CO₂ Storage Associated with CO₂ Enhanced Oil Recovery: A Statistical Analysis of Historical Operations

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ABSTRACT

This work analyzes a database of 31 existing CO₂ enhanced oil recovery (EOR) projects that was compiled for the estimation of oil reserves to better understand the CO₂ retention, incremental oil recovery, and net CO₂ utilization for these oil fields. The measured data begin at the start date of the CO₂ flood and extend through the year 2007. Cumulative CO₂ retention (in the formation), incremental oil recovery factors, and net CO₂ utilization factors were calculated for each of the sites. To express all site data on a common dimensionless scale, the data were extrapolated to 300% cumulative hydrocarbon pore volume (HCPV) by fitting nonlinear functions. Summary statistics were then calculated from 0% to 300% HCPV. Across all 31 sites, the 10th, 50th (median), and 90th percentile values for the three factors at 300% HCPV were: CO₂ retention: 23.1%, 48.3%, and 61.8% retained; incremental oil recovery: 5.3%, 12.2%, and 21.5% of OOIP (original oil in place); and net CO₂ utilization: 4.8, 8.7, and 10.5 Mscf/STB (stock-tank barrel). This work employs a novel approach that incorporates nonlinear functions to quantify uncertainty in the estimated values as a function of HCPV and to describe the shape of the CO₂ retention or incremental oil recovery response with a handful of parameters, providing insight into the behavior of the reservoir across the entire timeline of the CO₂ flood. These nonlinear curve fits are focused on statistical inference – i.e., what is the likely outcome and uncertainty ranges for CO₂ retention, incremental oil recovery, and net CO₂ utilization given the historical data from the 31 CO₂ EOR sites? However, the approach described in this work also

provides useful information for prediction – i.e., given a set of inputs from another site with similar geology, what are plausible ranges in outcomes for each of these factors? Consequently, the results of this work can be used to estimate the potential range of expected performance for similar candidate oil fields that are not currently undergoing CO₂ injection, including estimates of the associated CO₂ storage potential of these candidate fields. The results of this work allow estimation of CO₂ storage capacity in CO₂-EOR operations with various degrees of confidence. The sites in the dataset reflect water–alternating gas CO₂ floods – all within the continental United States and heavily dominated by the West Texas carbonate floods. Other floods outside of this region, where the data were available, are also included in this study (i.e., the Rocky Mountain region and the State of Oklahoma).

Keywords: CO₂ storage; CO₂ utilization; enhanced oil recovery; nonlinear regression; multi-field synthesis; verification of EOR models

INTRODUCTION

The need to simultaneously reduce atmospheric concentrations of carbon dioxide (CO₂) and provide energy to satisfy an ever-growing worldwide energy demand presents a seemingly intractable societal challenge. One proven technology which both produces oil and permanently stores CO₂ in the subsurface is CO₂ enhanced oil recovery (CO₂ EOR). CO₂ EOR refers to the process whereby CO₂ is injected into the subsurface at an oil field, after which it mixes with the oil to swell it and reduce the oil viscosity, making it lighter and detaching it from the rock surfaces. These subsurface alterations cause the oil to flow more freely within the reservoir so that it will flow from the injection well to producer wells. During this process, nearly all of the

purchased CO₂ delivered to the oil field remains securely trapped within the deep geologic formation (Melzer, 2012). Consequently, CO₂ EOR provides one viable means for offsetting carbon emissions from oil production and combustion via geologic storage of the CO₂. The CO₂ EOR technique was first tested at large scale in the 1970s in the Permian Basin of West Texas and southeastern New Mexico, thus it has been used in the United States for over 40 years. As of 2014, a total of 136 active CO₂ EOR projects have been identified in the U.S. (Kuuskraa and Wallace, 2014).

Historically, most of the CO₂ supply to CO₂ EOR projects has come from larger *natural* sources, which obviously do not contribute toward a reduction in *anthropogenic* CO₂ emissions (Kuuskraa and Wallace, 2014). However, in an effort to reduce concentrations of CO₂ in the atmosphere that are caused by anthropogenic sources, the U.S. Department of Energy (DOE) is pursuing carbon capture, utilization, and storage (CCUS) as one approach in a portfolio of greenhouse gas reduction strategies. CCUS involves (1) separating CO₂ from an industrial process;; (2) transporting the CO₂ to a geologic storage location; and (3) injecting and storing the CO₂ in a geologic reservoir for long-term isolation from the atmosphere (Intergovernmental Panel on Climate Change, 2005). In the case of CO₂ EOR, the CO₂ is “utilized” in the sense that it is serving an additional value-added purpose of producing incremental oil prior to geologic storage (in contrast to CO₂ injection into saline reservoirs which only serve as CO₂ storage units and do not provide incremental oil recovery). As part of its Carbon Storage Program, DOE is working toward the demonstration and commercialization of CCUS through its Infrastructure, Core Research and Development (R&D), and Global Collaborations areas (U.S. Department of Energy, 2013), which was also the source of funding for this study.

CO₂ EOR is most commonly a “tertiary production phase” process, which is used after the primary and secondary production phases have been completed. During the life-cycle of the CO₂ EOR process (commonly referred to as the “CO₂ flood”), CO₂ is injected into the reservoir at designated injection wells and a mixture of oil, CO₂, and water is produced at production wells. These produced fluids are separated at the surface. Oil is transported off-site to refineries and other end users. The produced CO₂ is separated from the other fluids (processed), dried, re-compressed and re-injected into the subsurface. This recycling of the produced CO₂ prevents it from being released to the atmosphere and provides substantial savings to the oil field operator that would otherwise have had to purchase replacement CO₂ volumes (DOE, 2010; Melzer, 2012). Therefore, the CO₂ EOR process is essentially a closed loop for CO₂. However, not all of the injected CO₂ is produced, as a significant fraction of the CO₂ is retained in the reservoir. To maintain a specified injection ratio of water and CO₂, the recycled CO₂ is supplemented with the purchased CO₂. Therefore, as the CO₂ flood continues through time, the total volume of injected CO₂ is comprised of both recycled CO₂ and purchased CO₂. Often, CO₂ floods proceed by alternating the injection of CO₂ and water, which are designated as “water-alternating-gas”, or WAG floods. The WAG approach helps to reduce the tendency for the lower viscosity CO₂ to finger its way ahead of the displaced oil and therefore improves the sweep efficiency of the flood (DOE, 2010). Sweep efficiency refers to the effectiveness of the injected CO₂ to contact the volume of the reservoir where the oil resides (Green and Willhite, 1998). The produced water may also be re-injected into the reservoir as part of the WAG process. Figure 1 illustrates the fluid flows (oil, CO₂, and water) in a typical CO₂ EOR project.

Industry experience and simulation studies suggest that the amount of CO₂ stored is a function of both geologic and operational controls. Geologic controls are specific to the

reservoir, and include lithology, permeability, heterogeneity, and other physical features unique to the reservoir. Operational controls are specific to the design and operation of the CO₂ flood, including injection pattern (the geometrical arrangement of injector and producer wells), pattern spacing (the distance between injectors and producers), the volume of CO₂ injected, and the ratio of injected water to injected CO₂ (the “WAG ratio”). The interplay of geologic and operational controls leads to uncertainty in the amount of CO₂ storage that occurs at an individual site. Analogously, these same controls affect the quantity of incremental oil that is produced (ARI and Melzer, 2010; Hill et al., 2013; van ’t Veld et al., 2013; 2014; Ettehadtavakkol, 2014).

The primary objective of this work is to improve the overall quantitative understanding of CO₂ retention, incremental oil recovery, and net CO₂ utilization, which are factors that significantly influence the long-term performance and economic viability of CO₂ EOR projects. CO₂ retention is a metric that expresses the fraction of total injected CO₂ that is not recycled but remains in the subsurface. CO₂ storage is a metric that expresses the fraction of total purchased CO₂ that remains in the subsurface. Incremental oil recovery is the amount of oil that is produced solely from the CO₂ flood (i.e., not from the previous primary and secondary production phases). Lastly, net CO₂ utilization tracks the amount of purchased CO₂ that is required to produce a barrel of oil. This work provides a statistical analysis of an historical industry dataset, which allows modeling results to be compared against real-world, observed injection and production data. Other authors have summarized multi-site CO₂ EOR field data in the past (e.g., Brock and Bryan, 1989; Hadlow, 1992; Manrique et al. 2007), or have extended predictions of CO₂ EOR performance into the future using simulation models (e.g., Merchant, 2010). However, this work differs significantly from past publications in three major ways. First, empirical models in this study were fit across 31 sites with real-world injection and production data, which represents one

of the largest CO₂ EOR datasets ever to be analyzed and summarized in the peer-reviewed literature. Second, by incorporating a statistical model that fits the entire data record, as opposed to extending long-term trends via decline-curve analysis or other forecasting tools, this approach allows inference about the overall shape of the CO₂ retention, incremental oil recovery, and net CO₂ utilization responses through time. Finally, this approach and data set significantly extend the understanding of CO₂ EOR behavior and uncertainty quantification further into the future (i.e., at higher total volumes of fluid injected into the reservoir) than has been presented in previous work.

MATERIALS AND METHODS

Industry Data Set and Parameters

Monthly reservoir performance data from 31 CO₂ EOR sites (hereafter referred to as the Industry Data Set) were provided by Melzer Consulting, Inc. and a worldwide reservoir appraisal company (confidential). These data have been used to develop petroleum reserve estimates for the operators of the field and to prepare annual petroleum reserves certifications for filers with the U.S. Securities and Exchange Commission. They include the following five parameters for each of the 31 CO₂ EOR sites:

- 1) Time (years): This is the time in years since the start of the CO₂ flood. All 31 sites are expressed on a common time scale such that time zero (t_0) represents the beginning of the CO₂ flood across all projects, with data continuing up to and including the year 2007;
- 2) CO₂ injected (%HCPV): This is the total cumulative volume of CO₂ injected (purchased plus recycled CO₂) expressed as %HCPV;

- 3) CO₂ produced (%HCPV): This is the total cumulative volume of CO₂ produced expressed as %HCPV. It is equivalent to the recycled volume of CO₂;
- 4) CO₂ + H₂O injected (%HCPV): This is the total cumulative volume of CO₂ and water injected expressed as %HCPV. Most, but not all, CO₂ floods utilize the WAG injection method wherein stages of gas injection (predominantly CO₂) are followed by injection of liquid only (predominantly water.) The normalizing factor used herein tracks both the CO₂ and the water volumes in contrast to just the CO₂ volumes; and
- 5) Cumulative incremental oil recovery (% original oil in place [OOIP]): The cumulative incremental oil recovery data are expressed as %OOIP, where the baseline waterflood and any infill drilling contributions have been subtracted from the total oil production to determine the incremental oil production resulting from CO₂ injection

Dimensionless Variables

In comparing reservoir performance data across multiple sites, it is useful to express the data using dimensionless variables, which are independent of any particular system. These calculations were conducted by the worldwide reservoir appraisal company who compiled the database. The first step is to define OOIP, which is the amount of oil in the reservoir prior to any production and is a function of the volume of the reservoir (area and thickness), porosity, and the original oil saturation, as shown in Eq. 1 (Green and Willhite, 1998).

$$N = Ah\phi S_{oi} \frac{1}{B_{oi}} \left(\frac{1}{5.615 \text{ ft}^3 / \text{bbl}} \right) \quad (1)$$

Where:

N = Original oil in place (stock tank barrels [STB]);

- A = Reservoir area (ft²);
- h = Reservoir thickness (ft);
- ϕ = Reservoir porosity (fraction);
- S_{oi} = Original oil saturation (volume fraction);
- B_{oi} = Initial oil formation volume factor (reservoir barrels [RB]/STB); and
- 1/5.615 = Conversion factor from cubic feet to barrels (ft³/bbl).

Reservoir barrel (RB) refers to the volume of oil at reservoir pressure and temperature conditions. Stock tank barrel (STB) refers to the volume of oil after production, at surface pressure and temperature, which has been established as 15.6°C and 101.325 kPa [60°F and 14.696 psia], respectively.]. OOIP is commonly reported in units of STB.

The volumes of CO₂ injected, CO₂ produced, and CO₂ + H₂O injected may be expressed as dimensionless variables in units of HCPV, as opposed to a volume or mass measure. HCPV represents the pore volume of the reservoir that is occupied by hydrocarbons. One hundred percent HCPV (which is equivalently reported in the literature as 1.0 HCPV) is equivalent to the OOIP. However, the amount of CO₂ or CO₂ + H₂O injected is not bounded between zero and 100%, as more than 100% HCPV may be injected into the reservoir over the life-cycle of the CO₂ flood due to the fact that there is not perfect displacement, i.e., sweep efficiency, of the OOIP, which requires the recycling of produced CO₂ plus additionally purchased CO₂ beyond 100% HCPV to achieve the desired oil recoveries (Figure 1). The formula for determining %HCPV of CO₂ injected or produced is as follows (Green and Willhite, 1998):

$$HCPV = \frac{RB CO_2}{OOIP \times B_{oi}} \quad (2)$$

Where:

- HCPV = Hydrocarbon pore volume (%);
RB CO₂ = Reservoir barrels (RB) of CO₂;
OOIP = Original oil in place [stock tank barrels (STB)]
B_{oi} = Initial oil formation volume factor (RB/STB)

Incremental oil recovery represents oil that is produced following the primary or secondary oil production, i.e., during tertiary recovery from the CO₂ flood, and hence incrementally adds to the entire oil production from the field. Incremental oil recovery may also be expressed as a dimensionless variable, the incremental oil recovery factor, which is expressed in units of %OOIP, as opposed to a volumetric measure, as shown in Eq. 3 (Green and Willhite, 1998).

$$RF = \frac{N_p}{N} \quad (3)$$

(3)

Where:

- RF = Incremental oil recovery factor [unitless];
N_p = Cumulative incremental oil production [STB]; and
N = Original oil in place [STB].

CO₂ Retention

The formula for CO₂ retention that is used throughout this paper (Eq. 4) is widely used within the oil and gas industry and expresses CO₂ retention as a fraction between 0 and 1 (Melzer, 2012):

$$\text{CO}_2 \text{ retention} = \frac{(\text{total CO}_2 \text{ injected} - \text{CO}_2 \text{ produced})}{\text{total CO}_2 \text{ injected}} \quad (4)$$

Where:

CO₂ retention = percent of injected CO₂ retained in the reservoir (%);

total CO₂ injected = total injected volumes of CO₂ [purchased plus recycled CO₂] (%HCPV);

and

CO₂ produced = total produced volumes of CO₂ [recycled CO₂] (%HCPV).

The CO₂ retention computed using Eq. 4 is a *cumulative* CO₂ retention, and represents the fraction of total injected CO₂ that is not recycled.

Net CO₂ Utilization Factors

This paper calculates and discusses *net* CO₂ utilization expressed as Mscf of CO₂ per STB of oil produced. Net CO₂ utilization does not include the recycled CO₂ component and, therefore, only incorporates the purchased CO₂ volumes into the calculation. In contrast, *gross* CO₂ utilization includes the total amount of CO₂ injected, which incorporates both purchased and recycled CO₂ volumes into the calculation as discussed further below.

The net CO₂ utilization factor is commonly expressed as the amount of purchased CO₂ used to recover a barrel of oil, in units of Mscf/STB (Wiggins and Hughes, 2005). The units needed to derive the CO₂ utilization factor are different from those provided in the Industry Data Set,

which expresses injection and production data using dimensionless variables – injected CO₂ volumes are in units of %HCPV (not Mscf) and incremental oil production is in units of %OOIP (not STB).

For the purposes of calculating net CO₂ utilization, this work assumed that the volume of purchased CO₂ is equal to the total CO₂ injected less the CO₂ recycled from the previous time step. This assumption was based on the fact that CO₂ losses are *de minimus*, and therefore, contribute a relatively small amount of error into the calculation (Fox, 2009; DOE, 2010a; Melzer, 2012). We then used OOIP, initial oil formation volume factor (B_{oi}), and CO₂ formation volume factor (B_{CO_2}) to derive the purchased CO₂ volume in units of Mscf, as per Eq. 5 (Green and Willhite, 1998):

$$V_{CO_2, purchased, Mscf} = \frac{V_{CO_2, purchased, HCPV} \times N \times B_{oi}}{B_{CO_2}} \quad (5)$$

Where:

$V_{CO_2, purchased, Mscf}$ = Cumulative volume of purchased CO₂ injected (Mscf);

$V_{CO_2, purchased, HCPV}$ = Cumulative volume of purchased CO₂ injected (HCPV);

N = Original oil in place [STB];

B_{oi} = Initial oil formation volume factor (RB/STB); and

B_{CO_2} = CO₂ formation volume factor (RB/Mscf).

The B_{oi} , B_{CO_2} , and N values for each site that were used in Eq. 5 to convert the units of the purchased CO₂ from %HCPV to Mscf were obtained from the literature; however, literature

values for all of these parameters were not available for all 31 sites. As a result, net CO₂ utilization factors could only be computed for 16 of the 31 sites.

Cumulative incremental oil recovery in the Industry Data Set is expressed as %OOIP. We converted %OOIP into units of STB prior to computing the net CO₂ utilization factor by rearranging Eq. 3, as shown in Eq. 6:

$$N_p = RF \times N \quad (6)$$

Where:

N_p = Cumulative incremental oil production [STB];

N = Original oil in place [STB]; and

RF = Incremental oil recovery factor [unitless].

For the 16 sites for which we could accurately express both the cumulative volume of purchased CO₂ injected (Mscf) and the cumulative incremental oil production (STB) in the appropriate units, the net CO₂ utilization factor for each site was calculated as follows (Eq. 7):

$$UF_{CO_2,net} = \frac{V_{CO_2,purchased,Mscf}}{N_p} \quad (7)$$

Where: $UF_{CO_2,net}$ = Net CO₂ utilization factor (Mscf/STB);

$V_{CO_2,purchased,Mscf}$ = Cumulative volume of purchased CO₂ injected (Mscf); and

N_p = Cumulative incremental oil production (STB).

The net CO₂ utilization factors computed in this paper are *cumulative* net CO₂ utilization factors for each site, where the cumulative CO₂ injected at the site is divided by the cumulative oil produced at the site up to the %HCPV that was selected for the calculation.

Nonlinear Regression

As previously noted the Industry Data Set includes measured data that begins at the start date of the CO₂ flood and extends up to and including the year 2007. It is difficult to assess CO₂ retention, incremental oil recovery, and net CO₂ utilization across multiple sites when there is no common basis for comparison. For example, at 10 years into the CO₂ flood, Sites A and B had injected 50% and 65% HCPV of CO₂ + H₂O, respectively; therefore, simply using the time since the start of the CO₂ flood is not a sufficient parameter with which to compare multiple sites. Therefore, to express all site data on a common dimensionless scale, the reservoir performance data were evaluated as a function of total CO₂ + H₂O injected in units of %HCPV, and were extrapolated to 300% HCPV for each of the sites to allow for multi-site comparisons of the above factors from 0% to 300% HCPV. This extrapolation was done by fitting a nonlinear function to the data using nonlinear regression. There were two steps to the nonlinear regression modeling: 1) selecting the nonlinear regression model form and 2) fitting the nonlinear regression model parameters.

The curves produced by plotting CO₂ retention and incremental oil recovery versus CO₂ + H₂O injected all exhibited a sigmoidal shape (Fig. 2 and Fig. 3, respectively). CO₂ retention and incremental oil recovery factors are both expressed as a value between 0 and 1 (i.e., a

percentage). Sigmoidal-shaped curves bounded by the interval from 0 to 1 are commonly modeled using a logistic function (Gelman and Hill, 2007; Carlin and Louis, 2009). However, the logistic function is symmetrical around its inflection point. Since the CO₂ retention and incremental oil recovery curves show a different type of response, i.e., the slopes are steeper at the early part of the CO₂ flood, it was necessary to fit these sigmoidal curves using a four-parameter log-logistic function. This function defines the response, y , at any value of x by an equation with four parameters: minimum response, maximum response, the natural log(inflection point), and the slope factor (Minitab Statistical Software, 2014):

$$y = A + (B - A) / \{1 + \exp[D \times \ln(x / C)]\}, \quad (8)$$

Where:

- y = CO₂ retention (%) or incremental oil recovery (%OOIP);
- x = total cumulative volume of CO₂ + H₂O injected (%HCPV);
- $\ln$ = natural log to the base e (approximately equal to 2.71828);
- A = fitted model parameter equal to the lower asymptote at infinite CO₂ + H₂O injected (for CO₂ retention) or the upper asymptote at infinite CO₂ + H₂O injected (for incremental oil recovery);
- B = fixed (constant) model parameter equal to the upper asymptote of 100% (for CO₂ retention) or the lower asymptote of 0% (for incremental oil recovery);
- C = fitted model parameter equal to the inflection point in the sigmoidal shape where the curve changes from concave to convex (for CO₂ retention) or from convex to concave (for incremental oil recovery); and

D = fitted model parameter for the slope factor of the curve between the upper and lower asymptotes.

As for the net CO₂ utilization versus CO₂ + H₂O injected curves, they all exhibited an asymptotic shape, with high values at low injection volumes and rapid decline to an asymptotic value of approximately 10 Mscf/STB (Fig. 4). Several different asymptotic model forms were explored, and ultimately these curves were fit using a two-parameter asymptotic model of the form:

$$\ln(y) = A + (B/x), \quad (9)$$

Where:

$\ln(y)$ = natural log of CO₂ net utilization (Mscf/STB);

x = total cumulative volume of CO₂ + H₂O injected (%HCPV);

A = fitted model parameter equal to the lower asymptote at infinite CO₂ + H₂O injected; and

B = fitted model parameter related to the slope of the curve from the maximum value to the asymptote.

Other model forms were evaluated for extrapolation to 300% HCPV, such as the exponential, harmonic, power, and hyperbolic forms, which are commonly used in decline-curve analysis (e.g., Arps, 1994; Guo et al., 2007; Poston and Poe, 2008). However, these decline-curve models are used to extend trends into the future, and are insufficient for modeling the entire shape of the

sigmoidal curve. This study was interested in not only extrapolating the data record to 300% HCPV, but also in fitting a function to the entire data record to allow inference about the overall shape of the curve and how that shape might relate to reservoir conditions and CO₂ flood design.

Model fits were evaluated using the root mean squared error (RMSE) as a gross measure of model goodness-of-fit across the data record. In addition, the residuals ($y_{\text{observed}} - y_{\text{predicted}}$) were plotted against cumulative total CO₂ + H₂O injected (x) to assess model fit as a function of %HCPV (Motulsky and Ransnas, 1987). The RMSE values and graphical assessment of residual fits were used to justify selection of a single model form used in the multi-site analysis, with priority given to models with better fits at higher %HCPV and to models that could reproduce the full shape of the curve. While there is no absolute criterion for a “good” value of RMSE, lower RMSE values across model forms represent better-fitting models. In addition, models with smaller residuals in the region of the curve where predictions are needed most (i.e., between 200% and 300% HCPV) represent better models for the goals of this study. Approximately 87% of the sites in the Industry Data Set have observed data through 100% HCPV; 60% of the sites have observed data through 200% HCPV; and less than 30% of the sites have observed data through 300% HCPV. Thus a target area for prediction in our work is the region between 200% and 300% HCPV. The reason for selecting a single model was so that the fitted parameters could be assessed across all sites. Using this logic, the four-parameter log-logistic model was determined to provide the best fit for CO₂ retention and incremental oil recovery, while the asymptotic model was determined to provide the best fit for net CO₂ utilization.

Parameters for each model were fit using the nonlinear regression module in Minitab® Statistical Software, Version 17 (Minitab Statistical Software, 2014). Initial starting values for each parameter were selected based on a graphical assessment and the geometric interpretation

of each parameter (i.e., asymptotes, inflection point, and slope factor). The Gauss-Newton algorithm was then used to minimize the sum of squared errors (SSE). Model fits were evaluated using a graphical assessment in addition to inspection of residuals and SSE.

RESULTS

Patterns in CO₂ Retention, Incremental Oil Recovery Factor, and CO₂ Net Utilization

The 31 sites had similar CO₂ retention patterns over time (Fig. 2) and show that a larger proportion of the injected CO₂ is retained in the reservoir (i.e., CO₂ recycle volumes are low) during the early years of a CO₂ EOR project (at low %HCPV), until reaching a near-horizontal slope (i.e., asymptote) in later years (at high %HCPV).

The incremental oil recovery factor trends were the inverse of CO₂ retention; the 31 sites showed low oil recovery at low %HCPV and an increased until reaching a stable, near-horizontal slope at higher %HCPV. These patterns show that during the early years of a CO₂ EOR project, a larger proportion of the injected CO₂ is retained in the reservoir with no commensurate increase in the incremental oil production, resulting in relatively low oil recovery factors (Fig. 3).

The 16 sites with corresponding data also showed similar net CO₂ utilization factor patterns over time, with higher net CO₂ utilization factors at low %HCPV and an exponential-type decline until reaching a stable, near-horizontal slope at higher %HCPV (Fig. 4). These patterns show that during the early years of a CO₂ EOR project (at low %HCPV), a larger proportion of the injected CO₂ is retained in the reservoir while little oil is produced, resulting in significantly higher net CO₂ utilization factors. At many of the sites, the CO₂ utilization factor exceeded 1000 Mscf/STB in the first several years before converging toward a more stable asymptotic value near 10 Mscf/STB.

Nonlinear Curve Fits of CO₂ Retention

The four-parameter log-logistic function was able to accurately describe the overall shape of the CO₂ retention curve across the 31 sites. Representative fits for six of the 31 sites are shown in Fig. 5. These sites reflect the variety of slopes, asymptotic values, and overall shapes observed in the data set and demonstrate the robustness of the four-parameter log-logistic function to accurately describe the patterns observed in the data. The median RMSE value across the CO₂ retention model fits from 50% to 300% HCPV for the 31 sites was 0.496, indicating a good overall model fit with average differences between observed and predicted values of about 0.5% CO₂ retention. A list of the parameter estimates for A through D for each of the 31 sites is compiled in Table 1.

The lower asymptotic values (parameter A) across the 31 sites, which represent CO₂ retention at infinite CO₂ + H₂O injected, ranged from 13.0% to 62.2%, with a median value of 47.7%. As noted in the introduction, uncertainty in CO₂ retention reflects the various site-specific geologic and operational factors that contribute to incidental CO₂ storage over the lifetime of the CO₂ flood.

From a CO₂ cost perspective, the ideal site would have low CO₂ retention and more rapidly transition from high to low CO₂ retention such that the CO₂ utilization would be less intensive over the lifetime of the CO₂ flood (i.e., less CO₂ would be required to produce an incremental barrel of oil). In terms of Eq. 8, this would translate into a low parameter A value (low CO₂ retention), low parameter C value (early inflection point in the CO₂ flood), and high parameter D value (steep slope).

Nonlinear Curve Fits of Incremental Oil Recovery

The four-parameter log-logistic function was also able to accurately describe the overall shape of the incremental oil recovery curve across the 31 sites. Representative fits for six of the 31 sites are shown in Fig. 6. These sites reflect the variety of slopes, asymptotic values, and overall shapes observed in the data set, and demonstrate the robustness of the four-parameter log-logistic function to accurately describe the data. The median RMSE value across the incremental oil recovery model fits from 50% to 300% HCPV for the 31 sites was 0.075, indicating a good overall model fit with average differences between observed and predicted values of less than 0.1% OOIP. A list of the parameter estimates for A through D for each of the 31 sites is compiled in Table 1.

The upper asymptotic values (parameter A) across the 31 sites, which represent incremental oil recovery at infinite $\text{CO}_2 + \text{H}_2\text{O}$ injected, ranged from 4.8% to 26.1%, with a median value of 13.5%. Analogous to CO_2 retention, the uncertainty in incremental oil recovery reflects the various site-specific geologic and operational factors.

From an oil production perspective, the ideal site would have a high incremental oil recovery and would more rapidly transition from low to high recovery such that the oil production would be more rapidly achieved in the early phases of the CO_2 flood. In terms of Eq. 8, this would translate to a high parameter A value (high incremental oil recovery), low parameter C value (early inflection point in the CO_2 flood), and high parameter D value (steep slope).

Nonlinear Curve Fits of CO_2 Net Utilization

As previously mentioned, net CO_2 utilization could only be calculated for 16 of the 31 sites because the B_{oi} , B_{CO_2} , or N values needed to convert from dimensionless variables to volumetric units were not available for all 31 sites. For the 16 sites for which we could accurately express

both the cumulative volume of purchased CO₂ injected and the cumulative incremental oil production, the two-parameter asymptotic function was able to accurately describe the overall shape of the net CO₂ utilization curves. Unlike CO₂ retention and incremental oil recovery, which had very low residuals across the entire data record for nearly all 31 sites, the net CO₂ utilization residuals were slightly higher. This was particularly true near the focus of the hyperbolic shape where the steep, near-vertical decline in net CO₂ utilization transitions to the asymptote. However, despite this phenomenon, the two-parameter asymptotic function was able to accurately describe the overall shape of the net CO₂ utilization curve and had small residuals at higher %HCPV. Representative fits for six of the 16 sites are shown in Fig. 7. The median RMSE value across the net CO₂ utilization model fits from 50% to 300% HCPV for the 16 sites was 0.593, indicating a good overall model fit with average differences between observed and predicted values of about 0.6 Mscf/STB. A list of the parameter estimates for A and B for each of the 16 sites is compiled in Table 1. Analogous to CO₂ retention and incremental oil recovery, the uncertainty in net CO₂ utilization reflects the various site-specific geologic and operational factors.

From a profitability perspective, the ideal site would have a steep slope, reflecting a rapid transition from high to low net CO₂ utilization, and asymptote to a low net CO₂ utilization. This combination of observations would yield a more rapid decline in the amount of CO₂ required to produce a barrel of oil over the lifetime of the CO₂ flood. In terms of Eq. 9, this translates to a low parameter A value (low net CO₂ utilization asymptote) and a high parameter B value (steep slope).

The lower asymptote (exponentiation of parameter A) represents net CO₂ utilization at infinite (CO₂ + H₂O) injected. However, it should be noted that it is not correct to interpret an

infinitely asymptotic behavior to net CO₂ utilization, as the true model form may be slightly curvilinear at higher %HCPV. Stated differently, net CO₂ utilization may increase beyond 300% HCPV and therefore may not be a true asymptote. The residuals within the modeled region used in this study (between 50% to 300% HCPVI) were generally less than 0.2 Mscf/STB, and therefore, the model form was appropriate for this intended use. However, interpretations should not be extended to outside this region of injection.

Uncertainty Quantification – Percentile Estimates from 0% to 300% HCPVI

The modeled responses from 0% to 300% HCPVI from each of the sites (31 sites for CO₂ retention and incremental oil recovery and 16 sites for net CO₂ utilization) were combined into a single data set to generate empirical percentile estimates across the sites. The model fits for CO₂ retention, incremental oil recovery, and net CO₂ utilization are shown in Fig. 8. The 10th, 25th (first quartile), 50th (median), 75th (third quartile), and 90th percentile values (P₁₀, P₂₅, P₅₀, P₇₅, and P₉₀, respectively) were used to describe the uncertainty in the response as a function of %HCPV. The P₅₀ estimate is the central value of the distribution. The P₂₅ to P₇₅ is the interquartile range (IQR) and the central 50 percent of the data would be found within this interval (dark gray shaded regions in Fig. 8). Lastly, the P₁₀ to P₉₀ is the range within which 80 percent of the data would be found (light gray shaded regions in Fig. 8).

The minimum, maximum, average, standard deviation, and percentile estimates are summarized in Table 2. The P₁₀, P₅₀, and P₉₀ estimates at 300% HCPV for the three responses modeled in this work were: CO₂ retention - 23.1%, 48.3%, and 61.8%; incremental oil recovery - 5.3%, 12.2%, and 21.5% OOIP; and net CO₂ utilization 4.8, 8.7, and 10.5 Mscf/STB.

DISCUSSION

Comparison to Other Published Studies

The results of this work at 300% HCPV compare well with other published studies that projected end-of-project estimates. For example, the patterns shown by Hadlow (1992) for simulation studies of incremental oil recovery as a function of time and different CO₂ injection methods (continuous CO₂; 1:1 conventional WAG; 1:1 hybrid WAG) demonstrate the sigmoidal shape used in the modeling work in this study. In addition, Hadlow (1992) also described the estimated end-of-project net CO₂ utilization for five major CO₂ EOR projects (Denver, Means, Rangely, Seminole, and E. Vacuum). The ranges in net CO₂ utilization were 6 to 11 Mscf/STB. These ranges agree well with the percentile estimates developed in the current work, which ranged from a P₁₀ value of 4.8 Mscf/STB to a P₉₀ value of 10.5 Mscf/STB across the 16 sites for which net CO₂ utilization values could be calculated.

Merchant (2010) evaluated oil recovery for WAG floods beyond 80% HCPV using numerical models. Data from that work, which included several of the sites that were also part of the Industry Data Set of this work, suggest tertiary oil recovery beyond 80% HCPV in the range of 5% to 25% OOIP, depending on the specific reservoir formation, field, or lease. These ranges agree well with the percentile estimates developed in the current work, which ranged from a P₁₀ value of 5.3% to a P₉₀ value of 21.5% across the 31 sites. Similar results were also observed for net CO₂ utilization. The ranges for net CO₂ utilization reported by Merchant (2010) were approximately 1 to 10 Mscf/STB, again dependent upon the specific reservoir formation, field, or lease, as compared to the P₁₀ and P₉₀ estimates developed in the current work, as noted above. Thus the model predictions of Merchant (2010) are verified by the observations of this study, which are based on empirical data from actual field results.

Lastly, Zhou et al. (2012) discuss incremental oil recovery in the range from 8% to 25% OOIP for Permian Basin CO₂ WAG injection, which agrees well with the percentile estimates developed in the current work. In addition, Zhou et al. (2012) estimated the net CO₂ utilization at continuous injection and WAGs with different WAG ratios. For continuous CO₂ injection up to WAG ratios of 4:1, predicted net CO₂ utilization ranged from 13 to 5 Mscf/STB, respectively. These ranges also agree well with the P₁₀ and P₉₀ values discussed in this current work.

Predictions of CO₂ Storage

The nonlinear curve fits and percentile estimates are focused on statistical *inference* – i.e., what is the likely outcome, and uncertainty ranges, for CO₂ retention, incremental oil recovery, and net CO₂ utilization given the historical data from 31 CO₂ EOR sites? However, the approach described in this work also provides useful information for *prediction* – i.e., given a set of inputs from another site with similar geology and operational factors, what are plausible ranges in outcomes? Generic predictions of CO₂ storage are possible using the results from this work. The volume of CO₂ stored is a function of OOIP, incremental oil recovery factor, and net CO₂ utilization factor, is shown below in Eq. 10. Generic predictions.¹⁰

$$\text{CO}_2 \text{ stored [Mscf]} = (\text{OOIP} \times \text{RF}) \times \text{UF}_{\text{CO}_2, \text{net}}, \quad (10)$$

Where:

OOIP = original oil in place (STB);

RF = incremental oil recovery factor (%); and

UF_{CO₂,net} = net CO₂ utilization factor (Mscf/STB)..

For example, assuming an OOIP of 500 million bbl, a point estimate of the volume of CO₂ stored using the median value for incremental oil recovery factor and UF_{CO₂,netnet} at 300% HCPV from Table 2 is:

$$\begin{aligned}\text{CO}_2 \text{ stored [Mscf]} &= (500,000,000 \text{ bbl} \times 0.122) \times 8.7 \text{ Mscf/STB} \\ &= 530,700,000 \text{ Mscf} \\ &= 27.6 \text{ Mt}\end{aligned}$$

The conversion from Mscf to tonnes assumes 1 tonne of CO₂ per 19.25 Mscf at standard conditions of 101.4 kPa (14.7 psi) and 21.1 degrees Celsius (70 degrees Fahrenheit) (DOE, 2010b).

For generic screening, however, it is recognized that the incremental oil recovery factor and UF_{CO₂,netnet} at each %HCPV are both uncertain quantities, with summary statistics from the Industry Data Set provided in Table 2. Therefore, estimates of these factors which better quantify the inherent uncertainty can be achieved through Monte Carlo simulation that takes into account this uncertainty. For example, using the same OOIP as above but accounting for the uncertainty in the estimates for incremental oil recovery factor and UF_{CO₂,netnet} at 300% HCPV, Monte Carlo simulation produces an interval estimate for the amount of CO₂ stored of 13.1, 25.3, and 42.4 Mt for the P₁₀, P₅₀, and P₉₀, respectively. A histogram of CO₂ stored using this Monte Carlo simulation approach is shown in Fig. 9. While this generic screening approach is rapid and straightforward to implement, the uncertainty in the inputs produces uncertainty in the estimates of CO₂ stored. This generic screening approach would be suitable for broad regional

assessments, and could perhaps provide useful information to make site-specific decisions about incremental oil recovery and associated CO₂ storage.

CO₂ Retention versus CO₂ Storage

It is important to emphasize that Eq. 4 quantifies CO₂ retention, not CO₂ storage, as the latter requires knowledge of purchased CO₂ volumes. For example, the formula for calculating CO₂ storage would be as follows (Eq. 11) (Melzer, 2012):

$$\text{CO}_2\text{storage} = \frac{(\text{total CO}_2 \text{ injected} - \text{CO}_2 \text{ produced} - \text{CO}_2 \text{ losses})}{\text{purchased CO}_2 \text{ injected}} \quad (11)$$

Where:

- CO₂ storage = percentage of purchased CO₂ stored (%);
- total CO₂ injected = total injected volumes of CO₂ [purchased plus recycled CO₂];
- CO₂ produced = total produced volumes of CO₂ [recycled CO₂];
- CO₂ losses = CO₂ losses from the injector/producer system; and
- purchased CO₂ injected = purchased CO₂ volumes.

Purchased CO₂ volumes are protected by confidentiality agreements between the buyers and sellers of CO₂, and were not available as part of the Industry Data Set. As a result of the protected nature of these data, there is widespread use of the non-confidential quantity of total injected CO₂ volumes (which includes the recycled CO₂ volumes), and hence the use of Eq. 4 rather than Eq. 11 (Melzer, 2012).

CO₂ losses from the injector/producer system can occur during an EOR project. For example, power outages or equipment repair can cause periods where CO₂ (and other gaseous substances) must be released to the atmosphere during the flaring of the gas. This is an example of surface CO₂ losses. In addition, lateral migration within the target injection zone and the inability to assure perfect lateral containment within the flooded area can also lead to CO₂ losses in the reservoir, i.e., CO₂ migrates outside of the producer wells and is therefore not captured in the recycling loop but remains in the subsurface (Melzer, 2012). These down-hole losses do not represent a loss of CO₂ storage; the CO₂ is still retained in the subsurface, but it is not captured in the recycle loop. These surface and down-hole losses would be subtracted from the numerator of Eq. 11, as they represent a component of the CO₂ stream that leaves the injection/production system and is not recycled. CO₂ losses (either surface or down-hole [i.e., in the reservoir]) were not quantified in the Industry Data Set; however, industry experience suggests that total CO₂ losses from these are small (<5%), with half allocated to surface losses and half allocated to down-hole losses (which do not contribute to a loss of storage) (Fox, 2009; DOE, 2010a; Melzer, 2012). This leads to CO₂ storage values greater than 95%.

As a result of the inability to quantify purchased CO₂ volumes and CO₂ losses from the Industry Data Set, this paper defines CO₂ retention as presented in Eq. 4, recognizing that the computed value represents the fraction of total CO₂ injected that is retained in the subsurface (i.e., not recycled), and that this quantity is not directly comparable to the percentage of stored CO₂ volumes as a fraction of the purchased CO₂ volumes. For example, the median CO₂ retention value of 48.5% determined as part of this work (i.e., the P₅₀ value) does not imply that the remaining 51.5% of the CO₂ was emitted to the atmosphere – the recycled CO₂ is captured for use at another CO₂ EOR site. The scarcity and cost of the CO₂ drives the operator to

recapture and conserve as much of the CO₂ as possible. The stored volumes of CO₂ in the reservoir are the purchased volumes of CO₂ minus negligible losses (Hill et al., 2013). Using this basis, life-cycle assessments have shown that more than 97% of purchased CO₂ volumes are retained in the subsurface (Fox, 2009). Thus, losses of purchased CO₂ to the atmosphere are on the order of a few percent.

CONCLUSIONS

CO₂ flooding is a proven method for extending oilfield life through EOR. Until recently, most of the CO₂ used for these operations was from natural geologic sources; however, with concerns over human-induced climate change, a lack of CO₂ supply for EOR, and hundreds of fields that are amenable to EOR, several anthropogenic CO₂ sources are now supplying EOR operations of the industry and resulting in the storage of CO₂ that would otherwise be emitted to the atmosphere. This work provides a statistical analysis of an historical industry data set, which allows modeled responses to be compared against real-world, observed injection and production data. The results of this study provide quantitative ranges for the potential EOR market for CO₂ as well as the potential incremental oil recovery from, and storage of CO₂ in, these oil fields. This work showed that a four-parameter log-logistic function was able to accurately describe the overall shape of the CO₂ retention and incremental oil recovery curves across the 31 sites, and that a two-parameter simple asymptotic function was able to accurately describe the overall shape of the net CO₂ utilization curves across the 16 sites for which net CO₂ utilization values could be calculated. These functions provide a practical approach for operators to summarize key performance metrics of their CO₂ EOR field data and forecast the performance into the future. In addition, these functions also provide useful screening tools for broad regional assessments of

the CO₂ storage resource associated with candidate CO₂ EOR fields. The results of this work allow estimation of CO₂ storage capacity in CO₂-EOR operations with various degrees of confidence. Additional investigation into the geologic and operational factors that control the parameters of the four-parameter log-logistic or two-parameter asymptotic functions may help to refine these screening tools and their estimates of associated CO₂ storage. The results of this work provide useful statistical information to estimate CO₂ storage in CO₂-EOR operations.

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Nomenclature

%	percent
A	fitted model parameter for either the four-parameter log-logistic, Eq. 4, or asymptotic model, Eq. 5
B	fitted model parameter for either the four-parameter log-logistic, Eq. 4, or asymptotic model, Eq. 5
B_{CO_2}	CO ₂ formation volume factor, RB/Mscf
B_{oi}	initial oil formation volume factor, RB/STB
C	fitted model parameter for the four-parameter log-logistic model, Eq. 4
CCS	carbon capture and storage
CO ₂	carbon dioxide
CO ₂ UF _{net}	net CO ₂ utilization factor, Mscf/STB
D	fitted model parameter for the four-parameter log-logistic model, Eq. 4
DOE	U.S. Department of Energy
EOR	enhanced oil recovery
H ₂ O	water
HCPVI	hydrocarbon pore volume injected
IPCC	Intergovernmental Panel on Climate
$\ln$	natural log (logarithm to the base $e = 2.71828$), Eq. 4 or Eq. 5
Mscf	thousand standard cubic feet
Mt	megatonne, equal to one million tonnes (10 ⁹ kg)

N_p	incremental oil production, STB
OOIP	original oil in place
P_{10}	10th percentile
P_{50}	50th percentile or median
P_{90}	90th percentile
R&D	research and development
RMSE	root mean squared error
SEC	U.S. Securities and Exchange Commission
SSE	sum of squared errors
STB	stock tank barrel
t_0	time zero (the beginning of the CO ₂ flood)
U.S.	United States of America
$V_{\text{CO}_2, \text{purchased}}$	cumulative volume of total CO ₂ injected (purchased volume), Mscf
WAG	water–alternating gas
x	model input (total cumulative volume of CO ₂ + H ₂ O injected, %HCPV), Eq. 4 or Eq. 5
y	modeled output (either CO ₂ retention, %; incremental oil recovery, %OOIP; or net CO ₂ utilization, Mscf/STB), Eq. 4 or Eq. 5
y_{observed}	observed (measured) Industry Data Set result (CO ₂ retention, %; incremental oil recovery, %OOIP; or net CO ₂ utilization. Mscf/STB)
$y_{\text{predicted}}$	predicted (modeled) industry data set result (CO ₂ retention, %; incremental oil recovery, %OOIP; or net CO ₂ utilization. Mscf/STB)

Metric Conversion Factors

$$\text{Mscf} \times 2.831685 \text{ E-02} = \text{m}^3$$

$$\text{RB} \times 1.589873 \text{ E-01} = \text{m}^3$$

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Table 1. Fitted parameters A, C, and D for the four-parameter log-logistic model (CO₂ retention and incremental oil recovery) and fitted parameters A and B for the two-parameter asymptotic model (net CO₂ utilization). The column showing the maximum value for %HCPV is the length of the measured data record from the Industry Data Set. Parameter B was constant in the four-parameter log-logistic model (100 for CO₂ retention or 0 for incremental oil recovery) and is therefore not shown in the table. Cells with an “---” indicate that insufficient data were available to calculate estimates.

	$x = \text{CO}_2 + \text{H}_2\text{O}$ Injected	$y = \text{CO}_2$ Retention	$y = \text{Incremental Oil}$ Recovery Factor	$y = \text{Net CO}_2$ Utilization
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Site Code	(%HCPV) Maximum Value	(%)			(%OOIP)			(Mscf/STB)	
		A	C	D	A	C	D	A	B
Site_A	245.8	62.2	42.6	2.3	12.3	108.4	2.8	1.9	90.5
Site_B	280.6	40.0	79.3	2.0	19.1	106.9	2.3	2.1	24.6
Site_C	147.8	61.6	30.8	2.2	12.4	77.4	3.0	1.9	62.6
Site_D	449.9	47.7	97.1	1.8	20.1	132.7	2.5	1.9	88.1
Site_E	242.1	59.1	67.7	2.2	13.8	114.6	2.0	2.4	43.1
Site_F	301.8	44.9	80.9	2.3	11.3	92.5	2.3	2.2	19.0
Site_G	148.3	25.0	34.1	1.6	9.3	83.1	2.0	1.5	8.8
Site_H	151.7	58.0	46.5	2.2	13.5	62.0	2.8	1.6	48.1
Site_I	478.1	26.9	48.6	1.9	7.0	89.5	1.5	1.7	41.9
Site_J	70.4	56.7	21.6	1.5	24.9	78.1	2.7	2.2	28.1
Site_K	649.8	39.0	46.9	1.3	5.7	92.7	1.7	2.2	16.5
Site_L	121.9	61.6	31.1	2.2	12.0	74.1	3.0	1.9	61.2
Site_M	94.9	26.4	39.2	2.5	5.2	17.8	2.1	2.1	5.1
Site_N	148.2	47.9	47.6	2.6	11.2	52.5	3.1	2.1	27.8
Site_O	92.2	57.1	12.0	1.2	6.7	27.8	2.8	---	---
Site_P	122.0	56.5	43.2	2.6	4.8	101.8	2.3	---	---
Site_Q	198.8	56.1	74.6	2.2	13.9	92.1	2.6	---	---
Site_R	378.0	57.6	66.3	2.1	17.0	114.4	1.6	1.8	9.8
Site_S	310.7	60.6	37.3	1.8	16.7	127.9	2.5	---	---
Site_T	238.1	38.2	26.3	2.0	6.5	103.5	2.2	---	---
Site_U	208.6	31.7	81.2	1.9	9.8	89.9	1.9	---	---
Site_V	253.6	15.3	85.3	3.1	10.1	64.3	3.5	---	---
Site_W	277.5	35.9	58.2	1.8	15.3	104.3	2.1	1.7	62.6
Site_X	434.7	50.6	73.0	2.1	13.1	118.2	2.3	---	---
Site_Y	188.3	13.0	25.8	1.3	13.5	45.8	3.1	---	---
Site_Z	446.5	50.3	32.2	1.2	16.0	68.8	1.9	---	---
Site_ZA	83.1	17.7	24.7	1.2	25.3	71.0	1.4	---	---
Site_ZB	341.1	13.1	151.0	1.1	26.1	108.1	2.0	---	---
Site_ZC	276.7	22.0	116.2	1.2	18.5	146.2	2.1	---	---
Site_ZD	281.0	40.6	86.2	2.4	16.2	86.2	2.4	---	---
Site_ZE	158.3	53.8	56.0	1.9	13.8	73.0	3.1	---	---
minimum =	70.4	13.0	12.0	1.1	4.8	17.8	1.4	1.5	5.1
median =	242.1	47.7	47.6	2.0	13.5	89.9	2.3	1.9	35.0
maximum =	649.8	62.2	151.0	3.1	26.1	146.2	3.5	2.4	90.5

Table 2. Multi-site empirical percentile estimates for CO₂ retention, incremental oil recovery factor, and net CO₂ utilization as a function of total CO₂ + H₂O injected (50%, 100%, 150%, 200%, 250%, and 300% HCPV). The modeled responses from each of the sites (31 sites for CO₂ retention and incremental oil recovery and 16 sites for net CO₂ utilization) were combined into a single data set to generate empirical percentile estimates across the sites.

x = CO ₂ + H ₂ O Injected (%HCPV)	y = CO ₂ Retention %								
	Min	P ₁₀	P ₂₅	Average	Std Dev	P ₅₀	P ₇₅	P ₉₀	Max
50	38.8	51.1	66.6	72.3	13.3	75.1	82.7	86.5	88.0
100	25.6	33.6	53.3	57.7	12.8	63.3	66.0	71.0	73.1
150	20.9	28.0	45.6	51.8	13.2	56.6	62.7	64.1	65.2
200	18.6	25.1	42.1	48.9	13.5	51.2	59.7	62.4	63.2

250	17.2	23.9	39.0	47.4	13.8	48.9	59.0	61.9	62.8
300	16.4	23.1	38.6	46.4	14.0	48.3	58.1	61.8	62.6
$x = \text{CO}_2 + \text{H}_2\text{O}$ Injected (%HCPV)	$y = \text{Incremental Oil Recovery Factor}$ (%OOIP)								
	Min	P ₁₀	P ₂₅	Average	Std Dev	P ₅₀	P ₇₅	P ₉₀	Max
50	0.8	1.3	1.8	3.3	2.0	2.7	4.7	5.8	9.6
100	3.2	5.5	7.7	3.4	7.3	9.9	12.4	16.4	
150	3.4	4.5	7.1	10.2	4.1	10.3	12.4	16.3	21.2
200	3.9	5.1	8.0	11.4	4.6	11.7	13.4	19.2	23.0
250	4.2	5.2	8.6	12.1	4.9	12.0	14.1	20.7	23.8
300	4.4	5.3	8.9	12.5	5.1	12.2	15.1	21.5	24.2
$x = \text{CO}_2 + \text{H}_2\text{O}$ Injected (%HCPV)	$y = \text{Net CO}_2 \text{ Utilization}$ (Mscf/STB)								
	Min	P ₁₀	P ₂₅	Average	Std Dev	P ₅₀	P ₇₅	P ₉₀	Max
50	7.4	8.6	12.3	18.2	10.0	13.8	23.9	39.1	41.7
100	4.2	6.0	8.4	11.0	3.5	10.6	12.8	16.6	16.9
150	3.2	5.5	7.5	9.4	2.6	9.8	10.6	13.0	14.3
200	2.8	5.3	6.9	8.7	2.4	9.4	10.1	11.5	13.3
250	2.6	5.0	6.6	8.4	2.3	8.9	9.6	10.8	12.7
300	2.5	4.8	6.4	8.1	2.2	8.7	9.2	10.5	12.4

Figure Captions

Fig. 1. Schematic of fluid flows in a CO₂ EOR project (Source: van 't Veld et al., 2013).

Fig. 2. Scatterplots of $x = \text{cumulative total CO}_2 + \text{H}_2\text{O}$ injected and $y = \text{CO}_2$ retention for each of the 31 CO₂ EOR sites included in the Industry Data Set. The red horizontal line across each panel represents 50% CO₂ retention.

Fig. 3. Scatterplots of $x = \text{cumulative total CO}_2 + \text{H}_2\text{O}$ injected and $y = \text{incremental oil recovery}$ for each of the 31 CO₂ EOR sites included in the Industry Data Set. The red horizontal line across each panel represents 10% OOIP.

Fig. 4. Scatterplots of $x = \text{cumulative total CO}_2 + \text{H}_2\text{O}$ injected and $y = \text{net CO}_2$ utilization factor for 16 of the 31 CO₂ EOR sites included in the Industry Data Set. The red horizontal line across each panel represents 10 Mscf/STB.

Fig. 5. Fits of CO₂ retention four-parameter log-logistic functions to six representative sites from the Industry Data Set. Blue circles represent observed data and the red line represents the fitted response from the four-parameter log-logistic model, Eq. 8.

Fig. 6. Fits of incremental oil recovery four-parameter log-logistic functions to six representative sites from the Industry Data Set. Blue circles represent observed data and the red line represents the fitted response from the four-parameter log-logistic model, Eq. 8.

Fig. 7. Fits of net CO₂ utilization two-parameter asymptotic functions to six representative sites from the Industry Data Set. Blue circles represent observed data and the red line represents the fitted response from the two-parameter asymptotic model, Eq. 9.

Fig. 8. Percentile estimates generated from multi-site nonlinear regression fits for CO₂ retention (top), incremental oil recovery (middle), and net CO₂ utilization (bottom). The light gray shaded regions bounded by dashed lines represent the 10th to 90th percentiles; the dark gray shaded regions bounded by dotted lines represent the 25th to 75th percentiles (interquartile range); and the P₅₀ estimate (solid black line) represents the central value of the distribution.

Fig. 9. Monte Carlo simulation results of the volume of CO₂ stored as a function of OOIP, incremental oil recovery factor, and net CO₂ utilization factor using Eq. 10 and an OOIP of 500,000,000 bbl. The y-axis shows the frequency out of 10,000 simulations. The red vertical lines at 13.1 and 42.4 Mt show the P₁₀ and P₉₀ estimates, respectively. The blue vertical line at 25.3 shows the P₅₀ (median).

Fig. 1. Schematic of fluid flows in a CO₂ EOR project. $q_{CO_2}^{pur}$ refers to purchased CO₂; $q_{CO_2}^{rec}$ refers to recycled CO₂; $q_{CO_2}^{inj}$ refers to total injected CO₂, which is comprised of both purchased CO₂ and recycled CO₂; $q_{CO_2}^{seq}$ refers to the sequestered CO₂ that is permanently stored in the

subsurface and not available for recycle; q_{wat}^{inj} refers to injected water; and q_{oil}^{prd} refers to incremental oil production (Source: van 't Veld et al., 2013).

Fig. 2. Scatterplots of x = cumulative total CO₂ + H₂O injected and y = CO₂ retention for each of the 31 CO₂ EOR sites included in the Industry Data Set. The red horizontal line across each panel represents 50% CO₂ retention.

Fig. 3. Scatterplots of x = cumulative total CO₂ + H₂O injected and y = incremental oil recovery for each of the 31 CO₂ EOR sites included in the Industry Data Set. The red horizontal line across each panel represents 10% OOIP.

Fig. 4. Scatterplots of x = cumulative total CO₂ + H₂O injected and y = net CO₂ utilization factor for 16 of the 31 CO₂ EOR sites included in the Industry Data Set. The red horizontal line across each panel represents 10 Mscf/STB. Note: y -axis is presented on a log-scale.

Fig. 5. Fits of CO₂ retention four-parameter log-logistic functions to six representative sites from the Industry Data Set. Blue circles represent observed data and the red line represents the fitted response from the four-parameter log-logistic model, Eq. 8.

Fig. 6. Fits of incremental oil recovery four-parameter log-logistic functions to six representative sites from the Industry Data Set. Blue circles represent observed data and the red line represents the fitted response from the four-parameter log-logistic model, Eq. 8.

Fig. 7. Fits of net CO₂ utilization two-parameter asymptotic functions to six representative sites from the Industry Data Set. Blue circles represent observed data and the red line represents the fitted response from the two-parameter asymptotic model, Eq. 9.

Fig. 8. Percentile estimates generated from multi-site nonlinear regression fits for CO₂ retention (top), incremental oil recovery (middle), and net CO₂ utilization (bottom). The light gray shaded regions bounded by dashed lines represent the 10th to 90th percentiles; the dark gray shaded regions bounded by dotted lines represent the 25th to 75th percentiles (interquartile range); and the P₅₀ estimate (solid black line) represents the central value of the distribution.

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