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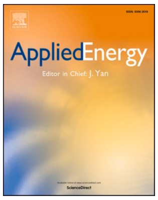

The declining performance of the oil sector: Implications for global climate change mitigation

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HIGHLIGHTS

- The declining performance of the oil sector is studied with relational analysis.
- Aging fields and unconventional sources may hinder climate change mitigation.
- Emissions per barrel are expected to increase by 6–26% in 40 years.
- The emission overhead is comparable to emissions of entire EU economic sectors.
- The option space of potential changes is explored by running “what if” simulations.

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ABSTRACT

This article presents a relational analysis of the performance of the petroleum sector in the context of climate change mitigation. The oil sector is described as a complex network of transformations carried out by structural and functional elements, exploiting different types of crude oils. Energy carrier requirements and emissions of viable sequential pathways of extraction and refining are assessed and scaled across different levels of organization, using the concept of metabolic processor. Based on the analysis of seventy-one oil fields around the world - about 25% of global production - we provide a diagnostic analysis of the current state and explore possible scenarios simulating the progressive aging of conventional oil sources and an increasing exploitation of unconventional crudes. Results show how future oil exploitation will be more energy intensive, entailing an increase of emissions per barrel in the range of 6–26% over the baseline, depending on the simulation. Under the existing policy frameworks and international pledges, this increase will translate into an amount of extra CO_2 comparable to entire European economic sectors. Implications of our findings for future energy policies are discussed and the need to complement Integrated Assessment Models (IAMs) with more robust methodologies is emphasized. It is concluded that the declining performance of the oil sector could potentially undermine the plausibility of global low-carbon aspirations.

1. Introduction

Climate change is on the front burner of the political agenda, given its huge potential impacts on the biosphere and the global economy [1,2]. A rapid decarbonization process is therefore advocated almost unanimously by all national governments and international bodies [3,4]. However, in the short term, the energy input required for such a radical transformation will have to be supplied by the current energy matrix, which still consists predominantly of fossil fuels (about 90% of the world energy consumption in 2019) [5,6]. Hence, during the transition period, the energy sector will have to provide not only a sufficient supply of net energy for the daily functioning of the economy, but also for the required extra investments in low-carbon technologies and infrastructures [7,8]. This (largely fossil) energy “overhead” translates into an overhead of CO_2 emissions, which will determine the biophysical pay-back time of the energy investment - i.e., the time required by alternative energy sources to compensate for the extra CO_2 emissions accumulated for building and operating green infrastructures and technologies [9,10].

Given the ubiquitous carbon lock-in in the primary and secondary

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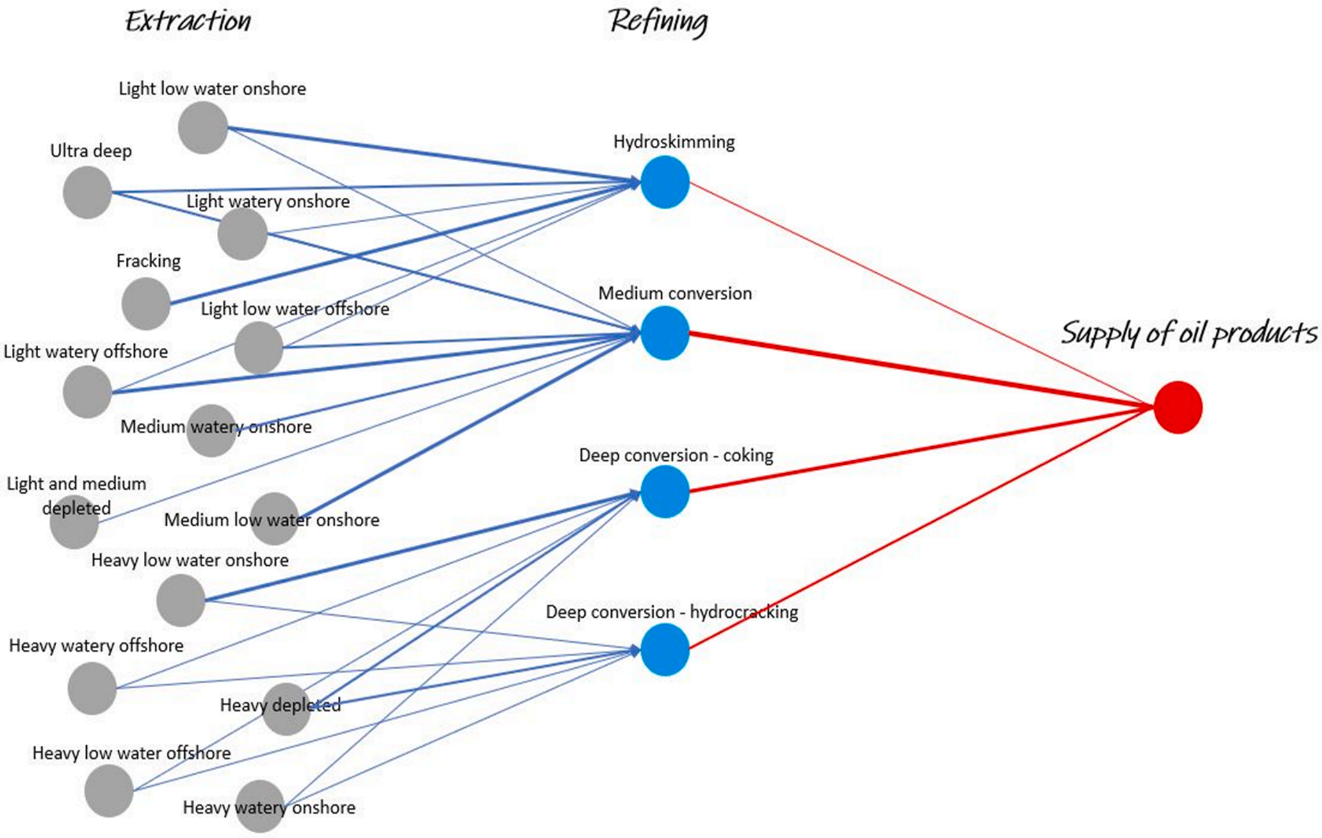


Fig. 1. The oil sector as a metabolic network. Extraction typologies are represented in grey, refining typologies in blue. Components are related by the functional entailment of producing fuels (red) at the superior scale. For the sake of simplicity, only functional elements are shown.

production sectors, it is unlikely that we will be able to radically change our energy matrix and substantially reduce CO_2 emissions in the near future [11,12]. Looking at current fossil fuel end-uses, we find that: (i) transportation is almost 100% petroleum based; (ii) industry is heavily dependent on petrochemical feedstocks and fuels for essential processes like plastic, cement, steel and glass production; (iii) agriculture completely depends on ammonia and machinery; (iv) electricity production is dominated by coal, natural gas and uranium [13,14]. To this picture we have to add the sunk-cost of the already existing technical capital [15], buildings [16] and infrastructures [17], which generates an important fossil fuel path dependency that is not easy to change. In addition, rapid population growth in some developing countries and the strive for better living conditions worldwide are likely to further increase fossil energy use and CO_2 emissions. Hence, not surprisingly, both fossil energy consumption and emissions continue to rise despite the Paris agreement, UNFCC and IPCC international meetings [18,19].

At the global level, oil still represents the first primary energy source (accounting for 33% of the total primary sources) [5]. Rather than a transition away from fossil fuels, two interrelated drivers of change dominate the oil sector: (i) the progressive depletion (aging) of conventional oil fields [20]; and (ii) a “fossil transition” from conventional to unconventional sources, entailing a complexification of the supply system [21]. The two processes are intrinsically entangled: while conventional oil production is progressively declining, an array of new oils, such as oil sands, tight oil, new heavy and extra-heavy oils, ultra-deep waters oils and oil shales is projected to fill the gap. From 2005 onwards, the world production has been sustained by US tight oil, which accounts for 60% of the global increase in supply. Conventional crude is expected to account for only 60% of liquid-fuel supply by 2040, compared to 80% in 2012 [22].

Based on the evidence reported in [20,23], about 60% of the global oil production comes from giant fields, whose major discoveries (in terms of production capacity) date back to the period 1940–1980. The progressive depletion of those fields makes the oil extraction more difficult [24] and Enhanced Oil Recovery (EOR) techniques of different complexity are increasingly needed to keep up the production. EOR entails more energy carriers (heat, electricity and fuels) and water use (to keep the reservoir in pressure and pump out fluids with increasing water-to-oil ratios), to produce the same amount of net supply. The consequence is a decline of the Energy Return On Investment (EROI) and higher emissions per unit of net supply [25,26]. The process of aging also affects the crude quality, with older fields often producing heavier and dirtier oils [27]. Therefore, considering an average age of currently depleted fields of around 80 years [28], the effects of this aging phenomenon will become fully evident between 2020 and 2060, which is the critical time window for climate change mitigation, according to the IPCC [29]. At the same time, the worldwide ongoing “unconventionalization” process of oil supplies affects the infrastructures and technologies needed for extraction, transportation and refining. More complex drilling and deeper refining of unconventional sources increase the energy intensity and the related emissions of the changing oil industry [30].

The effects of these two drivers challenge the plausibility of a rapid renewable energy transition and of climate change mitigation scenarios. Therefore, before making ambitious plans for a radical decarbonization of the global economy in 2050 [29,31], it is important to assess the wider impacts of the declining performance of the oil sector on our low-carbon future aspirations.

Currently commonly used methodological approaches, such as Life-Cycle Assessment (LCA), strive to produce accurate carbon intensity assessments for specific oil products (or net energy units) to inform policy-making [32,33]. For instance, LCA assessments have been

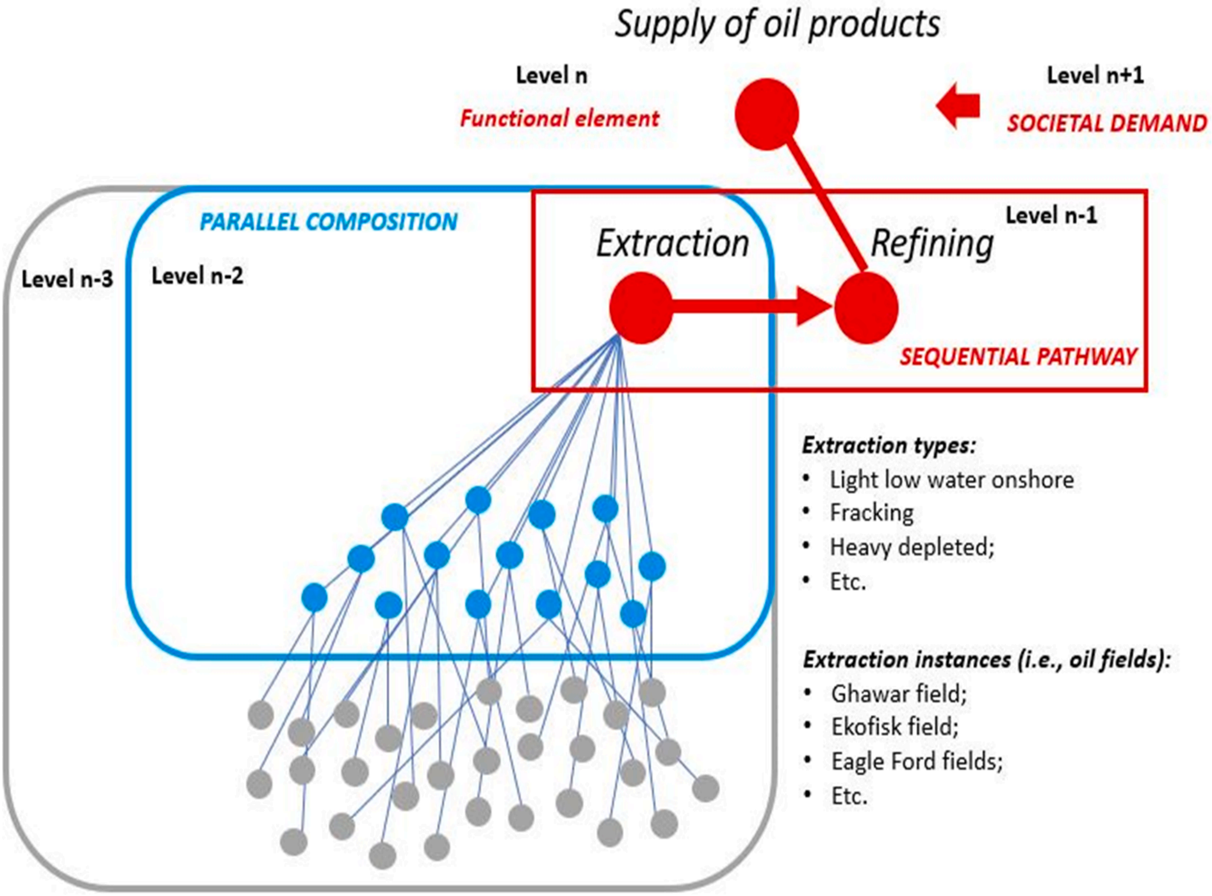


Fig. 2. Examples of scaling: sequential pathway and parallel composition of structural and functional elements. The sequential pathway represents a material entailment (directed edge): the output of extraction is the input for refining. The parallel composition represents a hierarchical entailment (undirected edges) and interrelates two or more levels: the elements are tied together by the same function at higher scales. NB. Elements can be either structural or functional, depending on the scale of observation: they can be functional processes in relation to higher levels, or structural types ('blueprints') for elements at lower levels.

provided for unconventional extraction [34], refining [35], and the entire well-to-wheel oil supply chain [28]. However, the findings of these LCA analyses are valid only within the (narrow) context defined by the assumptions of the analyst. Indeed, LCA results are highly sensitive to system boundaries definition, efficiency benchmarks and the taxonomy of functional units [36]: choosing different boundaries or allocation criteria among different products leads to significantly different assessments for the same fuel pathway [37,38]. In practice, these assessments generate questionable 'optimal' solutions for narrow policy domains (e.g., the California Low Carbon Fuel Standard, LCFS), rather than a multi-dimensional knowledge space for an informed discussion.

The same narrow optimization scope, but using highly-aggregated, general equilibrium models, is pursued by the IPCC's assessments of climate change mitigation pathways [29,39]. These models represent the current state-of-the-art of the Integrated Assessment Modelling (IAM) for climate change mitigation options, and push for innovation and efficiency towards a clean energy transition [40-42]. Nonetheless, these IAMs of energy and CO_2 emissions pathways have been widely criticized [43,44], in particular the basic assumption of energy-abundance [45]. Several studies, using different economic [46] and geological models [47,48] to relate CO_2 emissions and supply projections, have shown that a decline in fossil fuel production will constrain mitigation options and future climate impacts. Surprisingly, the structural implications of the fossil transition within the oil sector (aging of conventional oil fields and the transition to unconventional oils) on required energy investments and GHG emissions, and the resulting consequences for climate change mitigation pathways, are yet to be comprehensively investigated.

The purpose of this paper is to gain better insight into the effects of the aging and "unconventionalization" processes of the global oil sector, so as to support the assessment of the option space for plausible decarbonization pathways. By using relational analysis, we first characterize the biophysical performance of the global oil sector across multiple scales and dimensions, using data from seventy-one oil fields and associated refineries world-wide, representing about 25% of global production. Subsequently, we simulate a progressive aging of existing oil fields and an increasing exploitation of unconventional oil sources, and assess the related changes in the consumption of energy carriers and CO_2 emissions. For each simulation, we focus on the change in emissions and energy requirement per barrel, where the barrel is a weighted average of viable sequential pathways of oil extraction and refining. We then use the forecasted level of oil supply worldwide of the IEA "Stated Policies Scenarios" [49] to provide a rough estimate of the absolute magnitude of the increase in CO_2 emission that may be expected from the fossil transition in the oil sector.

The rest of this paper is structured as follows. Section 2 explains the methodology and data sources. Section 3 describes the results of the analyses. Section 4 discusses the strength and shortcomings of the approach. Section 5 provides some policy indications and concludes.

2. Materials and methods

2.1. Relational analysis of the oil sector

Our analytical framework is grounded in Rosen's theory of relational analysis (originally born as 'relational biology') and represents a relatively novel approach for characterizing the performance of complex systems, such as the energy sector [27,50].

In brief, in relational analysis an energy system is described as a metabolic network of structural and functional elements (Fig. 1). The study starts from an identification of functional elements for which it is possible to identify expected relations. Only in a second phase, the characteristics of structural elements are studied [51,52]. The distinction between structural and functional strictly depends on the scale of observation and the distinction between tangible (instances) or notional (types) elements considered in the representation. Structural elements are 'tangible elements' such as oil fields or refineries - e.g., the Ghawar field, Fig. 2. These structural elements are associated with structural typologies sharing a common set of metabolic attributes (inputs and outputs profile) - e.g., "Light watery offshore" fields in Fig. 2 or "Medium conversion" refineries in Fig. 1. Different structural elements can be combined together in order to express a functional element – i.e., a 'notional element' described in terms of expected profiles of inputs and outputs. In this case, the metabolic characteristics of functional elements - that are not tangible – can be assessed by calculating the characteristics of the particular mix of structural types making up the functional type. The use of notional elements is essential to describe the performance of the energy system. Examples of notional (functional) elements in Fig. 1 are "Light watery offshore" extraction or "Deep conversion – coking" refining. Both structural and functional elements can be described in quantitative terms as profiles of inputs and outputs through the use of metabolic processors (see section 2.3). The quantification of structural types is derived from the observations of equivalence classes of given instances of structural elements, while functional elements are observed as nodes in the network and calculated as combinations of the characteristics of mixes of structural elements (or functional elements at higher levels).

The relations over the nodes in the network (the *identities* of "metabolic processors" in the jargon of relational analysis) can be scaled in two different ways (see Fig. 2):

1. Parallel composition, when different profiles describing different classes of functional elements (i.e., different types of extraction or refining) are composed, according to their relative contribution (i.e., percentage in the mix), into an aggregated metabolic profile of the functional element defined at a higher level of analysis. This is illustrated by the undirected edges between nodes across levels in Fig. 2.
2. Sequential pathway, when different structural or functional elements are linked by a material entailment, i.e., the output of a node is the input of the next node. This is illustrated by the directed edge between 'Extraction' and 'Refining' (on the same level) in Fig. 2.

First, structural elements at *level n-3* are combined together in a parallel composition to form structural types at *level n-2*. In other words, different instances (fields) of oil extraction, such as the "Ghawar field", are combined together into different types of extraction, such as "Ultra-Deep". Then, those structural types are combined into the functional element "Extraction" at *level n-1*. At that level, different functional elements – i.e., Extraction and Refining – can be combined into a sequential pathway determining the characteristics of a functional element – i.e., "Fuels Supply" – defined at the superior *level n.* At the end of this chain, a mix of different final oil products (see appendix, Table A4) is made available for end-uses in the other sectors of society and in the energy sector itself (internal loop of energy carriers to produce energy carriers, i.e., 'energy-for-energy'). The composition of this final mix of oil products depends on the relative composition and specific identities of the structural and functional elements in the metabolic network.

In the present study, a two-stage sequential pathway has been considered: (i) extraction: extraction processes, in-site upgrading and/or transformations and transport to refineries; and (ii) refining. To simplify the analysis and for data availability reasons, the sequential stage of "transportation" has been included in the step of "extraction", as a flat overhead.

2.2. *Taxonomy of structural and functional elements*

2.2.1. *Oil fields and extraction*

The taxonomy of oil fields (typologies of structural elements) and the corresponding extraction processes (typologies of functional elements) has been defined based on the following criteria:

1. API Gravity – 3 categories: (i) light, (ii) medium, (iii) heavy oils;
2. Water content – 2 categories: (i) low water, (ii) watery;
3. Location – 2 categories: (i) onshore, (ii) offshore.

The combination of these criteria results in twelve different typologies of oil fields and corresponding extraction processes (illustrated in Fig. 1). To these, an additional four types were added, namely: (i) "Fracking" and (ii) "Ultra-Deep" crudes, both of which are characterized by distinct technologies of extraction with specific biophysical requirements and environmental burdens; (iii) "Light and medium depleted" and (iv) "Heavy depleted" oils, both characterized by a long history of exploitation and evident signs of aging (depletion).

In this work, only fracking and ultra-deep crudes are referred to as unconventional oils. Given the ambiguity in the use of the label "unconventional" [22,53], this semantic choice was made to distinguish them from the categories "heavy" and "heavy depleted". For the purpose of this analysis, heavy and depleted fields, that, under specific circumstances (like advanced EOR techniques or very high viscosity) can be considered unconventional oil, are accounted for separately, in order to enrich the taxonomy and appreciate the effect of time on a greater variety of crudes.

2.2.2. *Refineries and refining*

Four different typologies of refining processes (functional elements) have been considered to classify the refineries (facilities, structural elements) in our data base:

1. Hydroskimming conversion;
2. Medium conversion;
3. Deep conversion - coking;
4. Deep conversion – hydrocracking.

The choice of coking versus hydrocracking depends on the refiner. Hydrocracking maximizes middle distillates, while coking maximizes light distillates. The choice entails different input requirements and products outcome. As detailed in Section 2.4, all the deep conversion refining in our simulations is assumed to be coking, even if both typologies have been considered and assessed within the space of viable sequential pathways. Note that the complexity of refining increases with API gravity and sulfur content of the crude oil: more energy and technical intensive processes are required to transform the heavier and dirtier oils.

2.2.3. *Identifying viable sequential pathways*

Using the taxonomy of typologies of the structural and functional elements defined in the previous subsections, different sequential pathways were constructed according to the metabolic network shown in Fig. 1. Note that not all possible combinations of extraction and refining processes are viable: even if technologically possible, heavy oils usually are not processed in hydroskimming refineries due to the low yields of high quality (and high economic value) products such as gasoline and diesel. In the same way, the economic viability of low and medium complexity refineries is increased with the selective processing of light and medium oils. Hence, we have used the following criteria for generating sequential pathways:

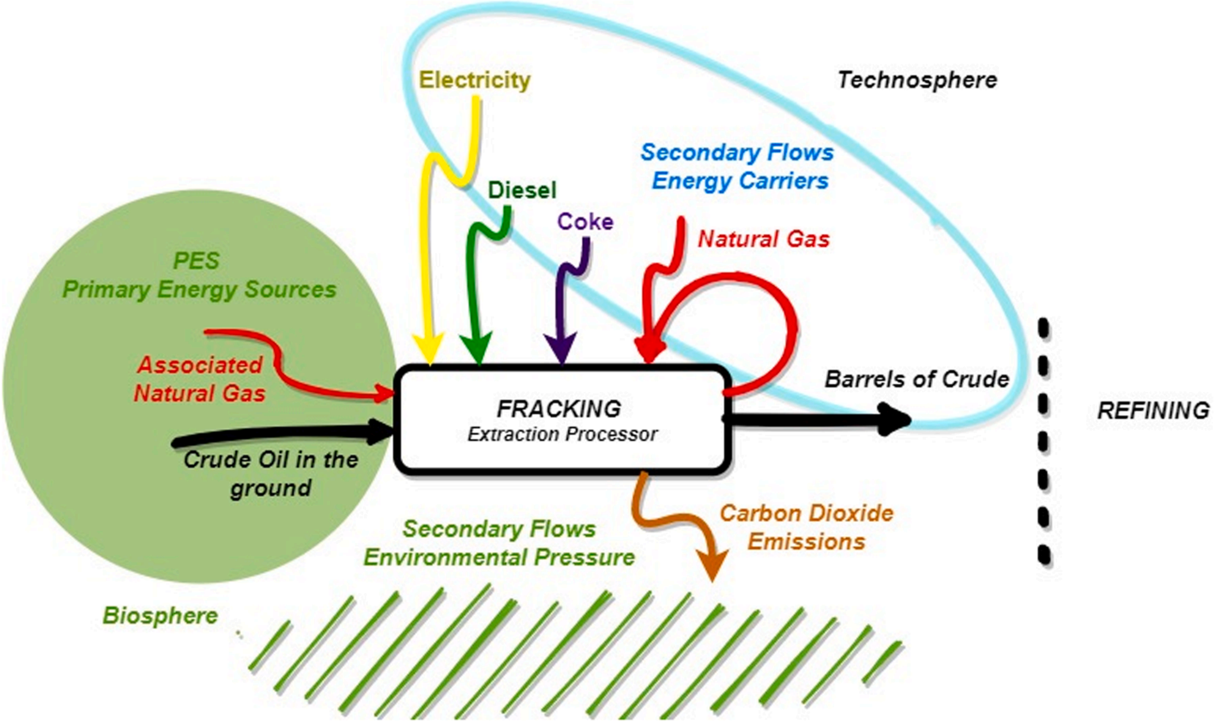


Fig. 3. Metabolic processor for the functional element "Fracking".

- Light, medium and ultra-deep oils are associated with hydroskimming or medium conversion refining depending on their sulfur content;
- Tight oil from fracking always goes to hydroskimming refineries;
- Heavy oils can be refined by medium or deep conversion plants, either by coking or hydrocracking facilities;
- For the purpose of refining, light, medium and heavy depleted oils are assumed to be equivalent (in physical–chemical properties) to their respective non-depleted variant and linked to same refining typology.

The resulting viable sequential pathways are characterized in the results section (see Section 3.1 and Table 3).

Once viable sequential pathways have been identified, it is possible to characterize their relative importance (contribution) in the supply chain. In this way, the analyst can scale up the assessment of the requirements of inputs (mix of energy carriers) and the CO_2 emissions produced for the supply of one barrel of products to the level *n*. This quantitative characterization has been done for the actual situation (diagnostic) and for scenarios. Results are reported in Section 3.

2.3. The metabolic processor

The metabolic processor is an analytical tool organizing quantitative information in the form of a data array. It can be interpreted as an extended production function in that it defines an expected (functional) or observed (structural) profile of inputs and outputs associated with a specific process, such as oil extraction or refining [54]. Metabolic processors allow for a quantitative representation of the relations between structural and functional elements across levels (Fig. 2). In this way, we can quantify the functional units of the oil sector by bridging the relations between processors, either looking at sequential pathways determined by a material entailment or by a parallel composition, when considering a functional entailment (different elements expressing the same function at the higher level). The choice of a mix of functional and structural elements depends both on biophysical (set of typologies of oil fields and refineries available) and socio-economic constraints (set of economically viable products determined by societal demand). The use of metabolic processors for the characterization of the metabolic pattern of social-ecological systems has been described in detail in [55].

Quantification starts out from data that refer to the characteristics of specific *instances* of structural elements, i.e., the observed fields and refineries. The inputs and outputs for the metabolic processors used in this study include:

- For extraction processors:

1. Net consumption of natural gas (NG) and refinery fuel gas (RFG) (MJ/bbl);
2. Net and indirect (associated with imports) consumption of electricity (MJ/bbl);
3. Net and indirect consumption of diesel (MJ/bbl);
4. On-site and indirect CO_2 emissions ($kgCO_2eq/bbl$);
5. Daily Production Capacity (bbl/day).

- For refining processors:

1. Net consumption of natural gas and refinery fuel gas (MJ/bbl);
2. Net consumption of electricity (MJ/bbl);
3. Net consumption of diesel (MJ/bbl);
4. Net consumption of coke (MJ/bbl);
5. On-site CO_2 emissions ($kgCO_2eq/bbl$);
6. Daily refining capacity (bbl/day);
7. Product slate (%).

For a detailed explanation of the data processing based on the OCI Climate Index data base within our relational procedure, see the Appendix.

Fig. 3 illustrates the processor of the functional element "Fracking" (extraction). This simplified illustration shows the main features of the organization of the information in a data array. The technosphere, shown in the upper right part of Fig. 3, refers to the conversions (end uses) of flows taking place under human control. This includes: (i) the input requirement of energy carriers (natural gas, diesel, electricity and coke) to produce oil (the energy-for-energy loop); and (ii) the output of barrels of crude (that then becomes the input consumed by refineries).

Table 1
Relative contribution of extraction typologies to the total oil supply in the current situation (2018) and in the four simulations. Unconventional oils are reported in green.

Extraction typologies	Current situation	Simulation 1	Simulation 2	Simulation 3	Simulation 4
Light low water onshore	16%	8%	0%	0%	1%
Light low water offshore	3%	3%	3%	3%	3%
Medium low water onshore	28%	14%	0%	0%	10%
Medium low water offshore	13%	13%	13%	13%	13%
Light watery onshore	2%	9%	12%	12%	2%
Light watery offshore	1%	1%	1%	1%	1%
Medium watery onshore	4%	16%	22%	22%	4%
Medium watery offshore	4%	4%	4%	4%	4%
Heavy low water onshore	4%	4%	4%	0%	4%
Heavy low water offshore	2%	2%	2%	0%	2%
Heavy watery onshore	6%	6%	6%	0%	6%
Heavy watery offshore	0%	0%	0%	0%	0%
Ultra-Deep	4%	4%	4%	4%	20%
Fracking	4%	4%	4%	4%	20%
Light and medium depleted	9%	12%	24%	24%	9%
Heavy depleted	1%	1%	1%	14%	1%
Total	**100%**	**100%**	**100%**	**100%**	**100%**

Note that the *internal* energy loop for natural gas is usually closed at the level of the extraction processor, while diesel, electricity and coke are coming from 'outside', i.e., either from a higher level of the oil sector (after refining) or from imports (nonetheless, for some oil fields also natural gas is imported). The information in the technosphere is relevant for the economic and technical viability of the process and to assess the correct output of oil products (Table A4). In the lower left part of Fig. 3, inputs and outputs that are relevant for studying processes outside of human control (in the biosphere) are shown. These include: (i) the supply capacity of oil (and associated gas) stocks (i.e., oil fields); and (ii) the sink capacity of primary biophysical flows (CO_2 emissions in this study).

The same structure of inputs and outputs is used to quantify relations between structural and functional elements across all levels of the entire metabolic network, thus allowing the generation of an integrated quantitative representation. Note that metabolic processors can be expressed either as extensive processors (based on a given size of the flows) or unitary processors (benchmarks, per unit of throughput) [54]. Further explanations on the construction of metabolic processors for the characterization of the performance of the oil sector are available in [27,50].

2.4. Data sources and assumptions

2.4.1. Diagnosis of the current situation

The relational analysis has been implemented using raw data from seventy-one oil fields and associated refineries world-wide, representing 25% of global production, from [28]. Specifically, OPGEE_v1.1_draft_e is the data source for extraction processors, while data for refining processors are from PRELIM v.1.2 (https://www.ucalgary.ca/energy-technology-assessment/open-source-models/prelim). In addition, in order to characterize the current supply system at the global level, data on the relative contribution of different crudes from [56] have been used, referring to the year 2017.

In 2017, light, medium and heavy oils represented 31.7%, 54.8% and 13.5% respectively of the total crudes extracted [56]. Tight oil (entirely light) from fracking accounts for 30% of the North American production (2018), that represents 12% of the world total extraction. We assumed that the amount from ultra-deep fields (>3000 m) worldwide equals that of tight oils, equally divided between light and medium crudes (this is relevant in order to associate the ultra-deep crudes with the appropriate refining). Therefore, overall unconventional oils (fracking and ultra-deep) are assumed to represent 7% of global production [57].

In order to assign a proper relative share to the other 14 categories, we used production capacity from OPGEE v1.1_draft_e assessment [28]. The formula used for the calculation is a weighted average on the production capacity of each typology:

$$A = \frac{\sum_{k}^{s}\sum_{j=1}^{r}\sum_{i=1}^{n}PC_{i,j,k}}{\sum_{k=1}^{s}PC_{k}}$$

Where PC is the production capacity, n = number of oil fields of the same typology, $\boldsymbol{r}$ refers to sub-typologies of extraction considering water content and location (4), $\boldsymbol{s}$ are the sub-typologies of extraction considering API gravity (3). The contribution from depleted fields was rounded to 10% ("Light and medium depleted" fields 9% and "Heavy depleted" fields 1% on the total). The final result is reported in the column 'current situation' in Table 1, showing the relative contributions of all extraction typologies and taken as baseline reference for generating simulations.

2.4.2. Anticipation of possible scenarios

Starting from the current situation defined above (the actual composition of the global supply), four different simulations were

Table 2
Refining shares associated with extraction typologies.

Associated refining types	Hydroskimming	Medium conversion	Deep conversion
Light low water onshore	74%	26%	0%
Light low water offshore	74%	26%	0%
Medium low water onshore	0%	100%	0%
Medium low water offshore	0%	100%	0%
Light watery onshore	74%	26%	0%
Light watery offshore	74%	26%	0%
Medium watery onshore	0%	100%	0%
Medium watery offshore	0%	100%	0%
Heavy low water onshore	0%	19%	81%
Heavy low water offshore	0%	19%	81%
Heavy watery onshore	0%	19%	81%
Heavy watery offshore	0%	19%	81%
Ultra-Deep	37%	63%	0%
Fracking	100%	0%	0%
Light and medium depleted	0%	100%	0%
Heavy depleted	0%	0%	100%

explored (see Table 1). In all simulations and also in the ‘current situation’, the same overall oil supply is guaranteed and kept constant at 105 million barrels per day – from IEA’s forecast “State Policies Scenario” (2030) - but the relative composition of the various structural and functional elements (extraction, refining) changes because of aging and the fossil transition toward unconventional sources. The assumptions for the simulations are:

- Simulation #1: 50% of the oil production from light and medium, low-water, onshore fields shifts to the respective watery types, and 50% of the light and medium, watery, onshore fields becomes depleted (“Light and medium depleted” fields).
- Simulation #2: the same as Simulation#1, but now 100% of the oil production from the selected types changes functional category;
- Simulation #3: same as Simulation #2, but in addition all heavy production types move to the heavy depleted type.
- Simulation #4: ultra-deep and fracking cover 40% of total production (20%+20%), at the expense of light and medium, low water and onshore pathways.

The first three simulations focus on the progressive decrease in the quality of existing oil fields (low-water fields becoming watery and depleted), which, based on the current evidence, is expected to take place during the next 40 years, as already stated in the introduction. The fourth simulation looks at the potential effects of a sensible increase in unconventional oil production, probably larger than what is considered plausible [57], but still useful to highlight possible trends. The simulations are implemented by changing the relative contributions of the different functional types of extraction to the global production. As stated earlier the overall supply remains constant. The characteristics (unitary representation) of each type of extraction processor (its identity) is based on the current situation, and are assumed to remain constant. This assumption is discussed in Section 4.2.

Information about the relative contributions of the specific sequential (extraction-refining) pathways inside the supply system is needed to scale up the information across the metabolic network both in the current situation and in the scenarios. These assessments are based on the data from [56]. Ultra-light and light & sweet oils (73.5% of light types) are associated with hydroskimming technology, medium and heavy sweet crudes are converted in medium conversion facilities while the sour heavy crudes in deep refining plants. Tight oil from fracking goes 100% to hydroskimming; light, ultra-deep oils are supposed to be 50% light and 50% medium and follow the rules above, light and medium depleted are 100% medium converted and, finally, heavy depleted are 100% led to deep conversion. The refining shares have been kept constant throughout all scenarios. Table 2 shows a schematic representation of the refining assumptions.

Note that all deep refining is assumed to be done with coking facilities. For our purposes, distinction between coking and hydrocracking has not been considered, since we are not taking into account changing demand patterns. However, a ‘hydrocracking’ scenario would be more emission intensive. Coking optimizes gasoline production. Its energy carrier input requirements as well as emissions are lower than with hydrocracking technology, which is better for diesel production.

2.4.3. *“Stated Policies Scenario”*

By combining the unitary quantification per barrel, obtained from the scaling of metabolic processors into viable sequential pathways, with the relative extraction and refining shares, it becomes possible to appreciate the actual consumption of energy carriers in the system and CO_2 emissions, as well as products output per barrel in each scenario. The size of the system (barrels produced per day/year) can be scaled up to the magnitude required. In this work, we refer to the International Energy Agency’s (IEA) *World Energy Outlook 2019* “Stated Policies Scenario” [49]: the global oil production is projected to be 105 million barrels per day in 2030 and 106 million in 2040. We use the former quantity to scale up the analysis to the global perspective, both in the current scenario and simulations. This was done to specifically assess the qualitative effects of aging and “unconventionalization” against a fixed (quantitative) supply.

2.4.4. *Data representation: Normalized chromatic intensity*

Maintaining data disaggregated is important for preserving a multi-dimensional information space (e.g., processors’ benchmarks for different typologies of energy carriers) and identifying useful patterns. However, data proliferation represents a significant challenge for the visualization of quantitative information. For this reason, in several tables (Tables 3–5), we have used Normalized Chromatic Intensity (NCI), that is gradients of color intensities, to facilitate the recognition of patterns [58]. The creation of NCI representations follows three steps: first, identifying the maximum and minimum values for the selected variable over the set of data; second, calculating the range of values for the variable (difference between maximum and minimum value of the series); and third, assigning proportional intensities of color for the intermediate values in relation to its normalized distance to the extremes of the interval (maximum color intensity for highest values and minimum intensity for lowest ones). In this way, chromatic visualizations of patterns over the observed dimensions are obtained and outliers in the data set are easily identified.

3. Results

3.1. *Typologies of production pathways and diagnostic of current situation*

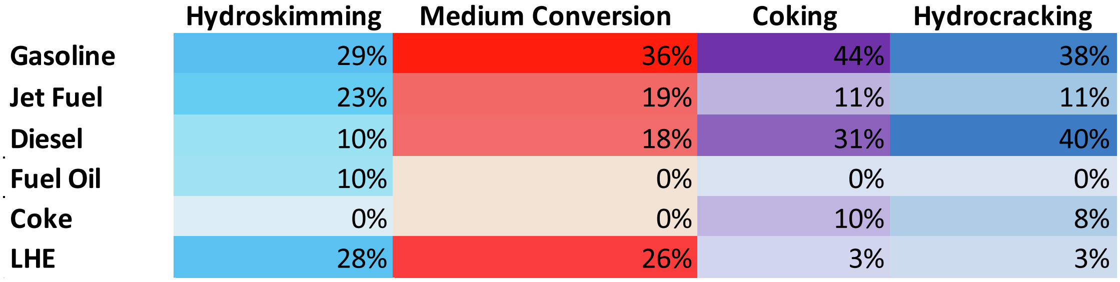
Table 3 summarizes the consumption of energy carriers and CO_2 emissions per barrel of oil products supplied across current, viable sequential pathways of the oil sector. Table 4 reports the arrays of oil products expected as outcome from each refining (functional) typology. Further details about mixes of oil products per sequential pathway are provided in the Appendix, Table A3, while in Tables A1 and A2 extraction and refining processes are separately reported.

From a unitary perspective, heavy and depleted pathways are, not

Table 3
Viable sequential pathways of the oil sector (extraction - refining), requirement of energy carriers (energy-for-energy loop) and CO_2 equivalent emissions per barrel, unitary description.

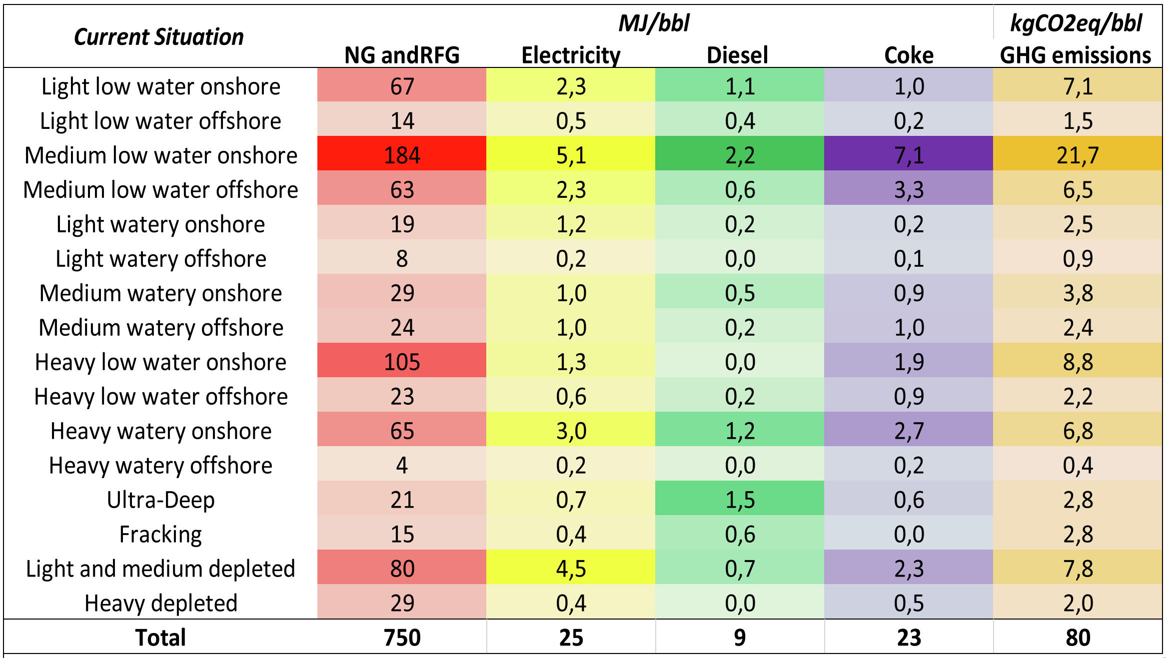
Sequential pathways		*MJ/bbl*				*KgCO2eq/bbl*
Types of extraction	**Associated types of refining**	**NG and RFG**	**Electricity**	**Diesel**	**Coke**	**GHG emissions**
Light low water onshore	Hydroskimming	387	13	7	0	42
	Medium conversion	545	19	7	25	56
Light low water offshore	Hydroskimming	473	17	13	0	50
	Medium conversion	630	23	13	25	63
Medium low water onshore	Hydroskimming	496	12	8	0	63
	Medium conversion	653	18	8	25	77
Medium low water offshore	Hydroskimming	330	12	5	0	37
	Medium conversion	487	17	5	25	50
Light watery onshore	Hydroskimming	722	47	6	0	95
	Medium conversion	879	53	6	25	109
Light watery offshore	Hydroskimming	820	18	5	0	92
	Medium conversion	977	23	5	25	105
Medium watery onshore	Hydroskimming	654	23	14	0	17
	Medium conversion	811	29	14	25	107
Medium watery offshore	Hydroskimming	471	21	4	0	48
	Medium conversion	628	27	4	25	62
Heavy low water onshore	Medium conversion	2025	27	1	25	174
	Deep conversion - coking	2544	32	1	49	214
	Deep conversion - hydrocracking	2848	39	1	41	236
Heavy low water offshore	Medium conversion	785	21	13	25	86
	Deep conversion - coking	1305	37	13	49	126
	Deep conversion - hydrocracking	1609	43	13	41	149
Heavy watery onshore	Medium conversion	672	37	20	25	83
	Deep conversion - coking	1192	53	20	49	123
	Deep conversion - hydrocracking	1496	60	20	41	145
Heavy watery offshore	Medium conversion	525	24	0	25	51
	Deep conversion - coking	1045	40	0	49	91
	Deep conversion - hydrocracking	1349	46	0	41	113
Ultra-Deep	Hydroskimming	496	15	40	0	68
	Medium conversion	654	21	40	25	82
Fracking	Hydroskimming	405	12	17	0	77
Light and medium depleted	Hydroskimming	728	44	7	0	72
	Medium conversion	886	50	7	25	86
Heavy depleted	Medium conversion	2391	26	1	25	158
	Deep conversion - coking	2911	42	1	49	199
	Deep conversion - hydrocracking	3215	48	1	41	221

Table 4
Relative composition of the oil products per barrel for different (functional) typologies of refining processors. Abbreviations: LHE: Liquid Heavy Ends.



	Hydroskimming	Medium Conversion	Coking	Hydrocracking
Gasoline	29%	36%	44%	38%
Jet Fuel	23%	19%	11%	11%
Diesel	10%	18%	31%	40%
Fuel Oil	10%	0%	0%	0%
Coke	0%	0%	10%	8%
LHE	28%	26%	3%	3%

Table 5
Requirement of energy carriers (energy-for-energy loop) and CO_2 equivalent emissions per barrel, weighted by the relative contribution of sequential pathways (Table 1) in the current situation. Unitary description.



Current Situation	*MJ/bbl*				*kgCO2eq/bbl*
	NG andRFG	Electricity	Diesel	Coke	GHG emissions
Light low water onshore	67	2,3	1,1	1,0	7,1
Light low water offshore	14	0,5	0,4	0,2	1,5
Medium low water onshore	184	5,1	2,2	7,1	21,7
Medium low water offshore	63	2,3	0,6	3,3	6,5
Light watery onshore	19	1,2	0,2	0,2	2,5
Light watery offshore	8	0,2	0,0	0,1	0,9
Medium watery onshore	29	1,0	0,5	0,9	3,8
Medium watery offshore	24	1,0	0,2	1,0	2,4
Heavy low water onshore	105	1,3	0,0	1,9	8,8
Heavy low water offshore	23	0,6	0,2	0,9	2,2
Heavy watery onshore	65	3,0	1,2	2,7	6,8
Heavy watery offshore	4	0,2	0,0	0,2	0,4
Ultra-Deep	21	0,7	1,5	0,6	2,8
Fracking	15	0,4	0,6	0,0	2,8
Light and medium depleted	80	4,5	0,7	2,3	7,8
Heavy depleted	29	0,4	0,0	0,5	2,0
Total	**750**	**25**	**9**	**23**	**80**

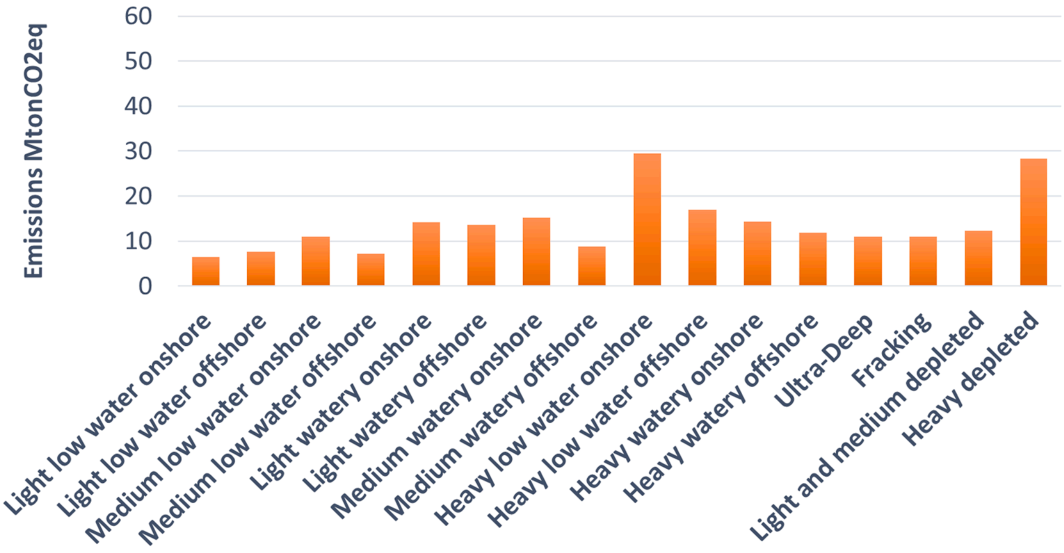


Fig. 4. Global annual absolute CO_2 emissions if oil supply would be equally distributed between sequential pathways - i.e., if every supply share in the columns of Table 1 were 6.25% - under the IEA's (World Energy Outlook 2019) "Stated Policies Scenario" 2030 production assumption (105 million barrels per day).

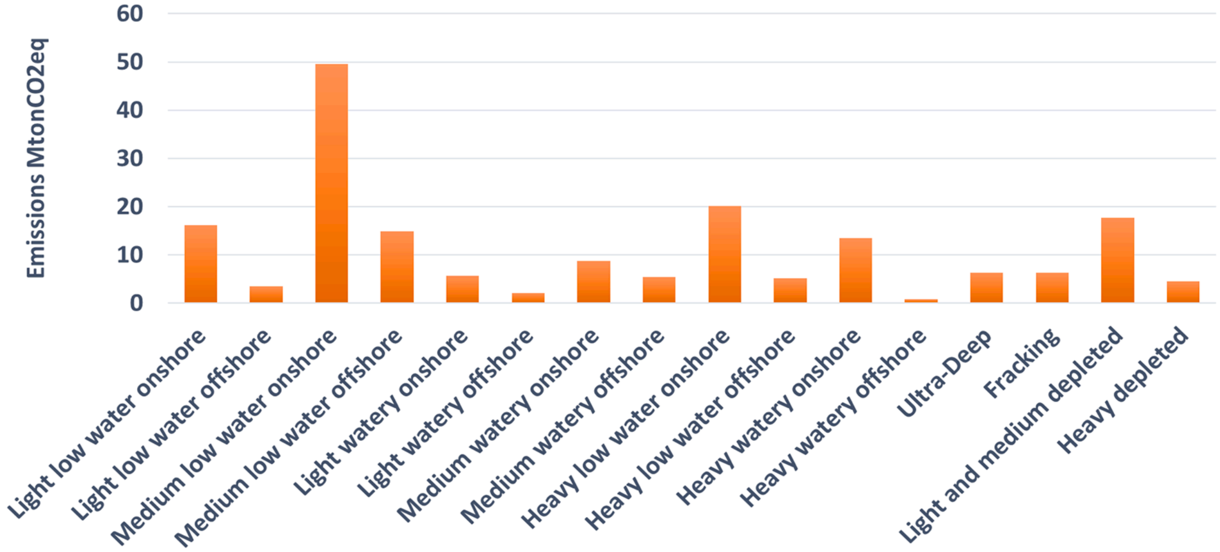


Fig. 5. Global annual absolute CO_2 emissions for the current relative composition of sequential pathways of oil supply under the IEA's (World Energy Outlook 2019) "Stated Policies Scenario" 2030 production assumption (105 million barrels per day).

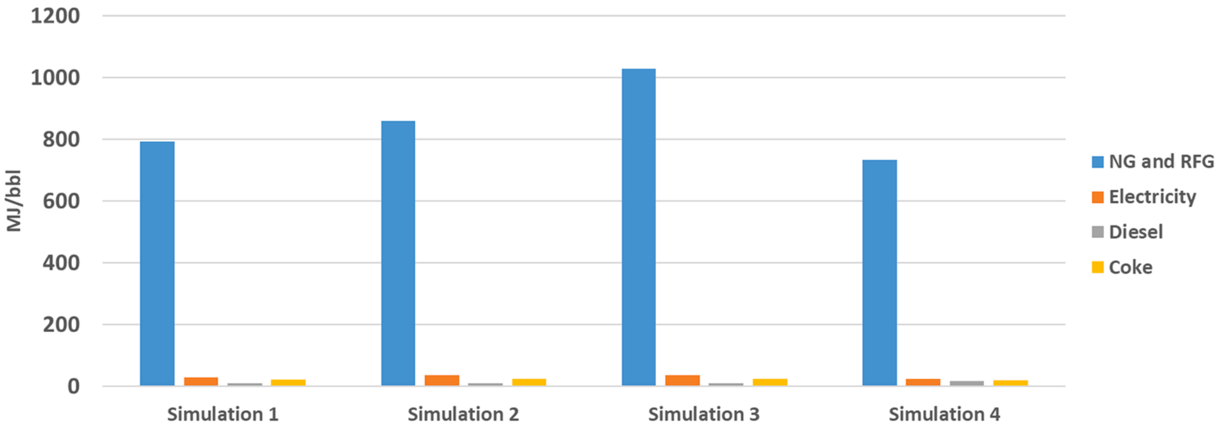


Fig. 6. Requirement of energy carriers per barrel of oil products for the four simulations provided.

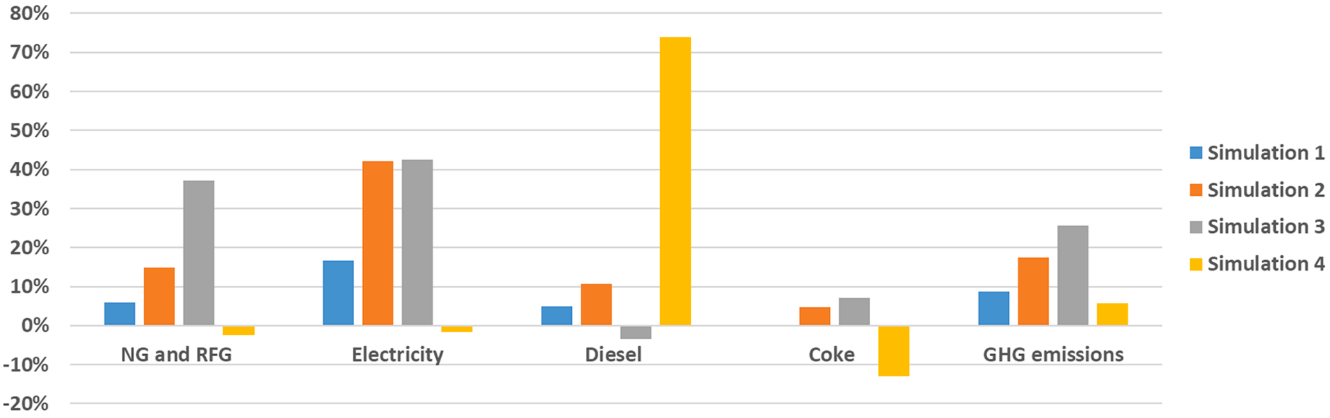


Fig. 7. Comparative average increase per barrel of oil products in the requirement of energy carriers and CO_2 emissions between the current situation (baseline) and the four simulations provided.

surprisingly, the most energy and emission intensive (Table 3 and Fig. 4). But when enlarging the scale of assessment, considering the global production capacities of each typology, the picture changes. In fact, heavy oils, although most polluting in unitary terms (Table 3), are not a major reason for concern because of their limited capacity of production. When studying them using the "extensive processor" (aggregated quantities of flows), they do not play a substantial role, neither in delivering fuels nor in consuming energy carriers and emitting

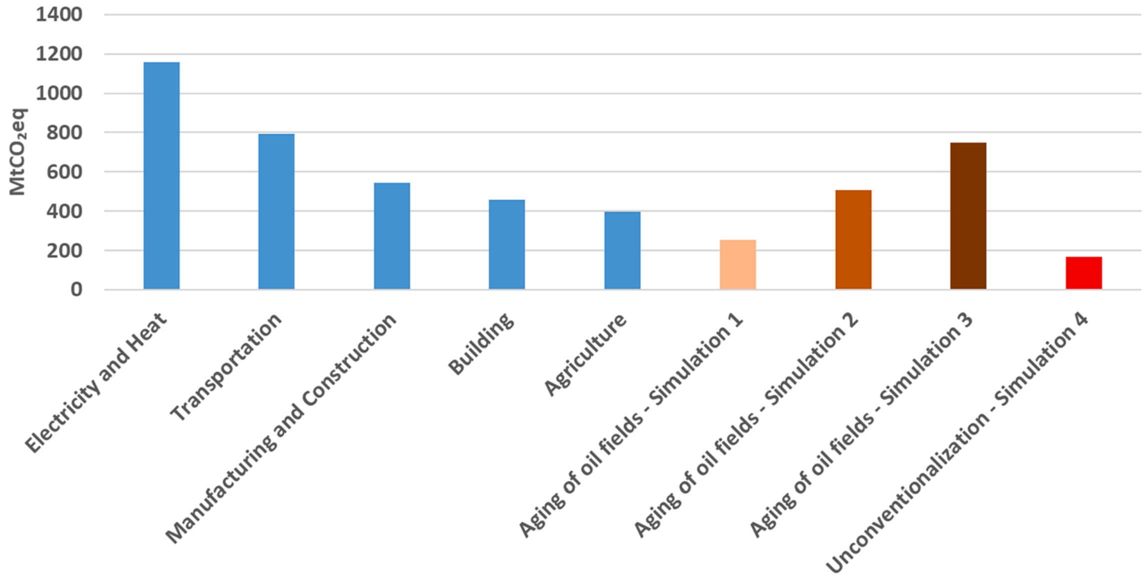


Fig. 8. CO_2 equivalent emissions per end-use in EU27 compared with the marginal emission increase for the four simulations performed.

CO_2 (Table 5 and Fig. 5).

Comparing “Heavy low water onshore” with “Light low water onshore” pathways on a per barrel basis, the former shows a + 311–562% emission range per barrel (depending on the typology of refining). However, the bulk of the global production (Table 1) is provided by light and medium, low-water and onshore fields, which together cover up to 45% of the worldwide crude supply. They account for the largest consumption of energy carriers and related emissions in the energy sector (Table 5 and Fig. 5). Currently, all the heavy and depleted pathways together account for only 28 $kgCO_2eq$ per barrel (‘GHG emission’ column, Table 5), equal to the sum of the light and medium low-water onshore pathways, at 29 $kgCO_2eq/bbl$. Nonetheless, heavy and depleted pathways are relevant considering their possible growth in the overall mix in the near future (“too big to ignore” [59]).

These results show the importance of maintaining non-equivalent representations of the oil sector to better inform decision makers by triangulating intensive (unitary benchmarks per types) and extensive descriptions (the extensive processors indicating the size of instances of types). Considering only emissions per barrel as if every sequential pathway had the same importance, misses the implications of the relative size and may lead to policy decisions with limited efficacy, as is the case with “smart taxes” on high-carbon oils [60].

3.2. Results of simulations

In this section, it is anticipated what will happen to the energy carrier requirements and CO_2 emissions of the energy sector when the relative contribution to the oil supply from depleted and watery oil fields progressively increases (simulations 1–3) or when the energy sector increasingly relies on unconventional sources (simulation 4).

Energy carrier requirements per barrel of oil for the four simulations is reported in Fig. 6. Energy carriers considered are natural gas (NG) and refinery fuel gas (RFG), electricity, diesel and coke. The relative increase in energy carrier requirements and CO_2 emissions of the 4 simulations compared to the current situation (baseline) is shown in Fig. 7.

In simulations 1–3, watery and depleted pathways progressively gain weight in the oil supply mix at the expense of light and medium low-water onshore ones. Since the former pathways are more intensive in terms of consumption of energy carriers and emissions, each barrel produced will cause higher emissions compared to the current situation. To maintain the current output of hydrocarbon fuels, a 6–26% increase in CO_2 emissions per barrel should be expected depending on the simulation considered (Fig. 7). The majority of those emissions are due to increased consumption of natural gas and electricity. Again, the difference between extensive and intensive characteristics is important here. Even if the use of natural gas and electricity as energy carriers is less emission intensive per unit of energy delivered (compared with diesel or coke, for example), it is the size of the supply of oil that matters. Incidentally, there are serious doubts about the possibility of maintaining oil production at the current level, since productivity per well drops substantially with reservoir depletion and the related increase in water content (waterflooding is a common secondary oil recovery technique to keep production high in spite of the deterioration of field quality) [61,62].

Compared to the effects of aging (simulations 1-3), a shift to unconventional pathways (simulation 4) appears less dramatic in terms of emission increases (Fig. 7). Although the use of diesel almost doubles in this simulation, in absolute terms this increase is much smaller than the increase in natural or refinery gas consumption observed in simulations 1-3, hence the relative emission increase per barrel is smaller. However, other relevant aspects, not explored in the present work, should be considered, such as technical difficulties in the extraction of ultra-deep fields [63] and their quick pace of decay, requiring a continuous capital investment in power capacity for drilling new wells [64].

The simulations indicate that the main drivers of increasing emissions are: (i) the increase in natural gas consumption because of aging; and (ii) the increase in diesel consumption for the “unconventionalization” of oil sources. Natural gas is used heavily in extraction to generate the heat needed for EOR techniques: waterflooding and most of tertiary EOR technologies employ natural gas to pump fluids (water, steam or gases) and generate steam or direct heat to reduce the viscosity in the reservoir in order to extract crude. Deep refining is especially intensive in natural gas use due to the various hydrocracking, hydrotreating, desulfurization and reforming facilities needed to treat heavy oils and make the fuels compliant with environmental laws. Diesel is used mainly in ultra-deep extraction, due to the (almost exclusively) offshore location and geological nature of the reservoir (depth). In Tables A1 and A2 of the appendix, more detailed quantitative results are provided.

A last observation is due on the quality of the oil products supplied. In our scenarios the relative composition of the mix of oil products supplied to society remains fairly constant (see Appendix, Table A4). This indicates that the quality of the final output is not significantly affected by aging or increased reliance on unconventional sources.

Given the large size of the global oil sector, these simulations are relevant for a responsible discussion about climate change. Depending on the simulation, the absolute increase in GHG emissions is between 251 and 747 $MtCO_2eq$/year for a total global production of 105 million barrels per day. These *extra* emissions are in the same order of magnitude as those of the agricultural or manufacturing & construction sector of the EU27 and, in simulation 3, nearly comparable to the emissions of the EU transportation system [65] (see Fig. 8).

Thus, if we want to meet the energy demand of 105 million barrels per day by 2030 under the current energy policy frameworks and international pledges worldwide (i.e., the “Stated Policies Scenario”), we need to compensate for the declining performance of the oil sector by reducing emissions elsewhere. The “unconventional revolution” [66] will aggravate, not solve the problem: even if the unconventional barrel is slightly less emission intensive than crude from depleted pathways, emissions per barrel increase compared to the current situation, especially due to intensive diesel consumption in ultra-deep extraction. Renovated abundance of unconventional oil resources will exacerbate the absolute GHG emissions and the pressure on the climate system.

4. Discussion

This section highlights the strength and the novelty of the proposed relational analysis and addresses the limitations of the current study with regard to (i) synchronic versus diachronic analysis to study aging; (ii) input/output variables considered in the metabolic process; (iii) the scope of the study.

4.1. The strength and novelty of relational analysis

Relational analysis provides a robust and versatile tool for biophysical assessment in that it can define *typologies* of extraction and refining processes through the generation of *unitary* metabolic processors based on benchmarks.

Typologies and their unitary processors can be easily compared to each other and can be used to construct scenarios in which the relative contributions of typologies vary. More precisely, different types of oil production and refining can be analyzed in functional terms in relation to the role they play inside the energy sector even when considering energy sectors of different size (either observed or simulated). Indeed, the representation of relational networks based on metabolic processors offers the analyst flexibility. Using this tool, it is possible to integrate the unitary (notional) description with the extensive description (based on observation i.e., statistical data), building a bridge across dimensions and levels of analysis and allowing for the consideration of the effect of size and the spatial location of the energy transformations. Biophysical costs, environmental pressures and the supply of products delivered to society can be scaled across levels and quantified using simultaneously different metrics. Two main advantages of these features are:

1. It allows the analyst to generate a multi-criteria performance space characterizing the supply of oil products using ad-hoc indicators (e.g., specific input/output ratios) related to costs, efficiency and pollution;
2. The multi-scale, multi-dimensional description across different levels of analysis can be tailored to the specific problem the analyst wants to study. For instance, the representation of performance can be fit to relevant levels of analysis, e.g., a single stage of the process, a specific functional element, or the whole supply system.

Finally, as shown in the current study, relational analysis can be meaningfully used in two ways:

1. Diagnostic mode, that is the description of the current metabolic pattern of the oil production sector across levels and dimensions of analysis;
2. Anticipation mode, that is the creation and evaluation of future scenarios by changing the wiring inside and across the sequential pathways or by assuming different technical coefficients for the structural elements in the nodes.

Defining the constraints on both the biophysical (production process) and socio-economic side (fuel demand), the coherence and sustainability of fuel consumption patterns can be identified and, playing with the relationships found, anticipated.

4.2. Synchronic versus diachronic analysis to study aging

In this study, the changes in time of the functional types of the oil sector (diachronic data of the CO_2 emissions per barrel) are inferred by combining: (i) the benchmarks of structural types observed at a given point in time (synchronic data of the technical characteristics of structural elements); and (ii) anticipated changes in the relative mix of these structural types. This procedure overlooks the effects of possible technological improvements taking place at the level of specific processes (e.g., pumping volumes of flows). Nonetheless, when considering aging and “unconventionalization” as drivers of change, the relational analysis is robust given the comparative relevance of: (i) a possible increase in the technical efficiency within a given structural typology; and (ii) an important change in the mix of structural typologies within the given functional types. Indeed, technical improvements in the efficiency of the technological devices operating at the oil wells (structural elements) are much less relevant than changes in the mix of structural elements (e.g., the relative share of “Heavy watery onshore” or “Light low-water onshore” oil fields) determining the functional typology. The extraction of oil from depleted fields comes with huge amounts of (contaminated) produced water (including formation and injection water and added chemicals). Low-water fields typically show water-to-oil benchmarks of less than 1/4 (80% oil vs 20% water). With progressive depletion, these proportions may easily reach up to 4/1 (20% oil vs 80% water). In such a situation, any potential efficiency improvements per barrel in the individual structural types (at best in the order of 20–30%) are more than offset by the huge increase in the extracted volume to be processed in the new (anticipated) mix determining the functional type. The same holds true for unconventional extraction due to the advanced techniques needed to extract difficult-to-access (ultra-deep and tight oil) crudes. Regarding refining, while ultra-deep and fracking crudes are not problematic for refiners, more complex facilities are needed to process dirtier or stickier oil from aged fields.

For these reasons, we believe that a reliable estimate of the changes in time of the overall performance of the oil sector can be obtained by simulating only the changes in the profile of structural elements, assuming current technical benchmarks to be constant. A study by Parra et al. [27], analyzing the aging of Ecuadorian oil reserves, validates these assumptions. Undoubtedly, for future analyses, it would be preferable to use time series of benchmarks from the same oil fields so as to include the combined effect of changes in technical characteristics of structural types and functional characteristics determined by the mix of structural types. However, historical series at the required level of data detail are generally not easily available.

4.3. Input/output variables included in the metabolic processors

The current study focused on energy carrier consumption and direct CO_2 emission in the oil sector to study the ‘aging trap’ of the energy transition. The economic – i.e., capital and operational expenditures –

and technical investments – i.e., kW of power machinery and quality of technology employed – were not included in the metabolic representation. The economic dimension, albeit relevant, is out of the scope of the biophysical representation presented in this study. Regarding the power capacity dimension, the issue is the lack of available data. To the best of our knowledge, only oil companies have data at that level of detail, and those are not publicly shared. However, in future and more refined analyses, it would be important to include economic and technical inputs too. In this way, one could study the effect of the continuous increase of investments in new technical capital, needed to overcome the challenges of aging (e.g., EOR) and the exploration and extraction of unconventional fields. In fact, rapidly decaying fracked wells [67], and sophisticated ultra-deep extraction technologies [63,68] entail not only more direct emissions, but also important energy requirements and emissions embodied in the installed power capacity. A methodological discussion of how to integrate power capacity into the processor's representation has been provided by Diaz-Maurin [69].

4.4. The scope of the study

The simulations presented in this paper are not meant to predict the future, but as a possible way to explore option spaces for energy transition by gaining insights into the consequences of the aging and complexification of the global oil sector. The main aim of the work is to provide a useful analytical framework for reflexive governance, capable of complementing the mainstream approach, which exclusively focuses on "optimization and control".

The selected taxonomy of extraction and refining processors is implicitly based on the historical and common accounting scheme adopted by oil companies, not on a cluster analysis of the biophysical profiles (input and output of primary and secondary flows) of the oil fields (see Appendix, Figs. A1, A2, A3). This choice has been made because, in the world of oil, every field is a complex object, difficult to geologically characterize and exploit by engineers: uncertainty is the norm and every producer employs specific sets of technologies [70]. Consequently, the biophysical profiles characterizing the extraction processors (but not the refining ones, that are less dispersed between instances of the same type) show high variability and every clustering constructed upon requirements of natural gas, diesel, electricity, coke and CO_2 emissions could easily be contested. Hence, in agreement with [28], we selected API gravity, water content, location and depth as relevant attributes because of their implications for the capital investments in extraction and refining technologies.

However, the choice of the taxonomy of structural and functional elements and the choice of inputs and outputs in the processors can always be contested within the relational framework. This predicament is unavoidable in any analysis of complex systems across different levels and dimensions. Relational analysis makes this choice transparent. In fact, we are not claiming that our numbers are correct or indisputable, nor that we are providing an accurate assessment of the increase in the emissions/supply ratio of oil products due to the aging and complexification of the oil sector. What we showed is that the "oil aging trap" is a relevant aspect of the problem of climate change mitigation that should be (better) addressed in the narratives about decarbonization of the economy (and in the making of IAMs). Grounding the representation of the oil sector in a metabolic perspective allows the analyst to obtain a broader view of the reality observed.

5. Conclusions

The modern energy matrix still relies predominantly on fossil fuels and the transition to renewable energy sources is expected to take decades at least. In this paper we have shown that, while the clock ticks, the aging and complexification of the oil sector, in the form of increasingly watery and depleted fields and a progressive switch to unconventional sources, lead to increased energy carrier consumption and CO_2 emissions per barrel produced by the oil industry. This phenomenon is the result of efforts to merely *maintain* the current size of fuels output. This "oil aging trap" is often overlooked – e.g., in the IPCC decarbonization scenarios based on IAMs – but has important implications for the international efforts to contain climate change in the next decades to come.

There are several potential applications of the findings of this paper. First, the findings indicate that focusing exclusively on the emissions per barrel for specific oil typologies – e.g., energy policies based on LCAs – is potentially misleading and may lead to ineffective carbon taxes and emission trade policies, because these assessments overlook the relative importance of the various sequential pathways in the overall oil mix.

Second, addressing the main drivers of increased CO_2 emissions in the oil sector, namely natural gas for more complex drilling and deeper refining, should be among the priority concerns of energy policies. Reducing the use of natural gas (in the form of hydrogen) in complex refining – needed to supply high quality fuels from low quality primary oils - could be useful for climate change mitigation. Hence, energy policies that stimulate burning cleaner fuels and the upgrading rate of refineries should be carefully evaluated in the face of (i) possible trade-off between pollution and CO_2 emissions; and (ii) the creation of additional fossil fuels path dependency in the economy.

Third, rather than focusing all attention on the use of renewables to replace fossil fuel, more research is needed on the possibility of using renewables in fossil fuel extraction. Technologies such as Solar Enhanced Oil Recovery could prove useful for reducing emissions and, at the same time, by-pass the main problems of large-scale, societal implementation of renewable sources, namely intermittency and storage.

The operational framework presented in this paper has been developed specifically for governance purposes. It allows analysts and policy makers to identify relations and trade-offs between relevant and conflicting concerns associated with the production of energy carriers in societies still heavily dependent on fossil fuels, but willing to reduce CO_2 emissions. Our analysis illustrates the potentiality of the approach in providing a useful integrated characterization of the diversity of processes of energy conversions taking place in the oil sector, and in identifying priority areas for further research. Decisions of policy-makers should not be based on simplistic indicators aimed at indicating optimal solution (often used out of context). Missing the big picture because of a reductionist approach and a simplistic thinking that we can solve climate change simply through technological innovations and business models will force us to run the Red Queen's Race: "It will take all the running we can do, just to keep in the same place" …but only for a limited time.

CRediT authorship contribution statement

Michele Manfroni: Conceptualization, Methodology, Formal analysis, Visualization, Writing - original draft, Writing - review & editing. **Sandra G.F. Bukkens:** Writing - review & editing. **Mario Giampietro:** Conceptualization, Methodology, Writing - review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

- *Additional data on the functional processors and sequential pathways referred to in the main text*

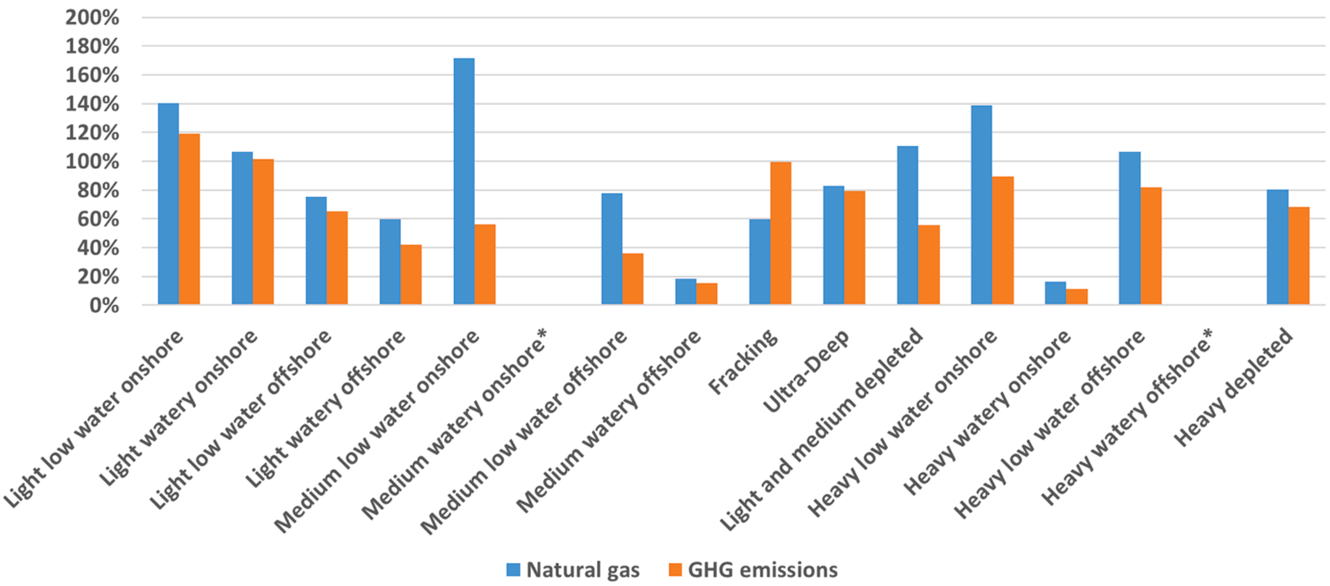

Fig. A1. Visualization of the ratio "Standard Deviation/Average" of the natural gas consumption (in blue) and GHG emissions (in orange), calculated over the specific oil fields (instances of extraction, structural elements) belonging to the same extraction (functional) typology. Standard deviation is consistently high for both flows for most extraction (functional) typologies, entailing high data variability for the characterization of oil fields. *benchmarks refer to a single field.

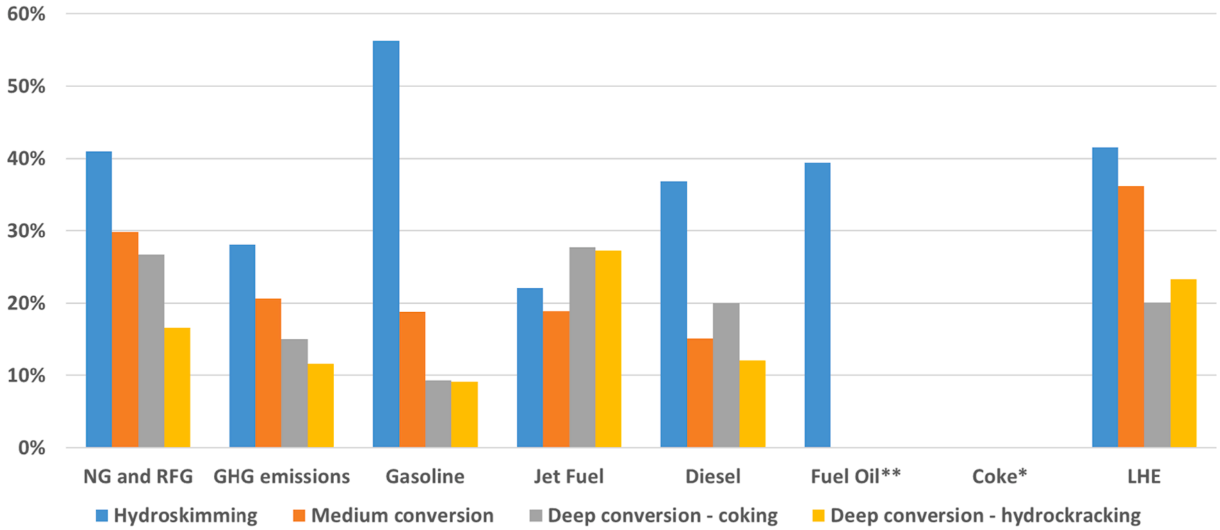

Fig. A2. Visualization of the ratio "Standard Deviation/Average" of the natural gas consumption, GHG emissions and oil products (gasoline, jet fuel, diesel, coke, Liquid Heavy Ends), calculated over the refineries (instances of refining, structural elements) belonging to the same refining (functional) typology. *PRELIM assumption: coke is not used in refining; **PRELIM assumption: fuel oil is completely converted to high-value products (gasoline or diesel) in refinery types other than hydroskimming.

Fig. A3. CO_2 emissions per barrel supplied, per oil field (e.g., "Nigeria Obagi", structural element in black) and per extraction typology (e.g., "Fracking", functional element in red). Note that large standard deviations are cause by the outliers in the upper part of the figure, however most of the fields are consistent with the benchmark of their reference type.

Table A1
Metabolic profiles (i.e., identities) of extraction processors: consumption of energy carriers and CO_2 emissions.

Extraction processors	MJ/bbl				$kgCO_2eq/bbl$
	NG and RFG	Electricity	Diesel	Coke	GHG emissions
Light low water onshore	90	4	7	0	25
Light low water offshore	176	7	13	0	32
Medium low water onshore	199	3	8	0	46
Medium low water offshore	33	2	5	0	20
Light watery onshore	425	38	6	0	78
Light watery offshore	523	8	5	0	74
Medium watery onshore	357	13	14	0	76
Medium watery offshore	174	11	4	0	31
Heavy low water onshore	1570	1	1	0	143
Heavy low water offshore	331	5	13	0	55
Heavy watery onshore	218	21	20	0	52
Heavy watery offshore	71	8	0	0	20
Ultra-Deep	199	6	40	0	51
Fracking	108	2	17	0	59
Light and medium depleted	431	35	7	0	55
Heavy depleted	1937	10	1	0	127

Table A2
Metabolic profiles of refining processors: consumption of energy carriers and CO_2 emissions.

Refining processors	MJ/bbl				$kgCO_2eq/bbl$
	NG and RFG	Electricity	Diesel	Coke	GHG emissions
Hydroskimming	297	10	0	0	17
Medium conversion	454	16	0	25	31
Deep conversion - coking	974	32	0	49	71
Deep conversion - hydrocracking	1278	38	0	41	94

Table A3
Viable sequential pathways of the oil sector: supply of oil products per barrel, unitary description.

Sequential pathways							
Types of extraction	**Associated types of refining**	**Gasoline**	**Jet Fuel**	**Diesel**	**Fuel Oil**	**Coke**	**LHE**
Light low water onshore	Hydroskimming	29%	23%	10%	10%	0%	28%
	Medium conversion	36%	19%	18%	0%	0%	26%
Light low water offshore	Hydroskimming	29%	23%	10%	10%	0%	28%
	Medium conversion	36%	19%	18%	0%	0%	26%
Medium low water onshore	Hydroskimming	29%	23%	10%	10%	0%	28%
	Medium conversion	36%	19%	18%	0%	0%	26%
Medium low water offshore	Hydroskimming	29%	23%	10%	10%	0%	28%
	Medium conversion	36%	19%	18%	0%	0%	26%
Light watery onshore	Hydroskimming	29%	23%	10%	10%	0%	28%
	Medium conversion	36%	19%	18%	0%	0%	26%
Light watery offshore	Hydroskimming	29%	23%	10%	10%	0%	28%
	Medium conversion	36%	19%	18%	0%	0%	26%
Medium watery onshore	Hydroskimming	29%	23%	10%	10%	0%	28%
	Medium conversion	36%	19%	18%	0%	0%	26%
Medium watery offshore	Hydroskimming	29%	23%	10%	10%	0%	28%
	Medium conversion	36%	19%	18%	0%	0%	26%
Heavy low water onshore	Medium conversion	36%	19%	18%	0%	0%	26%
	Deep conversion - coking	44%	11%	31%	0%	10%	3%
	Deep conversion - hydrocracking	38%	11%	40%	0%	8%	3%
Heavy low water offshore	Medium conversion	36%	19%	18%	0%	0%	26%
	Deep conversion - coking	44%	11%	31%	0%	10%	3%
	Deep conversion - hydrocracking	38%	11%	40%	0%	8%	3%
Heavy watery onshore	Medium conversion	36%	19%	18%	0%	0%	26%
	Deep conversion - coking	44%	11%	31%	0%	10%	3%
	Deep conversion - hydrocracking	38%	11%	40%	0%	8%	3%
Heavy watery offshore	Medium conversion	36%	19%	18%	0%	0%	26%
	Deep conversion - coking	44%	11%	31%	0%	10%	3%
	Deep conversion - hydrocracking	38%	11%	40%	0%	8%	3%
Ultra-Deep	Hydroskimming	29%	23%	10%	10%	0%	28%
	Medium conversion	36%	19%	18%	0%	0%	26%
Fracking	Hydroskimming	29%	23%	10%	10%	0%	28%
Light and medium depleted	Hydroskimming	29%	23%	10%	10%	0%	28%
	Medium conversion	36%	19%	18%	0%	0%	26%
Heavy depleted	Medium conversion	36%	19%	18%	0%	0%	26%
	Deep conversion - coking	44%	11%	31%	0%	10%	3%
	Deep conversion - hydrocracking	38%	11%	40%	0%	8%	3%

- *Extraction data processing from the OPGEE dataset*

Each oil field in the OPGEE_v.1.1_draft_e dataset presents different energy consumption and GHG emissions, that are reported in the "Energy consumption" and "GHG emission" sheets. Data from Table 3–6 ("Energy consumption") and total direct (Table 1, "GHG emission") and indirect emissions (Table 2, "GHG emission") have been used to construct the sixteen typologies of extraction processors. OPGEE data are reported in MMBtu/day and gCO_2eq/day, so for our scopes they all have been converted to MJ/bbl and $kgCO_2eq$/bbl of oil, using daily capacity production of respective fields. (See Tables A1-A3)

For each oil field, the following set of data has been collected, out of the whole information:

- Natural gas (NG): on-site (net) consumption;
- Diesel: imports (equal to the net consumption by OPGEE assumption) and indirect consumption associated with imports;
- Electricity, on-site (net) consumption (entirely imported due to OPGEE assumption) and indirect consumption associated with imports;
- GHG emissions: direct emissions due to the consumption of energy carriers on-site and indirect consumption associated to diesel and electricity imports;

Table A4
Mix of oil products, in quantity and quality, in the current situation and in the four simulations.

Simulations	Gasoline	Jet Fuel	ULSD	Fuel Oil	Coke	LHE
Current situation	36%	19%	18%	1%	1%	24%
Simulation 1	36%	19%	18%	1%	1%	24%
Simulation 2	36%	19%	18%	1%	1%	24%
Simulation 3	36%	18%	19%	1%	1%	24%
Simulation 4	34%	19%	16%	3%	1%	24%

- Production capacity per field, in order to make the conversions and to assess the magnitude of each typology in the production mix.

These are the five main categories of energy carriers. Direct GHG emissions are summed up and not reported for specific associated energy carrier. The dataset contains also information about:

- Water-to-Oil ratio;
- Field depth and location (onshore – offshore);
- Sulfur content.

This information was used to construct the extraction (functional) typologies, as reported in Table A5.

Table A5

Assumptions for identifying the taxonomy of extraction (functional) processors. Adapted from OCI – Oil Climate Index [28]

Classification	API crude category (API degrees)
Heavy	0–21,99
Medium	21,99–31,99
Light	>31,99
Sulfur content (S %wt)	
Sweet	<0,5
Sour	0,5
Depth (m)	
Shallow	0–2133,6
Ultra-Deep	>3352,8
Water-to-Oil ratio (bbl water/bbl oil)	
Low water	0–4
Watery	>4

In order to generate the unitary description and calculate the benchmarks for consumption of energy carriers per extraction type, values from specific oil fields have been weighted averaged on the production capacity. Using a bottom-up approach, we generated unitary benchmarks of extraction types observing special instances (structural elements) of oil fields:

$$EC_k = \frac{\sum_{i=1}^{n} EC_{i,k} Pr_i}{\sum_{i=1}^{n} Pr_i}$$

$$GHG_k = \frac{\sum_{i=1}^{n} GHG_{i,k} Pr_i}{\sum_{i=1}^{n} Pr_i}$$

Where k = category of carriers (for instance, NG exports), n = number of oil fields of the same type, EC = energy carrier in MJ/bbl (natural and refinery gas, diesel, electricity), GHG = GHG emissions in kgCO_2eq/bbl, Pr = production capacity per day (bbl/day). In this way, it is possible to define a general taxonomy based on intensive (unitary) processors that can be tailored to specific cases by simply introducing the size of the system under analysis. Note that the average is weighted on the extraction capacity (volume of barrels extracted per day). Therefore, bigger fields assume more importance than smaller ones inside the network representation.

- **Refining data processing from the PRELIM dataset**

Data for each refinery have been collected from the “Main input & output” sheet of PRELIM model v1.2. In the column “Energy use”, types of carriers reported are heat, steam, hydrogen (SMR, Steam Methane Reformer and CNR, Catalytic Naphtha Reformer), electricity, FCC (Fluid Catalytic Cracking) catalyst Regeneration and excess of RFG (Refinery Fuel Gas). For our scope, we defined the following categories and performed a mapping with PRELIM categories:

- Natural gas and refinery fuel gas (NG + RFG);
- Electricity;
- Diesel;
- Coke;
- GHG emissions.

Electricity matches straightly between the two sets of accounting. Heat, steam and hydrogen SMR sub-categories are summed up and the total goes to “NG + RFG”. Hydrogen via CNR is supposed to be entirely obtained from natural gas. FCC Cat. Regeneration is supposed to be done through coke burning. Diesel use in refineries is zero. The “Diesel” category is conserved for matching with extraction categories, but there is no direct diesel use in refining (Table A2). Excess of RFG is always zero due to PRELIM assumptions. Regarding GHG emissions, total emissions are directly reported under the “GHG emissions” category in our model. Refineries have been grouped according to their configuration into the four typologies of the selected taxonomy and benchmarks obtained using simple average calculation. No weighted average has been performed this time, since refinery capacity production is elastic and very dependent on external factors (market).

The categories of oil products selected for our model are reported in the list below, and another mapping with PRELIM's one has been done:

- Gasoline;
- Jet Fuel;
- Diesel;
- Fuel Oil;
- Coke;

Gasoline maps directly with PRELIM's "Blended Gasoline", Jet Fuel with Jet-A/AVTUR, Diesel with ULSD (Ultra Light Sulphur Diesel), Fuel Oil, Coke and Liquid Heavy Ends (LHE) are the same of PRELIM's. Surplus of Refiney Fuel gas is always zero for PRELIM's assumption.

- **Network scaling with Metabolic Processors**

The semantic framework adopted by relational analysis is based on the four Aristotelian causes: (i) material cause, the material input coming from nature – this is useful to identify external constraints; (ii) formal cause, the organizational structure (recorded in blueprints/know-how) and the set of cybernetic controls that can be stored as recorded information – this is useful to study the role of technology and know-how; (iii) efficient cause, the agents of change expressing the required functions – this is the semantically open part of the representation, because the same function can be expressed by different combinations of material and formal causes; and (iv) final cause, defining the purpose of the energy system for the embedding social system.

The analysis of energy systems based on metabolic processors provides three important advantages:

1. The set of relations characterized by a processor avoids the simplifications typical of reductionism

A processor integrates a set of non-equivalent descriptions of the observed system in the form of a data array. The same structure of the data array can be used to characterize the metabolic attributes of both structural and functional elements and of functional elements generated by a combination of lower-level functional elements, when moving the analysis to upper levels. The data sources used to describe the various elements across levels are non-reducible to each other in a common metric. Thus, establishing congruent relations between processors describing structural elements and functional elements across levels allows to generate a coherent representation across scales inside the metabolic pattern. Data about the flows "coming from" and "going to" the technosphere (flows having a technical and an economic relevance) can be used to check the performance in terms of technical coefficients, labor requirement, economic costs and revenues. Data about the flows "coming from" and "going to" the biosphere (water, primary sources on the supply side and emissions and pollutants on the sink side) can be used to assess environmental pressures and, when georeferenced, to check potential environmental impacts. Combining structural and functional representations in a coherent analytical tool allows to track what is produced and consumed, how is produced and consumed, at what biophysical and environmental costs in relation to which societal purposes.

Five different categories of inputs and outputs are represented in Fig. A4:

τ_i = secondary flow inputs: circulating flow elements required by processes coming from the technosphere (processes under human control), e.g., electricity, fuels;
θ_i = secondary fund inputs: fixed fund elements required by processes coming from the technosphere (processes under human control), e.g., hours of workers, power capacity;
β_i = primary supplies of inputs coming from processes outside human control (biosphere): availability of primary sources (either fund-flow or stock depletion), e.g., oil, gas;

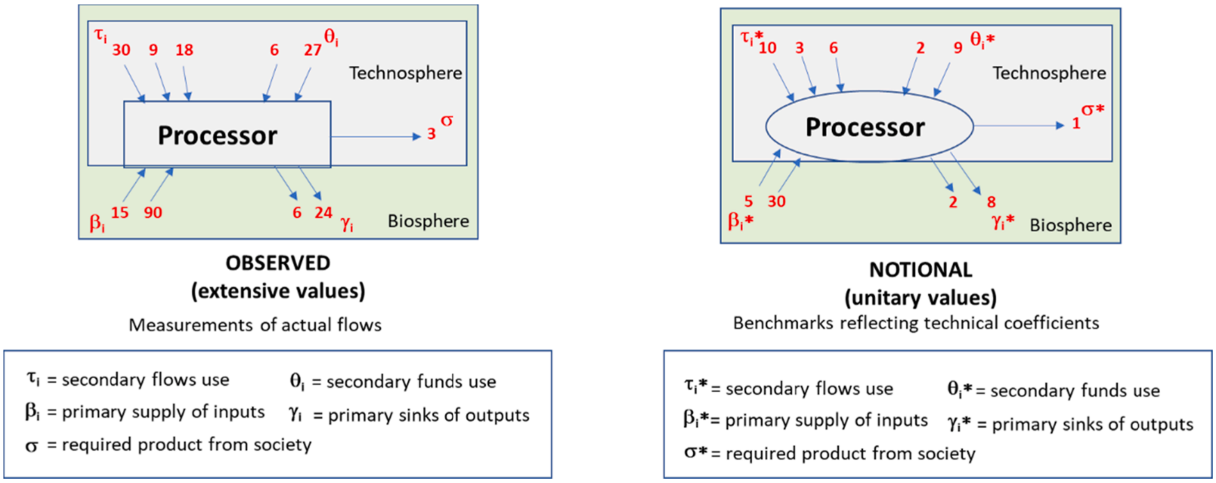

Fig. A4. Representation of the data array associated with a metabolic processor.

γ_i = primary sinks of outputs provided by processes outside human control (biosphere): availability of primary sink capacity (either fund-flow or sink filling), e.g., GHG emissions, polluting water;
σ = secondary flow outputs: products required from society determined in both quantity and quality, e.g., crude oil, refinery products.

The relations over the quantities of these different flow and fund elements can be expressed using two non-equivalent representations:

- Extensive values: the values observed for specific processes;
- Unitary values: technical coefficients calculated as benchmarks of given functional or structural elements.

2. It is possible to move the representation given by processors across different levels of analysis and scales, maintaining coherence between the various quantitative assessments

Different definitions of a functional unit, viewed as an effective combination of lower-level components, are illustrated in Fig. A5. On the lower-left corner, different functional units of extractions (e.g., different types of fields operating at level n-2) are combined together to generate a functional unit of “extraction” at the level n-1. On the upper left corner, we see a sequential pathway of processes (“extraction” →“transportation” →“refinery”), which can be considered as a functional unit “oil products production” at level n (on the right-upper corner). Each sequential pathway is composed by a series of functional units defined at level n-1 (blue double arrow).Fig. A6.

Using this accounting framework, we can integrate non-equivalent descriptions referring to structural and functional elements: (i) the WHAT/HOW can be characterized by looking at the structural aspects of the elements: the “WHAT” is the specific transformation and the “HOW” is a characterization based on benchmarks of the processes carried out, i.e. the material infrastructures and the material flows coming in and getting out associated with the necessary know-how and the observed technical coefficients (bottom-up analysis); and (ii) the WHAT/WHY can be defined by looking at the functional role played by the element inside the rest of the system, i.e. the purposes justifying the expression of the process in the first place (why society supports the reproduction of it) and the specific combination of element in a functional units (top-down analysis).

3. It is possible to generate contextualization for the performance of the oil sector and its higher and lower-level components

The energy sector is a component interacting with the rest society, the oil sector is a component of the energy sector, and the compartment of extraction is just a component of the oil sector. Since complex socio-ecological systems are hierarchically structured [71,72], keeping a holistic picture of the relations over hierarchical elements inside the metabolic pattern expressed at different levels is vital. This helps to check the correctness of the representation given and to grasp the meaning of different components inside the system (the big picture) [73].

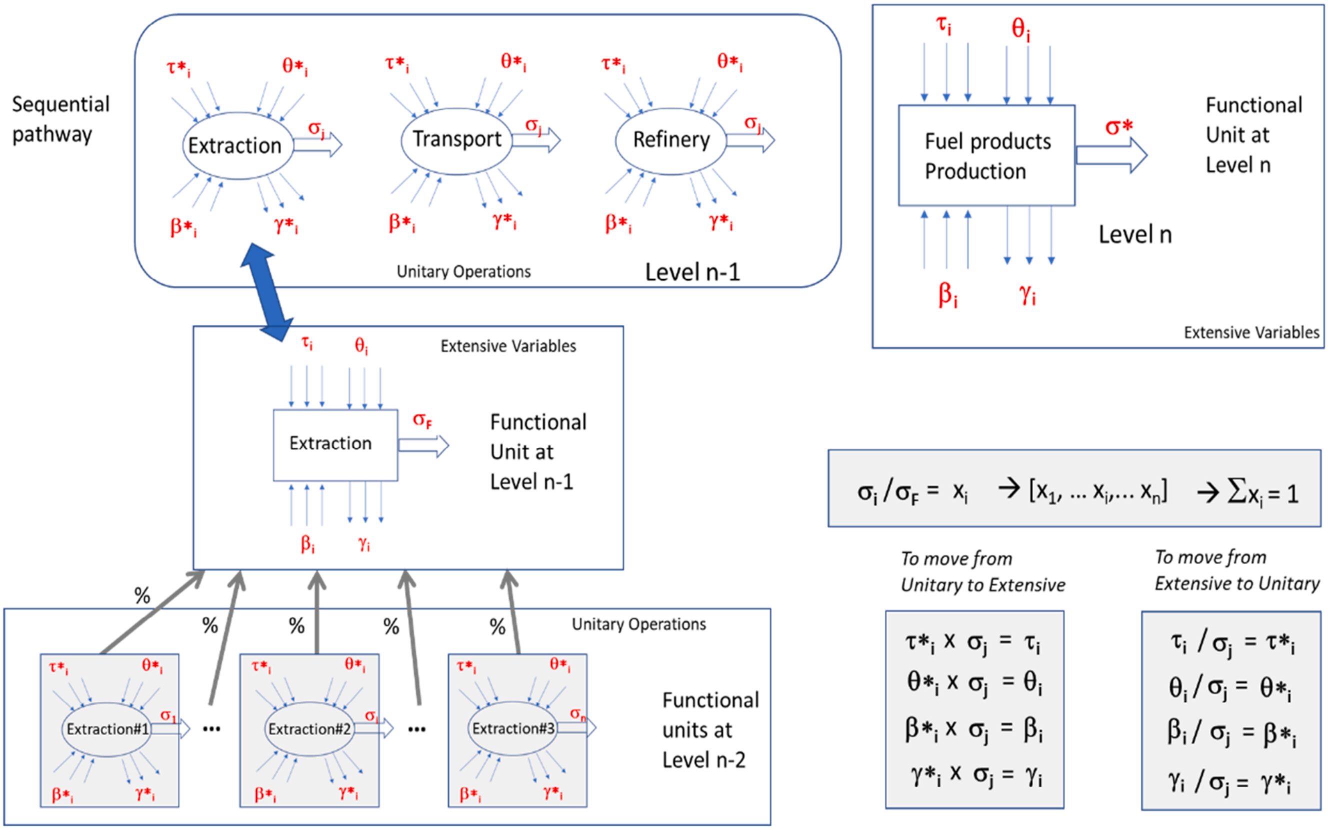

Fig. A5. Moving the assessment of the oil sector across different scales (non-equivalent definitions of functional units) and hierarchical levels.

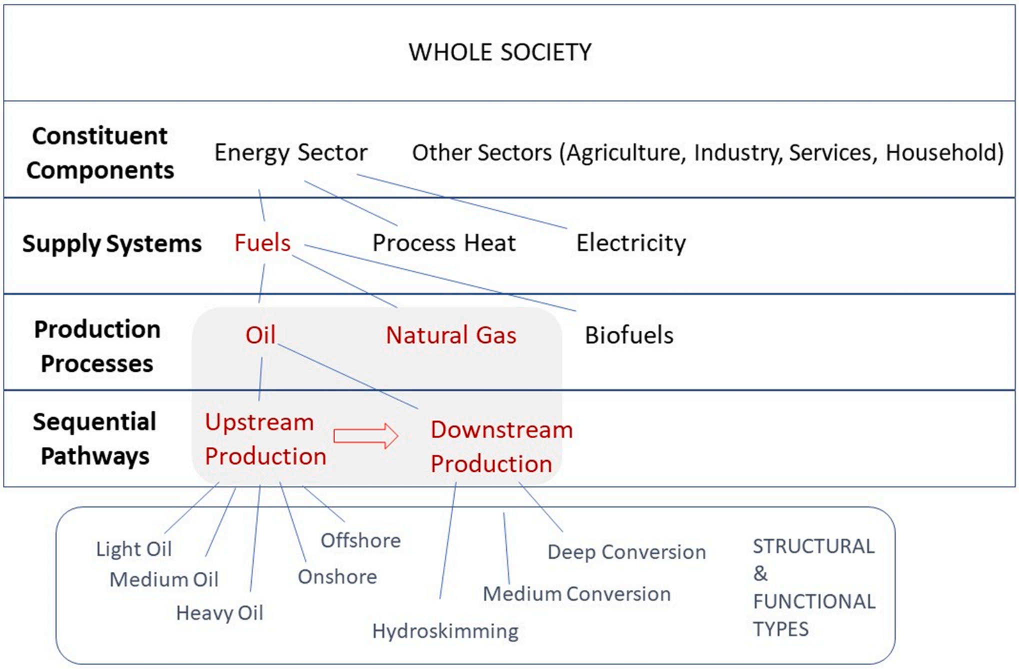

Fig. A6. Map contextualizing the role of structural and functional elements within the energy sector and within the rest of the society.

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