# Oil carbon intensity impacts of COVID-19 and other short-term demand shocks

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**Physical Sciences - Article**

**Keywords:** Oil carbon intensity, oil production

**Posted Date:** December 1st, 2020

**DOI:** https://doi.org/10.21203/rs.3.rs-113456/v1



**Version of Record:** A version of this preprint was published at Nature on November 3rd, 2021. See the published version at https://doi.org/10.1038/s41586-021-03932-2.

# Abstract

Oil production choices are influenced by the interaction of oilfield production costs and the global price of oil. What are the characteristics of less economic oilfields, fields whose profitably is at the margin? These oilfields may differ from average fields in terms of geographical location, crude type, production practices, and carbon intensity (CI). Because these economically-marginal fields are the ones likely to respond to drop in demand (e.g., due to 2020 COVID-19 pandemic, or a rapid shift to alternatives), they represent the likely sources of oil that would be displaced. The present paper links the field-by-field costs of 1933 oilfields (representing ~ 90% of 2015 worldwide crude production) with their production environmental footprint. We show that many marginal fields also have high CI. We estimate that the fields at margin due to the 2020 COVID-19 pandemic demand reduction have upstream CI and marginal cost of production ~ 35% and 3 times higher than global average, respectively. The production termination of these fields could result in 181 Mtonne $CO_2$Eq. annual reduction in upstream emissions in the short-term. The marginal producers in a generic small demand shock (5% or ~ 3.6 mmbbl/d drop) have an upstream CI 26% higher than average global oil producers, and at our larger generic demand shock (20% or ~ 14.3 mmbbl/d drop) have CI that is 5% higher than average. Heavy oilfields have the highest volume share in marginal crudes in all scenarios. These results further suggest that life cycle benefits of alternative fuels or vehicles or regulations that lead to reduced oil consumption are systematically larger than those typically estimated when displaced emissions are modeled using average crudes. The results only cover the upstream production CI and do not include synergistic impacts of differences in refining CI of different types of crudes, and thus could underestimate the total life cycle differences between marginal and average crudes.


# Introduction

The life cycle environmental footprint of transportation fuels (e.g. gasoline, diesel) includes the greenhouse gas (GHG) emissions resulting from the combustion of fuels themselves as well as emissions from production and refining of petroleum products. So-called “upstream” emissions from exploration, extraction, and transportation of crude oil differ widely between oilfields (~ 20–300 kg $CO_2$eq./bbl oil) due to diverse sub-surface geological properties of the deposit, physical and thermodynamic properties of the hydrocarbons, and production and resource management practices[1]. Similarly, “midstream” emissions from refining vary on a refinery-by-refinery base (~ 10–60 kg $CO_2$eq./bbl oil) due to the quality of the stream of crude being processed and the refining technologies applied. These highly variable emissions contribute to the life cycle carbon intensity (CI) of a particular crude oil supply chain, as used in life cycle analysis (LCA) of crude oils and refined products.

The economic variability of crude oils somewhat mirrors the heterogeneity presents in the CI. Different geological formations make the extraction and the exploration costs heterogeneous across fields, such that some regions have very low cost of extraction and are highly profitable, while others barely break even. However, the refining process transforms different qualities of crude into fuels indistinguishable by consumers and creates a global market of largely interchangeable fuel products.

Recent studies have analyzed the environmental[1,2] and economic[3] heterogeneity of the oil market. However, the interaction between the two remains poorly understood. Crude oil production choices are influenced by the interaction of local production costs and the global price of oil. But the characteristics of marginally economic oilfields, such as geographic location, crude type, production practices, are not systematically available. These questions matter because they affect the magnitude of emissions mitigation potential as less profitable oil producers are displaced when a shock of reduced demand occurs. Such demand drops can be caused by socio-economic situations (e.g.,

COVID-19 pandemic) leading to significantly lower fuel (gasoline/diesel/jet fuel) consumption[4] due to reduced travel and reduced overall economic activity, or greater fuel efficiency, or more extensive use of alternative fuels and vehicles. Also, while it is known that there is feedback between the price of crude and the cost of extraction, little is known about how temporal trends in the oil price affect the production cost of marginal crudes.

The linkages of economic and environmental characteristics of oilfields are particularly important for computing the life cycle CI of crudes relative to their alternatives. In the last decade, development of “consequential” LCA has aimed to incorporate market effects into previously static engineering-based analysis. These consequential analyses attempt to model substitution and consumption effects of introducing alternative products, instead of simply assuming that a new product directly displaces an old product. To date, this consequential LCA paradigm has not reached crude oil LCA, and studies of alternatives to crude oil (e.g., electric vehicles) nearly always assume that an alternative simply displaces average crude oil.

The present paper examines the links between CI and profitability at a field-by-field level. The former is calculated using a well-to-refinery CI estimation tool, which assesses the emissions due to the production of an additional barrel of crude from a particular oilfield. The latter is calculated using a microeconomic model, which determines how much money a company is willing to pay to manage an additional barrel of crude in that field. To our knowledge, this study is the first consequential LCA study of global oil production.

The integration of field-specific CIs with the profitability analysis allows us to identify the emissions of fields close to the break-even point. In other words, we can isolate the emissions of those fields where the management choice hangs in the balance between ‘how much should I produce?’ and ‘should I invest in maintaining output capacity?’.

We analyze a total of 1933 oilfields, which account for ~ 90% of the 2015 global crude oil and condensate production. The empirical results suggest that an environmental policy designed around non-market informed LCA results could ignore first-order effects. We find that the least profitable fields produce oil with more $CO_2$eq./bbl, and so that actions (or events) leading to fuel demand reduction could have a non-linear effect on emissions, reducing the environmental footprint more than proportionally. Our model has also the ability to predict the short- and mid-term asset-level impact of demand reduction, e.g., due to 2020 COVID-19 pandemic. These results could also serve public (e.g., the U.S. Department of Energy National Energy Modeling System) and private energy system models assessing the benefits of alternative fuels and vehicles, and greater vehicle efficiency.

# Method

### Research Scope

This work covers upstream costs and emissions including production and transport of crude oil. Due to lack of access to refinery cost data, we cannot yet generate similar results for refining and thus assemble a fully market-informed (consequential) well-to-tank or well-to-wheel emissions analysis.

### Economic Model

We frame our economic research question within a traditional profit maximization problem, where a large number of independent firms produce a substitutable good. More precisely, we assume that every oilfield is a risk-neutral firm, which exerts no market power. In other words, the production decisions of a single field do not affect the market price and all non-oil prices are given. The aim of management is to maximize the field profits

Profits = (Oil Price * Volumes of Oil Extracted) – Extraction Costs – Exploration Costs

Profits are the difference between the field revenues (Oil Price * Volumes of Oil Extracted) and the field costs, which are divided into two macro-classes: costs to extract the oil (Extraction Costs) and the costs to discover new oil (Exploration Costs).

At every point in time, the management makes two simultaneous decisions for a given field: *how much oil to extract* from existing known capacity/reserves? and *how much money to spend in exploration*[5,6] to identify new capacity/reserves. While making these decisions the management faces two physical constraints. First, the cumulative depletion of the field at time *t* equals the cumulative depletion until time *t*-1 plus the Volumes of Oil Extracted at time *t*. Second, the cumulative discoveries at time *t* equals the cumulative discoveries until time *t*-1 plus the discoveries at time *t*.

The first order condition of the optimization problem with respect to the Volumes of Oil Extracted identifies how much money a producer is willing to pay to manage one extra barrel of oil. This value is the Shadow Price (SP),

Shadow Price = Oil Price – Marginal Extraction Costs

where the Marginal Extraction Costs is the first-order derivative of the Extraction Costs with respect to Volumes of Oil Extracted [7] . For example, if a field sells its output at 50 $/bbl and the Marginal Extraction Costs (i.e., the cost of extracting the next barrel) is 40 $/bbl, the owner of the field is willing to spend (up to) $ 10 to manage one more barrel in that particular field. Section 1 of the Supplementary Material (SM) provides mathematical details of the economic framework linking the concept of Shadow Price to standard oil economics models.

As the SP of a field approaches zero, the management problem shifts from *'how much should I produce?'* (intensive margin choice) to *'should I produce or not?'* (extensive margin choice). In other words, the fields with a shadow price around zero identify the *extensive margin of the oil industry*. The emissions of this portion of the industry will be the most sensitive to demand shocks.

In this economic framework, we develop a universal model to estimate shadow prices. As in most exhaustible resources models, the shadow price is the market price net of the marginal cost. The former can be reverse engineered using the prices of publicly traded crudes. The later must be estimated. Accurate measurement of marginal costs of global oil fields is difficult. Among other problems, it is difficult to differentiate which factors of production are fixed and which are variable. We do not claim to flawlessly compute the marginal extraction costs of every field in the dataset, but rather that a combination of standard econometric techniques with a large longitudinal dataset allows us to approximate how much it costs to extract the next barrel across different types of formations and then to link this analysis to the environmental characteristics of the marginal producer.

**Econometric Analysis**: The SP of a particular field is the difference between the field-level expected price and its marginal extraction costs. Both variables are unobserved. To estimate them, we face two econometric problems: 1) the non-stationary nature of oil prices, and 2) the endogenous link between costs and quantities. We solve these problems using standard econometric techniques.

Since the commercial agreements between oil producers and oil refiners are generally not disclosed, we do not know the price at which a particular field sells its output. However, we know the prices for different publicly traded classes of oils. More precisely, we know the landed costs of imported crudes in the United States from 1979 to 2018, as reported by the Energy Information Administration [8] , and the chemical characteristics of every traded class, as

reported from the PSA Management and Services BV dataset [9] (see Fig. 1 of SM). From those, we regress the prices of the publicly traded oil classes against their API gravity, their sulfur content and a homogenous time trend. In doing so, we isolate the impact of the chemical properties of each crude from overall price trends driven by global oil demand. According to our estimates, increasing API gravity by one degree changes the value of a crude by + 0.07 $/bbl, while increasing sulfur content by 1% changes the value by −2.21 $/bbl (see SM, Sect. 2.1).

Under mild assumptions, we can use these two structural coefficients to estimate field-level selling prices for the fields in our basket of crudes (see SM, Sect. 2.1, Eq. 8). For example, in 2015, when the part of the inverse oil demand, absent effects from gravity and Sulfur, was estimated to be 49.80 $/bbl, a field with an API gravity of 55.00 and a sulfur content of 3% could sell its output at an estimated price of:

Oil Price = 49.80 + (0.07 * 55) – (2.21 * 0.03) = 53.58 $/bbl.

Using the API and sulfur content reported in the 2018 Wood Mackenzie (WM) dataset[10], we estimate the selling price of 1933 “parent project” fields over the decade 2009–2018, thereby obtaining 1933 * 10 = 19,330 simulated selling prices. See Fig. 1 of SM for a cross-sectional snapshot. The section entitled Firm Expected Prices in SM (Sect. 2) provides econometric details of the estimate.

Next we must estimate the other component of SP: marginal extraction cost. Using the WM dataset, we obtain yearly cost data for the same 1933 fields over the time interval 2009–2018. Then we obtain Extraction Costs by summing the operational expenditures (OPEX, which include consumable inputs, labor, maintenance, repairs, accounting costs, license fees, office expenses, utilities and insurance) and the capital expenditures not linked to exploration activities (non-exploration CAPEX, which include installation, acquisition, upgrading and restoring of the physical assets used to extract the oil). After computing the Extraction Costs, we regress them against the Volumes of Oil Extracted while controlling for the depletion level of the field, a technological trend and the geologic class of the field[3]. The estimated first order derivative of the fit with respect of the Volumes of Oil Extracted returns the estimated Marginal Extraction Costs. Section 2.3 of SM provides all the econometric details.

Since this estimate of extraction costs includes non-exploration development costs, its validity is maintained over a few-year period. Cutting field development expenditures can lower the costs in the short-run (e.g., months), but in the long-run (years to decades) exploration and development investment is needed to maintain a given level of production. Therefore, our time scale of marginality is representative of an intermediate 3 to 5 year time period.

Using estimated Oil Prices and estimated Marginal Extraction Costs (MC), we estimate the SP. For example, if the above example field extracts the next barrel at a marginal cost of 43.58 $/bbl, the Shadow Price is then

Shadow Price = 53.58 $/bbl – 43.58 $/bbl = 10.00 $/bbl.

In other words, this field is $ 10.00 away from the extensive margin of the industry. As a result, if the price of oil would decline by 10.00 $/bbl or the MC would increase by 10.00 $/bbl, the management problem shifts from *‘how much should I produce?’* to *‘should I produce or not?’*.

### Carbon Intensity Model

The field-level CI is estimated using the Oil Production Greenhouse Gas Emissions Estimator (OPGEE version 2.0)[11–13]. OPGEE is an open-source, peer-reviewed [11,14–23], bottom-up, engineering-based model. The OPGEE system boundary is “well-to-refinery” (WTR, i.e., exploration, drilling & development, production & extraction, surface

processing, maintenance, waste disposal, and crude transport to the refinery). Reported emissions are measured in $gCO_2Eq.$ emitted per 1 MJ LHV of crude petroleum delivered to the refinery entrance gate. All GHGs are converted to $gCO_2Eq.$ using AR5 GWP100 conversion factors (without carbon feedback)[24]. See the OPGEE user guide[11] for more details of each process stage.

OPGEE estimates CI using up to 50 parameters as input data for each modeled oilfield. If input data are not available for some parameters (common), OPGEE supplies defaults based on statistical analysis of petroleum engineering literature and commercial data sources (e.g. Oil & Gas Journal O&GJ[25]) enabling the software to estimate a field's CI without complete data [25,11]. In this work, field exploration emissions are excluded from CIs reported in prior work[1] to estimate GHG emissions associated with production of the next barrel of crude oil (i.e., marginal upstream CIs).

Crude oil transportation GHG emissions are generally a minor contributor to CI. Due to volatility of crude oil trading patterns and lack of data availability on these trades, we use identical OPGEE defaults for crude transportation for all studied oilfields (ocean tanker: 8,000 miles; ocean tanker size: 250,000 tons; pipeline: 1,000 miles). Energy-based allocation of emissions is used to divide emissions given co-production of gas.

### Covered Global Oilfields

In the previous work[1], CIs were estimated for 8,966 global active oilfields (so-called "child" fields) supplying 78.9 million barrels per day, and capturing ~ 98% of 2015 global crude oil and condensate production[26]. Fields with gas-oil-ratio (GOR, scf natural gas produced/bbl crude oil produced) of < 10,000 scf/bbl are considered as oilfields. A combination of government reported data (Norway[27,28], Canada[29–32], Denmark[33], UK[34], Nigeria[35], and US California[36], US Alaska[37], and US shale oils[38]), public literature (total of nearly 800 sources) and proprietary/commercial data sources (O&G J 2015 survey[25] and WM oilfield datasets[10]) were used as input data[1]. Government and public literature data were collected and used for 1,009 global fields, accounting for about 64.3% of global crude oil production. Commercial data are utilized for the remainder (mostly small fields). The year 2015 is selected as the reference year due to lags in some data sources. See our previous study SM document[1] for further details.

This previous work on the CI of global oilfields[1] is provided at a "child" field level. Child fields are individual discoveries that are part of a parent project. Parent fields are combinations of geologic deposits collected for the purposes of a combined valuation. The linkage with the economic data (see above), available only at parent-level requires to match the child-field CIs[1] to parent fields. The majority of the child non-technical oil fields from WM datasets[10] (accessed 2018) - whose corresponding parent fields are available - directly matched with the OPGEE global dataset. We paired the remaining with smart string search and string distance matching using *R* program script, as well as by-hand manual matching for the countries with poor total production coverage.

Finally, additional treatments are conducted on two important global producers (Canada and U.S.) based on the available data (see Sect. 4 of SM).

### Data Coverage

After the matching process is completed, it is important to examine to what extent the matched fields covered in this work are representative of total production of different countries. Table 6 of SM gives a coverage summary for the top 20 largest global producers, showing that the integrated global economic and emission dataset in this work is a good representation of the global picture. In total, 1933 parent fields located in 77 countries are matched. These

oilfields have combined oil production of ~ 71 mmbbl/d, capturing ~ 90% of 2015 global crude oil and condensate production[26]. The geographical location of covered global oilfields and their qualitative volumetric production magnitude and CI are mapped in Figs. 7 and 8 of SM.

# Results And Discussion

### Country-level

Figure 1 presents the global map of national volume-weighted-average (VWA) marginal production costs (MC) in 2015. The numbers below the name of each country in the map are the corresponding upstream VWA CIs (in kg $CO_2$eq./bbl). The global average MC estimate – shown by the horizontal dashed line in Fig. 1 – is ~ 5.9 $/bbl crude oil. Lower MC is generally associated with higher shadow price (SP). Fields with the lowest production costs are mainly conventional resources located in the Middle East and North Africa. However, there is a wide range of production emissions associated with these countries, with routine flaring as the major driver of high CI due to lack of investment/infrastructure for gas handling (as discussed later in Fig. 2).

Among the large global producers, Venezuelan and Canadian oils are expensive, and also have high production CIs. The U.S. oil industry stands near the global average in terms of GHG emissions but has a high marginal cost of production (~ 8.2 $/bbl).

Note that the dynamics of the MC and emissions presented in Fig. 1 can vary over time[17]. Time-series operation data are generally missing on a global basis and so we are unable to estimate temporal trends in global emissions. However, due to the fact that substantial change in production strategies takes time, the relative magnitude of the presented emissions is likely valid for a medium-term period of time (i.e., 5–10 years). See below (Fig. 4) for MC time-series dissection of production economics.

### Crude-type

Table 1 groups field-level results into summary statistics of a set of global crude classes. Heavy fields (mostly located in Venezuela) and extra heavy fields (mostly located in Canada) are the least economic fields with relatively high MC, low oil price, and therefore low SP. Although the MC of production of oil sands (all located in Canada in the dataset) are lower than heavy crudes; their relatively lower sale price (due to API and sulfur properties) reduces their SP. Consequently, these are vulnerable crudes to be displaced due to oil demand reduction. Carbon taxation would also significantly affect their economics due to their high marginal CI associated with upstream production emissions.

Compared to heavy crudes, shale and tight oil resources (314 fields) are somewhat more competitive, with relatively higher profit margins, lower emissions, and lighter density crude (higher value and lower refining emissions). Conventional light & medium fields (1259 fields) are the largest source of crude oil and the most competitive sector with the lowest MC, and highest oil price and SP, and relatively low CI. Gas management (i.e., routine gas flaring and methane venting and fugitives) is the major CI contributor for light & medium and shale & tight oil crudes. The economics of these fields are therefore exposed to gas management regulations (e.g., production restriction as imposed in eastern Canada[39]).

Table 1
2015 Global oilfields characteristics based on crude type.

| Crude type | Share in global production, % | Total # of fields | CI[b], kg $CO_2$eq./bbl | MC, $/bbl | Oil price, $/bbl | SP[b], $/bbl | API gravity, °API | GOR[b], scf/bbl |
|---|---|---|---|---|---|---|---|---|
| Light & Medium | 77.5% | 1259 | 49 | 4.3 | 49.4 | 45.2 | 33.7 | 154.8 |
| Heavy | 8.6% | 157 | 61 | 16.9 | 47.1 | 30.4 | 17.1 | 122.4 |
| Shale & Tight Oil | 7.7% | 314 | 53 | 7.9 | 49.1 | 42.1 | 28.2 | 193.7 |
| Oil sands | 2.0% | 21 | 129 | 6.4 | 45.3 | 39.0 | 19.3 | 2.0 |
| Extra Heavy | 0.5% | 9 | 60 | 19.7 | 48.8 | 29.1 | 13.6 | 32.3 |
| Other Oil[c] | 3.6% | 173 | 42 | 6.4 | 49.8 | 43.8 | 36.5 | 84.4 |
| Global avg. | 100.0% | 1933 | 52 | 5.9 | 49.1 | 43.4 | 31.6 | 148.7 |

[a] *Global production covered in this work: 71.0 mmbbl/d.*

[b] *Volume-weighted-average based on field-level share of production.*

[c] *Fields that are not characterized in the used dataset and are excluded in the paper discussions.*

**Field-level**

To estimate GHG emissions associated with production of the next barrel of crude oil (i.e., marginal upstream CIs), we modify the emissions results of Masnadi et al. [1] to exclude emissions from exploration and drilling & development. Next, the computed shadow prices of global fields (see Methods) and their corresponding CI estimates and marginal production cost data are sorted from smallest to largest shadow price (i.e., low to high profitability). Figure 2 combines the upstream cumulative VWA CIs (left-axis), and the sorted shadow prices and the marginal cost of production of the next barrel of crude oil (right-axis), against the percentage of total oil production covered in this work. Analogous to the upstream GHG emissions [1] , the presented wide range of shadow prices clearly illustrates heterogeneity of production costs due to diverse operational, physical, chemical, and geological properties of different oilfields [3] . Fields in the highest 5th percentile (> 50.5 $/bbl) make over 13% more profit per barrel than the median field (44.5 $/bbl).

Each local peak along the CI curve in Fig. 2 indicates an addition of a field with relatively high CI and production rate compared to the preceding covered fields. Large peaks in cumulative CIs at the beginning (0–20% of total production) imply that many less-economic fields with relatively low shadow prices also emit high GHG emissions (few exceptions are depleted conventional fields with low SP and low emissions). These marginal oilfields are consequently more vulnerable to any future carbon taxation regimes and more likely to be displaced by alternative resources. As we include more profitable fields (higher shadow prices), the cumulative CI curve trends downward due to covering fewer emitting fields until reaching 51.9 kg $CO_2$eq./bbl (at 100% production coverage) which is the global VWA marginal CI.

The increase of the SP resonates with a decrease in the production MCs (grey lines in Fig. 2). However, despite an overall downward trend (see Fig. 2 dashed line), the fluctuations in MC reflect the variations in modeled selling price (see Methods and elsewhere[3]). See the SM Excel file for field-level data.

Figure 3 shows the global field-level shadow-price supply curve, identifying fields using three different type of descriptors. Each bar width reflects the oil production of a particular field in 2015. Figure 3(a) characterizes each field based on its corresponding CI percentile. The least profitable 10% of global production volume includes several fields with high CI (dark green) mainly due to crude's high density (requiring thermal enhanced recovery) and/or high gas flaring rates (see Fig. 3(b)). Approximately 76% of these marginal crudes (~ 5.4 mmbbl/d) correspond to oil sands, heavy and extra heavy unconventional fields (see Fig. 3(c)).

In the current world where upstream GHG emissions are not regulated globally, a high CI is not always associated with low profitability. Figure 3 illustrates that many fields in the highest 10% of global profitability (90–100%) have high shadow prices but release high GHG emissions mainly due to routine flaring of large amounts of gas. These economically productive fields are mostly conventional onshore located in the Middle East and North Africa. The oilfields in the dataset are ~ 25 years old in average with Deepwater fields as the youngest geological group. In particular, the ones containing Light & Medium crude are in average ~ 9 years old. A younger deepwater field implies, ceteris paribus, a higher reservoir pressure which is a strong driving force in reducing extraction energy intensity and marginal costs of production. Thus, the competitiveness of these formations could change over time as become more depleted.

## Displacement Implications

Many reports have estimated the near-term and long-term volume of oil that is going to be displaced by regulatory measures leading to reduced crude oil consumption, such as further penetration of alternatives, particularly by electrification of light duty transportation[40–44]. These estimates depend on numerous scenario assumptions (e.g., growth rate of electric vehicles – EVs) and differ markedly.

Instead of selecting any one scenario to model, we create abstract "round number" shocks to demand. Such shocks might stem from policies to counter climate change such as rapid penetration of alternative fuel and vehicle systems (e.g., EVs), economic slowdowns, geopolitical conflict, or (as the case in 2020) global disease crises. We consider two generic scenarios that reduce oil demand by 5% (~ 3.6 mbbl/d) and 20% (~ 14.3 mmbbl/d) respectively (see vertical lines in Fig. 2). The smaller shock could be considered as resulting from a modest introduction of alternative vehicles and fuels, while the larger shock represents an extreme scenario which might result from vigorous adoption of alternatives or a major macroeconomic shocks. We also include an special scenario for the COVID-19 pandemic which caused ~ 10% oil demand reduction in 2020[4,45]. As the estimated production marginal costs and emissions are more valid for a short period of time, within the exploration margin but including redevelopment and capital investment in existing fields, these shocks could be imagined occurring over 3-to-5-year time scales.

The marginal fields for all scenarios are mostly small producers with median production of 4000–9000 bbl/d (Table 2, and small bar widths in Fig. 3). The VWA production MC and CI of these fields are much higher than the global average MC of ~ 6 $/bbl. The CI of the crudes displaced by the small shock is 26% larger than the global average of 51.9 kg $CO_2$eq./bbl, while that of the COVID-19 and large shocks are 35% and 5% larger than the average, respectively. From Fig. 2 and Table 2, we see that in the small shock case the fields in the marginal crudes basket are overwhelmingly heavy crudes, whereas in the large shock case there is greater share of shale and sands, but the total share of unconventional (by volume) decreases. In the small shock scenario, none of the oil sands production

becomes marginal, whereas with a large shock, ~ 54% of oil sands global production is estimated to be displaced. Our results show that small, COVID-19, and large reduction shocks in the global oil demand would result in elimination of 85, 181, and 284 × $10^6$ tonne $CO_2$Eq. per year of upstream emissions, respectively. Larger reductions of GHG emissions associated with refining of this oil and the final combustion of corresponding products would also occur, but are not included in these calculations.

In this work, we only included the production economics and identified the extensive margin of the oil industry under some assumptions on the market structure (see Methods). However, various other dynamic forces such as production agreements (e.g., OPEC), regulations (e.g., fuel standard policies), geopolitics (e.g., sanctions, trade wars), technical advances, and incidental events could move a particular oilfield toward or away from the margin. A pertinent example: fields with high routine flaring (and therefore high CI, see Fig. 3(b)) and a medium shadow price would be significantly affected by a carbon tax and may become marginal. Further analysis of these factors is beyond the scope of this work, but could be pursued in future research.

Table 2
Characteristics of small and large shock scenarios for crude oil demand reduction.

| | Small-shock, 5% reduction | COVID-19 shock, 10% reduction | Large-shock, 20% reduction | Total (reference) |
|---|---|---|---|---|
| Displaced volume, mmbbl/d | 3.6 | 7.1 | 14.3 | N/A |
| Median production rate, bbl/d | 8767 | 4658 | 6438 | 7507 |
| VWA MC of production, $/bbl | 23 | 18 | 13 | 6 |
| VWA CI, kg $CO_2$eq./bbl | 65 | 70 | 54 | 52 |
| Oil sands share, vol. % | 0 | 8 | 5 | 2 |
| Heavy crudes share, vol. % | 92 | 63 | 34 | 9 |
| Extra heavy crudes share, vol. % | 3 | 5 | 2 | 1 |
| Shale & tight oil share, vol. % | 0 | 8 | 12 | 8 |
| Unconven. crudes total share, vol. % | 95 | 84 | 54 | 19 |
| Annual upstream mitigation potential, mmtonne $CO_2$eq. | 85 | 181 | 284 | N/A |

The above shocks might be due to different events; For example, if modest environmental regulation and/or limited diffusion of alternative transportation technologies causes a small reduction in the long-run oil demand, oil prices might decline. This marginal decline might be too small to incentivize the Organization of Petroleum Exporting Countries (OPEC), or its recent extension (OPEC+), to coordinate a set of production cuts among its members. In the absence of an OPEC response, the fields more likely to exit the market are the ones identified by our small shock scenario. In the same way, if global economic growth overcompensates for the impact of regulation and technological change, we might observe a small increase in the long-run oil demand. The resulting increase in oil prices, even if small in magnitude, disincentives OPEC to coordinate production decisions making the organization operate more like an oligopolist and less as a cartel. As a result, the fields more likely to invest in exploration activities and find new oil are, once again, the ones at the extensive margin of the industry.

To the contrary, let us suppose that a major reduction in long-run oil demand occurs. A resulting sharp decline in oil prices would incentivize OPEC to coordinate major production cuts to keep prices high, while protecting its market share. The post-shock equilibrium would identify prices similar to the pre-shock level, but with a major decline in quantities produced. In this case, the CI displaced would be more similar to the one of the average crude since a significant proportion of reduction in production would likely come from OPEC fields. In the same way, a sharp increase in oil prices would incentivize every field to invest in exploration activity, including depleted fields, whose CI is similar to the one of the average crude.

In other words, the smaller the shock the more probable that the CI displaced will be larger than the one of the average oilfield. This suggests that life cycle analysis studies of higher vehicle efficiency or oil-displacing alternatives fuels and vehicles may underestimate the marginal GHG benefits of these measures.

### Temporal Trends

Our analysis gives a single-year snapshot relationship between shadow prices and CIs for 2015, the latest year for which a comprehensive data set was available. However, both these variables can vary over time and therefore, understanding their temporal trends is essential. Shadow prices can change with changes in oil prices and/or changes in marginal costs. The marginal costs and shadow prices are also coupled in complex ways. Figure 4 plots the estimated marginal cost of production in different years of the WM dataset from oilfields, sorted in descending order. It is evident that the marginal cost of production in different years for some crudes is influenced by the status of the global oil market. As the oil price increases, competition intensifies and producers attempt to increase output, leading to higher prices for oilfield services, increasing wages, and increasing prices for raw materials (e.g., fracturing sand). In contrast, as the oil price drops, producers find ways to reduce their production costs to remain in business. For example, the pronounced oil price drop after 2014 forced the marginal cost of production per barrel downward presumably due to lowering production and processing capacity, trimming operating costs (e.g., new drillings) and reducing wages. Reports[46–50] in recent years describe relentless production cost-cutting by unconventional producers (e.g., oil sands of Canada and U.S. shale) in the aftermath of this price drop, confirming this dynamic adjustment, in good agreement with Fig. 4 estimates. Figure 4 also shows how more competitive producers with lower MC of production are less vulnerable to the oil price shocks and reduce production costs proportionately less.

Crude oil carbon intensities also change with time. This paper cannot provide insights about the dynamics of emissions, as time-series upstream operation data are generally missing on a global scale. However, prior work has shown that the energy intensity of crude oil production tends to increase with depletion[19,51] as a result of increased work of lifting of fluids as an oilfield ages, as well as increased injection of fluids as part of secondary and tertiary recovery schemes. This trend, coupled with the shift to unconventional resources, suggests that the CI of both average and marginal petroleum resources is likely to increase slowly over time[52].

Furthermore, shadow prices and CIs are subject to technological change. In our economic model the management is trying to maximize the field's profits. This behavior is equivalent to trying to transform a set of inputs (e.g., steel, water, steam, labor, etc.) into a group of valuable outputs (oil, gas, etc.) in the most efficient way. In this context, technological change happens when producers adjust processes or technologies to respond to shifts in the price of input(s) relative to outputs. For example, if the price of oil decreases, producers will aim to find substitutes for the more expensive inputs of their production process. For example, the cost to construct a new oil sands project was estimated to be between 25–33% cheaper in 2018 than in 2014.[46,47] Deflation in capital costs was a factor, but reengineering efforts such as simplifying project designs, and speeding construction played a role in the reductions.

Operating costs fell by more than 40% on average from 2014 to 2018 due to reducing facility downtime and increasing fluid throughput through facilities[46,47].

These temporal trends may offset the tendency of alternative vehicles and fuels to drive oil out of the market. It is generally thought that as alternatives such as EVs become cheaper and consequently start to penetrate in the global transport market, the demand for crude oil will decline, resulting in a drop in the oil price and shutting in of oilfields. However, the dynamic responses of marginal oil producers to recent oil price shocks demonstrates how this effect might be muted which could hinder penetration of these oil-displacing alternatives.

# Conclusions And Future Research Needs

We developed a techno-economic analysis of the global oil supply, which connects the economics and the environmental characteristics of different oil fields. Our aim was to identify the volume of $CO_2$Eq. reduction due to a decrease in oil demand.

In our small shock scenario (-5%), the upstream CI of displaced crudes is 26% larger than that of global average crudes. In our large shock scenario (-20%), the equivalent difference is 5%. This suggests that studies of oil-displacing alternative fuels or fuel economy regulations may underestimate the GHG benefits of these alternatives.

If refining emissions would somehow mirror the upstream CI and are higher for the displaced crudes (likely to be true for heavy crudes), these differences will be seen in refining emissions as well. Linking these results to refining emissions estimates is an obvious area for future research. Such work would need to model midstream emissions as well as the corresponding refining economics, which may affect the rank order of marginal oils. Including refining estimates as well would allow estimation of the life cycle GHG emissions mitigation magnitude of displacing the crudes at margin.

Questions about the time frame of displacement loom large. These estimates rely on short- to mid-term marginal costs of production. But what are the mid- to long-term elasticities of petroleum supply for various conventional and unconventional crudes? Coupling such estimates to elasticities of demand curves may allow integrated modeling of the impacts of environmental policies, e.g., vehicle efficiency and alternative transport technologies, on GHG emissions.[52] Such an analysis is even more challenging due to the need to model profound technological change as seen over long periods in the oil industry (e.g., past-decade expansion of hydraulic fracturing).

Furthermore, it is unclear how the time frame for petroleum supply-demand considerations interact with the long-term time frame for climate change. Do near-term reductions in petroleum demand simply delay, but not prevent, the consumption of marginal petroleum over the relevant time frame, or can such a delay buy time for eventual changes in technology or climate policy, such that in total more environmentally friendly petroleum is ultimately extracted?

# Declarations

### Author contributions

M.S.M, G.B., and A.R.B. developed the carbon model and linked the granular economic and environmental data. G.B., A.M., V.D., and P.J. developed the economic model. M.S.M, G.B., A.R.B., J.E.A., T.J.W., R.D.K., and H.E. contributed on the broader implications of the study. M.S.M., G.B., A.M., and H.M.E. contributed to improve the manuscript figures. M.S.M. organized and processed the material and wrote the paper.

### Competing interests

Work at Stanford University on this project (supporting A.R.B., M.S.M, G.B.) was primarily funded by Ford Motor Company through a gift to Stanford University. Other funding was provided by Aramco Downstream Services Ltd, a subsidiary of Saudi Aramco. Some co-authors are employed by Ford Motor Company (J.E.A, T.J.W, R.D.K.) or Saudi Aramco (H.M.E.). While these companies are in sectors affected by the phenomena studied in this work (e.g., vehicle and petroleum sectors), every effort was made to maintain independence and accuracy of this work. Industry collaborations were vital to obtaining and accurately analyzing the detailed oilfield financial data used in this study.

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# Figures

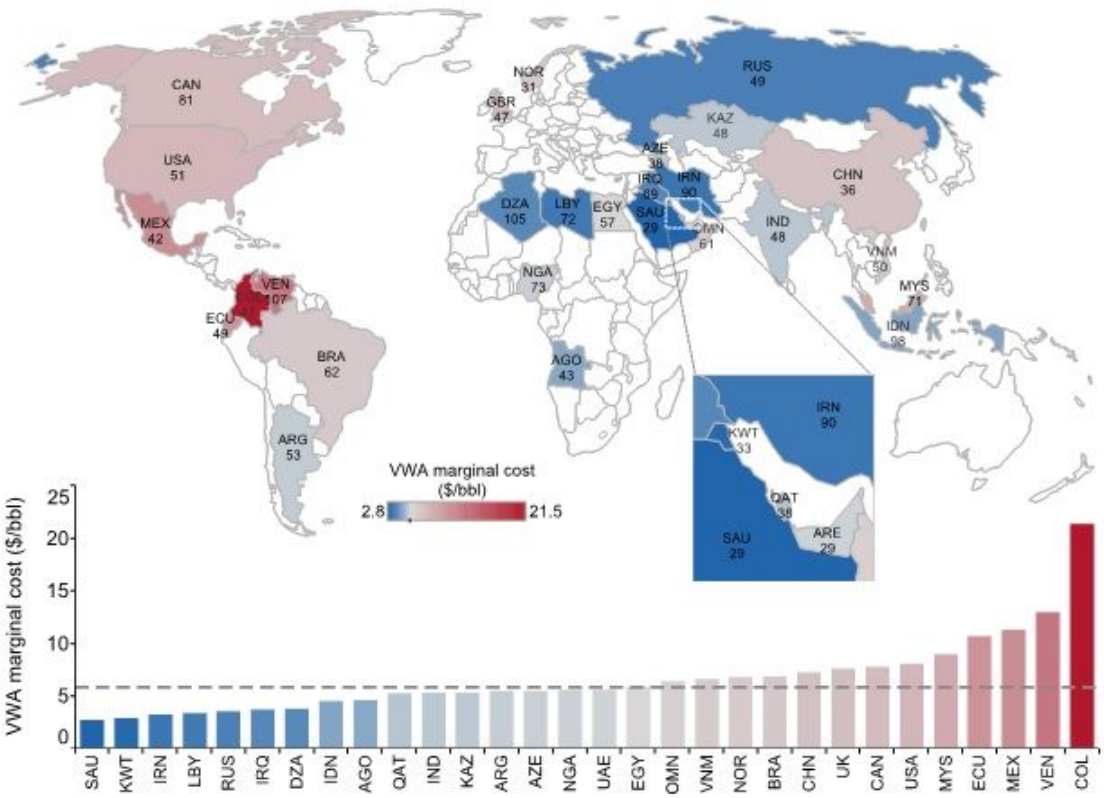
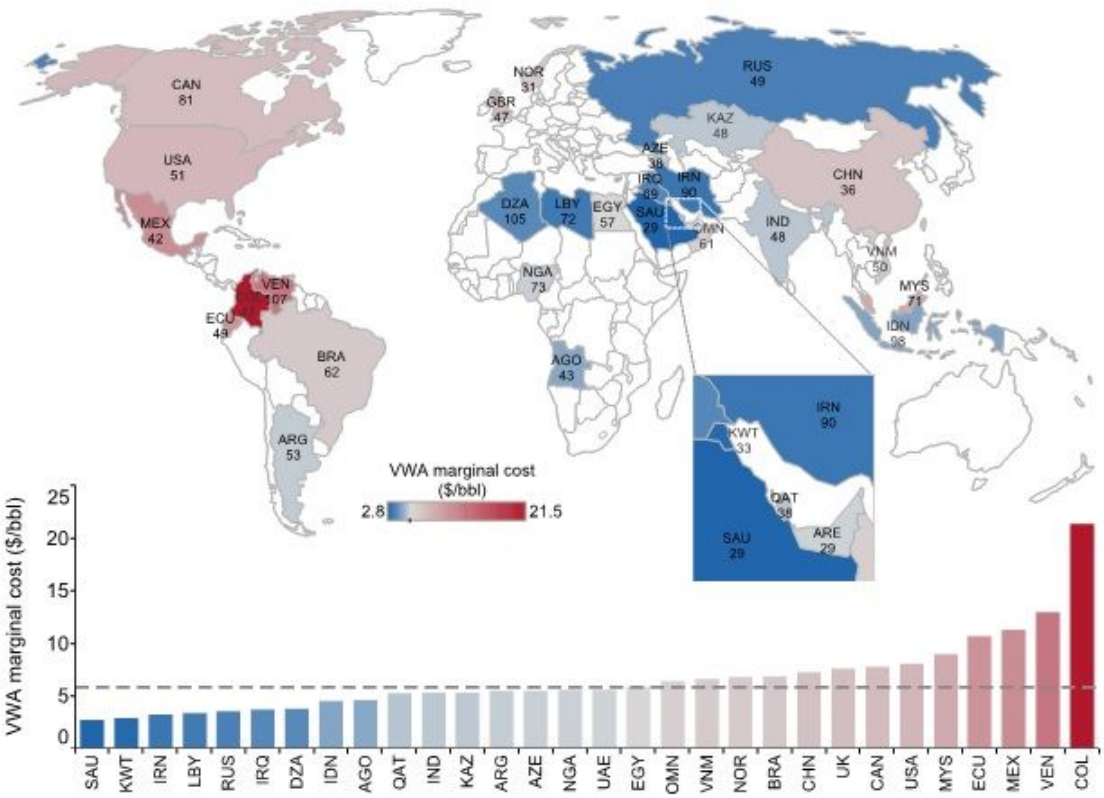



**Figure 1**

Estimated global crude oil upstream marginal cost of production (2015): national volume weighted average (VWA) upstream marginal cost of production in $/bbl crude oil produced. Map shows national VWA upstream marginal CI below each country name (in kg CO2eq./bbl crude oil delivered to refinery). The global VWA MC estimate is shown by the dashed line (~5.9 $/bbl). Reference year is 2015. Top 30 global producers are mapped (see the SM Excel file for full list). Countries are named based on their ISO 3 code. Color scheme reflects national VWA MC: dark blue for lowest MC, dark red for highest MC. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

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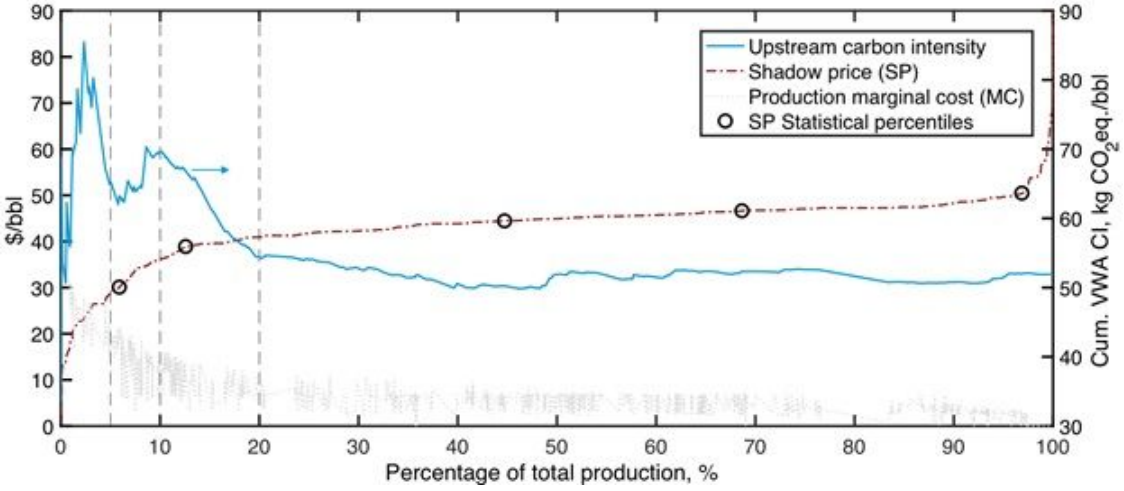
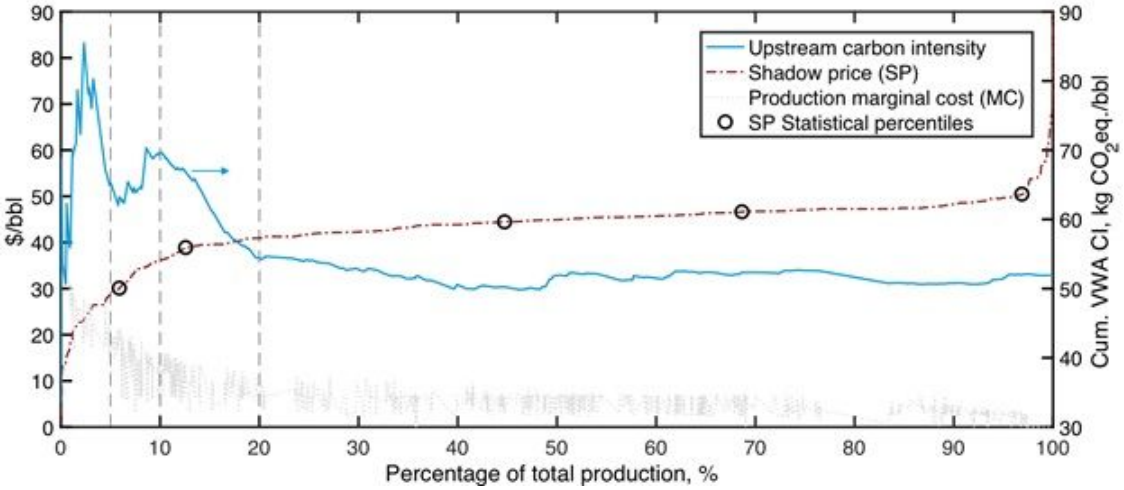



**Figure 2**

Upstream cumulative volume weighted average CIs (right axis), sorted shadow prices (right axis) and their statistical percentiles, and production marginal cost (left axis) for global oilfields versus the percentage of total oil production in 2015. The vertical dotted lines represent demand reduction capacity based on different scenarios (see Table 2).

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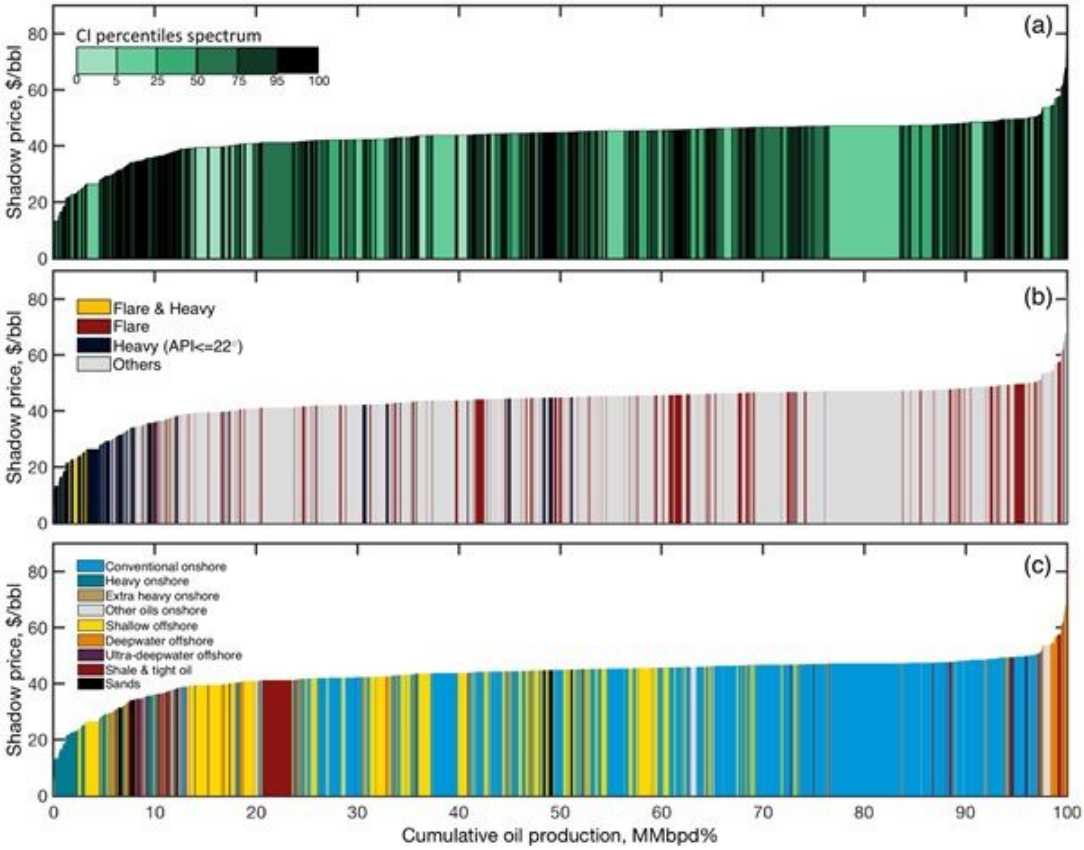
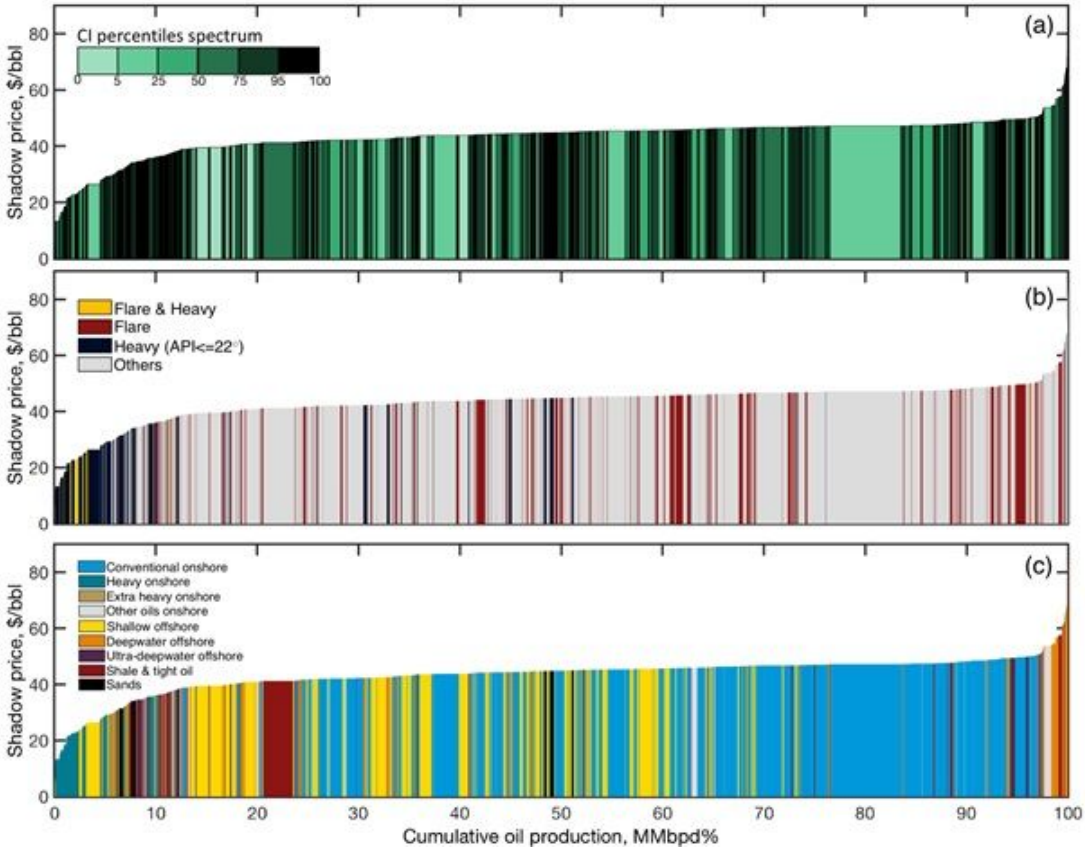



**Figure 3**

Shadow price supply curve of 1933 parent global oilfields versus the cumulative volumetric oil production. Bar width reflects the oil production of a particular field in 2015. The bars are colored based on: (a) CI percentiles (b) contribution of high flaring (“Flare” with FOR >75th percentile of all fields) and oil density (”Heavy” with API gravity ≤22°) (c) oilfield type/geology.




## Figure 3

Shadow price supply curve of 1933 parent global oilfields versus the cumulative volumetric oil production. Bar width reflects the oil production of a particular field in 2015. The bars are colored based on: (a) CI percentiles (b) contribution of high flaring (“Flare” with FOR >75th percentile of all fields) and oil density (”Heavy” with API gravity ≤22°) (c) oilfield type/geology.

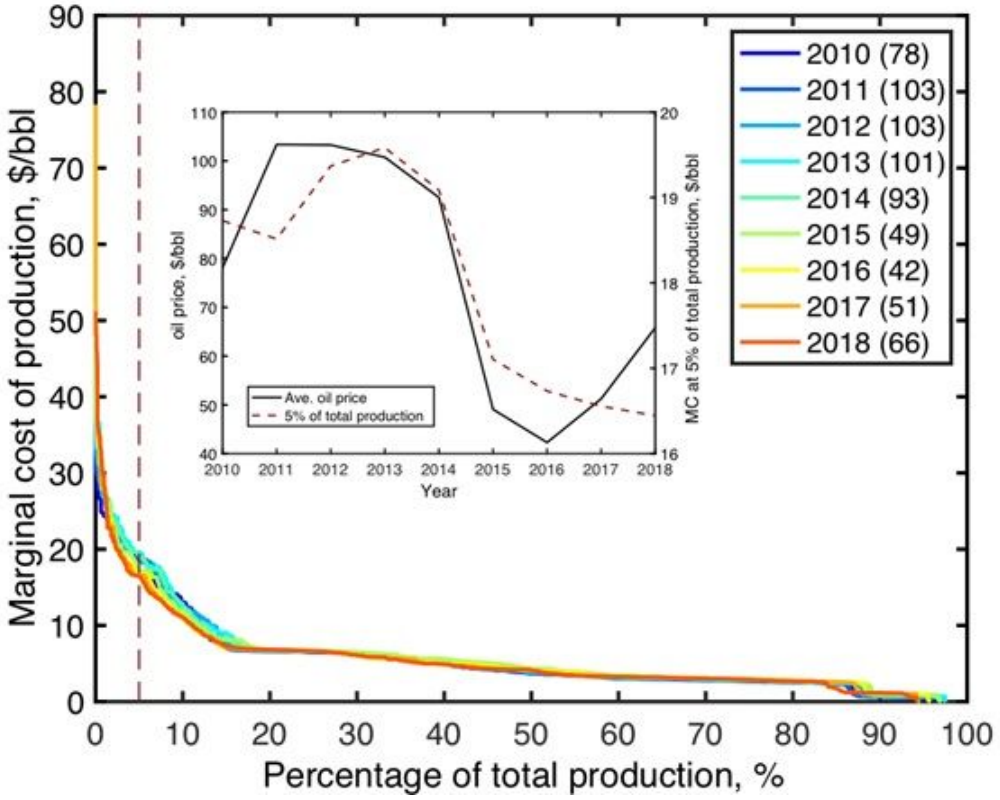
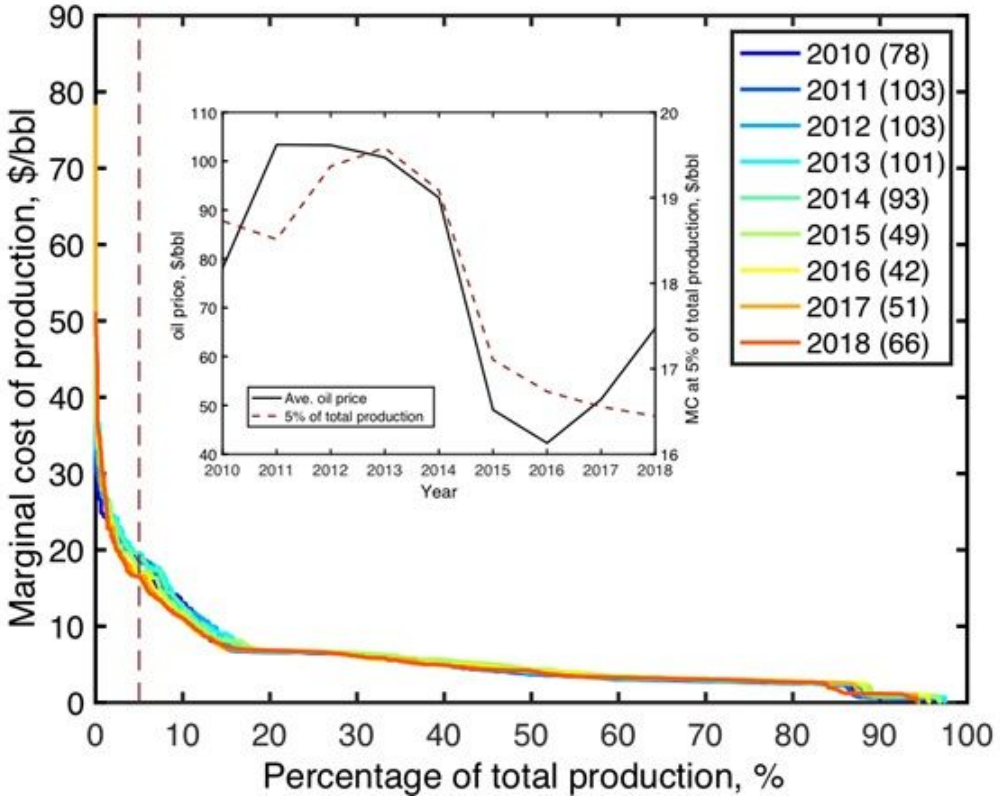



Figure 4

Year 2010-2018 descending temporal marginal cost of production of global oilfields versus cumulative volumetric oil production. The oil prices listed in the legend are annual VWA prices in the corresponding year. The inset graph illustrates the average oil price and marginal costs by displacing 5% of total production in different years.

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## Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryMaterial.pdf
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- Results.xlsx
- Results.xlsx