Cite this: DOI: 10.1039/xxxxxxxxxx

CO₂ enhanced oil recovery: a catalyst for gigatonne-scale carbon capture and storage deployment?[†]

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Received Date

Accepted Date

DOI: 10.1039/xxxxxxxxxx

www.rsc.org/journalname

Using carbon dioxide for enhanced oil recovery (CO₂-EOR) has been widely cited as a potential catalyst for gigatonne-scale carbon capture and storage (CCS) deployment. Carbon dioxide enhanced oil recovery could provide revenues for CO₂ capture projects in the absence of strong carbon taxes, providing a means for technological learning and economies of scale to reduce the cost of CCS. We develop an open-source techno-economic Model of Iterative Investment in CCS with CO₂-EOR (MIICE), using dynamic technology deployment modeling to assess the impact of CO₂-EOR on the deployment of CCS. Synthetic sets of potential CCS with EOR projects are created with typical field characteristics and dynamic oil and CO₂ production profiles. Investment decisions are made iteratively over a 35 year simulation period, and long-term changes to technology cost and revenues are tracked. Installed capacity at 2050 is used as an indicator, with 1 gigatonne per year of CO₂ capture used as a benchmark for successful large-scale CCS deployment. Results show that current CO₂ tax and oil price conditions do not incentivize gigatonne-scale investment in CCS. For current oil prices (\$45/bbl - \$55/bbl), the final CO₂ tax must reach \$70/tCO₂ for gigatonne-scale deployment. If oil price alone is expected to induce CCS deployment and learning, oil prices above \$85/bbl are required to promote the development of a gigatonne-scale CCS industry. Nonlinear feedbacks between early deployment and learning result in large changes in final state due to small changes in initial conditions. We investigate the future of CCS in five potential 'states of the world': an optimistic 'Base Case' with a low CO₂ tax and low oil price, a 'Climate Action' world with high CO₂ tax, a 'High Oil' world with high oil prices, a 'Depleting Resources' world with an increasing deficit in oil supply, and a 'Forward Learning' world where mechanisms are in place to drive down the cost of CCS at rates similar to other clean energy technologies. Through multidimensional sensitivity analysis we outline combinations of conditions that result in gigatonne-scale CCS. This study provides insight levels of taxes, learning rates, and oil prices required for successful scale-up of the CCS industry.

1 Introduction

Carbon capture and storage (CCS) has been recognized as a key technology for reducing greenhouse gas (GHG) emissions. Numerous studies find that CCS is a vital part of least-cost climate change mitigation^{1–3}. For example, in 2014 the International Energy Agency (IEA)⁴ found that CCS is expected to achieve 6 GtCO₂/year capture capacity by 2050. However, the future of

CCS faces a number of roadblocks. In IEA 'Blue Map' scenarios, the contribution of CCS to emissions mitigation dropped from 19% in the 2010 report to 13% in the 2015 report⁵. This is due to increased urgency of climate change mitigation, rapidly falling costs of renewables, and the high cost of CCS.

Despite its acknowledged long-term potential, CCS deployment is currently far too slow to address mid-century mitigation targets, and CCS costs are not falling at similar rates to those of other low-carbon power options. Currently, there is only 27 MtCO₂/year capacity of CCS deployed globally⁶. In the power sector, only two large-scale CCS plants are operational globally, capturing 2.4 MtCO₂/year (Saskpower Boundary Dam in Saskatchewan, Canada and Parish Petra Nova CCS in Texas, U.S.A.)^{6–12}. These projects each incurred a capital cost of the order of billions of US dollars and both sell their CO₂ for use in enhanced oil recovery

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(EOR). Other CCS projects are either over budget or have been recently canceled. There is a material risk that CCS falls behind other low-carbon power technologies and will therefore be unable to contribute to the climate solution at mid-century. In this study, we build an open-source technology deployment simulation tool to examine whether CO₂ enhanced oil recovery (CO₂ EOR) might serve as a “catalyst” to reduce long-run costs of CCS and induce gigatonne-scale deployments.

During CO₂ enhanced oil recovery (CO₂-EOR) supercritical CO₂ is injected into the pay zone of an oil reservoir to increase oil production. In the most typical approach, the injection occurs after more conventional production techniques have been applied. The CO₂ acts as a solvent, mobilizing previously trapped isolated pockets of immobile oil, while also swelling and reducing the viscosity of the fluid^{13,14}. Combined, these effects can boost oil recovery by several percentage points over what is possible with conventional production. Carbon dioxide EOR has been conducted primarily in North America since the 1970s due to abundant sources of natural CO₂. In recent years a lack of cheap CO₂ supply and a low oil price has stymied new projects. From 2012 - 2014, 11 new miscible CO₂-EOR projects were reported in the US, while 2014-2016 only saw 3 new projects¹⁴. Approximately 80% of current CO₂ used for EOR comes from natural sources of CO₂ instead of abundant anthropogenic sources¹⁵.

In 2010, Herzog¹⁶ raised the challenges of a megatonne to gigatonne upscaling of CCS. The study highlighted the need for a clear business model for large scale investment and the uncertainty around sufficient storage capacity for gigatonne-scale CCS deployment. However, with the increasing interest and literature around CCS alone and with CO₂-EOR across the globe, it is clear that there is interest in upscaling CCS^{17–22}. Storage capacity and availability for CO₂, in depleted oil reservoirs with EOR or in saline aquifers, has also since been clarified and studied extensively^{23–27}.

The utilization rate of CO₂ for EOR affects net emissions abatement. Life cycle assessments (LCAs) have been conducted on CO₂-EOR, with a wide range of results^{24,28–32}. For CO₂-EOR, the LCAs differ most significantly on the accounting treatment of produced oil. An assumption of *additionality* assumes that producing oil via CO₂-EOR will add to the global supply of oil and therefore LCAs should include emissions from the combustion of the resulting petroleum products (i.e., diesel fuel). Additionality results in CO₂-EOR with net positive emissions^{24,29}. The alternative assumption of *displacement* assumes that EOR-derived oil displaces oil that would have come from another source. Displacement results in net negative emissions from CO₂-EOR^{30,31}. ARI and Melzer Consulting Group found total CO₂ emissions from CO₂-EOR operations are of 474 kgCO₂/bbl of oil produced and 74 kgCO₂/bbl of oil produced when excluding end-use of crude oil recovered. Cooney et al. studied the gate-to-gate GHG emissions from CO₂-EOR, which included the impact on land use, and found that for advanced EOR operations, the GHG emissions are between 592 and 995 kgCO₂e/bbl of crude³³. This serves to illustrate the complexity in assessing the environmental impacts of CO₂ utilization, such as EOR.

Commercial CO₂-EOR practice does not emphasize long-term

storage; at end of pattern life CO₂ is often produced from the well to induce last oil production, then CO₂ is recycled for other oil fields, resold, or vented. This does not reflect the ability to store CO₂ in depleted oil fields³⁴. Scott et al. 2015³⁵ categorize storage with CO₂ EOR as “easy to manage and inherently safe” due to the volume (and pressure) replaced in the process (i.e. volume of produced oil replaced by equivalent volume of dense phase CO₂ injected), comparing it to saline aquifer storage which is “complex to manage although expected to be secure”³⁵.

This study presents our efforts to simulate CCS deployment to determine the conditions that would result in gigatonne-scale CCS deployment. This paper presents one of the first detailed works to assess the commercial value of CCS with CO₂-EOR in this new and unfavorable economic environment. It does so by developing a novel and open-source model of iterative investment in CCS with CO₂-EOR (MIICE) that takes into account the techno-economic dynamics of CCS and CO₂-EOR and assumes a large variety of well characterized oilfields in order to discuss what technological, economic, and regulatory advances are needed for CO₂-EOR to accelerate gigatonne-scale CCS deployment. One of the major novelties of this work is the dynamic approach to assessing CCS coupled with CO₂-EOR whereby costs and revenue streams change over time as a result of changing prices and accumulated experience modeled as technological learning or learning-by-doing. Another novelty lies in the way CO₂-EOR operations are modeled. Without the complexity and computational intensity of reservoir simulations, the model includes ample detail on potential fields, their production profiles and field development to simulate uncertainty in CO₂-EOR dynamics.

First we outline our methodology, including the techno-economic CCS model and modeling of EOR projects. We next describe five indicative scenarios explored in detail, and outline sensitivity cases that explore key drivers of model outcomes. We then present results for our five indicative scenarios, as well as sensitivity plots illustrating single-variable and multi-variable explorations of outcome. We conclude with qualitative lessons learned and next steps.

2 Methodology

2.1 Overview

First we provide an overview of the basic MIICE (model of iterative investment in CCS with CO₂-EOR) work-flow (Figure 1). MIICE begins by generating a candidate world containing illustrative oil fields. In the initial model year, potential EOR projects in these oil fields are evaluated given the oil price, CO₂ tax, and cost of CO₂ capture in that time period. Projects with positive net present value (NPV) are developed in accordance with standing limits on investment rate. A positive NPV is also defined by an investment’s internal rate of return (IRR) being greater than the discount rate assumed. The simulation then steps forward, updating the list of potential EOR fields to remove developed projects, simulating technological learning, and tracking CO₂ stored and oil produced from operating projects. The remaining potential projects are re-evaluated given updated conditions (e.g., updated CO₂ tax and oil price, learning-adjusted cost of CO₂ capture). The

model continues year-by-year until the simulation period is complete.

The baseline assumptions made for key model parameters are

Fig. 1 Flow diagram representing the process and economic evaluation mechanism adopted in MIICE. GROWTH LIMIT refers to the industry growth rate ceiling. The dotted line focuses on pattern deployment strategy and illustrated in more detail in Figure S3.

listed below in Table 1. The study boundary includes capturing, transporting and injecting CO₂ and producing oil via EOR. Our boundary excludes power plant investment (i.e., assumes a separate stakeholder investment in a new power plant or continuation of an existing power plant). NPV is calculated by performing a discounted cash flow analysis of revenues from oil production and CO₂ storage. Negative cash flows include CO₂ tax for CO₂ that is not captured, leaked in EOR, or not stored in field operations, as well as variable and operating and maintenance (O&M) costs for CO₂ capture, transport, storage and EOR management. All cash flows are adjusted for inflation. Initial upfront capital investment includes all project inputs, amortized over project lifetime of 30 years with a fixed charge factor (also known as capital recovery factor)³⁶, of 0.118 [1/y]. MIICE is initiated in year 2016 and runs to year 2050. Though based largely on North American data, particularly in considering CO₂-EOR field data and operation, the model is assumed to be geographically neutral.

2.2 CO₂ Enhanced Oil Recovery

The model initially generates 10,000 possible oil fields based on randomized combinations of characteristics with ranges derived from a database of existing CO₂-EOR projects⁴¹ (see

Table 1 Parameters used to compute net present value (NPV) of a CCS + CO₂-EOR project

Parameter	Value	Assumption/Reference
Project lifetime	30 years	Model based assumption ³⁷
Nominal discount rate (NDR)	15 %	High risk fossil fuel projects ³⁸
Currency value	2016 US\$	All costs are adjusted for constant \$
Equity	100%	High risk fossil fuel projects ³⁸
Yearly inflation rate	3.3%	Model based assumption ³⁷
Fixed charge factor	0.1185	Calculated based on NDR and inflation rate
Tax rate on oil revenue		North America based oil production practice ^{39,40}
Royalties	15%	Will depend on state legislation (W. Texas based ⁴⁰)
Severance tax	2%	Percentage of royalty tax (W. Texas based ⁴⁰)
Ad valorem tax	1.5%	Percentage of royalty tax (W. Texas based ⁴⁰)
Corporate tax on CO ₂ storage revenue	0%	Unclear on the taxation scheme of a credit
Limit on technological learning	First 1000 projects	Study based assumption

Table 2). The model eliminates nonsensical combinations (see Supplementary Information (SI) Section S1) and keeps 1,000 fields randomly from the population of feasible fields. By using a database of existing CO₂-EOR projects, we assume that similar fields will be chosen going forward. The database provides characteristic values for reservoir permeability, porosity, depth, and field areal extent. Distributions are drawn to include 85% of database observations (see SI Figure S2). These are limited to fields in which miscible EOR is conducted as this is most widely applied and understood, achieving better recovery than immiscible EOR^{42,43}. Initial water saturation and net pay thickness - the thickness of the targeted hydrocarbon rich region of the oil field - are not tabulated in the database, so representative values are obtained from literature and personal communications⁴⁴⁻⁴⁷.

The CO₂-EOR industry has historically been limited by a lack of low-cost CO₂¹³. Operations have therefore sought to minimize fresh CO₂ purchased. This is manifested by CO₂ recycling and alternating injection of CO₂ with water (=water-alternating-gas, or WAG). WAG is common in the CO₂-EOR industry and is said in some instances to improve the contact between CO₂ and oil in the reservoir^{13,24,48}, while others find that WAG does not necessarily improve the recovery of oil compared to continuous CO₂ injection⁴⁹⁻⁵². In a world of emissions limits, continuous CO₂ injection and limited CO₂ recycling could be incentivized⁵³. MIICE assumes operations and costs for continuous CO₂ injection only. For a limited project and field lifetime of 30 years, as assumed here, including WAG would change project economics by reducing CO₂ storage. Hence, MIICE provides an upper bound of sequestration potential for CO₂-EOR.

Fluid properties for CO₂ and oil are functions of multiple quadratic equations that would significantly increase the computational intensity of the model. Hence, constant fluid properties are assumed for CO₂ and oil. The hydrostatic pressure gradient is equivalent to the US Gulf coast at 10.52 kPa/m (0.465 psi/foot)⁵⁴, the temperature gradient assumed is 30°C/km and surface temperature is 15°C⁵⁵. CO₂ density and viscosity are estimated at the median of the reservoir depth range of 2026 m as 614.08 kg/m³ and 47.8 microPa.S. The minimum miscibility pressure (MMP) sets a minimum CO₂ injection pressure (key for miscible CO₂-EOR). Average MMP is calculated using the Cronquist correlation (see SI Equation S1)⁵⁶. Tank oil gravity of 37 API and oil formation volume factor at initial reservoir conditions of 1.3 are assumed^{53,57}. These parameters are summarized in SI Table S4.

Table 2 Characteristic values for potential CO₂-EOR fields based on existing data from the Oil & Gas Journal EOR Survey and field data of miscible EOR operations

Characteristic	Lower Bound	Higher Bound	Unit
Permeability	1	110	milliDarcy
Porosity	5	30	fraction
Reservoir depth	914	3140	meters
Reservoir area	8,094,000	80,920,000	m ²
Initial water saturation	15	75	fraction
Net pay thickness	10	50	meters

Oil production rates and CO₂ production rates are a function of cumulative CO₂ injected. Both are dimensionless variables normalized by hydrocarbon pore volume (HCPV). HCPV refers to the pore volume of the reservoir that is filled with hydrocarbons:

$$HCPV = Ah\phi(1 - S_{wi}) \quad (1)$$

where $HCPV$ is the hydrocarbon pore volume at surface conditions [m³], A is Pattern area [m²] h is net pay thickness [m], ϕ is Average field porosity [fraction] and S_{wi} is initial water saturation [fraction]. The original oil in place is defined as $OOIP = HCPV/\beta_{oi}$ where β_{oi} is the initial oil formation volume factor. Each field has a unique HCPV, which will determine its production rates of CO₂ and oil.

An injection pattern refers to the arrangement of production and injection wells for EOR. Multiple well arrangement injection patterns exist including two-spot, three-spot, five-spot, nine-spot and twelve-spot. These can either be centered around a producer (called normal) or an injector (called inverted). Here, MIICE assumes that all patterns are 5-spot inverted patterns with 1 injector and 4 producers as this is commonplace in CO₂-EOR practice^{39,40,56,58}. As a rule of thumb each pattern has a surface area of 40-acres and on a field-scale it is assumed that the ratio of producers to injectors is 1.8:1, which corresponds to nine adjacent 5-spot patterns. This is assumed constant in current MIICE version. However, as more patterns are developed together, side by side, this ratio would decrease. This can be modified in MIICE as provided here (see SI Section S6).

Reservoir simulations are typically used to model the rate of oil production and CO₂ injection and production from a CO₂-EOR process in one given field using proprietary tools such as ECLIPSE and CMG. However, these require large and complex data inputs for model initialization, history matching and pressure dynamics⁴³. Therefore, in order to allow for MIICE to be broadly applicable, the CO₂-EOR process is modeled with a set of normalized outputs from such simulations: relationships defining the cumulative production profiles of oil and CO₂ as a function of the cumulative CO₂ injected. Data profiles for cumulative production of oil and cumulative production of CO₂ as a function of cumulative CO₂ injected are obtained for 6 fields from literature⁵⁹. Also, P10, P50 and P90 statistical results for a U.S.-based CO₂ EOR reservoir simulation were obtained⁶⁰. Each of these profiles is fitted with eq. 2 for cumulative oil production and eq. 3 for cumulative CO₂ production^{43,61}. Cumulative production of oil as a function of CO₂ injection follows a logistic curve with fitting parameters a , b ,

c and d , while the cumulative production of CO₂ as a function of cumulative CO₂ injected follows an exponential curve with fitting parameters a^* , b^* , c^* and d^* . All production profiles quoted refer to CO₂-EOR operations after primary and secondary recovery including water flooding.

$$Q_{oil} = \frac{a}{1 + \exp(-b(Q_{CO_2in} - c))} - d \quad (2)$$

with Q_{oil} representing normalized cumulative oil production (1/OOIP) and Q_{CO_2in} representing cumulative CO₂ injection (1/HCPV). Also:

$$Q_{CO_2out} = a^* \exp(b^*(Q_{CO_2in} - c^*)) - d^* \quad (3)$$

with Q_{CO_2out} representing cumulative CO₂ production (1/HCPV) and Q_{CO_2in} representing cumulative CO₂ injection (1/HCPV).

Three of the nine cumulative production profile pairs are used to represent low, medium and high oil recovery and CO₂ production cases (see Figure 2). Each time the model assesses the economics of a CCS with CO₂-EOR project, a profile is chosen randomly. All patterns within one field follow the same profile and operations - CO₂ injection, production and storage rate, and oil productions rate - are modeled on a yearly basis. The model assumes that during the lifetime of a field, CO₂ that is produced at one time step is recycled and re-injected into the field at the next time step. The recycled CO₂ is coupled with fresh CO₂ from the capture plant assumed to be distributed evenly into all open patterns. A total of 0.5 % of CO₂ produced is assumed to leak while the rest is recycled and re-injected. The rate of CO₂ storage is taken as the difference between the incremental CO₂ injected and the incremental CO₂ produced. The HCPV and OOIP, unique to each field, determine the total CO₂ stored and oil produced at each pattern.

Each field has an area A and a maximum number of patterns that can be deployed. At every field iteration, the model calculates the minimum amount of patterns p_{min} needed for injection of all the fresh CO₂ from the capture plant at a pressure differing by a safety factor f_{oil} of the maximum allowable injection rate, Q_{max} . Q_{max} for each well within a pattern is defined using Darcy's law for radial flow:

$$Q_{max} = \frac{2\pi kh(\Delta P)}{\mu \ln \frac{r_e}{r_w}} \quad (4)$$

with Q_{max} representing the maximum volumetric flow rate at the injection point [m³/s], k , the average reservoir permeability [m²], h , the field thickness (net pay thickness) [m]. ΔP , the pressure differential [Pa], μ the viscosity of CO₂ [Pa.s], r_e the drainage radius assumed to be 1000 feet (304.8 m), and r_w the wellbore radius assumed to be 6 inches (0.1524 m).

Production of oil progresses along the cumulative curve profiles, and injection ceases once the following condition is met: $Q_{oil}/Q_{CO_2in} \leq 0.1$. After a set of patterns p_{min} cease injection, a set of new patterns is opened, repeated until field area or the project duration limit is reached. f_{oil} is chosen so that the field size can process 30-years worth of CO₂ captured. This will vary with each

(a)

(b)

Fig. 2 Cumulative production of CO₂ (dash) and oil (solid) on a HCPV basis. (a) Reproduction of 9 empirical curves^{59,60} (b) Low, medium, and high cases for simulation.

project size and for each field coupling considered. The process is described in SI Figure S3. The fracture gradient assumed is 0.926 psi/ft and hydrostatic gradient is 0.465 psi/ft⁶². We require that injection pressure never exceeds 80% of fracturing pressure.

The model computes well costs, CO₂ costs, and operating & maintenance (O&M) costs. Capital costs for CO₂-EOR include well design and installation of production and injection wells, drilling and completion (D&C), well conversion for CO₂-EOR operation, all of which are a function of the depth of the field. Capital costs also include CO₂ separation units, a function of the maximum recycling rate, and distribution infrastructure. We assume redevelopment of old fields, converting 3/4 of injection and production wells previously used for primary production and WAG, so only 1/4 of wells are assumed to be new^{17,40}. Operating costs included are periodic O&M costs, which are a function of field depth, oil and water lifting costs, which are a function of oil price, and CO₂ recycling O&M, a function of the initial oil price and CO₂ recycling volume. Monitoring cost is assumed at 2 M\$/y per field⁶³. These assumptions and values are clearly outlined in the open-source MIICE script provided here (see SI Section S6). Qualitative details of the capital and operating cost parameters assumed for CO₂-EOR operations in MIICE are outlined in Tables 3 and 4. Detailed cost equations are provided and can be accessed in the open-source MIICE (see SI Section S6).

The model assesses four project sizes for each CO₂ capture plant: 1, 2, 3 and 4 MtCO₂/year. These sizes encompass current and planned CCS projects (current 1-2 MtCO₂/year from 100-300 MW coal plants, prospective 3-4 MtCO₂/year from coal plants of 450 - 600 MW⁶).

Table 3 Capital cost parameters and assumptions for CO₂-EOR with detailed equations presented in the MIICE script.

Cost Parameter	Function of	Assumption(s)	Reference
Field Production equipment	Depth of site	CO ₂ processing & lease equipment L&A regression cost model, on a per pattern basis	
CO ₂ Recycling plant	Maximum CO ₂ injection rate	Capital cost of a recycling facility of sufficient size that can separate CO ₂ from produced fluids at maximum production & injection rates	40,58 converted from 2004 US\$ 39,44,64-66 converted from 2014 US\$
CO ₂ Trunkline cost	Fixed cost	Per pattern	39
CO ₂ Transport & Distribution Cost	Trunkline distance, cost of trunkline	Per pattern basis, includes fixed and variable costs associated with transporting the volume of CO ₂ from regional pipeline to EOR site as well as equipment required for on site distribution (from wells to recycling facility)	39,44,64-66 converted from 2014 US\$
Pattern equipment cost			
Production well equipment cost	Depth of site	New well cost, on a per pattern basis, based on L&A regression equation, includes tangible and tangible costs associated with production well equipment	40,58 converted from 2004 US\$
Injection well equipment cost	Depth of site	New well cost, on a per pattern basis, based on L&A regression equation, includes tangible and tangible costs associated with injection well equipment	40,58 converted from 2004 US\$
Drilling & Completion cost (D&C)	Depth of site	New well cost, on a per pattern basis, based on L&A regression equation, includes tangible and intangible costs associated with on-site drilling and completion phases for production & injection wells (e.g. casing, cementing, plugging)	40,58 converted from 2004 US\$
Production well work-over cost	Fraction of new well cost + D&C cost	3/4 of wells are worked over	40,58 converted from 2004 US\$
Injection well work-over cost	Fraction of new well cost + D&C cost	3/4 of wells are worked over	40,58 converted from 2004 US\$

Table 4 Operating cost parameters and assumptions for CO₂-EOR with detailed equations presented in the MIICE script.

Cost Parameter	Function of	Assumption(s)	Reference
Periodic O&M Costs	Depth of field, on a per pattern basis	Based on L&A regression model, includes periodic well work-overs and other surface/subsurface repairs	40 converted from 2004 US\$
Liquid Lifting Costs	Stock Tank Barrels of liquids processed (oil + water)	Typically provided by the user, on a per pattern basis, includes operating costs of pumping, managing and distributing liquids produced	40,44 converted from 2004 US\$
CO ₂ Recycling O&M	Initial Oil Price & CO ₂ volumetric flow rate	CO ₂ density at STP 1.977 kg/m ³ used to convert to surface conditions and cost given on a per pattern basis	44 converted from 2004 US\$
General & Administrative cost	Fraction of Periodic O&M Costs and Liquid Lifting Costs	Per pattern basis, includes staff salaries/wages, insurance, accounting, consulting, management and record keeping	39,44 converted from 2014 US\$
CO ₂ Monitoring cost	Fixed cost assumed	Cost applied to a whole EOR site regardless of pattern number, 2010 USD 2 Million	63 converted from 2010 US\$

2.3 Cost of Carbon Capture and Transport

CO₂ capture is the most cost intensive part of CCS and contributes 60% to 85% of total costs^{36,67}. Actual costs of CCS plants have been higher than estimated first-of-a-kind (FOAK) costs⁶⁸. We initialize learning models with initial capacity of 2.4 MtCO₂/y.

In order to initialize the learning model, introduced in the next section, we need upfront capital cost as a function of capture capacity measured in M\$/MtCO₂/y.

In 2015, Rubin et al.³⁶ reviewed CCS costs and found current values for overnight capital cost of post-combustion capture of 242-453 M\$/MtCO₂/y. They find that older studies overestimate CCS costs because newer cost estimates use more-efficient proprietary amines. The study does not make a clear distinction whether FOAK or NOAK costs are estimated. The most recent real project of post-combustion capture on a coal-fired power plant had capital costs of \$714 M\$/MtCO₂/y (Petra Nova project cost US\$ 1 billion to capture 1.4 MtCO₂/y)^{8,9}.

CCS prospects rely on its application to various types of thermal plants (e.g. coal-fired and gas-fired) as well as industrial plants (e.g. cement production, iron and steel production, hydrogen production) and costs will differ depending on plant application. CO₂ capture applications to industrial processes with high concentrations of CO₂ will have a substantially lower cost than when applied to power plants⁶⁹⁻⁷¹. We therefore explore a range of initial costs between 200 M\$ and 714 M\$/MtCO₂/y.

Power costs are wholesale electricity prices of US\$ 39.67/MWh (Intercontinental Exchange (ICE) of the weighted average electricity cost for 2014-2016⁷²). O&M costs include both variable and fixed O&M costs for labor, material and equipment^{37,73}.

For the range of capital costs considered, given a fixed charge factor of 0.1185, this is equivalent to an initial annualized cost of capture ranging from \$100/tCO₂ to \$39/tCO₂.

Capital and operating costs of transporting 1 - 4 MtCO₂/year are included⁷⁴. Pipeline dimensions for transport are derived from NETL⁷⁵ and all pipelines are assumed 100km (62 miles) long.

2.4 Technological learning and industry growth

The model assumes that technological learning reduces capital costs as cumulative CCS deployment increases. CCS infrastructure is assumed to decline in costs, while EOR costs are assumed not to decline due to decades of experience with EOR. Learning is assumed to cross regional boundaries. The Wright progress curve, also defined as "learning-by-doing" is used⁷⁶⁻⁷⁹:

$$C = C_i \left(\frac{Q}{Q_i} \right)^{-b} \quad (5)$$

with C , the updated capital cost, Q , the updated cumulative capacity installed, C_i , initial capital cost, and Q_i the initial capacity installed. The learning variable b is defined as $b = -\log(1 - LR)/\log(2)$ where LR is the cost reduction per doubling.

Learning rates are uncertain. Observed learning resulted in the second commercial CCS plant costing 50% less than the first^{6,7}. Such learning is unlikely to continue: the high cost of capital

Table 5 Key variables assumed for each of the five world scenarios

World Scenario	Price of oil in 2016 \$/bbl	Tax/credit on CO ₂ in 2016 \$/tCO ₂	Tax rate increase \$/tCO ₂ /year	Learning rate	Oil price growth rate (inflation adj.)
Base Case (BC)	55	25	+1	10%	0%/y
Climate Action (CA)	55	100	+2	10%	0%/y
High Oil (HO)	110	25	+1	10%	0%/y
Forward Learning (FL)	55	25	+1	14%	0%/y
Depleting Resources (DR)	55	25	+1	10%	2%/y

of Boundary Dam have been explained with circumstantial, case-specific factors⁶⁸. Circumstantial costs can include location of plant build, better company practices and market fluctuations affecting the price of steel for example. Literature on CCS learning rates have mostly assimilated it to large-scale chemical plants that take years to build, such as flue gas desulphurization and have assumed ranges of learning rates from 3% to 14%⁷⁷. This differs from smaller scale products' technological learning that can be produced in larger quantities at a faster pace and have seen technological learning rates of over 20%, such as solar PV.

The model also includes a set of growth rate limitations. New energy technologies see rapid exponential growth until the technology reaches "materiality" (previously defined as a 1% market share)⁸⁰. Here, we define materiality as 100 MtCO₂/year installed capacity. Our pre- and post-materiality growth rate limits are 25% and 10%, respectively⁸¹. Furthermore, only one project can be commissioned per year for the first five years (representing slow growth until wide-spread confidence).

3 Scenarios & Model Analysis

3.1 Five World Scenarios

We first create five 'world' scenarios (see Table 5). The 'Base Case' world assumes the following: (1) a constant inflation-adjusted price of oil at its 2016 peak of \$55/bbl⁸²; (2) CO₂ tax of \$25/tCO₂ starting in 2016 and growing by \$1/year (3) a learning rate $LR = 10\%$, (4) initial overnight capital cost is \$600 Million/MtCO₂/y. The 'Climate Action' world adopts a CO₂ tax of \$100/tCO₂ in 2016 which increases by \$2/year. The 'High Oil' world has a constant inflation-adjusted oil price of \$110/bbl (similar to 6DS scenario in⁶³). In the 'Depleting Resources world', oil starts at inflation-adjusted price of \$55/bbl and increases at a rate of 2%/year. Finally, the 'Forward Learning' world assumes effective R&D for CCS so LR is 14%, similar to that of flue gas desulphurization^{77–79}.

3.2 Single-parameter sensitivity analysis

A single-parameter sensitivity analysis to Base Case assumptions is performed. We use cumulative CCS capacity investment achieved by 2050 as the comparison variable. Sensitivity parameters include: inflation rate, nominal discount rate, cost of electricity, initial capital cost of CO₂ capture, capital cost per CO₂-EOR pattern and CO₂ capture rate per power plant. Each of these are varied by $\pm 10\%$ to assess their impact. We also explore assump-

tions of industry growth limitations, use of near-site saline aquifer storage at \$60/tCO₂ or \$20/tCO₂, CO₂ tax/credit scheme, project debt-to-equity ratios and responsibility for the CO₂ transport system. Finally, we assess the sensitivity of MIICE to the MATLAB randomization seed for EOR field generation.

3.3 Exploration of key variables

In addition to the single-parameter sensitivity analysis described above, we iterate through combined ranges of key parameters. These include initial oil price, a CO₂ credit/tax rate, learning rate, FOAK capital cost, and oil price growth rate. A total of 36,036 combinations are evaluated. Ranges of variables are:

- Initial price of oil from \$45/bbl to \$140/bbl.
- CO₂ tax from \$0/tCO₂ to \$200/tCO₂.
- Initial capital cost of capture from 714 M\$ to 200 M\$ for every 1 MtCO₂ captured/year.
- Learning rate from 0.00 to 0.20.
- Growth rates of oil at 0%/y, -2%/y, and 2%/y.

We use cumulative CCS capacity investment achieved by 2050 as the comparison variable.

4 Results & Discussion

4.1 Five World Scenarios

Figures 3, 4, 6 and 5 present outputs from the Five World scenarios. CO₂ storage and oil production values are given as cumulative values over a projects' 30-year duration and presented in the year that a project receives investment (see SI Figure S4).

Figure 3 shows the cumulative CCS capacity investment made in each of the five worlds (bottom) and the resulting CO₂ capture cost decrease (top). All five worlds have an initial annualized cost of capture of \$86.7/tCO₂ assuming the fixed charge factor of 0.1185. These worlds show similar slow rates of CCS capacity deployment in the first 10 to 15 years. After 2030 scenario settings cause divergence in investment. In the 'Climate Action' world, the CO₂ tax exceeds \$130/tCO₂ by the 2030s and the cost of CO₂ capture has decreased to \$61/tCO₂ (as shown on the top graph of Figure 3). Thus, in 'Climate Action' world, the projects with highest IRR are those that capture more CO₂ and target smaller oil resources (see SI Figure S5). Nevertheless, all world scenarios succeed in driving down the cost of CO₂ capture to below \$50/tCO₂ by 2045 given technological learning. The 'Climate Action', 'High Oil' and 'Depleting Resources' scenarios follow the same capture cost reduction trends to 2050. The 'Forward Learning' scenario drives the cost below \$50/tCO₂ by 2033 and to \$40/tCO₂ by 2045, which allows it to diverge away from the 'Base Case'. The steep reduction in CO₂ capture cost obtained in the 'Forward Learning' scenario makes up for a low CO₂ tax and a low oil price. It behaves as a high CO₂ tax by providing more incentive for larger CO₂ capture plant projects that were not previously lucrative and that are more economically favorable to storing CO₂ rather than producing oil. This explains the peak in

cumulative investment observed after 2045.

Figure 4 presents the cumulative projects' net CO₂ stored from CO₂ EOR projects. The top graph excludes the CO₂ emitted from combustion of produced oil (i.e., *displacement* assumption), while the bottom subtracts the CO₂ emitted in the combustion of produced oil from the total CO₂ stored in each project (i.e., *additionality* assumption). Using the displacement assumption, cumulative storage by 2050 is in the range of 50 Gt in the 'Climate Action' world and 10-20 Gt in all other worlds. If we include end-use emissions from crude oil consumption, only the 'Climate Action' world results in net CO₂ storage. In this case, the 'Climate Action' world achieves net storage by 2035. The 'sub-worlds' presented in Figure 4 represent alternative 'Climate Action' worlds, with CO₂ taxes starting at 60, 65, 70, 75, 80, 85, 90 and 95 \$/tCO₂ in 2016 and alternative High Oil worlds with oil prices of 60, 70, 80, 90, 100 and 120 \$/bbl. The alternative 'Climate Action' worlds show significantly different cumulative storage by 2050, while the effect of oil price variation is muted.

Figure 5 (top) shows revenues from oil and gas, illustrating that revenue from oil production dominates in all five worlds until 2030. Except in the 'Climate Action' world, oil revenue is ≈ 40 times CO₂ storage revenues. This is because the first projects that receive investment are those that have most favorable and known field characteristics for oil production and CO₂ storage and highest NPVs evaluated. In the 'Climate Action' world, CO₂ revenue exceeds oil revenue by 2030, and oil produced per tonne of CO₂ stored reaches 0 by 2050. In this case projects are built for the sole purpose of storing CO₂.

Figure 6 shows oil volumes produced per unit of CO₂ injected, captured or stored. The values plotted in Figure 6 align with other studies: Azzolina et al. 2015⁶¹ found a range of oil production from CO₂-EOR of 1.7 - 6.3 bbl/tCO₂ used, while the IEA study that looked at the ability to store CO₂ through enhanced oil recovery found a range of 1.1 - 3.3 bbl/tCO₂ captured depending on whether an oil-driven or storage-driven EOR process was conducted⁶³.

The compound annual growth rate by 2050 in each world scenarios is compared against global and regional predictions for CCS deployment and oil production from CO₂-EOR in Table 6. As expected, the 'High Oil' and 'Depleting Resources' worlds are the ones to achieve the highest growth rates for the CO₂-EOR industry, exceeding those predicted for the U.S. by 2020. However, no scenario comes close to reaching the target growth required by the IEA for CCS deployment by 2050, though the 'Climate Action' world falls short of less than four percentage points. We would expect that CCS with saline aquifer storage would also be deployed (not modeled here), once the cost of CCS has been driven down. This could contribute to a higher overall growth rate of CCS.

4.2 Sensitivity to endogenous and exogenous model parameters

As highlighted in Figure 3, the 'Base Case' world scenario fails to reach the gigatonne scale of CCS capacity investment by 2050. Figure 7 demonstrates the sensitivity of this result to various assumptions.

Table 6 Compound annual growth rate of the CCS industry and CO₂-EOR industry by 2050 in the five world scenarios compared with industry projections for CCS deployment needed by 2050 and U.S. CO₂-EOR industry expansion by 2020

World Scenario	CAGR CCS Industry	CAGR CO ₂ -EOR Industry
Base Case	9.73 %	8.12 %
Climate Action	12.91 %	5.17 %
High Oil	11.16 %	8.93 %
Forward Learning	11.48 %	8.31 %
Depleting Resources	11.23 %	8.93 %
Industry predictions (IEA 2050 CCS projection/ US CO ₂ -EOR 2020 Projection)	16.69 %	8.21 %

First, by varying six parameter values by 10%, we find that the results are most sensitive to nominal discount rate and CO₂ capture rate. Each of these change the CCS capacity investment received during the period investigated by up to 15%. The initial capital cost of capture and capital cost of EOR per pattern significantly impact the investment choices made.

The impact of the industry growth limitations are also assessed. While a slower industry scenario sets back the growth rate of CCS, the fast industry growth ceiling does not enable many more projects to be built. The availability of "cheap" saline aquifer storage for residual produced CO₂ at \$20/tCO₂ results in 25% more projects receiving investment. Meanwhile, no CO₂ tax at all, reduces cumulative project investment by 19%.

We also investigate the sensitivity to investment schemes. A 40:60 debt:equity ratio at a 6% rate of interest does not strongly affect results. Including the liability and cost of CO₂ transport infrastructure in the investment model has little effect on CCS investment. Finally, we conduct 1,000 realizations of our field generation process to explore the effects of generating candidate fields using a random number generator. Final project investment is affected by $\pm 5\%$ at the ± 1 SD level.

Note that all of these sensitivity studies fail to bring the Base Case scenario to gigatonne scale by 2050.

4.3 Sensitivity of CO₂ capacity, CO₂ storage and oil production to variations in 2 input parameters at a time

Lastly, we explore simultaneous variations in multiple key parameters across a range of conditions, resulting in $\geq 30,000$ end-point estimates for 2050 CO₂ capture capacity. Figure 8 shows two variable "slices" through the array of resulting CCS capacity investment by 2050. Values greater than 1,000 represent gigatonne-scale industry. Variables not shown in contour plot axes are set to Base Case values. Scenario worlds are plotted as red points (e.g., CA represents Climate Action world).

Contour plots show required shifts to push Base Case investment to gigatonne-scale by 2050. In the upper left we see that a 2050 CO₂ tax of ≥ 70 \$/t or an oil price of ≥ 85 \$/bbl are required to induce gigatonne scale by 2050. In the upper right, it becomes evident that beyond 70 \$/t the starting CO₂ tax in 2016 is more important than the learning rate in driving gigatonne emissions (note downward slope of isolines). However, at lower CO₂ tax rates, technological learning reduces the need for a high CO₂ tax at simulation start, though at 2015 observed carbon price levels of

Fig. 3 CCS capacity investment achieved as a result of each of the 5 world scenarios (bottom) and cost of CO₂ capture driven down as a result of technological learning (top).

Fig. 4 Net CO₂ stored as a result of CCS with CO₂-EOR project investment in all 5 world scenarios accounting for emissions from crude oil processing activities with (bottom) and without (top) crude oil end-use emissions including Sub-world scenarios describing 10 alternative 'Climate Action' world scenarios and 6 'High Oil' world scenarios.

Fig. 5 Proportion of revenue generated from oil production compared with that from CO₂ storage in each world scenario (top) and average NPV for successful projects assessed at a given year (bottom) in all 5 world scenarios

Fig. 6 Rates of oil production per metric tonne of CO₂ stored, net used (total CO₂ captured) and gross used (total CO₂ injected) for all 5 world scenarios

\$10-\$15/tCO₂ in EU and California carbon markets, the required learning rate must be at or above above 18% to achieve gigatonne scale (an unrealistically high value for *LR*). At the assumed base case CO₂ tax starting 25 \$/tCO₂, which remains overly optimistic for most of the world, a doubling in technological learning rate (from 7% to 14 %) results in a near doubling of CCS deployment as well (from 597 MtCO₂/y CCS deployment to 1210 MtCO₂/y). Moving to the lower left, the initial cost of capture is surprisingly unimportant towards the likelihood of achieving gigatonne scale. The isolines are very steeply sloping, suggesting larger impacts from initial carbon taxes than capital cost. A challenge is evident in setting initial capital cost to that observed at real projects (i.e., 715 M\$/Mt/y observed at Petra Nova). In that case, an initial CO₂ tax of almost 50 \$/t is required to achieve gigatonne scale. Lastly, we see in the lower right that oil prices must return to recent historical highs of $\approx$ 100 \$/bbl to induce gigatonne scale with Base Case initial costs of capture. This is perhaps unrealistic given recent developments and expansion of so-called “tight oil” driving oil prices to the 50 \$/bbl range.

5 Conclusions

As expected, today’s low or non-existent CO₂ taxes and low oil prices are insufficient to trigger an upscaling of CCS to the gigatonne level. For the IRR-driven private sector, the revenue from EOR activities is currently too low to justify investment, as seen between 2014 and 2016 with a slow down of CO₂-EOR projects in the US. However, with higher CO₂ taxes or oil prices (or a combination of the two), CO₂-EOR does make CCS more attractive. Crucially, the revenue from oil in any CCS with CO₂-EOR project will initially provide the highest proportion of profit. This testifies to the benefit that CO₂-EOR brings to CCS when trying to portray it as a lucrative, investment-worthy endeavor, particularly when considering private sector involvement.

Although reservoir simulation for EOR operations in specific fields are not conducted here (as done by Dai et al. 2016⁸³ and Fukai et al. 2016³⁹), this model incorporates a randomized selection of plausible fields and production profiles for CO₂-EOR and storage. This enables us to assess general conditions under which gigatonne-scale CCS deployment can occur by 2050. This study extends the quantitative understanding to policy makers as to how much incentive is needed for CCS to become economically viable from an investment standpoint.

The specific trigger for investment matters. Whether EOR is induced by a CO₂ tax or a high oil price has clear effects on types of projects that are selected. High CO₂ taxes favor larger CO₂ capture projects and lower production rates of oil with smaller fields (in area and net pay thickness). High oil prices drive CCS capacity deployment but do not favor net carbon sequestration. As shown in Figure 8, given the base case assumptions considered here, gigatonne-scale of CCS deployment only becomes possible in regions where:

- CO₂ tax exceeds \$40/tCO₂ in 2016 and reaches over \$ 75/tCO₂ by 2050 or,
- Oil price is in excess of \$85/bbl or,

Fig. 7 Effect of key parameters, variables and randomization factors on 'Base Case' cumulative CCS capacity investment by 2050.

- The learning rate for every doubling is at least over 14%.

However, current EU Emissions Trading Scheme conditions give a market price for CO₂ of less than \$10/t⁸⁴. Assuming this would increase gradually by 2050, this would require a learning rate in excess of 20% to reach gigatonne-scale of CCS deployment. With such low CO₂ taxes, recent oil prices fluctuating below \$ 50/bbl and a capital cost of CO₂ capture of over 700 \$M/MtCO₂/y only half-gigatonne CCS deployment is reached by mid-century, falling short of the gigatonne-scale expected.

The model developed here, MIICE, provides insight on the quantitative conditions required for CCS investment to reach gigatonne scale with private sector investment. Future work could improve detail of the model and add scenarios with costs of various carbon capture technologies or technological breakthroughs (e.g., new solvents). The addition of regional parameters might be explored. This may strongly affect the extension of a transport network and development of infrastructure. Finally, the model could be extended to include actors with more or less stringent requirements on their returns and the risk they associate to such an investment (e.g., governments or government-corporate partnerships).

Fig. 8 Heat maps showing contours of CCS investment achieved by 2050 in terms of CO_2 capture capacity (MtCO_2/y) as a function of (a) the CO_2 tax achieved by 2050 and the price of oil, (b) the CO_2 tax in 2016 and the amount of technological learning assumed, (c) the price of oil and the initial capital cost of capture assumed per MtCO_2 capture capacity in 2016, and (d) the price of oil and the initial capital cost of capture assumed per MtCO_2 capture capacity in 2016.

Acknowledgments

This work was funded by the UK Natural Environment Research Council (NERC).

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Supplementary Information

S6 MIICE MATLAB Code

See the MIICE MATLAB code attached.

S1 Model scoping and assumptions

Fig. S1 Conceptual representation of the CCS + CO₂-EOR model envelope (dotted line box) without considering physical flow streams

S1.1 CCS and CO₂ Enhanced Oil Recovery Field Development and Cost Modeling

CO₂ Capture Cost in Literature and Model-based Assumptions

Table S1 Real-time and literature-based capital cost values of amine-based CO₂ post-combustion capture plants coupled with supercritical pulverized coal fired plants adjusted to 1 MtCO₂ captured per year

Reference Source	Capital Cost Value (2016 US\$/MtCO ₂ captured)	Information & Assumptions
Boundary Dam CCS ^{S6}	\$1.5 billion	Successfully deployed project, over-budget
Petra Nova Parish CCS ^{S7-S10}	\$714 million	Successfully deployed project, on-budget
Rubin et al. Study ^{S36}	\$326 million	Literature based study for new build power plants with CCS
Adjusted SRCCS study ^{S36}	\$270 million	Literature based study conducted in 2005 ^{S1} for a new build power plant + CCS
Worley Parsons Report ^{S37}	\$209 million	Literature based study for a new build power plant + CCS

Table S2 Operating costs for CO₂ capture as reported by Worley Parsons and adjusted to a MtCO₂ basis - all cost values adjusted to 2016 US\$.

Parameter	Worley Parsons Report	Adjusted Calculations for this Study
Type of power plant considered	Pulverized coal firing	idem
Type of capture technology	Post-combustion amine scrubbing	idem
Net Power Output	546 MW	approx. 110 MW
Capture rate	90%	90%
CO ₂ Captured	4.98 Mt/year	1 Mt/year
Power associated with capture plant	87 MW	17.5 MW
Cost of electricity consumed	\$30.25 million/year	\$6.07 million/year
Variable O&M	\$4.53 million/MWh	\$0.69 million/year
Fixed O&M	\$11.41 million	\$2.29 million

S1.2 CO₂ Transport Cost

S1.3 EOR Field Model Development and Assumptions

Equation S1 is used to calculate the minimum miscibility pressure (MMP) required for CO₂ to be miscible with oil at injection. This is based on characteristic assumptions presented in Table S4.

$$MMP = 15.988 \times T(0.744206 + 0.0011038 \times MWC5) \quad (S1)$$

Table S3 Capital and operating costs for transport pipelines from source to sink required for projects of 1- 4MtCO₂/year capture rates (M\$ = \$ million)

Cost type	Function of	1MtCO ₂ /year	2 - 3MtCO ₂ /year	>3MtCO ₂ /year
Pipeline Capital Costs				
Materials	Diameter (D) & Length (L)	7.223 M\$	11.115 M\$	15.377 M\$
Labor	D & L	28.209 M\$	32.976 M\$	36.672 M\$
Miscellaneous	D & L	7.825 M\$	11.287 M\$	13.815 M\$
Right of Way	D & L	2.976 M\$	3.172 M\$	3.1547 M\$
CO ₂ surge tank	Fixed	1.332 M\$	idem	idem
Pipeline control system	Fixed	0.120 M\$	idem	idem
Total Capital Costs		47.686 M\$	60.003 M\$	75.567 M\$
Pipeline Operating Costs				
Operating & Maintenance	L	0.561 M\$	idem	idem
Total Operating Costs		0.561 M\$/year	idem	idem

with

MMP: minimum miscibility pressure (psi)

T: reservoir temperature (Fahrenheit)

MWCS: molecular weight of pentanes & heavier fractions of oil

Table S4 Reservoir characteristics assumed and calculated in order to obtain fluid properties

Parameter	Value	Unit	Reference
Median reservoir depth	2026	m	S41
Pressure gradient	10.52	kPa/m	S54
Temperature gradient	30	°C/km	S55
Surface temperature	15	°C	Assumption of study
Reservoir pressure (P)	21.3	MPa	Calculated
Reservoir temperature (T)	75.8	°C	Calculated
CO ₂ density at reservoir P & T	614.08	kg/m ³	S85
CO ₂ viscosity at reservoir P& T	47.8	microPa.s	S85
CO ₂ fluid phase	Supercritical		S85
Average reservoir oil gravity	37	API	S41
MWCS +	183.67	g/mol	S56
Average MMP	17.6	MPa	Calculated
Formation volume factor	1.3	m ³ /m ³	Assumption of study

Fig. S2 Distributions of reservoir characteristics including depth (m), porosity (%), permeability (mD) and field area (m²) for oil fields with CO₂-EOR activity in the U.S. as well as Prudhoe Bay hydrocarbon miscible injection field based on Oil & Gas Journal 2014 Survey data.

S1.4 CO₂-EOR Pattern Deployment Strategy

Fig. S3 Flow diagram describing the decision strategy process for CO₂-EOR pattern deployment within a field k.

S1.5 EOR Production Profile Fit Parameters

Table S5 Parameters of logistic and exponential equations of curve fits for production profiles of oil and CO₂ as a percentage of OOIP and HCPV respectively

Oil production fit	d	a	b	c	RMSE/R-Square
Low	0.0	0.105	9.813	0.4213	0.001414/0.9977
Medium	0.01	0.1774	4.86	0.447	0.002853/0.9954
High	0.09	0.3818	3.449	0.3415	
CO ₂ production fit	d'	a'	b'	c'	RMSE/R-Square
Low	0.33	0.3155	0.8515	0.1492	0.01481/0.9751
Medium	0.4	0.6357	0.9292	0.5785	0.009409/0.997
High	0.4792	1.276	0.9086	1.078	

S2 Cost inflation factors

Table S6 Inflation factors used to convert US\$ costs from literature to constant 2016 US\$ based on the Bureau of Labor Statistics Consumer Price Index inflation calculator^{S86}.

Year of cost reported	Inflation factor to 2016 US\$
2004	1.270
2010	1.100
2013	1.030
2014	1.017

S3 Compound annual growth rates

A compound annual growth rate (CAGR) is used to compare results of cumulative CCS capacity deployed by 2050 and cumulative oil production rates to both industries' growth rate predictions. The CAGR describes a rate at which an industry would need to grow by every year, if this were at a steady rate, to achieve a

final industry objective size. These rates are calculated against values of oil production from CO₂-EOR in the US, which was at 156.95 MMbbl/year in 2015^{S87} and the global value for CO₂ captured in 2016 of 27 MtCO₂/year^{S25}.

S4 Slow and Fast Industry Growth Scenarios

In a slow deployment scenario, we assume that the 5-year demonstration period is followed by a growth to materiality of 20% per year (lower than the exponential growth assumed), followed by a stagnated growth of 3% per year based on a low carbon technology study by Napp et al.^{S88}. Meanwhile, a much faster industry growth scenario considers that the first 5 years of project initiation has an upper bound of 2^{year} project investments. In the 10 years that follow, the number of projects that can be built is limited by a 40% growth rate year on year. The 10 years that follow see a slower allowable growth rate as momentum is reduced to a 20% growth rate and the 10 years that follow are limited by a 10% yearly growth rate.

S7 Results

S1 Five World Scenarios

S1.1 Cumulative CO₂ Stored and Oil Produced

Fig. S4 Graph showing cumulative CO₂ stored and oil produced as a result of successful projects obtained in each of the Five World Scenarios

S1.2 Average Field Characteristics of Successful Projects

Fig. S5 Bar chart showing the total average field characteristics for all successful projects resulting from each of the five world scenarios from the pool of 1000 fields

S2 Heat Maps showing 2-D variation

Fig. S7 Heat maps showing contours of CO₂ storage achieved for all invested CCS with CO₂-EOR projects by 2050 as a function of (a) the CO₂ tax achieved by 2050 and the price of oil, (b) the CO₂ tax in 2016 and the amount of technological learning assumed, (c) the price of oil and the initial capital cost of capture assumed per MtCO₂ capture capacity in 2016, and (d) the price of oil and the initial capital cost of capture assumed per MtCO₂ capture capacity in 2016.

(a)

(b)

(c)

(d)

Fig. S8 Heat maps showing contours of Oil production for all invested CCS with CO₂-EOR projects by 2050 as a function of (a) the CO₂ tax achieved by 2050 and the price of oil, (b) the CO₂ tax in 2016 and the amount of technological learning assumed, (c) the price of oil and the initial capital cost of capture assumed per MtCO₂ capture capacity in 2016, and (d) the price of oil and the initial capital cost of capture assumed per MtCO₂ capture capacity in 2016.