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Quantitatively evaluating greenhouse gas leakage from CO_2 enhanced oil recovery fields

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Abstract:
Greenhouse gas (mainly CO_2 and CH_4) leakage from abandoned wells in CO_2 enhanced oil recovery sites is a long-standing environmental concern and health hazard. Although multiple CO_2 capture, utilization, and storage programs, e.g., CarbonSAFE and Regional Carbon Storage Partnerships, have been developed in the U.S. to reach the net-zero emission target by 2050, one cannot neglect the significant amount of CO_2 and CH_4 leakage from abandoned wells. This study will investigate the potential of CO_2 and oil components leakages from the abandoned wellbore and develop the first-ever quantitative approach to evaluating CO_2 and oil component leakage from a CO_2 enhanced oil recovery field. Results show that in addition to a large amount of CO_2 leakage, a significant amount of light and intermediate oil components leaked through the wellbore. In contrast, a minimal amount of heavy oil component leaked. Oil components' leakage is mainly through the gas phase rather than the liquid phase. CO_2 leakage is positively correlated to reservoir depth, wellbore pressure, and permeability through sensitivity analysis. In contrast, it is negatively related to net-to-gross ratio, residual oil saturation, and mole fraction of CH_4. On the other hand, oil component leakages are positively correlated to all uncertain parameters, except the net-to-gross ratio. Lastly, the reduced-order models generated using the machine learning technique have a relatively high fidelity.

1. Introduction

Carbon capture and storage is needed now more than ever to combat the current emissions levels and restore the concentrations to a manageable level (Lackner, 2003). While being the direct source of these emissions by providing fossil fuels, subsurface systems provide unmatched capacity to host the captured CO_2 (Middleton et al., 2012). CO_2 storage has been in saline aquifers (Yang et al., 2010; Iglauer and Al-Yaseri, 2021) and depleted hydrocarbon reservoirs (Boot-Handford et al., 2014; Zhang et al., 2019). In addition, CO_2 has been previously utilized to enhance oil recovery (EOR) in numerous reservoirs (Bui et al., 2018; Mehana et al., 2020c). Owing to its superior dissolution and adsorption properties, CO_2 is miscible with the in-situ oil at relatively lower pressures, making CO_2 an effective agent to extract the hydrocarbons from the pores through several mechanisms such as oil swelling, viscosity reduction, and interfacial tension reduction (Lake et al., 2014; Mehana et al., 2018).

These CO_2-filled reservoirs are a ticking time bomb for potential leaks (Viswanathan et al., 2008). Fortunately, the numerical simulation could provide the tool to optimize and engineer our CO_2-EOR operations (Dai et al., 2016; Middleton et al., 2020). However, these reservoirs are complex, challenging to characterize, and difficult to control (Vafai, 2015). Therefore, augmenting reservoir simulations with uncertainty quantifications tools is necessary to estimate the associated risk properly. However, the computational intensity of the reservoir simulations becomes intractable, as the complexity of the reservoir system increases. Therefore, reduced-order models (ROMs) are introduced to overcome the prohibitive computational cost of high-fidelity models. To this end, it becomes feasible to conduct risk assessment analysis.

The characterization of subsurface reservoirs is always prone to uncertainty (Lake, 1986). These reservoirs lie thou-

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sands of meters below the ground and span thousands of meters. Relying on the geophysical surveys to infer the geological features and relying on the core measurements for the petrophysical data is not enough to estimate the input parameters for reservoir modeling. Therefore, it is always encouraged to account for the uncertainty in the model parameters and perform sensitivity analysis to identify the main parameters controlling the performance and transport behavior. Monte Carlo simulation is a widely used uncertainty quantification method where the multi-dimensional parameter space is effectively sampled (Mehana et al., 2020a). Recently, the multifidility Monte Carlo method has shown promising results, producing tighter distributions while reducing the computational cost (O'Malley et al., 2018).

Previously, several studies focused on optimizing and quantifying the uncertainty associated with CO_2-EOR operations. For instance, Dai et al. (2014b) used Monte Carlo simulation of the reactive transport of CO_2 during CO_2-EOR to quantify the inherited uncertainty. They highlight the significance of reservoir characterization on the economics of CO_2-EOR. Then, they extended their scope and developed an integrated framework to optimize the CO_2-EOR operations (Dai et al., 2014a). They identified that porosity, permeability, formation thickness, and depth are the main intrinsic parameters controlling the performance. On the other hand, the main operational parameters are the well spacing and the sequence of alternating CO_2 and water. In the same vein, Chen et al. (2018) demonstrated the impact of reservoir management and operation strategies on CO_2 storage and oil recovery. They reported better performance when jointly-optimized well completions and well controls than solely-optimizing well controls. Then, they proposed another approach to calibrate their reservoir model with monitoring data to reduce the uncertainty associated with the risk assessment (Chen et al., 2020).

The development of ROMs and surrogate models was also the focus of several studies (Mehana et al., 2020b). In one of the early studies, McMillan et al. (2008) developed a reduced-order model for CO_2 injection based on modified Buckley-Leverett theory, which estimated gas saturation distribution at a reasonable accuracy. Similarly, Nordbotten and Celia (2011), Nordbotten et al. (2005a, 2005b) developed an ensemble of simplified-physics models assuming vertical equilibrium to simulate CO_2 migration, assuming vertical equilibrium efficiently. In the same vein, In an effort, Bao et al. (2013) developed a reduced-order model (ROM) based on reservoir simulations, relating the reservoir properties to the pressure build-up to quantify the impact of caprock and reservoir properties on the ground surface displacement and induced seismicity.

This is the first study to quantitatively evaluate greenhouse gas leakage from CO_2-EOR sites, and the reduced-order models were first generated for predicting CO_2/oil component leakages from a CO_2-EOR site. The remaining of this paper were arranged as follows: First, an overview of the simulation systems and sensitivity analysis were presented. Second, the results for reduced-order model development were presented. Third, the main findings and implications of this research were summarized.

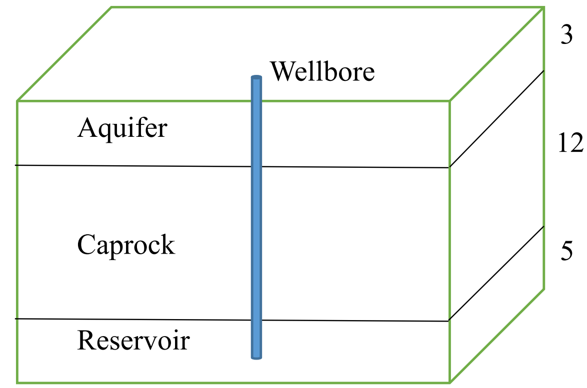

Fig. 1. Conceptual model for CO_2/oil leakage analysis.

2. Model setup and sensitivity analysis

2.1 Model setup

A conceptual model for modeling CO_2/oil flow in the reservoir and the leakage of CO_2/oil from the wellbore to aquifer was created. Fig. 1 shows the conceptual model that contains the components of reservoir, caprock, aquifer and a wellbore at the center of the model. The number of gridblocks in x, y and z directions are 51, 51 and 20 respectively. In the vertical direction, 3, 12 and 5 layers were used to model the aquifer, caprock and reservoir respectively. The assumptions for reservoir modeling and simulation include:

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

2.2 Verification of CO_2/oil component leakage

To verify the leakage of CO_2 and oil from cemented wellbore, a case with effective wellbore perm is set up to equal to 100 mD. The permeabilities for reservoir and aquifer are both set to be 100 mD. The reservoir simulation was performed with Eclipse 300. Fig. 2 shows the amount and fraction of CO_2 and oil leakage from the reservoir. As can be seen, CO_2 has the highest amount of leakage, and the light and intermediate oil components (i.e., C1 and C4) have more amount of leakage than heavy component (i.e., C10). It is also observed that the total fractions of leakage for both CO_2 and oil components are less than 0.1% by the end of 100 years, and the leakage of heavy oil component (i.e., C10) is negligible.

Fig. 3 shows the gas saturation evolution over time. The mole fraction of CO_2 and oil components in gas phase are displayed in Fig. 4. Fig. 5 shows the oil saturation changing over time and the associated mole fraction of CO_2 and oil components in oil phase are presented in Fig. 6. As can be se-

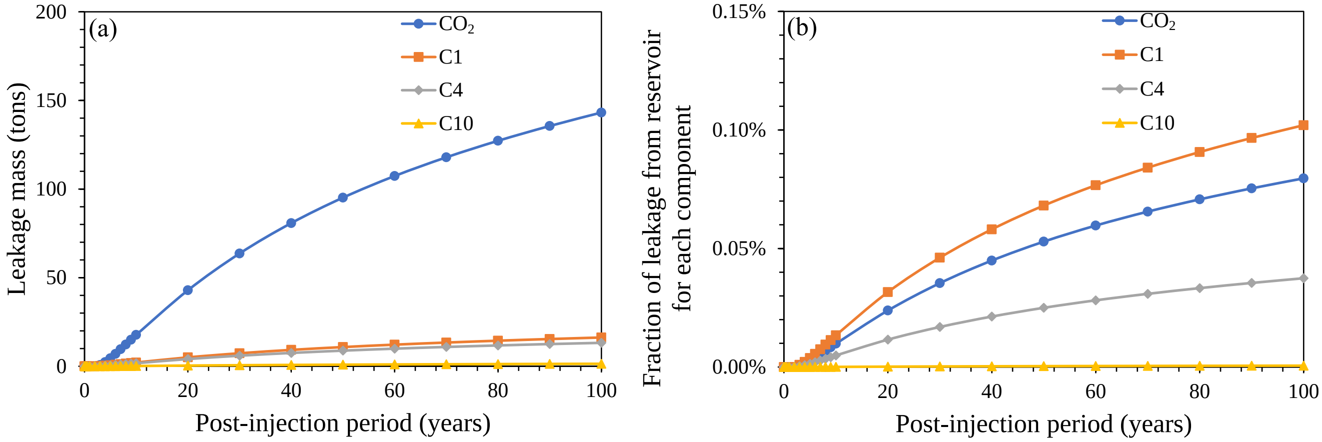

Fig. 2. (a) CO_2/oil leakage and (b) fraction of leakage.

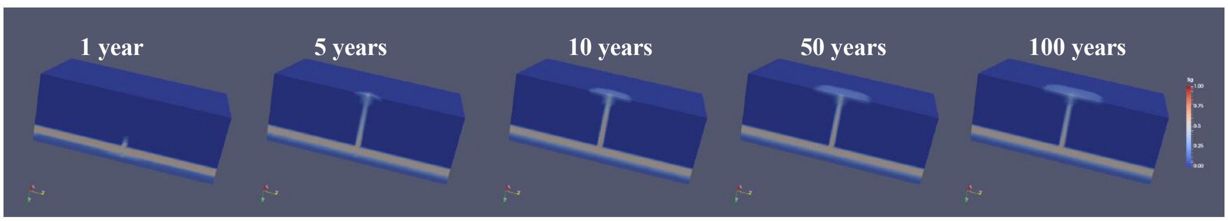

Fig. 3. Gas saturation evolution over time.

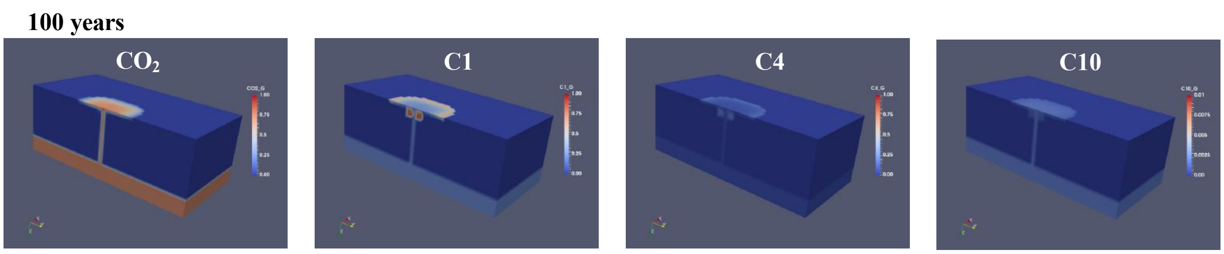

Fig. 4. Mole fraction of CO_2 and oil components in gas phase.

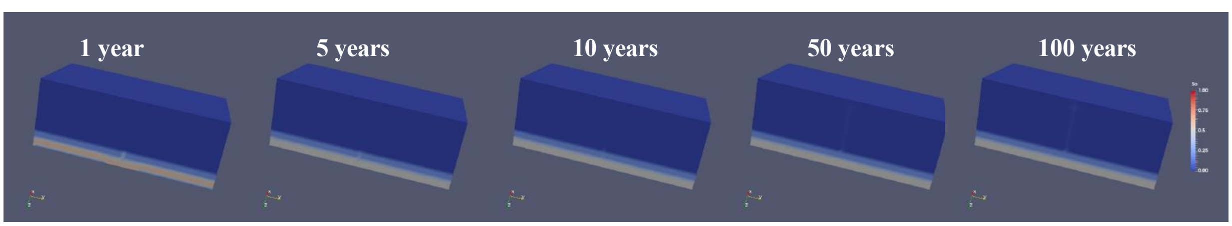

Fig. 5. Oil saturation evolution over time.

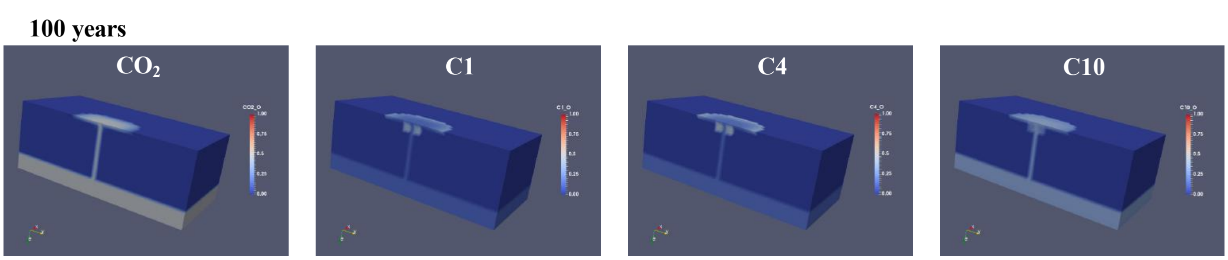

Fig. 6. Mole fraction of CO_2 and oil components in oil phase.

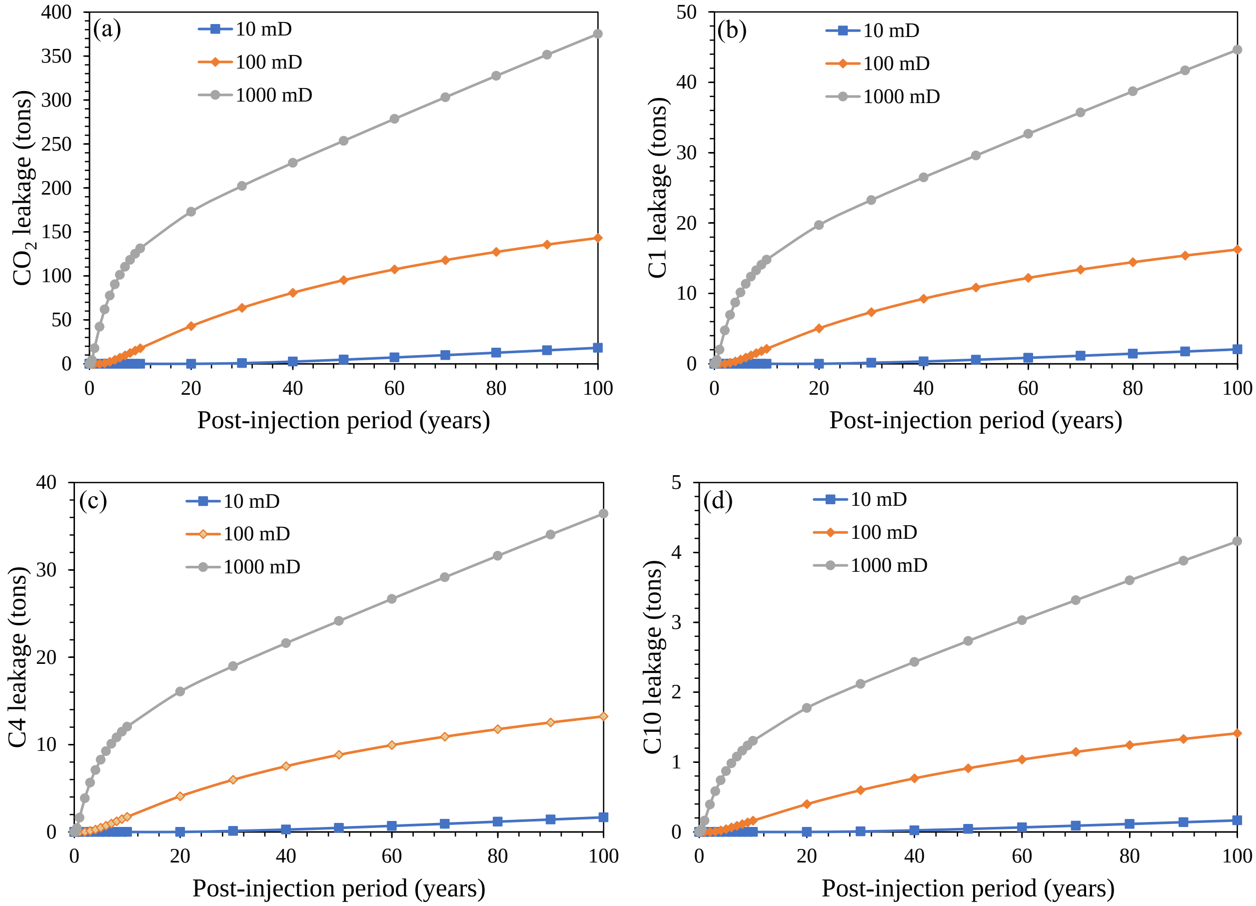

Fig. 7. Impact of effective wellbore permeability on CO_2 and oil components leakage: (a) CO_2, (b) C1, (c) C4 and (d) C10.

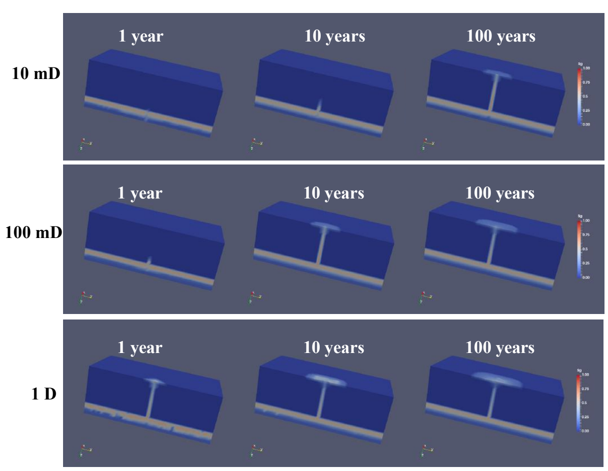

Fig. 8. Gas saturation evolution over permeability and time.

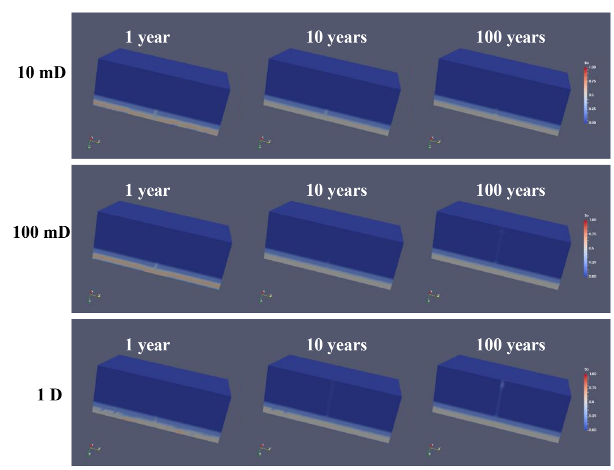

Fig. 9. Oil saturation evolution over permeability and time.

en from these figures, CO_2 and oil are leaked mainly from the gas phase rather than the oil phase.

2.3 Effect of effective wellbore permeability

To investigate the impact of effective wellbore permeability, three different values, i.e., 10, 100 and 1,000 mD were considered. Fig. 7 shows the CO_2 and oil component leakages under three different wellbore permeabilities. As can be seen the higher permeability generally leads to higher amount of leakage. Under the same wellbore permeability, CO_2 has the highest leakage amount, while C10 has the smallest amount of leakage. Figs. 8 and 9, respectively, show the gas and oil saturations changing over effective wellbore permeability and time. It is observed that the higher wellbore permeability leads to more leakage for both gas and oil phases. However, the leakage from oil phase is much smaller than the leakage from

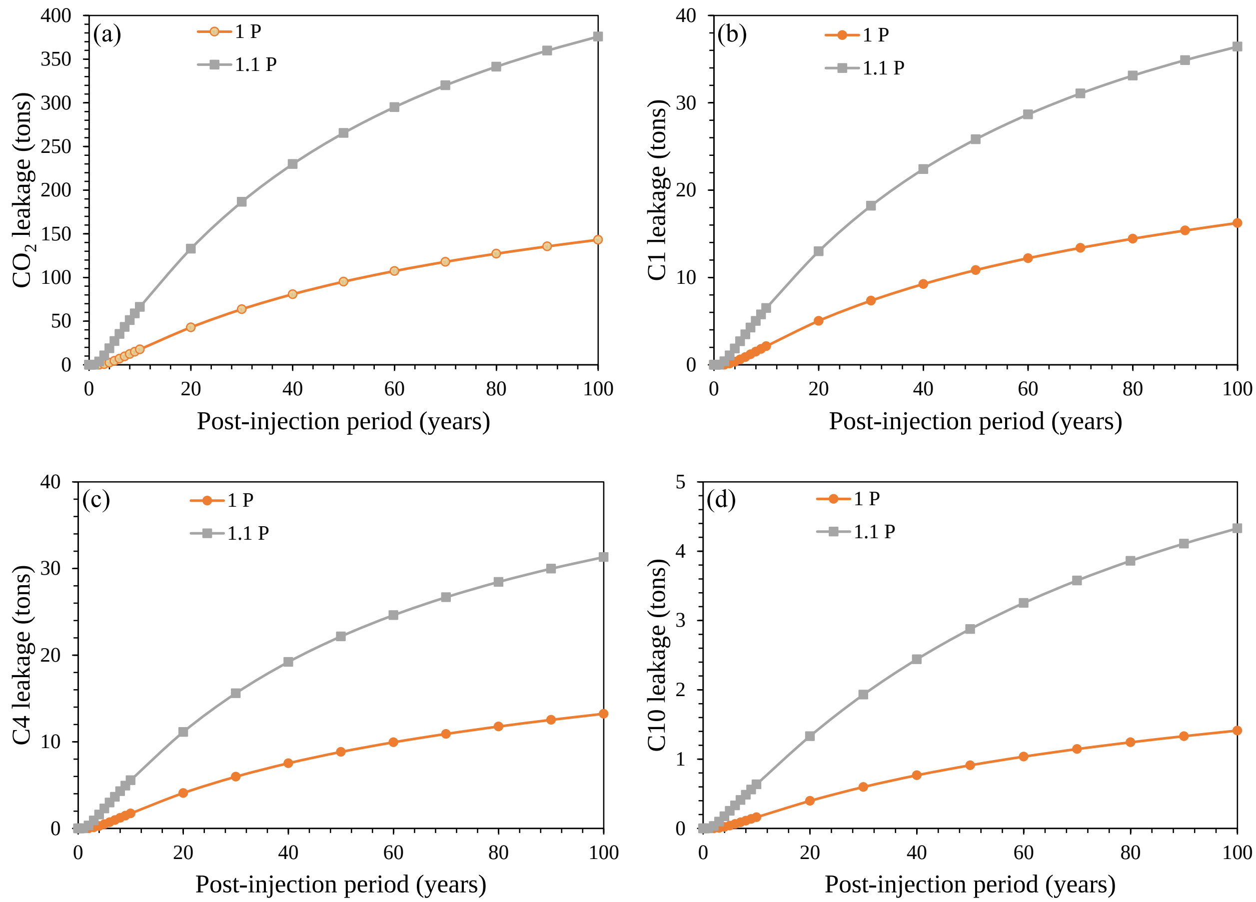

Fig. 10. Impact of reservoir pressure on CO_2 and oil component leakages: (a) CO_2, (b) C1, (c) C4 and (d) C10.

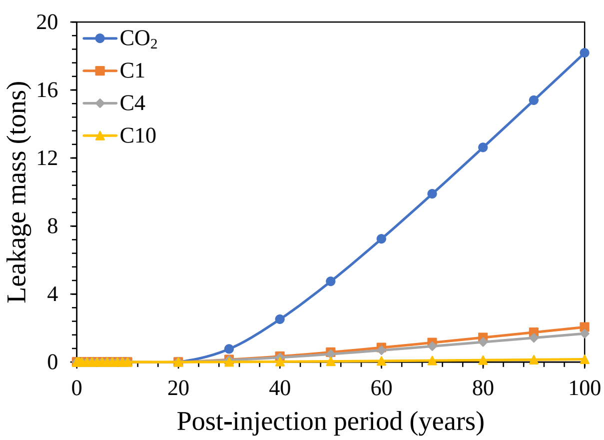

Fig. 11. CO_2/oil component leakage with caprock thickness equal to 240 ft.

gas phase.

2.4 Effect of reservoir pressure

The reservoir pressure also has impact on the leakage of CO_2 and oil components. Here, two different pressures were considered: Initial reservoir pressure (P) and pressure equal to 1.1 P. As can be seen from Fig. 10, the amount of CO_2 and oil leakage under 1.1 P is about two times larger than the amount of leakage under initial reservoir pressure, which indicates that reservoir pressure plays a critical role in CO_2 and oil leakage, and the reservoir pressure should not be too high if storing CO_2 in depleted EOR fields is considered.

2.5 Effect of caprock thickness

The effect of caprock thickness on CO_2/oil leakage was investigated by increasing the caprock thickness from 240 ft to 1,200 ft. Here, the effective wellbore permeability was set equal to 10 mD. The CO_2/oil component leakages with caprock thickness equal to 240 ft were shown in Fig. 11. As can be seen that the total amount of CO_2 leakage is about 18 tons by the end of 100 years. The total amount of each oil component leakage is less than 4 tons, which is significant smaller than the CO_2 leakage. It is also observed that there is no CO_2 and oil leakages under the scenario of thickness equal to 1,200 ft.

3. Reduced-order model development

To develop the fast predictive model to predict the CO_2 and oil component (especially CH_4) leakages from the reservoir, it is need to identify the uncertain parameters that may affect the leakage. Table 1 lists the uncertain parameter and its range for reduce-order model (ROM) development. 250 training samples were generated using Latin Hypercube Sampling approach. All

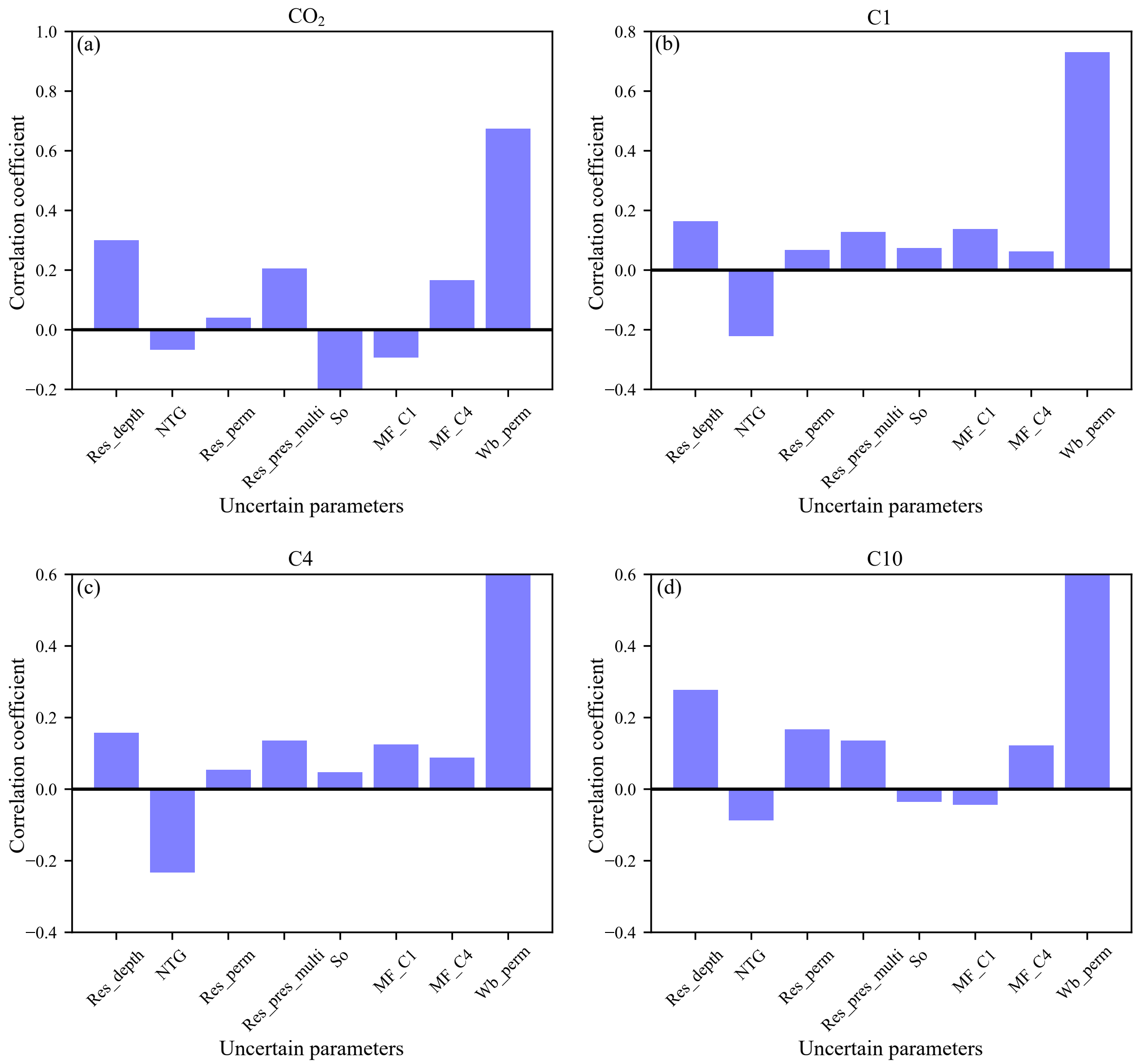

Fig. 12. Sensitivity analysis using Pearson's Correlation: (a) Total amount of CO_2 leakage, (b) Total amount of C1 leakage, (c) Total amount of C4 leakage and (d) Total amount of C10 leakage.

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

Parameters	Values
Storage reservoir depth	3,000-9,000 ft
Abandoned reservoir pressure multiplier	1.0-1.2
Caprock thickness	200-1,500 ft
Effective wellbore perm	0.5-1,000 mD
Reservoir permeability	10-100 mD
Net to gross ratio	0.4-1
Initial oil saturation (So)	0.2-0.4
Residual CO_2 saturation	1-So-0.3
Fraction of C1 (Light component)	0.1-0.3
Fraction of C4 (Intermediate component)	0.15-0.45
Fraction of C10 (Heavy component)	1-fC1-fC10

the training simulations were performed by using Eclipse 300.

Fig. 12 shows the results of sensitivity analysis using Pearson's correlation. As can be seen, CO_2 leakage is positively correlated to reservoir depth, reservoir pressure, mole fraction of intermediate component (i.e., C4) and wellbore permeability. However, it is negatively correlated to oil saturation and mole fraction of light component (C1). C1 and C4 leakages are positively correlated to all the uncertain parameters except for net-to-gross ratio.

The ROMs for the prediction of CO_2/oil leakage (in unit of lb) were developed using MARS. Fig. 13 shows the 10-fold cross validation for each ROM. The R^2 values for the ROM of CO_2, C1 and C4 leakage are all over 0.9. The R^2 value for the ROM of C10 is about 0.8. As can be seen, the ROMs developed can provide a relatively accurate prediction of CO_2 and oil leakage. In our future work, different machine learning algorithms such as neural network and generation of more training samples will be explored to improve the predictive

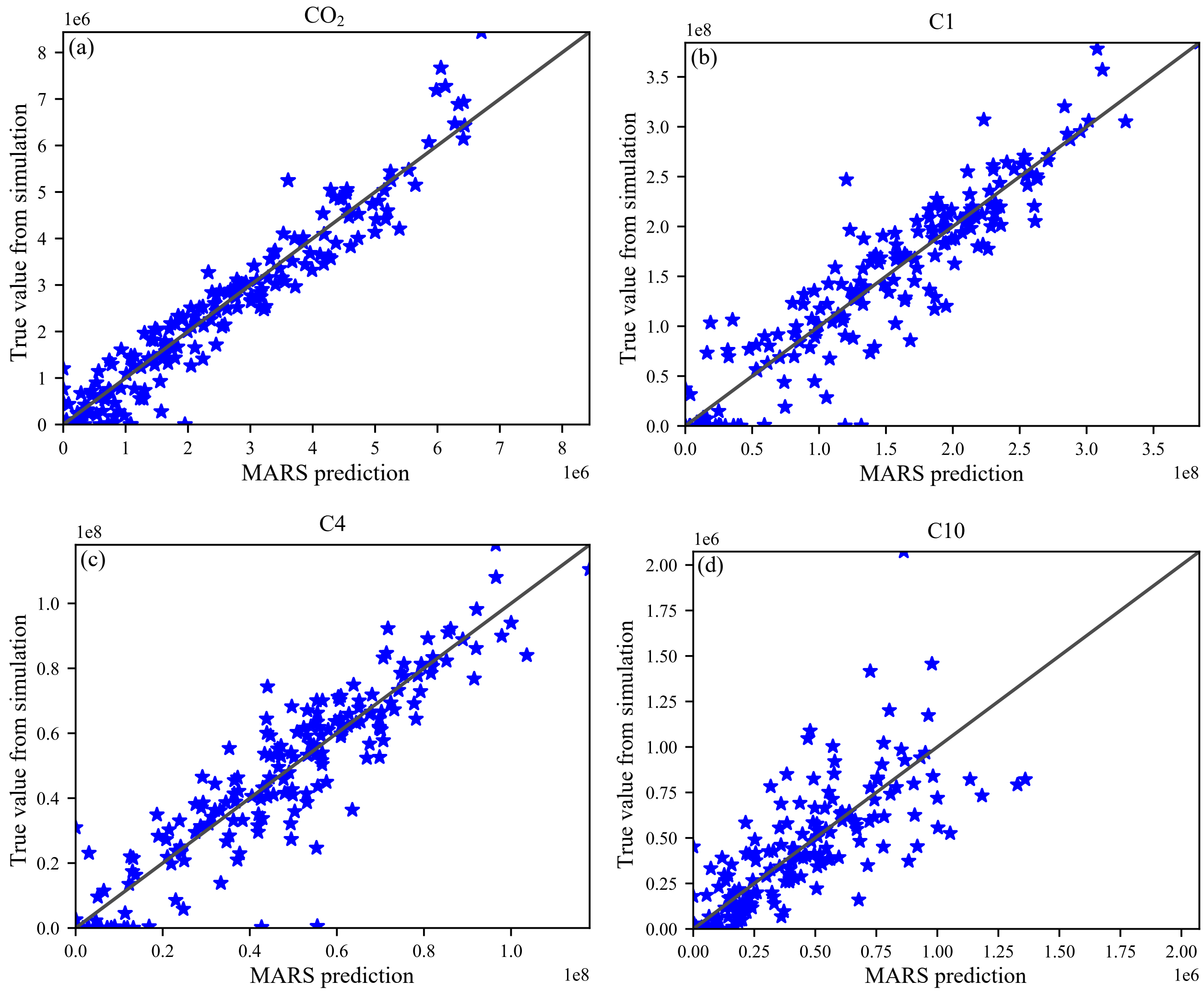

Fig. 13. 10-fold cross validation for the ROMs of CO_2 and oil component leakage prediction: (a) CO_2, (b) C1, (c) C4 and (d) C10.

accuracy of the ROMs.

4. Conclusions

In this work, wellbore leakage analysis for the CO_2-EOR field was performed. Numerical simulations were also conducted to investigate the impact of a variety of uncertain characteristics. The ROMs for the predictions of CO_2 and oil leakage from the reservoir were also developed. The following conclusions can be drawn from this study:

1) In addition to a large amount of CO_2 leakage, a significant amount of light and intermediate oil components (i.e., C1 and C4) leaked through the wellbore. In contrast, a minimal amount of heavy oil component (C10) leaked.
2) Oil components' leakage is mainly through the gas phase rather than the liquid phase.
3) CO_2 leakage is positively correlated to reservoir depth, reservoir pressure, and permeability through sensitivity analysis. In contrast, it is negatively related to net-to-gross ratio, residual oil saturation, and mole fraction of CH_4. On the other hand, oil component leakages (C1 and C4) are positively correlated to all uncertain parameters, except the net-to-gross ratio.
4) The ROMs generated using the machine learning technique MARS have relatively high fidelity (R^2 values are all over 0.8). They can be used as a fast evaluation tool to quantify the amount of CO_2 and oil leakage from an EOR field. In our future work, different machine learning algorithms (e.g., convolutional neural network) will be explored to improve the predictive accuracy of ROMs.

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Conflict of interest

The authors declare no competing interest.

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