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

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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 per bbl–\$55 per bbl), the final CO₂ tax must reach \$70 per tCO₂ for gigatonne-scale deployment. If oil price alone is expected to induce CCS deployment and learning, oil prices above \$85 per 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.

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Broader context

Carbon capture and storage (CCS) is recognized as being imperative for least-cost climate change mitigation by decarbonizing the power and industrial sectors. Nevertheless, CCS has seen a sluggish growth in terms of large-scale deployment due to the lack of robust and universal incentives for CO₂ capture. The current rate of CO₂ capture globally is of the order of 10 s of million tonnes. Utilizing carbon dioxide for enhanced oil recovery (CO₂-EOR) is a well-known process that has been conducted in the United States since the 1970s as well as in parts of Canada and now, Saudi Arabia. Considering a global emissions rate of 37 Gt CO₂ per year, CO₂-EOR currently provides the largest available market demand for CO₂, with the potential to generate revenue from the production of over 1000 billion barrels of oil while storing over 300 Gt CO₂ globally. The revenue generated from EOR has the potential to cover the high cost of CO₂ capture, but may prove to be insufficient at a current price of oil fluctuating around \$50 per bbl. In this work, we systematically assess and quantify the potential for CO₂-EOR to catalyse CCS deployment while prolonging the lifetime of developed oil fields with our Model of Iterative Investment in CCS with CO₂-EOR (MIICE). For this study, we ask ourselves what are the key monetized factors that will allow for the transition from the million tonne to gigatonne scale of CCS deployment globally with the financial incentive from EOR.

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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 per 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 report.⁵ 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 per year capacity of CCS deployed globally.⁶ In the power sector, only two large-scale CCS plants are operational globally, capturing 2.4 MtCO₂ per year (Saskpower Boundary Dam in Saskatchewan, Canada and Parish Petra Nova CCS in Texas, USA).^{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 (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 projects. 14. Approximately 80% of current CO₂ used for EOR comes from natural sources of CO₂ instead of abundant anthropogenic sources.¹⁵

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 per bbl of oil produced and 74 kgCO₂ per 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 per bbl of crude.³³ 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 fields.³⁴ 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 (Fig. 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,

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

Parameter	Value	Assumption/ref.
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 \$ ⁸⁶
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

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 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 [year⁻¹]. 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 2). The model eliminates nonsensical combinations (see ESI,† Section S1) and keeps 1000 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 ESI,† Fig. S2). These are limited to fields in which miscible EOR is

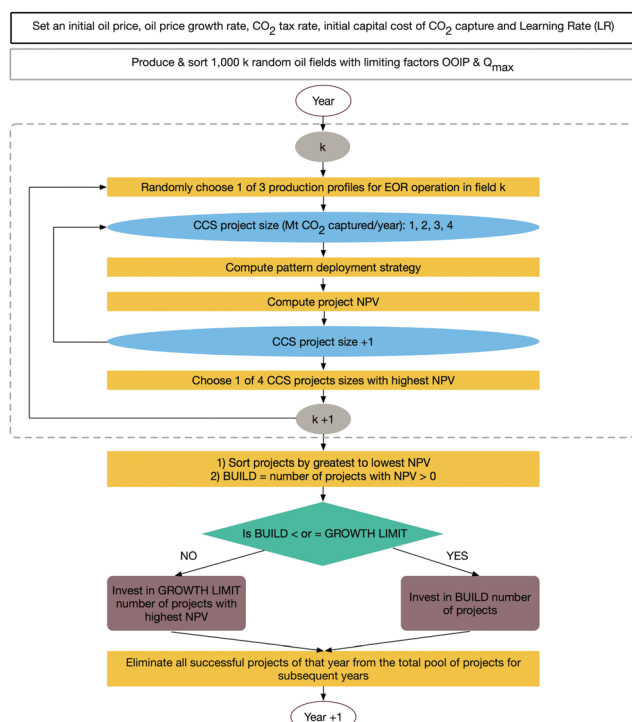


Fig. 1 Flow diagram representing the process and economic evaluation mechanism adopted in MIICE. GROWTH LIMIT refers to the industry growth rate ceiling. The dotted line focuses on pattern deployment strategy and illustrated in more detail in Fig. S3 (ESI†).

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

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 communications.^{44–47}

The CO₂-EOR industry has historically been limited by a lack of low-cost CO₂.¹³ 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 injection.^{49–52} In a world of emissions limits, continuous CO₂ injection and limited CO₂ recycling could be incentivized.⁵³ 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^{−1} (0.465 psi per foot),⁵⁴ the temperature gradient assumed is 30 °C km^{−1} and surface temperature is 15 °C.⁵⁵ CO₂ density and viscosity are estimated at the median of the reservoir depth range of 2026 m as 614.08 kg m^{−3} and 47.8 microPa s.⁸⁵ 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 ESI,† eqn (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 ESI,† Table S4.

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:

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

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/ β_{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 ESI,† 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 dynamics.⁴³ 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 literature.⁵⁹ Also, P10, P50 and P90 statistical results for a U.S.-based CO₂ EOR reservoir simulation were obtained.⁶⁰ Each of these profiles is fitted with eqn (2) for cumulative oil production and eqn (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_{CO₂in}* representing cumulative CO₂ injection (1/HCPV). Also:

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

with *Q_{CO₂out}* representing cumulative CO₂ production (1/HCPV) and *Q_{CO₂in}* 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 Fig. 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

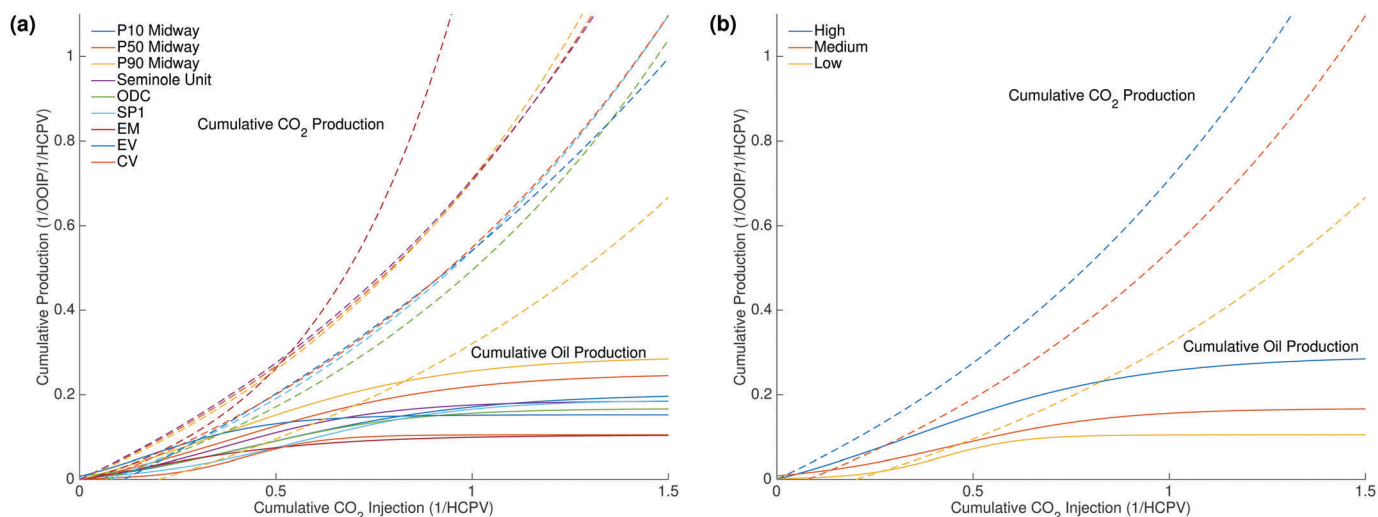


Fig. 2 Cumulative production of CO₂ (dash) and oil (solid) on a HCPV basis. (a) Reproduction of 9 empirical curves^{59,60} (b) low, medium, and high cases for simulation.

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 [$\text{m}^3 \text{s}^{-1}$], k , the average reservoir permeability [m^2], 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: $Q_{\text{oil}}/Q_{\text{CO}_2\text{in}} \leq 0.1$. 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 project size and for each field coupling considered.

The process is described in ESI,[†] Fig. S3. The fracture gradient assumed is 0.926 psi per ft and hydrostatic gradient is 0.465 psi per ft.⁶² 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\$ per year per field.⁶³ These assumptions and values are clearly outlined in the open-source MIICE script provided here (see ESI,[†] 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 ESI,[†] Section S6).

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

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) costs.⁶⁸ We initialize learning models with initial capacity of 2.4 MtCO₂ per year.

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

Cost parameter	Function of	Assumption(s)	Ref.
CO ₂ processing & lease equipment			
Field production equipment	Depth of site	L&A regression cost model, on a per pattern basis	40 and 58 converted from 2004 US\$
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	39, 44 and 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 and 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 intangible costs associated with production well equipment	40 and 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 intangible costs associated with injection well equipment	40 and 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 and 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 and 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 and 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)	Ref.
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 and 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 and 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\$

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\$ per MtCO₂ per year.

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\$ per MtCO₂ per year. 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\$ per MtCO₂ per year (Petra Nova project cost US\$ 1 billion to capture 1.4 MtCO₂ per year)^{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 plants.^{69–71} We therefore explore a range of initial costs between 200 M\$ and 714 M\$ per MtCO₂ per year.

Power costs are wholesale electricity prices of US\$ 39.67 per MW h (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 per tCO₂ to \$39 per tCO₂.

Capital and operating costs of transporting 1–4 MtCO₂ per year are included.⁷⁴ Pipeline dimensions for transport are derived from NETL⁷⁵ and all pipelines are assumed 100 km (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 used:^{76–79}

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

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 $b = -\log(1 - \text{LR})/\log(2)$ 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 of Boundary Dam have been explained with circumstantial, case-specific factors.⁶⁸ 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 per year installed capacity. Our pre- and post-materiality growth rate limits are 25% and 10%, respectively.⁸¹ 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 per bbl;⁸² (2) CO₂ tax of \$25 per tCO₂ starting in 2016 and growing by \$1 per year (3) a learning rate LR = 10%, (4) initial overnight capital cost is \$600 million per MtCO₂ per year. The ‘Climate Action’ world adopts a CO₂ tax of \$100 per tCO₂ in 2016 which increases by \$2 per year. The ‘High Oil’ world has a constant inflation-adjusted oil price of \$110 per bbl (similar to 6DS scenario in ref. 63). In the ‘Depleting Resources world’, oil starts at inflation-adjusted price of

\$55 per bbl and increases at a rate of 2% per 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 assumptions of industry growth limitations,⁸⁸ use of near-site saline aquifer storage at \$60 per tCO₂ or \$20 per 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 per bbl to \$140 per bbl.
- CO₂ tax from \$0 per tCO₂ to \$200 per tCO₂.
- Initial capital cost of capture from 714 M\$ to 200 M\$ for every 1 MtCO₂ captured per year.
- Learning rate from 0.00 to 0.20.
- Growth rates of oil at 0% per year, -2% per year, and 2% per year.

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

4 Results & discussion

4.1 Five world scenarios

Fig. 3–6 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 ESI,† Fig. S4).

Fig. 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 per tCO₂ assuming the fixed charge factor of 0.1185. These worlds show similar slow rates of CCS capacity

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

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

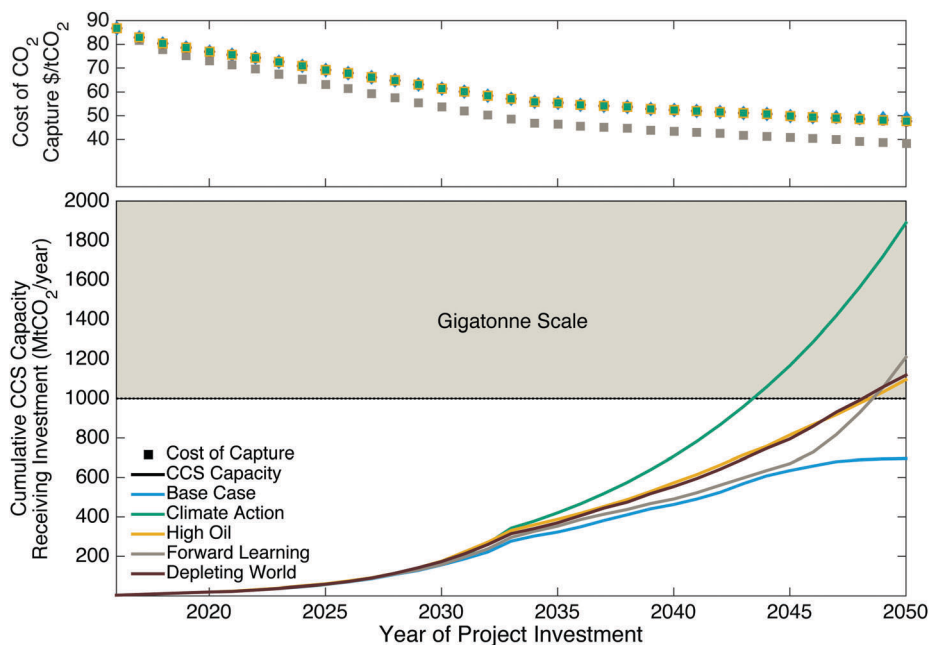


Fig. 3 CCS capacity investment achieved as a result of each of the 5 world scenarios (bottom) and cost of CO₂ capture driven down as a result of technological learning (top).

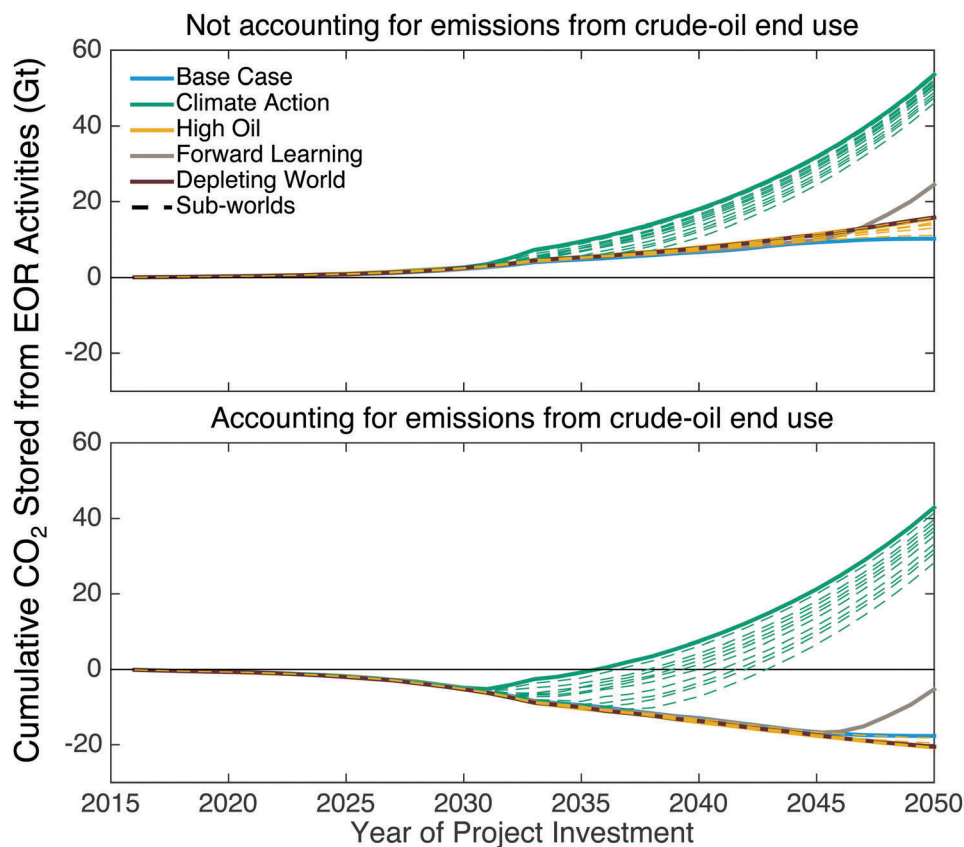


Fig. 4 Net CO₂ stored as a result of CCS with CO₂-EOR project investment in all 5 world scenarios accounting for emissions from crude oil processing activities with (bottom) and without (top) crude oil end-use emissions including sub-world scenarios describing 10 alternative 'Climate Action' world scenarios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

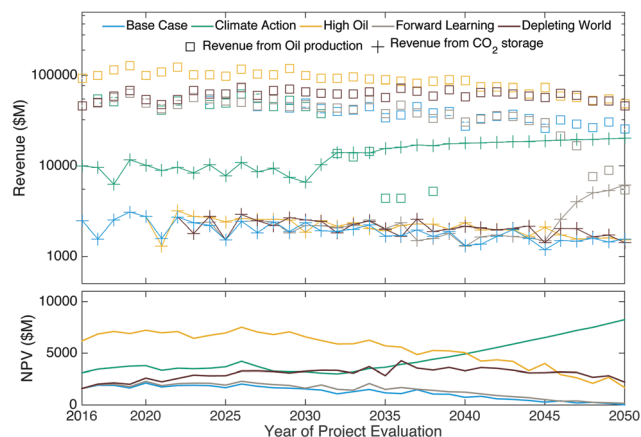


Fig. 5 Proportion of revenue generated from oil production compared with that from CO₂ storage in each world scenario (top) and average NPV for successful projects assessed at a given year (bottom) in all 5 world scenarios.

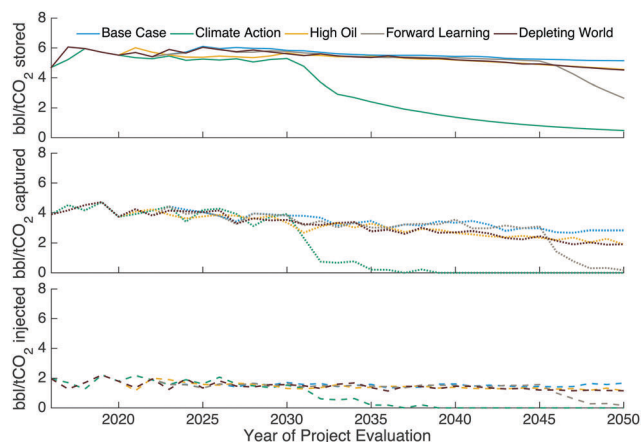


Fig. 6 Rates of oil production per metric tonne of CO₂ stored, net used (total CO₂ captured) and gross used (total CO₂ injected) for all 5 world scenarios.

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 per tCO₂ by the 2030s and the cost of CO₂ capture has decreased to \$61 per tCO₂ (as shown on the top graph of Fig. 3). Thus, in 'Climate Action' world, the projects with highest IRR are those that capture more CO₂ and target smaller oil resources (see ESI,† Fig. S5). Nevertheless, all world scenarios succeed in driving down the cost of CO₂ capture to below \$50 per 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 per tCO₂ by 2033 and to \$40 per 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.

Fig. 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 Fig. 4 represent alternative 'Climate Action' worlds, with CO₂ taxes starting at 60, 65, 70, 75, 80, 85, 90 and 95 \$ per tCO₂ in 2016 and alternative High Oil worlds with oil prices of 60, 70, 80, 90, 100 and 120 \$ per bbl. The alternative 'Climate Action' worlds show significantly different cumulative storage by 2050, while the effect of oil price variation is muted.

Fig. 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.

Fig. 6 shows oil volumes produced per unit of CO₂ injected, captured or stored. The values plotted in Fig. 6 align with other studies: Azzolina *et al.* 2015⁶¹ found a range of oil production from CO₂-EOR of 1.7–6.3 bbl per 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 per tCO₂ captured depending on whether an oil-driven or storage-driven EOR process was conducted.⁶³

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.

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 ⁸⁷	16.69	8.21
(IEA 2050 CCS projection/US CO ₂ -EOR 2020 projection)		

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

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 per 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 1000 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 $\geq 30\,000$ endpoint estimates for 2050 CO₂ capture capacity. Fig. 8 shows two variable "slices" through the array of resulting CCS capacity investment by 2050. Values greater than 1000 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 \$ per t or an oil price of ≥ 85 \$ per bbl are required to induce gigatonne scale by 2050. In the upper right, it becomes evident that beyond 70 \$ per 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 \$10–\$15 per tCO₂ in EU and California carbon markets, the required learning rate must be at or above 18% to achieve gigatonne scale (an unrealistically high value for LR). At the assumed base case CO₂ tax starting 25 \$ per 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 per year CCS deployment to 1210 MtCO₂ per year). Moving to the lower left, the initial cost of capture is surprisingly unimportant towards the likelihood of achieving gigatonne scale. The isolines

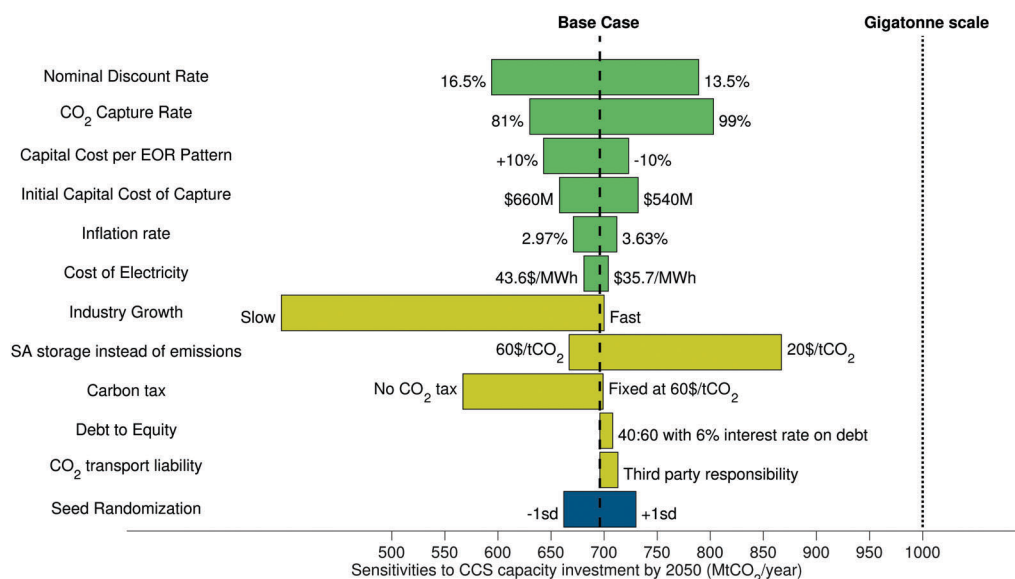


Fig. 7 Effect of key parameters, variables and randomization factors on 'Base Case' cumulative CCS capacity investment by 2050.

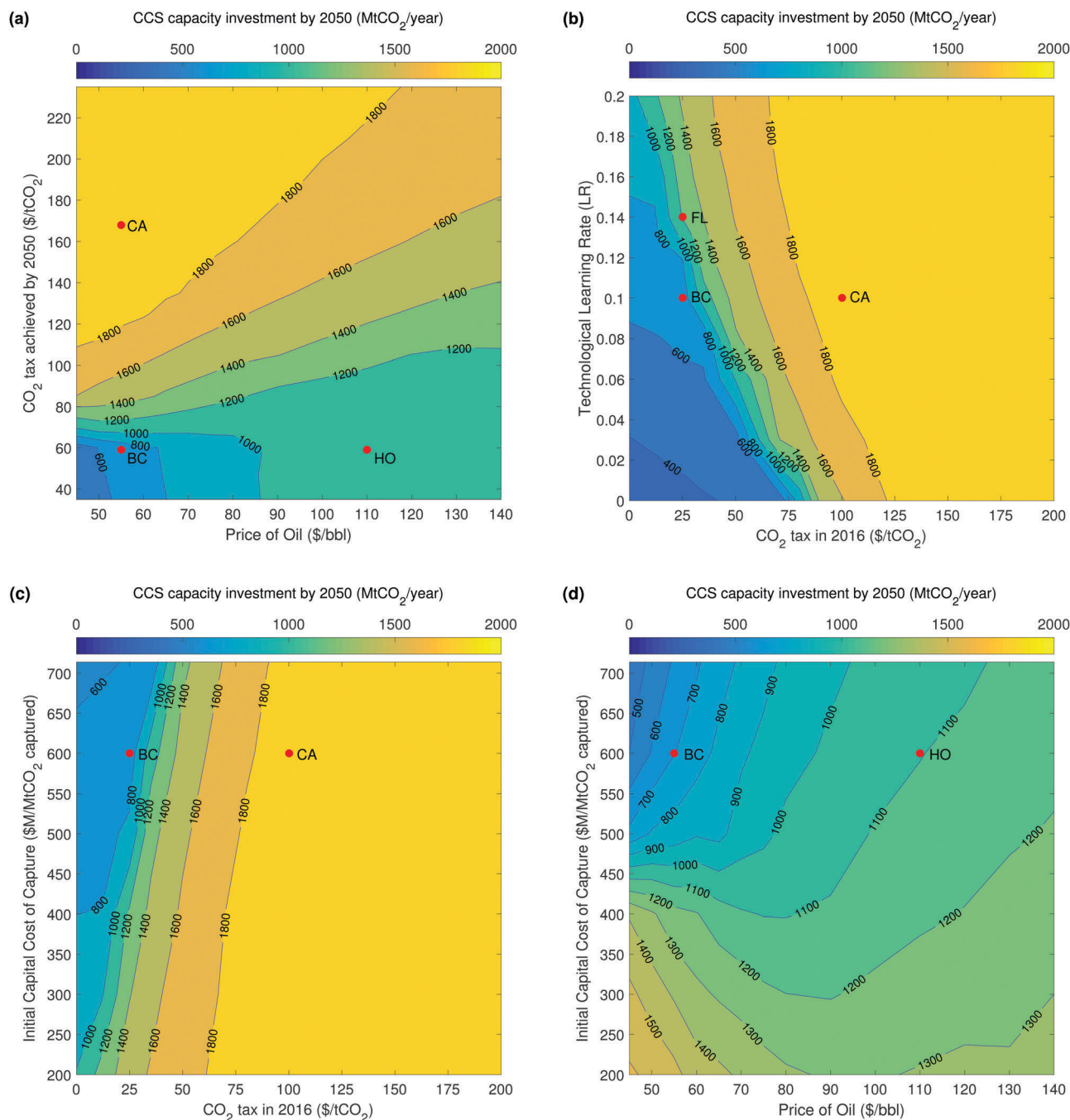


Fig. 8 Heat maps showing contours of CCS investment achieved by 2050 in terms of CO₂ capture capacity (MtCO₂ per year) as a function of (a) the CO₂ tax achieved by 2050 and the price of oil, (b) the CO₂ tax in 2016 and the amount of technological learning assumed, (c) the price of oil and the initial 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.

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\$ per Mt per year observed at Petra Nova). In that case, an initial CO₂ tax of almost 50 \$ per t is required to achieve gigatonne scale. Lastly, we see in the lower right that oil prices must return to recent historical highs of ≈ 100 \$ per 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 \$ per 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 Fig. 8, given the base case assumptions considered here, gigatonne-scale of CCS deployment only becomes possible in regions where:

- CO₂ tax exceeds \$40 per tCO₂ in 2016 and reaches over \$ 75 per tCO₂ by 2050 or,
- Oil price is in excess of \$85 per bbl or,
- 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 per t.⁸⁴ 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 per bbl and a capital cost of CO₂ capture of over 700 \$M per MtCO₂ per year 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).

Conflicts of interest

There are no conflicts to declare.

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