CO_2 Enhanced Oil Recovery Through Digital Shadow Modeling

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SUMMARY

This paper introduces a Digital Shadow for CO_2 Enhanced Oil Recovery (EOR). Built upon conditional normalizing flows, this Digital Shadow is potentially applicable to large-scale field CO_2 EOR projects, such as those in the Permian Basin. EOR, aimed at increasing oil production after primary recovery, utilizes CO_2 for its ability to dissolve in oil, reducing viscosity and making it easier to extract. Additionally, CO_2 EOR may play a significant role in addressing climate change by facilitating CO_2 storage. The Digital Shadow models the movement of CO_2 and oil by incorporating high-fidelity reservoir simulations, synthetic seismic data, and observed seismic field data. CO_2 and oil saturation are essential for assessing oil recovery and sweep efficiency, both of which are critical to the success of CO_2 EOR projects.

INTRODUCTION

Enhanced oil recovery (EOR) is a critical technique in the oil and gas industry, employing various methods to maximize oil recovery from reservoirs. Among these, CO_2 injection stands out as one of the most promising techniques, as it increases reservoir pressure and improves oil displacement efficiency (Godec et al., 2011; Blunt et al., 1993). CO_2 EOR has gained significant attention not only for its ability to enhance recovery but also for its potential to reduce the environmental impact of CO_2 emissions by storing CO_2 underground (Núñez-López and Moskal, 2019).

The concept of a Digital Shadow for CO_2 EOR involves creating a surrogate model that replicates the reservoir's behavior using detailed reservoir simulations and simulated time-lapse seismic, while conditioning the surrogate model on the observed seismic field data to improve the accuracy of predictions (Gahlot et al., 2024b). The Digital Shadow addresses the challenges encountered in modeling CO_2 and oil movement by applying solutions that include advanced rock-physics modeling, uncertainty quantification and efficient data assimilation.

CO_2 EOR

Reservoir modeling and initial states

We leverage the high-performance reservoir simulation software JululDarcy.jl (Møyner, 2024) to conduct the CO_2 EOR simulations. The static reservoir model used in this study is based on a 512×256 grid, with a cell size of 6.25 meters in both the x and y directions, and a thickness of 100 meters. The model includes CO_2, oil (C6-13, referring to a mixture of hydrocarbons with 6 to 13 carbon atoms)), and brine as the primary phases, with each phase characterized by its respective physical properties, as detailed in Table 1.

Property	CO_2	Oil (C6-13)
Molar Mass (kg/mol)	0.04401	0.117740
Critical Pressure (Pa)	7.3866e6	3.345e6
Critical Temperature (K)	304.200	597.497
Critical Volume (m^3/mol)	9.2634e-05	3.8116e-04
Acentric Factor	0.228	0.38609

Table 1: Molecular properties used for CO_2 and oil (C6-13) in the CO_2 EOR model.

Initially, the reservoir contains no CO_2, with oil occupying specific regions below the seal. The remaining volume is filled with brine. The initial pressure is estimated based on this mixture of oil and brine. For simplicity, porosity is assumed to be uniform at 0.25 throughout the reservoir. The porosity on the boundary of the simulation box is assumed to be very large, simulating an open reservoir where flow can easily move across the boundaries of the simulation domain.

Equation of State and Binary Interaction Coefficients

In reservoir simulations, the Equation of State (EOS) plays a crucial role in describing the thermodynamic behavior of the fluid phases. EOS models the phase behavior and interactions between various fluid components, CO_2, oil, and brine, under varying pressure and temperature conditions.

The general form of the mass balance equation for each component i in a multi-phase, multi-component system can be expressed as:

$$\frac{\partial}{\partial t}\left(\phi S_k \rho_k X_{ik}\right) + \nabla \cdot \left(\rho_k X_{ik} \mathbf{v}_k\right) = q_{ik} \tag{1}$$

where:

- ϕ is the porosity of the medium.
- S_k is the saturation of phase k.
- ρ_k is the density of phase k.
- X_{ik} is the mole fraction of component i in phase k.
- $\mathbf{v}_k$ is the velocity vector of phase k.
- q_{ik} is the source/sink term for component i in phase k.

This equation describes the conservation of mass for component i in phase k, considering both the temporal change of the component's quantity and its movement through the reservoir. In the context of CO_2 EOR, this formulation is used to model the movement of CO_2, oil and brine within the reservoir, helping to predict the distribution of CO_2, oil, and brine at various stages of the injection and production processes (Wang et al., 2021).

CO_2 injection strategy

The CO_2 injection in this study is modeled using the continuous injection strategy for its simplicity and ease of implementation in simulations. This strategy maintains a steady flow of CO_2 into the reservoir, providing a consistent pressure buildup, which allows for more predictable outcomes in terms of sweep efficiency and oil recovery. The total injection period is set to 10 years, with an injection rate of 0.05 m^3/s, a typical value used in industry studies for long-term CO_2 injection in enhanced oil recovery projects (Li et al., 2021). The total amount of CO_2 injected over this period is 9.46 Mt.

EXTENDED ROCK PHYSICS

To translate reservoir state (CO_2 and oil saturation) changes due to CO_2 injection into acoustic properties (velocity and density) variations, a nonlinear rock physics model, $\mathscr{R}$, is employed by adapting the two-phase, two-components, immiscible flow system from Li et al. (2020); Yin et al. (2023) to a three-phase, three-components, miscible flow system. Under the assumption of negligible pressure-induced velocity changes and patchy oil and CO_2 distributions, variations in oil and CO_2 saturation are mapped to corresponding changes in seismic properties. The patchy saturation model Avseth et al. (2010) describes how increasing oil and CO_2 saturation leads to a decrease in acoustic wavespeed, and density. Given the baseline seismic properties $\mathbf{m}_0 = (\mathbf{v}_0, \rho_0)$, the seismic model ($\mathbf{m}$) at monitoring time step is expressed as,

$$\mathbf{m} = \mathscr{R}(\mathbf{m}_0, \mathbf{x}) \tag{2}$$

where $\mathbf{x}$ is a vector containing oil and CO_2 saturations.

DIGITAL SHADOW

In our study, we adopt a Digital Shadow framework to model the behavior of CO_2 injection in EOR processes, combining multi-phase flow simulations with simulated time-lapse datasets (Gahlot et al., 2024b). The Digital Shadow is a data-driven modeling tool that uses simulations and real-time observations to estimate and predict the state of CO_2 plumes, oil saturation in the reservoir. The goal is to track the dynamics of the CO_2 injection and oil recovery process.

The equation governing the evolution of the state variables is expressed as:

$$\begin{aligned} \mathbf{x}_k &= \mathscr{M}_k(\mathbf{x}_{k-1}, \kappa; t_{k-1}, t_k) \\ &= \mathscr{M}_k(\mathbf{x}_{k-1}, \kappa), \quad \kappa \sim p(\kappa) \quad \text{for} \quad k = 1 \cdots K. \end{aligned} \tag{3}$$

where:

- $\mathbf{x}_k$ represents the state of the system at time step k, including CO_2 saturation, oil saturation.
- $\mathscr{M}_k$ is the dynamics operator at time k, which governs the transitions between time steps.
- $\mathbf{x}_{k-1}$ is the state at the previous time step, capturing the previous conditions of CO_2 and oil saturation.
- κ refers to the permeability field, and is considered a stochastic parameter in the model.
- $p(\kappa)$ is the probability distribution for permeability.
- t_k is the time step at which observations are made.

The life cycle of the CO_2 EOR Digital Shadow begins with the Forecast Step. The state at the previous timestep $\hat{\mathbf{x}}_{k-1}$, drawn from the prior samples $p(\hat{\mathbf{x}}_{k-1})$, is used as the initial state in fluid-flow simulator to predict the state at the next timestep $\mathbf{x}_k$. Using enhanced rock physics models for three-phase, three-components, miscible flow system on the state at the next timestep $\mathbf{x}_k$, these predictions are used to obtain the timelpase changes in velocity and density fields. These changes in velocity and density samples are then used to generate synthetic observations through forward seismic simulations, represented by $\mathbf{y}_k$.

During the Training Step, samples from the joint distribution $p(\mathbf{x}_k, \mathbf{y}_k)$ form a simulated training ensemble, $\{\mathbf{x}_k^{(m)}, \mathbf{y}_k^{(m)}\}_{m=1}^M$, consisting of $M = 128$ training pairs, which are used to train the Conditional Normalizing Flow (CNF), $p_{\hat{\phi}_k}(\mathbf{x}_k \mid \mathbf{y}_k)$, to approximate the posterior distribution.

After training, during the Analysis Step, the predicted CO_2 and oil saturation, $\hat{\mathbf{x}}_k$ is conditioned on the observed field data $\mathbf{y}_k^{\text{obs}}$, to produce the samples from the CO_2 plume and oil saturation posterior distribution, $p_{\hat{\phi}_k}(\hat{\mathbf{x}}_k \mid \mathbf{y}_k^{\text{obs}})$. These samples for the state serve as "priors" for the next time step. The symbol $\hat{}$ distinguishes between predicted "digital states" and the analyzed states, which are conditioned on the observed field data $\mathbf{y}_k^{obs}$.

EXPERIMENTS

EOR simulation samples

The uncertainty of the CO_2 EOR simulation samples comes from the unknown permeability, which is represented as a random field. For the ground truth permeability, we consider a cross-section Compass model Jones et al. (2012), which is located in the North Sea. Then, using the full-waveform variational Inference via Subsurface Extensions (WISE), we obtain the permeability distribution from the posterior distribution of WISE (Yin et al., 2024).

We randomly draw $M = 128$ permeability realizations from the WISE-generated permeability distribution. Using the initial conditions described in the "Reservoir Modeling and Initial States" Subsection, we perform CO_2 EOR simulations on the different permeability samples. We inject CO_2 for 10 years, and $M = 128$ samples of the CO_2 saturation, oil saturation at year 10 are used as the training data for the state variable $\mathbf{x}_1$ in Digital Shadow.

To visualize CO_2 EOR simulation results, selected samples of the CO_2 saturation and oil saturation are shown in Figures 2,

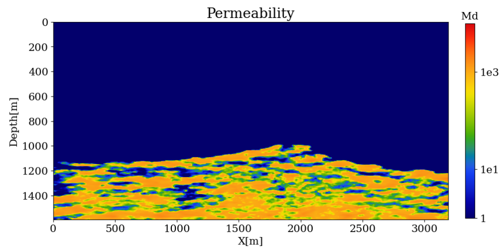

Figure 1: Permeability sample.

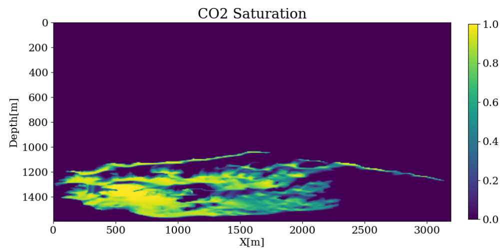

Figure 2: CO_2 saturation sample.

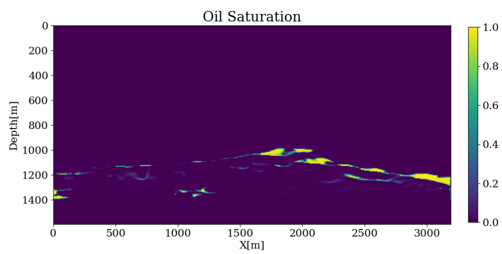

Figure 3: Oil saturation sample.

3. The corresponding permeability sample is also included in Figure 1.

Trained Digital Shadow

After training the Conditional Normalizing Flow (CNF) for 120 epochs, conditioned on the imaged time-lapse data, $\mathbf{y}_1^{\text{obs}}$, in Figures 10, the conditional mean of oil and CO_2 saturation reached an SSIM of 0.7998, as shown in Figure 5 and 8. The ground truth oil and CO_2 saturation are displayed in Figures 4 and 7, while a selected posterior sample of oil and CO_2 saturation is shown in Figures6 and 9. The RMSE (Root Mean Square Error) for oil and CO_2 saturation are displayed in Figures 11 and 13, and the std (standard deviation) of these variables is shown in the Figures 12 and 14. While the results are preliminary, the overall shape and structure of oil and CO_2 saturation are modeled accurately.

CONCLUSION AND DISCUSSION

Thanks to the seismic observations, the CO_2 EOR Digital Shadow can estimate the movement of CO_2 and oil, which is vital for improving the performance of CO_2 EOR operations. The enhanced rock physics model for a multiphase-phase, multi-

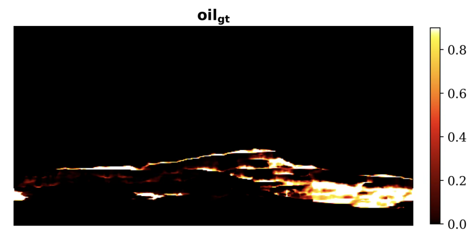

Figure 4: Ground truth oil saturation.

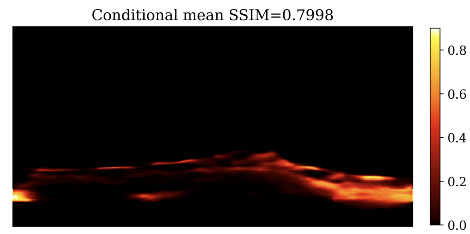

Figure 5: Oil saturation conditional mean.

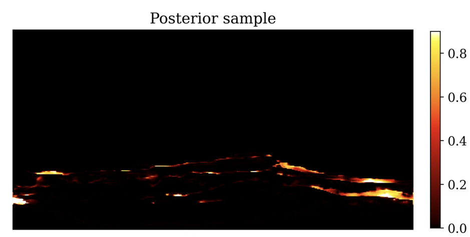

Figure 6: Oil saturation posterior sample.

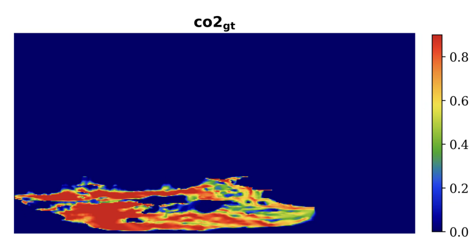

Figure 7: Ground truth CO_2 saturation.

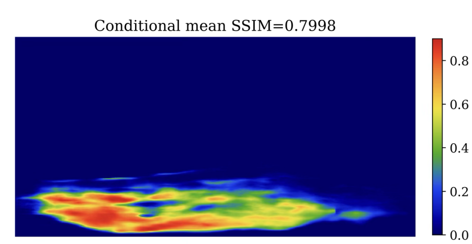

Figure 8: CO_2 saturation conditional mean.

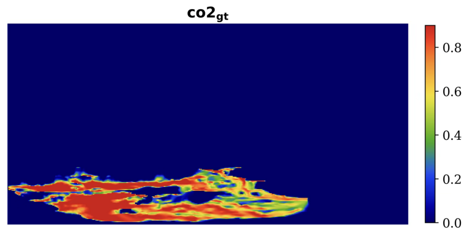

Figure 9: CO_2 saturation posterior sample.

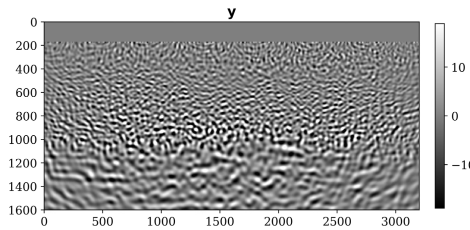

Figure 10: Observed field data.

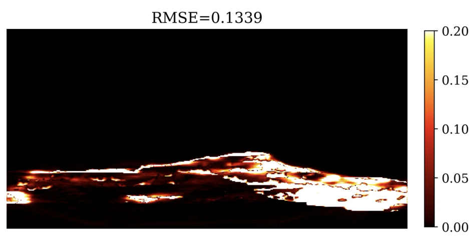

Figure 11: Oil saturation RMSE.

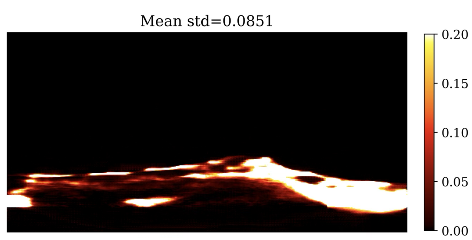

Figure 12: Oil saturation std.

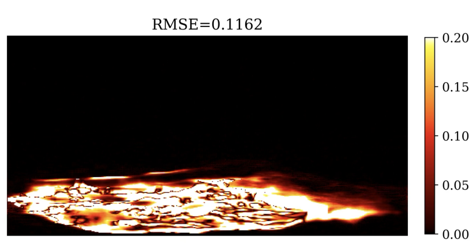

Figure 13: CO_2 saturation RSME.

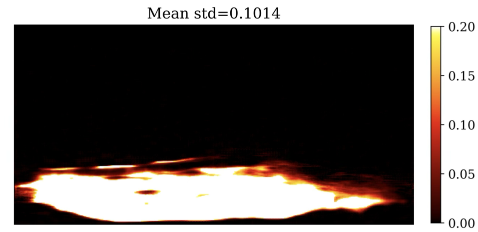

Figure 14: CO_2 saturation std.

components, miscible flow system enables the determination of EOR-induced timelapse changes in the acoustic wavespeed and density, which is critical for conducting seismic experiments.

Looking ahead, future work will focus on expanding the Digital Shadow framework into a full Digital Twin for CO_2 EOR. This Digital Twin will support decision-making processes aimed at optimizing sweep efficiency and maximizing oil recovery. Furthermore, our work on a controlled Digital Twin for Carbon Capture and Storage (CCS) (Gahlot et al., 2024a) will serve as a valuable reference for further developing the CO_2 EOR Digital Twin.

ACKNOWLEDGMENTS

This research was carried out with the support of Georgia Research Alliance and partners of the ML4Seismic Center. This research was also supported in part by the US National Science Foundation grant OAC 2203821.

Additionally, this work benefited from the use of AI-assisted writing tools, including OpenAI's ChatGPT, to refine text structure, improve clarity, and enhance readability. All technical content, research findings, and analytical conclusions were developed by the authors.

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