monitoring design: A machine learning and uncertainty quantification based approach. *Applied energy* **225**: 332-345.

Chen, Bailian, Mehana, Mohamed Z, and Pawar, Rajesh J. 2022. Towards Quantitative Approach to Evaluating Greenhouse Gas Leakage from CO2 Enhanced Oil Recovery Fields. *Proc.,* SPE Improved Oil Recovery Conference.

Fan, Junliang, Ma, Xin, Wu, Lifeng et al. 2019. Light Gradient Boosting Machine: An efficient soft computing model for estimating daily reference evapotranspiration with local and external meteorological data. *Agricultural Water Management* **225**: 105758.

Friedman, Jerome H. 1991. Multivariate adaptive regression splines. *The annals of statistics* **19** (1): 1-67.

Harp, Dylan R, Pawar, Rajesh, Carey, J William et al. 2016. Reduced order models of transient CO2 and brine leakage along abandoned wellbores from geologic carbon sequestration reservoirs. *International Journal of Greenhouse Gas Control* **45**: 150-162.

Li, Zhaowen, Dong, Mingzhe, Li, Shuliang et al. 2006. CO2 sequestration in depleted oil and gas reservoirs—caprock characterization and storage capacity. *Energy Conversion and Management* **47** (11-12): 1372-1382.

Meguerdijian, Saro, Pawar, Rajesh J, Harp, Dylan R et al. 2022. Thermal and solubility effects on fault leakage during geologic carbon storage. *International Journal of Greenhouse Gas Control* **116**: 103633.

Mehana, Mohamed, Fahes, Mashhad, and Huang, Liangliang. 2018. The density of oil/gas mixtures: insights from molecular simulations. *SPE Journal* **23** (05): 1798-1808.

Mehana, Mohamed, Hosseini, Seyyed A, Meckel, Timothy A et al. 2020. Modeling CO2 plume migration using an invasion-percolation approach that includes dissolution. *Greenhouse Gases: Science and Technology* **10** (2): 283-295.

Mehana, Mohamed, Kang, Qinjun, Nasrabadi, Hadi et al. 2021. Molecular modeling of subsurface phenomena related to petroleum engineering. *Energy & Fuels* **35** (4): 2851-2869.

Watson, Theresa L and Bachu, Stefan. 2009. Evaluation of the potential for gas and CO2 leakage along wellbores. *SPE Drilling & Completion* **24** (01): 115-126.

Weisberg, Sanford. 2005. *Applied linear regression*, Vol. 528: John Wiley & Sons.

Yamasaki, Akihiro. 2003. An overview of CO2 mitigation options for global warming—emphasizing CO2 sequestration options. *Journal of chemical engineering of Japan* **36** (4): 361-375.