DOCTORAL THESIS

Daniel Enrique Cortés Borda

CONTRIBUTION TO THE DEVELOPMENT OF MORE EFFICIENT ENVIRONMENTAL POLICIES VIA MULTI-OBJECTIVE OPTIMIZATION AND ENVIRONMENTALLY EXTENDED INPUT-OUTPUT MODELS

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CERTIFY:

That the present study entitled “Contribution to the development of more efficient environmental policies via multi-objective optimization and environmentally extended input-output models”, presented by Daniel Enrique Cortés Borda for the award of the degree of Doctor, has been carried out under our supervision at the Chemical Engineering Department of the University Rovira i Virgili.

Tarragona, 12th June 2014,

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Summary

In today's globalized market, most goods and services daily consumed around the world are produced by a diverse set of countries that take part in different stages of their life cycle. In this general context, the environmental impacts of final products strongly depend on the production technologies of the manufacturing countries. International trade, along with the globalization of markets, has accelerated the socioeconomic development of nations, but has in turn led to undesirable effects like the externalization of environmental impacts. Yet, little is known about how environmental impacts embodied in international trade are distributed among nations. This lack of knowledge hampers the design of effective and fair policies for reducing the degradation of the world at a global scale.

Governments are nowadays searching for policies that promote a more sustainable development. The design of effective environmental regulations is challenging, mainly because in order to ensure a fair allocation of environmental responsibilities one needs to understand how international supply chains of goods and services operate.

This doctoral thesis applies systematic tools to shed light on the environmental impact of international trade and the most effective corrective measures to reduce it. Particularly, a toolkit of methods including environmentally extended input-output models, multi-objective optimization and life cycle assessment are applied to international databases to get insight into the environmental impact of human activities at a global scale. This general approach is applied to a wide variety of problems, including: the quantification of environmental loads associated to the consumption and production of goods and services; the assessment of environmental pressures transferred via international trade; the assessment of the level of equity with which natural resources are consumed worldwide; and the identification of key economic sectors to be regulated so as to improve to the maximum extent possible the environmental performance without compromising too much the environmental impact.

The work developed during the doctoral research and compiled in this PhD dissertation is presented in 3 main chapters. The first chapter proposes a quantitative method based on macroeconomic models to assess a set of consumption-based and production-based environmental indicators, including standard LCA metrics; environmental pressures embodied in trade, and indicators of the environmental equity with which such indicators are distributed. The second chapter applies a systematic

approach that integrates multi-objective optimization with environmentally extended input-output models to guide the search for optimal solutions that minimize the environmental impact of a given economy by compromising the minimum extent possible the economic output. The third chapter introduces a multi-objective optimization approach that facilitates decision-making in environmental problems like the ones explored in previous chapters.

In wider detail, the first chapter applies a holistic approach based on macro-economic input-output models to quantify the extent to which countries contribute to the overall anthropogenic environmental impact. The study covers more than 30 million economic transactions taking place between 35 economic sectors of 40 countries representing 85% of the world gross domestic product for the period 1995-2009. A total of 69 environmental metrics classified into air emissions, land occupation, and the consumption of energy, water and natural resources are investigated. Results shed light on how the environmental loads are externalized via international trade; and the level of environmental equity with which the 69 environmental indicators are distributed worldwide (and how this distribution has evolved over time in the last decades).

We pay special attention to two energy indicators: solar energy, both thermal and photovoltaic, and nuclear energy. Both energy sources mitigate global warming, but the later shows significant potential negative impacts while the former does not. By analyzing both, we assess the extent to which countries committed with greenhouse gas-reduction agreements are moving towards an energy system with fewer emissions.

The second chapter applies a systematic multi-objective optimization approach for simultaneously minimizing the global warming potential (assessed via life cycle assessment) and maximizing the total economic output of the European Union. The problem of identifying key economic sectors whose regulation leads to significant reductions in global warming potential (and minimum impact in economic output) is posed in mathematical terms as a bi-criteria linear program that seeks to optimize the total economic output and the life cycle CO_2 emissions simultaneously. The calculations are performed using an environmentally extended input-output model based on a macroeconomic database that covers 487 sectors (including productive sectors and a series of household consumption activities with direct emissions, such as automobile driving, cooking and heating, and a number of postconsumer waste management sectors) for the European economy for year 2006. The use of a highly disaggregated database allows identifying specific economic activities that are ultimately responsible for the overall environmental impact (by adopting a life cycle perspective). Numerical results show that, with the existing technology and current international trade network; it is possible to reduce the global warming potential by restricting adequately the demand of certain sectors. Our approach identifies key sectors that contribute significantly to the total impact but marginally to the total economic output. Some of these sectors have low direct emissions, and are therefore difficult to uncover with standard production-based approaches. These key sectors include the use of household appliances, the consumption of certain apparels, and the consumption of sausages and other prepared meat products. The analysis reveals that minor changes in consuming habits could lead to significant environmental savings without modifying the overall economic structure.

The third chapter presents a method based on linear programming to facilitate decision-making in life cycle assessment studies. Our method is based on a sort of reverse-engineering approach that tackles the decision-making problem in an inverse manner. That is, given a set of solutions proposed for improving the environmental performance of a system, the goal is to find the lower and upper limits of the intervals within which the weights to be attached to a set of environmental and economic indicators must fall so that the selected solution becomes optimal over the rest of alternatives. This method eliminates the need of assigning weights to the environmental metrics; instead, it determines the intervals within which these weights should fall considering all the alternatives available. This approach allows calculating the monetary units (*i.e.* economic penalties) that decision-makers are willing to pay for the damage caused when a given alternative is chosen. The results from this analysis are valuable for decision-makers since they allow ranking alternatives on a common scoring system based on monetary units. This methodology facilitates decision-making in life cycle assessment studies, and it is particularly suited for problems with a large number of alternatives and objectives to be considered.

In summary, this thesis has applied a set of systematic tools to several environmental problems at a global scale, with the final goals of (i) shedding light on how nations contribute to the global environmental impact, (ii) identifying key economic sectors to be regulated so as to reduce the environmental impact while keeping the economic performance as high as possible, and (iii) assisting decision-makers in the selection of alternatives with different economic and environmental performance.

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1 INTRODUCTION

International trade is nowadays highly globalized, to the point that a diverse set of countries take part in the supply chains of many products daily consumed worldwide. Globalization of international markets has accelerated the economic development of industrialized countries. This trend has caused a significant environmental degradation, and has resulted in a constant growth of the anthropogenic environmental impacts of nations. In this context, governments have started to formulate policies which promote the sustainable development of the economy (*i.e.* policies that ensure the socio-economic growth and simultaneously curb the environmental detriment).

The design of effective environmental policies is challenging, because many countries take part in the life cycle of goods and services. That is, international trade establishes connections between countries through which environmental impacts are traded, thereby hindering the formulation of effective environmental policies. Disclosing which countries ultimately cause the environmental impacts; and which suffer their negative effects is not a trivial task. This information is important, because on its basis it would be possible to establish a fair allocation of responsibilities among countries. This would avoid scenarios in which regions geographically located far from the consumption place are drastically degraded to satisfy the needs of other nations [1].

Then, the use of environmentally extended input-output models, multi-objective optimization and life cycle assessment applied to international databases provides a valuable understanding of the environmental impact of human activities at a global scale, facilitating a fair allocation of environmental responsibilities. These combined methodologies allow assessing a wide variety of problems, including: the quantification of environmental loads associated to the consumption and production of goods and services; the assessment of environmental pressures transferred via international trade; the assessment of the level of equity with which natural resources are consumed worldwide; and the identification of key economic sectors to be regulated so as to improve to the maximum extent possible the environmental performance without compromising too much the environmental impact.

1.1 Macro-economic input-output models and their environmental extensions

1.1.1 Allocation of the environmental responsibilities via input-output models

Differences between environmental policies based on production and consumption may lead to conflicting opinions regarding the allocation of responsibilities. Production-based environmental policies focus on impacts associated to gross inland consumption, regardless of the final destination of the goods produced within the boundaries of the country (*i.e.* national consumption or exports). Environmental assessments based on production can be easily performed with the aid of specialized databases containing detailed information on the amount of resources consumed by all the productive sectors and households for a wide variety of nations (*e.g.* International Energy Agency, 2013 [2]). However, environmental regulations based on production (rather than on consumption), are unfair, because they do not penalize those countries which ultimately take advantage of the externalized environmental degradation. Moreover, they make it possible to avoid penalties by displacing the manufacturing tasks to countries with less stringent regulations [3].

On the contrary, consumption-based environmental metrics take into account both:

- The impacts associated to goods produced and consumed locally.
- The impacts embodied in the goods imported from abroad.

These policies consider the environmental loads associated with products/goods along all the stages of their life cycle [4]. Standard life cycle assessment (LCA) studies of goods and services uncover direct and indirect effects of consumption. Unfortunately, LCA studies require large amounts of data, and their application is often hindered by data gaps concerning mass and energy flows involved in the life cycle of products internationally traded.

Macroeconomic input-output models [5] offer an appealing framework to fill these data gaps. Input-output models have been widely applied in many areas over the last 40 years [6]. They provide an exhaustive description of the economic transactions between final consumers and productive sectors in an international scenario, thereby revealing connections between sectors and nations given by their production/consumption flows. Moreover, input-output models can be complemented by environmental information. This leads to “environmentally extended” [7] input-output models that establish links between the economic output of each country (and sector) and its corresponding pollution intensities. Environmentally extended input-output (EEIO) models translate economic output into tangible impacts. So far, EEIO models have been accepted to conduct LCA studies [8], which allows evaluating several environmental indicators, including the assessment of energy-related CO_2 emissions [9-13]; and the amount of direct and indirect energy consumption in households [14-19] and other specific sectors [20-24].Most of the studies based on EEIO models have restricted the environmental analysis to the assessment of air emissions resulting from the combustion of fossil fuels. Very little has been published, on the contrary, on the use of EEIO models to evaluate other environmental indicators (*i.e.* land, materials, water and energy use).

From a wide variety of environmental impacts, global warming is currently the most relevant one. Greenhouse gas (GHG) emissions are mainly produced from the combustion of fossil fuels, whose demand has grown drastically in the recent past [25]. The European Union (EU), through the Kyoto protocol, agreed a common GHG reduction of 8% during the period 2008-2012 with respect to 1990. In this context, low GHG energy sources (like solar and nuclear energy) play a key role in the accomplishment of the GHG-targets sought. Specifically, the European commission established the objective of covering with renewable energies (mainly biomass, hydropower, wind energy and solar energy), 12% of the EU’s gross inland energy consumption by 2010 [26]. It later established target shares of renewable energy sources in the individual member states in 2010 [27]; and more recently established long term environmental policies related to the use of renewable energies [28].

Meeting the growing energy demand while keeping the CO_2 emissions low, requires embracing alternative energy sources with low CO_2 intensity, such as renewable energies and nuclear energy. Both energy sources could be appealing alternatives to mitigate global warming, but the later shows significant potential negative impacts while the former does not.

In the current energy scenario, renewable and nuclear energies are unable to fully substitute fossil fuels to a sufficient extent. Moreover, such energy sources have some major shortcomings that remain unsolved. Renewable energy technologies are still expensive [29], and their energy yield is highly constrained by on-site resources availability. On the other hand, nuclear power has received significant criticism. Particularly, some studies claim that the life cycle emissions of a nuclear plant (including mining, milling and transporting of uranium) are similar to those of a natural gas power plant [30]. In addition, there is a long list of environmental and economic externalities of nuclear energy on current and future generations. Nuclear power depends on mining of uranium rich ores. Mining, processing and enrichment of this mineral cause substantial damage to the nearby ecosystems and waterways [31]. Moreover, nuclear power plants require large amounts of cooling water that may cause thermal pollution when discharged into the local ecosystem [32]. Overall, the largest and more serious externalities related to nuclear energy are:

- The risk of a nuclear accident with very high environmental impact (*e.g.* Three Mile Island, Chernobyl and Fukushima).
- The generation of radioactive residues, whose handling and disposal causes serious environmental and safety issues in the long term.

Recent advances in nuclear industry safety have reduced the probability of experiencing future incidents. However, there are some risks that cannot be entirely eliminated (*e.g.* natural disasters). Regarding nuclear residues, safe ultra-long-term storage of nuclear waste is still un-resolved and causes serious future externalities including human health effects, biodiversity loss, land degradation, diverse social costs, etc. that cannot be easily quantified or predicted. Such effects have led to social reactions evidencing that these activities raise serious concerns in the population.

1.1.2 Environmental loads embodied in international trade

In today's globalized market, countries without direct generation of specific environmental loads may indirectly cause them through the trade of goods and services produced abroad. Thereby, such countries externalize the negative impacts to the manufacturing countries. Regarding the positive consequences of implementing measures for environmental improvement (*e.g.* using renewable energies), there are situations in which one nation with a significant renewable energy share (*e.g.* solar energy, whose social perception is much better than that of nuclear energy) will import goods from a third nation with an energy system yet based on fossil fuels.

EEIO models allow determining whether a country is a net importer or exporter of environmental loads. The net environmental loads are the difference between the environmental loads associated to the production of the exported goods and services, minus the environmental loads associated with the imported goods and services [33, 34], measured in a wide variety of environmental indicators.

Net importers externalize the production-based environmental loads to their providers (*i.e.* the former benefit from the imported goods and services without suffering the negative effects of the production processes implemented in the later). Quantifying the impact that one country causes to the other is valuable for the national governments of exporting countries, since the local environmental impacts caused in their national territory ultimately implies more investments in health and social security [35]. Then, such countries could better evaluate the economic profit of the internationally traded goods, and the need to define special taxes on them if required. In other words, this analysis allows identifying if one economic activity is in line with the sustainability principles, by contrasting the economic benefit with environmental and social welfare.

Different policy instruments have been recently proposed to promote the consumption of environmentally efficient products among consumers. Particularly, there is a growing interest on Eco-labeled products [36]. Eco-labels quantify the environmental performance across the whole product supply chain in terms of a wide variety of impacts taking place in different stages of the life cycle of the product/service under study. Hence, the use of eco-labels might lead to global environmental savings (in addition to other local benefits), which are ultimately achieved by guiding customers towards products/services with less environmental impact.

The definition of eco-labels requires detailed information on international trade of goods and services. EEIO models allow for the simultaneous assessment of the economic and environmental performance of international economic transactions, thereby providing a sound basis for eco-labeling. The very first EEIO models [37] were used to assess the air emissions of different nations. Since then, EEIO models have been applied in different areas, including the estimation of the level and composition of GHG emissions as a function of the demand [38], and the assessment of several environmental impacts [39], and other toxic emissions (*e.g.* sulphur oxides, nitrogen oxides, ammonia, particulate matter and other hazardous materials) [40, 41]. In the context of energy related topics, EEIO models have also been extensively used in the assessment of the GHG emissions embodied in international trade [42-45], and the evaluation of specific environmental policies [46, 47].

1.1.3 Environmental inequality

Globalization and international trade has led to an asymmetric consumption of resources worldwide. Assessing the level of equity with which environmental loads are distributed among countries is of capital importance for defining more efficient environmental regulations.

Gini coefficients [48, 49] are used to assess economic equity and, more recently, to evaluate environmental equity [50-52]. The interpretation of the Gini coefficients is as follows:

- An environmental Gini coefficient of 0 corresponds to perfect equity.
- An environmental Gini coefficient of 1 corresponds to a situation where all the environmental impact is generated by a single person in the world.

Under the assumption that there is an even distribution of consumption (or pollution) within the population of a country, global Gini coefficients assess the environmental equity among nations. That is, they quantify the level of equity with which environmental loads are generated worldwide. By combining EEIO models and Gini coefficients, we can therefore shed light on how anthropogenic impacts are generated and distributed worldwide.

1.2 Combining linear programming with macro-economic models

EEIO models have found a wide variety of applications. EEIO models provide information on how impacts are generated at the macro-scale level, but offer no guidelines on how to reduce them. Some authors used EEIO models to identify strategies for reducing certain impacts (*e.g.* global warming) by performing punctual changes in the economy of a region [53,54], or to study the effect of environmental policies and economic scenarios on global warming mitigation [55-57]. However, the aforementioned studies are based on "what if" analysis, that is, they explore the consequences of a set of scenarios defined beforehand. This restricts the analysis to a reduced number of alternatives, which may eventually result in suboptimal solutions.

A possible manner to enhance the capabilities of EEIO models consists of integrating them with systematic optimization tools. In particular, linear programming (LP) is well suited for minimizing the environmental impact of processes, and has been already coupled with input-output analyses for solving environmental problems [58]. Lin [59] solved a LP problem based on EEIO models to identify the lowest-emission alternative in a waste water treatment plant. San Cristóbal [60] proposed an environmental input-output LP model to meet the Kyoto's protocol GHG targets in the Spanish economy. Hristu-Varsakelis *et al*. [61] explored the sector-by-sector reallocation of production in Greece to optimize economic and environmental objectives. Hondo *et al.* [62] used an input-output model to find the housing insulation technologies that minimize households' CO_2 emissions in Japan. Kondo and Nakamura [63] developed an LP model based on input-output to search an optimal solid waste management and recycling strategy among a set of alternatives. Duchin and Lange [64] minimized the cost for choosing among alternative technologies into an 85-sector static input-output model of the U.S. economy. Oliveira and Antunes [65] performed the multi-objective optimization of economic, energy and environmental objectives using input-output models for Portugal. Cho [66] developed a multi-objective programming method based on input-output to maximize the economic growth and simultaneously minimize the environmental pollution and energy consumption.

The combination of EEIO models with multi-objective optimization allows identifying the economic sectors that should be firstly regulated in order to minimize the environmental impact while at the same time maximizing the total output. Note that the complex interactions between sectors make it difficult to identify at a first glance the sectors to be firstly regulated. For instance, sectors with small production-based emissions might consume intermediate goods and services from very polluting sectors, which masks the negative impacts caused by the former. In this context, EEIO models help to uncover these complex relationships, thereby identifying the ultimate source of impact. The problem of identifying economic sectors that contribute significantly to an impact (*e.g.* global warming) can be posed in mathematical terms as a bi-criteria linear program that seeks to optimize the economic and environmental performance (considering the whole life cycle) simultaneously.

Environmental and economic objectives are often competitive, so trade-offs will naturally exist between both objectives. The result of the multi-objective optimization is represented by a set of Pareto optimal points (for details on the definition of Pareto optimality see for instance Ehrgott [67]), each of them achieving a unique combination of economic output and environmental loads.

There are different methods available for solving multi-objective optimization; among them, the epsilon-constraint method, which consists of solving a series of single objective sub-problems, where one criterion is kept as main objective while the others are transferred to auxiliary constraints that impose limits on them [68]. Once the Pareto solutions have been calculated, it is possible to choose the most appropriate one by modulating policy-makers' goals and bearing always in mind the applicable legislation as well as the stakeholder's preferences.

Through a detailed sector-by-sector analysis, the multi-objective environmental and economic optimization of EEIO models pinpoints precisely which are the sectors leading to major environmental savings with the least economic impact. The identification of sectors whose regulation leads to major environmental savings at a marginal decrease in economic performance might help to establish effective environmental policies that make minor changes in consuming habits leading to significant environmental savings, without the need to perform drastic adjustments in the overall economic structure.

1.3 Multi-objective optimization and the willingness to pay for a given alternative

Multi-objective optimization provides as output a set of Pareto solutions representing the optimal compromise between the objectives considered in the analysis. Decision-makers must then choose the best alternative according to their preferences. Hence, a major goal in LCA studies is to identify, from a set of alternatives that could potentially lead to environmental improvements, the one to be finally implemented in practice. Different strategies are available for this, including traditional methods like rules of thumb or heuristics, and more sophisticated ones based on multi-criteria decision-making tools. This task is in general straightforward when one option under study scores better than the rest in all of the impact metrics simultaneously, but becomes difficult otherwise. We review in the next sections the main methods available to carry out this task.

Multi-criteria decision-making (MCDM) is a formal approach for solving problems in which several conflicting criteria must be accounted for [69]. This strategy works iteratively, and typically comprises four steps: problem structuring, evaluation of the alternatives' performance, elicitation of decision-makers' preferences, and problem resolution [70]. MCDM can be broadly divided into multi-objective decision making (MODM), and multi-attribute decision making (MADM) [71].

MODM analyses a search space restricted by constraints to identify the set of solutions representing the optimal compromise among the objectives considered in the analysis [72]. Recently, MODM has been used in the context of LCA studies for automating the search for alternatives leading to environmental savings [73].

In contrast, MADM is typically employed to select or evaluate a set of well-defined discrete alternatives in terms of a set of attributes. These methods can be used to assist practitioners in LCA studies, where several alternatives showing different performance in a set of impact metrics must be analyzed [74]. In turn, MCDA methods can be divided into two groups: utility or value-function based methods and outranking methods [75]. Several authors have applied outranking methods in environmental decision-making problems [76, 77], including LCA studies [71].

Aggregated environmental indicators represent another alternative to aid decision-making in LCA studies that consists of assigning weights to the impacts and sum them up to obtain a single environmental performance metric, which is finally used to rank alternatives. The use of weighting schemes in LCA requires quantifying and comparing the value of different environmental impacts (even when their units and scales differ), which represents a major challenge.

The weights used for aggregation are typically defined by a panel of experts or using some customized methods (*e.g.* distance-to-target or monetization). This approach facilitates the interpretation of a multi-dimensional system. Unfortunately, monetization and in general, the value-laden approaches of LCA, have been criticized due to the moral implications associated to giving monetary value to the environment and/or biasing the interests of decision-makers. Aggregation is also rather sensitive to the normalization and weighting scheme used.

A wide variety of weighting methods with different preference elicitation processes have been proposed in the literature. The Eco-indicator 95 [78] uses a weighted sum over three particular safeguard subjects. This aggregation step was criticized due to the subjectivity of the weighting and safeguard subjects. Particularly, Tietje *et al.* [79] emphasized the importance of taking into account the differences in the perception of risks influencing the quantification of impacts. The Eco-Indicator 98 emerged to improve its predecessor by emphasizing on a better definition of damage categories along with a management system of value choices based on cultural perspectives [80]. Particularly, Hofstetter [81] proposed to manage subjectivity by considering only three perspectives in societal decision-making: the individualist, egalitarian, and hierarchical. This consideration led to the Eco-indicator 99, an aggregated impact metric that follows this perspective approach. The use of perspectives leads to several versions of the methodology [82], and hence to different "best" alternatives depending on the one used.

The evidence that LCA results may be subjective is clearly exposed by different surveys [83,84], which showed that common LCA studies differ in the commercial software, LCA tools, characterization methods, impact assessment, and weighting schemes applied. Particularly, the authors identified up to six weighting methods that may lead to different practical results. The relative importance of several environmental impacts and their aggregation into category indicators has attracted significant interest in the LCA literature [85-87]. The general conclusion is that the outcomes of the LCA studies may be biased.

Bearing in mind the subjectivity of many LCA approaches, some authors have proposed methods to avoid value-lading on environmental criteria. Hofstetter [88] introduced a ternary diagram to graphically represent the areas in which, depending on the weighting combination, one solution behaves better than the rest. This methodology was later used in other studies that attempted to avoid the subjectivity implied in weighting [89-91]. The main drawback of this approach is that it restricts the analysis to three environmental indicators that are represented in a two dimensional plot. Furthermore, this analysis is somehow straightforward when a reduced number of solutions is considered, but may become cumbersome as the number of objectives and solutions increase.

In the next section we state the objectives of the thesis, which were defined bearing in mind the methods and tools available defined before.

1.4 Objectives

The main objective of this doctoral thesis is to study ways to reduce the environmental impact at a global scale by applying a toolkit of systematic tools. The particular objectives of this Thesis are:

- To understand how environmental impacts are generated globally considering both, production and consumption-based environmental effects.
- To assess the level of inequality with which the environmental loads are distributed among nations using objective metrics such as the Gini coefficient.
- To identify key economic sectors that should be regulated in Europe in order to reduce the environmental impact to the maximum extent possible while keeping the economic output as high as possible.
- To explore the advantages of systematic tools in the analysis of the environmental impact at a global scale. These tools include, EEIO models, hybrid models that integrated EEIO tables and multi-objective optimization, and LCA studies.

The remaining of this document is organized as follows. We first apply EEIO models to get insight into how environmental impacts are generated at a global scale and the level of equity with which these impacts are distributed among nations. A novel approach based on multi-objective optimization is next introduced to identify key European economic sectors whose regulation has the potential to enhance the environmental performance. This approach provides as output a set of Pareto alternatives, each achieving a unique combination of economic and environmental performance. From this set, policy makers should identify the best according to their preferences and applicable legislation. To facilitate this task, we propose in the following chapter an objective manner to translate preferences into monetary units.

1.5 Nomenclature

1.5.1 Abbreviations

EEIO	*Environmentally extended input-output*
EU	*European Union*
GHG	*Greenhouse gases*
LCA	*Life cycle assessment*
LP	*Linear programming*
MADM	*Multi-attribute decision-making*
MCDM	*Multi-criteria decision-making*
MODM	*Multi-objective decision-making*

2 ENVIRONMENTAL LOADS EMBODIED IN INTERNATIONAL TRADE AND ENVIRONMENTAL INEQUALITY FROM A MACRO-ECONOMIC PERSPECTIVE.

2.1 Introduction

Anthropogenic environmental impacts have increased drastically over the last decades, prompting governments to adopt emission-reduction policies in an attempt to meet stringent targets [92]. In today's globalized markets, designing these environmental policies is challenging because trade of goods and services creates international channels through which impacts are exported and imported between nations [1, 93-98]. These flows enable the degradation of regions located far away from the consumption point, making it difficult to identify the ultimate origin of the impact. Therefore, environmental policies focusing on production-based environmental accounts may fail to penalize those who benefit from the degradation, leading to unfair and inefficient outcomes. Only by adopting a global perspective, based on an analysis of international supply chains of goods and services, one can enforce a fair allocation of responsibility among the parties involved. Unfortunately, the effect of international trade on anthropogenic impacts is still poorly understood, which hampers the design of effective and fair environmental regulations.

In this chapter, we apply a holistic approach based on macro-economic input-output models [5] to quantify the extent to which countries contribute to the overall anthropogenic impact and the level of equity in such distribution of impacts. Multi-regional environmentally extended input-output (EEIO) data are used to assess more than 30 million economic transactions taking place between35 economic sectors of 40 countries (27 European countries and 13 other major nations representing more than 85% of the world gross domestic product for the period 1995-2009) on the basis of 69 environmental indicators related to air emissions and resources deployment. Details on the methodology of the approach followed and the underlying data are given in section 2.2.

Through this method, we assess the environmental footprints of international supply chains of goods/services related to air emissions, land occupation, and the consumption of energy, water and natural resources. This study uncovers the important effects of trade on the environment at all levels, therefore facilitating the design of more effective and fair environmental regulations across international supply chains. It is worth mentioning that this approach takes into consideration the environmental repercussions over all the stages in the life cycle of the goods/services being analyzed regardless of where they take place.

We start by analyzing the environmental impact of nations according to 69 environmental indicators following the so called production-based and consumption-based assessments, including their temporal evolution in the period 1995-2009. We discuss in more detail two energy indicators (*i.e.* consumption of solar energy, both thermal and photovoltaic, and consumption of nuclear energy). Both energy sources mitigate global warming, but the latter shows some significant negative impacts while the former does not. We assess the extent to which countries committed with greenhouse gas-reduction agreements are moving towards an energy system based on solar energy; and the extent to which the world's main economies are using solar and nuclear energy, considering both their national energy grids, and those of the countries from where they import goods and services.

We then assess the environmental loads embodied in international trade (quantified via 69 indicators) to determine whether a country is next exporter or importer of impact. We pay special attention to solar and nuclear energy, given their potential to reduce global warming. We finally use environmental Gini coefficients to study at a global scale the environmental equity with which the 69 environmental indicators are distributed worldwide (including their evolution in the last decades).

2.2 Method description

In this section we present a brief description of the EEIO models. For wider details please refer to other literature (*e.g.* Miller and Blair, [6]).

2.2.1 Economy of a single country: input-output analysis

We consider the economy of one country, which is separated into different economic sectors. We study the economic flows z_{ij} of products (goods or services) from sector *i* (producer) to sector *j* (consumer) expressed in monetary terms for a period of one year. Note that indices *i* and *j* run through all sectors. Hence, in a given year, sector *j*'s inputs from other sectors are partially given by the goods/services produced by the same sector *j* (in the same time period). In addition, there are other external (exogenous) buyers than industrial sectors (*e.g.* households, government and international final consumers). The goods demanded by external entities are final goods not used as inputs to other industrial processes. Hence, we refer to them as final demand.

Given an economy with *n* sectors, we denote by x_i the total output of sector *i*, and by y_i the total final demand for the product of sector *i*. Then, the total output of sector *i* is determined by Eq. (2.1).

$$x_i = z_{i1} + \ldots + z_{ij} + \ldots + z_{in} + y_i = \sum_{j=1}^{n} z_{ij} + y_i \tag{2.1}$$

Here, the z_{ij}'s represent the intermediate sales of sector *i* from all sectors *j* (including *j*=*i*). Eq. (2.1) represents the distribution of the output of sector *i*, which accounts for the sales of each of the *n* sectors, as shown in Eqs. (2.2).

$$\begin{aligned}
x_1 &= z_{11} + \ldots + z_{1j} + \ldots + z_{1n} + y_1 = \sum_{j=1}^{n} z_{1j} + y_1 \\
&\vdots \\
x_i &= z_{i1} + \ldots + z_{ij} + \ldots + z_{in} + y_i = \sum_{j=1}^{n} z_{ij} + y_i \\
&\vdots \\
x_n &= z_{n1} + \ldots + z_{nj} + \ldots + z_{nn} + y_n = \sum_{j=1}^{n} z_{nj} + y_n
\end{aligned} \tag{2.2}$$

Using capital letters for matrices and vectors; and lowercase letters for their elements, we can write the outputs, intermediate sales and final demands in matrix notation as shown in Eq. (2.3).

$$X = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}, Z = \begin{bmatrix} z_{11} & \cdots & z_{1n} \\ \vdots & \ddots & \vdots \\ z_{n1} & \cdots & z_{nn} \end{bmatrix}, and\, Y = \begin{bmatrix} y_i \\ \vdots \\ y_n \end{bmatrix} \quad (2.3)$$

Thus, Eqs. (2.2) can be rewritten in matrix notation as given in Eq. (2.4).

$$X = Z \cdot \hat{i} + Y \quad (2.4)$$

Where $\hat{i}$ is the "summation vector", a column vector of dimension *n* whose entries are all equal to one. Note that the post-multiplication of a matrix with $\hat{i}$ creates a column vector whose elements correspond to the summation of the columns of each row of the original matrix. Similarly, $\hat{i}'$ is a row vector of 1's (with consistent dimension). Hence, pre-multiplication of a matrix by $\hat{i}'$ creates a row vector whose elements are the summation of the rows of the original matrix.

A basic assumption in input-output models is to consider that the inter-sector flows from *i* to *j* depend entirely on the total output of sector *j*. In mathematical terms, this is expresses via Eq. (2.5).

$$a_{ij} = \frac{z_{ij}}{x_j}$$

(2.5)

Where a_{ij} is a technical coefficient, which is assumed to remain constant during a given time period. Let *A* be the matrix of technical coefficients, given as in Eq. (2.6).

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \quad (2.6)$$

These fixed technical coefficients allow setting direct relationships between sectors' inputs and outputs by rewriting Eq. (2.4) as Eq. (2.7).

$$X = A \cdot X + Y \quad (2.7)$$

Let I be the $n \times n$ identity matrix. Following standard matrix algebra operations, Eq. (2.7) could be expressed as Eq. (2.8), where $(I - A)^{-1}=L$ is known as the *Leontief inverse* matrix (1).

$$X = (I - A)^{-1} \cdot Y = L \cdot Y \quad (2.8)$$

2.2.2 Multi-regional economy input-output analysis

In a multi-regional input-output model, the number of matrices and their size increase rapidly. Although the methodology is similar, let us consider a p-region model (a model containing p regions), where each region (country) is divided into n sectors. The multi-regional Z matrix contains p^2 sub-matrices of $n \times n$ elements. We use superscripts to denote regions and subscripts to denote sectors. Based on this nomenclature, we define the sub-matrices $Z^{rr'}$, indicating the intermediate sales from r to r'. Each sub-matrix can be unfolded into an $n \times n$ matrix as in Eq. (2.3), hence, an element $z_{ij}^{rr'}$ corresponds to the sales from sector i of region r to sector j of region r'. The matrices of the diagonal correspond to intermediate sales within one region (economic transactions when $r=r'$), and the remaining matrices represent international trade (economic transactions between regions r and r', where $r \neq r'$). Then, the multi-regional matrix Z is as shown in Eq. (2.9).

$$Z = \begin{bmatrix} Z^{11} & \dots & Z^{1p} \\ \vdots & \ddots & \vdots \\ Z^{p1} & \dots & Z^{pp} \end{bmatrix} \tag{2.9}$$

And one sub-matrix unfolds as in Eq. (2.10)

$$Z^{rr'} = \begin{bmatrix} z_{11}^{rr'} & \dots & z_{1n}^{rr'} \\ \vdots & \ddots & \vdots \\ z_{n1}^{rr'} & \dots & z_{nn}^{rr'} \end{bmatrix} \tag{2.10}$$

The intermediate sales matrix *Z* and the matrix of technical coefficients *A* grows with the number of regions. Hence, matrix *A* contains p^2 sub-matrices (each one denoted as $A^{rr\prime}$) of n^2 elements (technical coefficients, denoted as $a_{ij}^{rr\prime}$), that unfold as in Eq. (2.11).

$$A = \begin{bmatrix} A^{11} & \dots & A^{1p} \\ \vdots & \ddots & \vdots \\ A^{p1} & \dots & A^{pp} \end{bmatrix} \tag{2.11}$$

Regarding the final demand, each region *r'* satisfies its final demand with local and/or imported products. Then, we denote as $Y^{r\prime}$ the column vector of *np* elements representing the amount of products that region *r'* demands for all of the regions and sectors. In greater detail, if we denote as $Y^{rr\prime}$ the column vector (of *n* elements) of products demanded from *r'* to *r*, the vector $Y^{r\prime}$ is the set of all $Y^{rr\prime}$ vectors stacked one on top of the other as given in Eq. (2.12).

$$Y^{r'} = \begin{bmatrix} Y^{1r'} \\ \vdots \\ Y^{rr'} \\ \vdots \\ Y^{pr'} \end{bmatrix} \tag{2.12}$$

Where each $Y^{rr'}$ unfolds into *n* elements of type $y_i^{rr'}$ as in Eq. (2.13).

$$Y^{rr'} = \begin{bmatrix} y_1^{rr'} \\ \vdots \\ y_i^{rr'} \\ \vdots \\ y_n^{rr'} \end{bmatrix} \tag{2.13}$$

We consider as many demands as regions. Hence, we define matrix Y_mr in Eq. (2.14) as the multi-regional matrix of demands, which is composed by *p* column vectors ($Y^{r'}$) each one corresponding to a different region, (with each column vector containing *np* elements).

$$Y\_mr = \begin{bmatrix} y_1^{11} & & y_1^{1r'} & & y_1^{1p} \\ \vdots & & \vdots & & \vdots \\ y_i^{r1} & \cdots & y_i^{rr'} & \cdots & y_i^{rp} \\ \vdots & & \vdots & & \vdots \\ y_n^{p1} & & y_n^{pr'} & & y_n^{pp} \end{bmatrix} \tag{2.14}$$

From the multi-regional matrix of demands, we determine the world's demand to each region and sector (denoted as $\hat{Y}$). This is done by multiplying Y_mr with the summation vector as shown in Eq. (2.15).

$$\hat{Y} = Y\_mr \cdot \hat{i} \tag{2.15}$$

Where $\hat{Y}$ is the column vector of *np* elements of type $\hat{y}_i^r$, as shown in Eq. (2.16).

$$\hat{Y} = \begin{bmatrix} \hat{y}_1^1 \\ \vdots \\ \hat{y}_i^r \\ \vdots \\ \hat{y}_n^p \end{bmatrix} \tag{2.16}$$

Similarly, in the multi-regional model, the total output *X* takes the form of a column vector of *np* elements. Matrix *X* contains a set of vectors denoting the regional outputs (X^r), which are stacked one on to another as shown in Eq. (2.17). Each regional output vector contains *n* elements of type x_i^r. It is important to highlight that Eq. (2.8) is still valid for multi-regional models.

$$X = \begin{bmatrix} X^1 \\ \vdots \\ X^r \\ \vdots \\ X^p \end{bmatrix} \tag{2.17}$$

2.2.3 Consumption-based and production-based environmental assessment

We used the world input-output database (WIOD) [99] to construct 15 multi-regional Leontief inverse matrices for each year during the period 1995-2009. We obtained the yearly total output of all world's regions and sectors (*X*) through Eq. (2.8), by using the multi-regional matrix *A*, and replacing *Y* by the world's demand $\hat{Y}$.

We first determine the production-based and consumption-based environmental loads of each region. For both approaches, we require a vector of "*pollution intensity*" indicating the amount of pollution (or environmental load) per monetary unit (for every region and sector). The information available in the WIOD allows retrieving the world's pollution intensity vectors for 69 different environmental indicators for a 15-years period.

First, let us define as PI^k the pollution intensity of indicator k (*e.g.* CO_2, land use, etc.). The PI^k vector contains *np* elements and consists of a set of sub-vectors $PI^{r\,k}$ representing the pollution intensity of each region *r*. Each of such vectors contains *n* elements denoted by $pi_i^{r\,k}$ (one for each sector). Then, the pollution intensity is mathematically defined as in Eq. (2.18).

$$PI^k = \begin{bmatrix} PI^{1k} & \dots & PI^{r\,k} & \dots & PI^{p\,k} \end{bmatrix} \quad (2.18)$$

From the X and PI^k vectors for the period 1995-2009, we calculate the world's production-based environmental loads for each indicator (Imp_P^k) by using Eq. (2.19).

$$Imp\_P^k = PI^k \cdot X \quad (2.19)$$

Note that, as shown in Eqs. (2.17) and (2.18), both X and PI^k contain smaller vectors corresponding to each region. Then, the production-based impact of type k in region r ($Imp\_P^{r\,k}$) is defined as in Eq. (2.20).

$$Imp\_P^{r\,k} = PI^{r\,k} \cdot X^r \quad (2.20)$$

In the consumption-based approach, we calculate the impact associated to the international transactions that are required to satisfy the final demand of a given region. In other words, the consumption-based impact in category k (Imp_C^k) is the life cycle impact of the goods/services demanded by a given region (the LCA of $Y^{r'}$). Hence, by using the multi-regional matrix A, and replacing Y by $Y^{r'}$ in Eq. (2.8), we calculate the output of all countries and sectors necessary to satisfy the demand of region r' ($X^{*r'}$, a column vector of *np* elements). Therefore, we assume that the world's economy has as unique goal to cover the demand of a given country. Then, the consumption-based impact in category *k* of region *r'* is given by Eq. (2.21).

$$Imp\_C^{r\,k} = PI^{k} \cdot X^{*r'} \tag{2.21}$$

2.2.4 Assessment of the trade-embodied environmental loads

Through both environmental accounting approaches, we study the environmental impact of 40 regions over a 15-years period in 69 different impact indicators. In addition to the national impacts, we are interested in the trade of environmental loads between regions. The environmental loads traded from *r* to *r'* are embodied in intermediate sales and sales that satisfy the final demand. The intermediate sales from *r* to *r'* are given by the "sub-matrix" shown in Eq. (2.10), and the final demand of *r'* is given in (2.13). Hence, the total environmental load in category *k* exported from *r* to *r'* ($Imp^{rr'k}$) is given in Eq. (2.22).

$$Imp^{rr'k} = PI^{r\,k} \cdot \left(Z^{rr'} \cdot \hat{i} \right) + PI^{r\,k} \cdot Y^{rr'} \tag{2.22}$$

There are p^2 $Imp^{rr'k}$ elements (for all of the possible transactions between regions). We denote by IMP^{k} a matrix of p^2 elements that groups all the $Imp^{rr'k}$ elements, as shown in (2.23).

$$IMP^{k} = \begin{bmatrix} Imp^{11k} & \cdots & Imp^{1p\,k} \\ \vdots & \ddots & \vdots \\ Imp^{p1k} & \cdots & Imp^{pp\,k} \end{bmatrix} \tag{2.23}$$

Then, IMP^{k} is a square matrix that represents the total impact (or environmental loads) associated to the economic transactions from region *r* to region *r'*. The diagonal of this matrix (*r*=*r'*) represents the national sales/purchases, whereas the remaining elements of the matrix ($r \neq r'$) are associated with international trade. On this basis, let Imp_N^k be the environmental loads (of type k) associated to products that are consumed in the country of origin (impact that is not internationally traded). Note that Imp_N^k is the total summation of the main diagonal of matrix IMP^k , as shown in Eq. (2.24).

$$Imp\_N^k = \sum_{r=1}^{p}\sum_{r'=1}^{p} Imp^{rr'} \quad \forall r \neq r' \tag{2.24}$$

The impact in category k embodied in trade (Imp_T^k) is given in Eq. (2.25) by the difference between the total impact k and the impact that is not internationally traded.

$$Imp\_T^k = \hat{i}' \cdot \left(IMP^k \cdot \hat{i} \right) - Imp\_N^k \tag{2.25}$$

Another of our interests is to determine whether a region is a net importer or net exporter of impact. From the Imp^k matrix, we can determine the total exports and total imports of each region. Recall that in this matrix the rows represent sales from r to all r' (including $r=r'$) and columns represent purchases from r' to all r. Then, the total impact in category k exported by each region, denoted by EX^k as shown in Eq. (2.26), is represented by a column vector of p elements of type $ex^{r\,k}$. Each of the elements of this vector denotes the total impact in a different category k exported by region r.

$$EX^k = Imp^k \cdot \hat{i} \tag{2.26}$$

Similarly, the total impact in category k due to imports is given in Eq. (2.27). IM^k is a vector (row) of p elements of type $im^{r\,k}$, where each element is the total impact in category k imported by region r.

$$IM^k = \hat{i} \cdot Imp^k \tag{2.27}$$

To calculate the "net" imports/exports, we exclude the sales/purchases within the region being assessed (those transactions for which $r=r'$). Hence, the net imports and exports of impact k are given by the difference between EX^k and the transpose of IM^k (denoted by $IM^{k\prime}$) as shown in Eq. (2.28).

$$NET^k = EX^k - IM^{k}\,' \tag{2.28}$$

NET^k is a column vector, in which each element represents the net imported/exported impact k in region r. Since in Eq. (2.28) we place the sales in the minuend, one region r is net-exporter of impact k when $net^{r\,k} > 0$; conversely it is net-importer when $net^{r\,k} < 0$. Each element of the vector NET^k represents the net imports/exports, expressed as a percentage of the total world consumption for each impact as follows:

$$\%net^{r\,k} = \frac{net^{r\,k}}{\hat{i}\,'\cdot\left(IMP^k \cdot \hat{i}\right)} \tag{2.29}$$

The calculations mentioned above were repeated for each year in the period 1995-2009, so as to study the temporal evolution of the trade-embodied impacts over time.

2.2.5 Measuring environmental equity through environmental Gini coefficients

In addition to determining the production-based and consumption-based impacts and compare them, we assess the equity with which these impacts are distributed internationally. We calculated (for both, consumption and production-based approaches) environmental Gini coefficients based on the Lorenz curve following a similar procedure to that employed in the calculation of economic Gini coefficients.

To this end, for each region we calculate the percentage of impact k with respect to the total impact k as given in Eq. (2.30) and Eq. (2.31).

$$\%Imp\_P^{r\,k} = \frac{Imp\_P^{r\,k}}{\hat{i}\,'\cdot\left(IMP^{k}\cdot\hat{i}\right)} \tag{2.30}$$

$$\%Imp\_C^{r\,k} = \frac{Imp\_C^{r\,k}}{\hat{i}\,'\cdot\left(IMP^{k}\cdot\hat{i}\right)} \tag{2.31}$$

Let us now denote by *Population* a column vector of *p* elements, in which each element $Population_r$ corresponds to the population of region *r*. This information is available in public databases like the developed by the World Bank [100]. The percentage of the population that belongs to each region *r* is obtained as in Eq. (2.32).

$$\%Population_r = \frac{Population_r}{\hat{i}\,'\cdot Population} \tag{2.32}$$

The ratio between the percentage of impact *k* in region *r* ($ratio^{r\,k}$) and its corresponding population is calculated as shown in Eq. (2.33)

$$ratio^{r\,k} = \frac{\%Imp\_P^{r\,k}}{\%Population_r} \quad or \quad \frac{\%Imp\_C^{r\,k}}{\%Population_r} \tag{2.33}$$

We obtain next the Lorenz curve for each impact, where the vertical axis shows the cumulative percentage of impact, while the horizontal one depicts the cumulative percentage of population. The Lorenz curve provides the impact distribution among the parties involved. The diagonal of the plot represents a scenario of perfect equality, in which all the regions show the same per capita impact (see Figure 2.1).

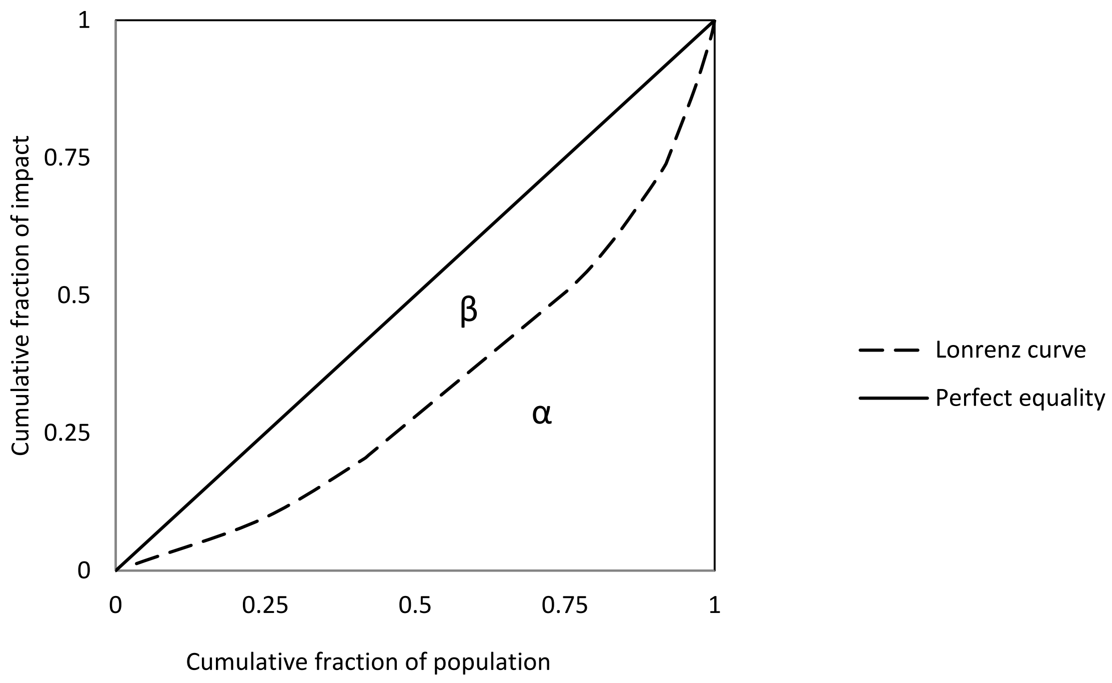


Figure 2.1:. Illustrative example of a Lorenz curve.

Gini coefficients associated with each impact *k* ($Gini^k$) are determined as the ratio between the area below the Lorenz curve and the area below the perfect-equality line. The area below the Lorenz curve (α) is obtained by numeric integration, while the area below the perfect equality line ($\alpha + \beta$) is ½ (since it forms a triangle with two edges of magnitude 1). Hence, the $Gini^k$ is calculated as given in Eq. (2.34).

$$Gini^k = \frac{\alpha}{\alpha + \beta} \tag{2.34}$$

We calculated (for both, consumption and production-based approaches) 69 Gini coefficients (one per indicator), and studied their temporal evolution in the last 15 years.

2.3 Results

2.3.1 Consumption-based and production-based assessment of the 69 environmental indicators of the world input-output database

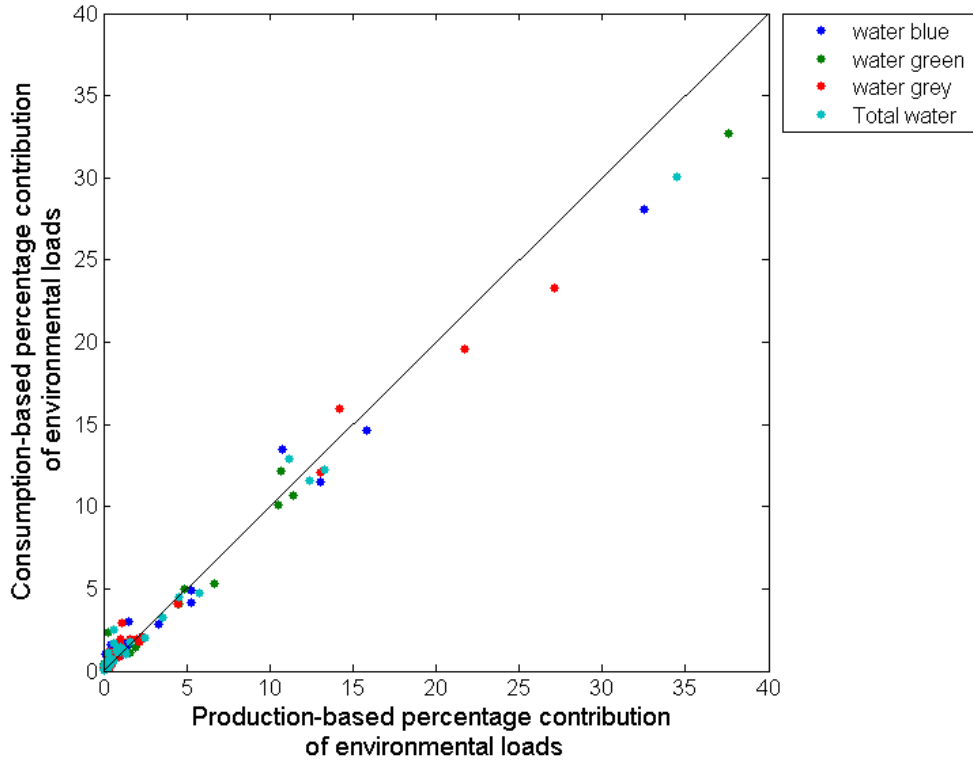
We use Eqs. (2.20) and (2.21) to study the production/consumption-based impact pattern for 40 countries in an international trade network in order shed light on how anthropogenic impacts are globally generated. The environmental performance is quantified via 69 environmental indicators grouped in five families: emissions to air, land occupation, water usage, materials consumption and energy consumption (for details on these indicators, please refer to the WIOD [99]).

Figure 2.2 compares the production-based and consumption-based approaches. The figure contains 5 scatter plots (one for each of the five aforementioned groups of impacts), in which the 15-years average values of the 69 environmental indicators obtained following each of the aforementioned approaches (*i.e.* production-based and consumption-based) are shown. Values under the diagonal line score higher environmental loads from a production based-assessment than from the consumption-based one (and vice versa). The figure allows determining for each country the main source of impact, and particularly whether the environmental pressures are generated locally or imported from foreign countries. Each of the series in Figure 2.2 represents an environmental indicator, and each of the points denotes the environmental performance of a country (from both approaches) in a given indicator.

The contribution of each country to the global environmental pressure differs according to the accounting approach used (*i.e.* production or consumption). The differences between the approaches are highly dependent on the environmental indicator being evaluated. Among the indicators with the greatest differences, we find some fossil resources (*i.e.* gas, oil and coal), and the consumption of metallic minerals. In contrast, other indicators such as diesel, gasoline, and bio-gasoline show very little differences between the two assessments. From this analysis we also found that some countries (*e.g.* China or Russia) export a large amount of impact via trade, while the impact associated with local consumption of goods is much smaller. The opposite situation occurs in countries like USA, where the consumption-based environmental loads are generally higher than the production-based ones in most of the environmental indicators.

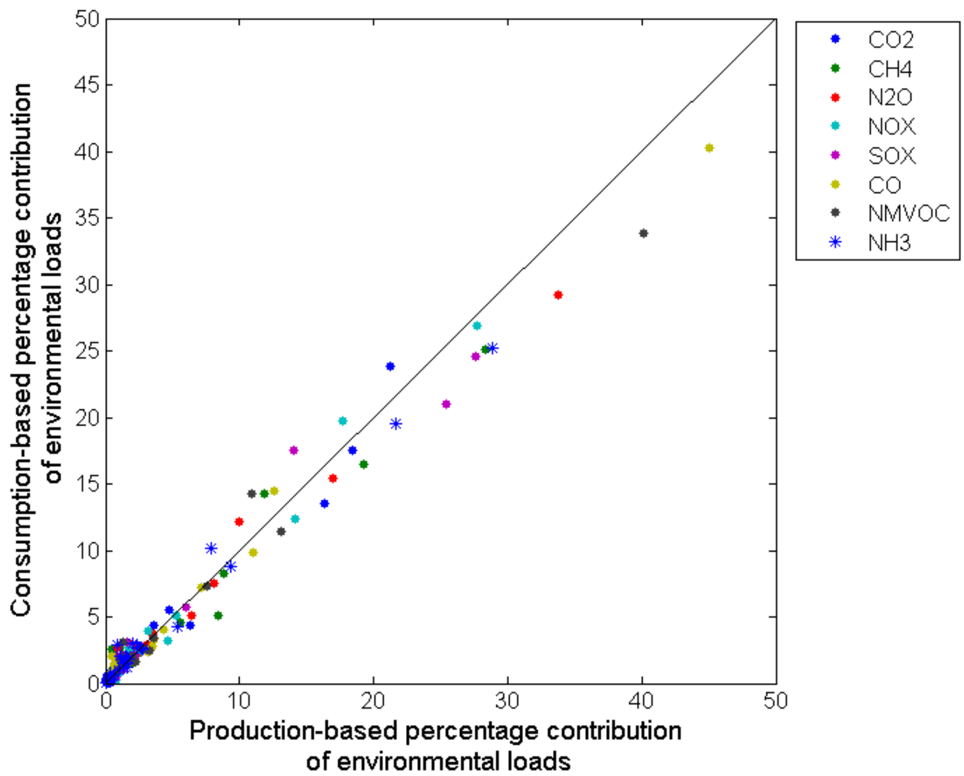
Note that some environmental indicators represent local impacts, while others reflect global impacts. By externalizing some local impacts that ultimately will cause desertification, acidification, etc., the demanding countries may deteriorate significantly those countries from where they import goods/services. Note that in the case of global impacts (*e.g.* global warming potential), the damage caused is suffered by both the country that imports goods and the one that exports them. Note also that, in general, international trade may increase the global impact due to the transportation activities required to deliver the goods.

a)



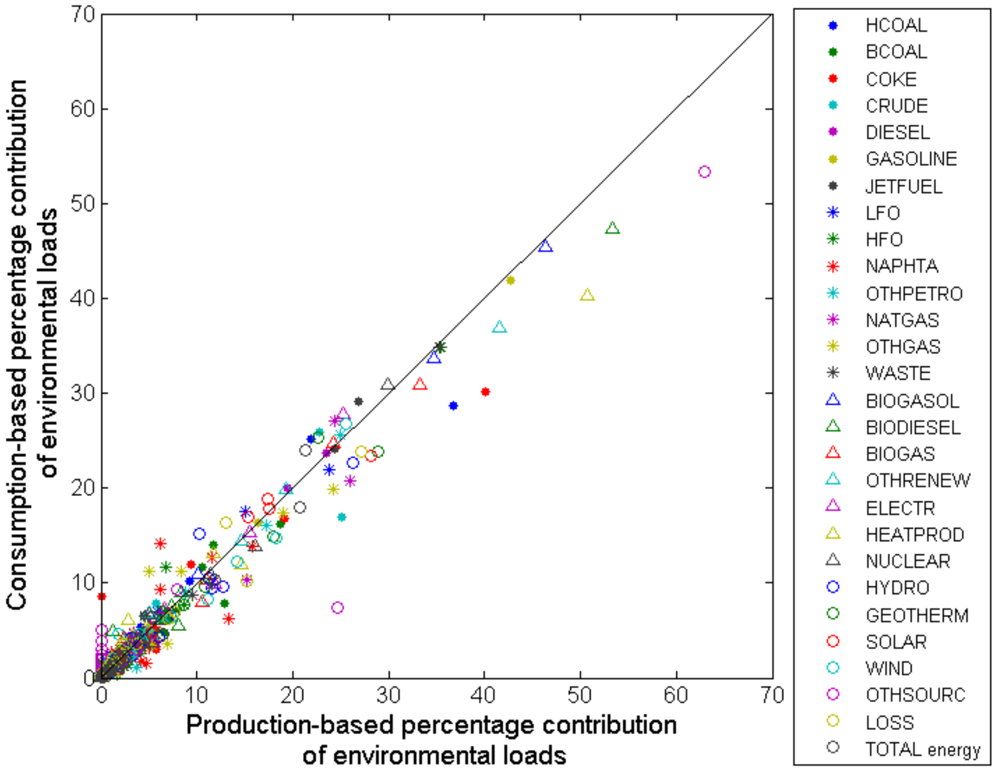
40
35
30
25
20
15
10
5
0
0
5
10
15
20
25
30
35
40
Consumption-based percentage contribution of environmental loads
Production-based percentage contribution of environmental loads
water blue
water green
water grey
Total water

b)

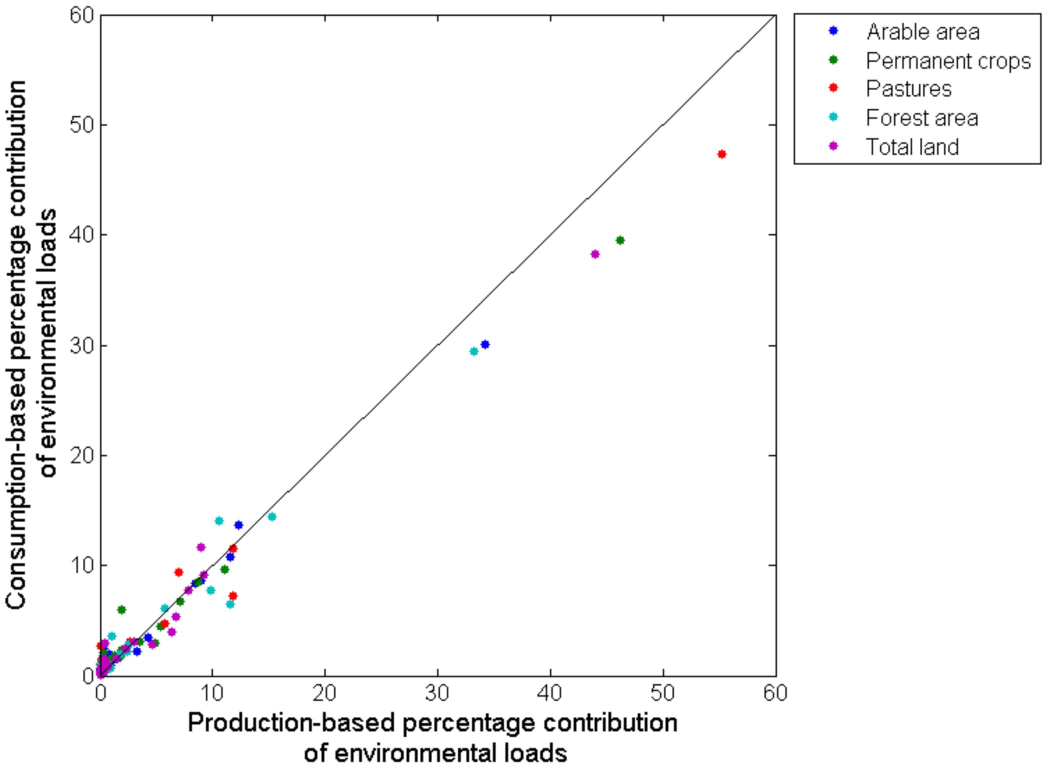


50
45
40
35
30
25
20
15
10
5
0
0
10
20
30
40
50
Consumption-based percentage contribution of environmental loads
Production-based percentage contribution of environmental loads
CO2
CH4
N2O
NOX
SOX
CO
NMVOC
NH3

c)


Consumption-based percentage contribution of environmental loads
Production-based percentage contribution of environmental loads
0
10
20
30
40
50
60
70
HCOAL
BCOAL
COKE
CRUDE
DIESEL
GASOLINE
JETFUEL
LFO
HFO
NAPHTA
OTHPETRO
NATGAS
OTHGAS
WASTE
BIOGASOL
BIODIESEL
BIOGAS
OTHRENEW
ELECTR
HEATPROD
NUCLEAR
HYDRO
GEOTHERM
SOLAR
WIND
OTHSOURC
LOSS
TOTAL energy

d)


Consumption-based percentage contribution of environmental loads
Production-based percentage contribution of environmental loads
0
10
20
30
40
50
60
Arable area
Permanent crops
Pastures
Forest area
Total land

e)

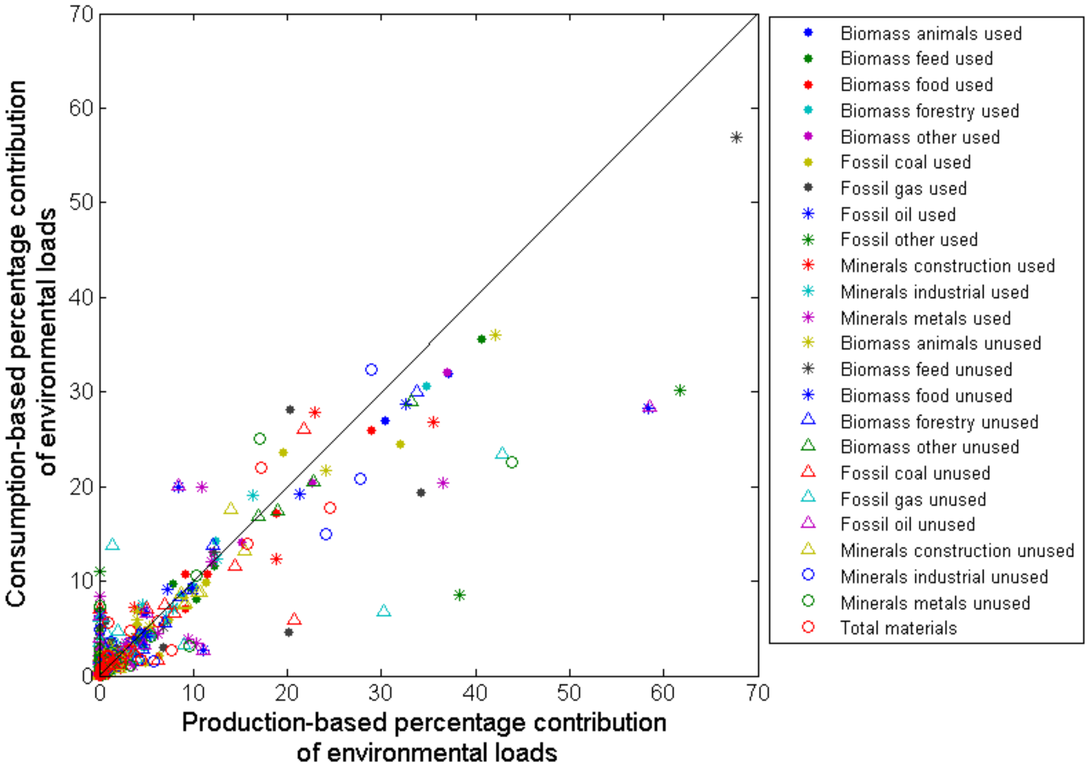


Figure 2.2: Scatter plots contrasting the production-based and consumption-based assessments in 69 environmental indicators that are grouped in 5 families: water use (Figure 2.2a), emissions to air (Figure 2.2b), energy use (Figure 2.2c), land occupation (Figure 2.2d), and use of materials (Figure 2.2e). The horizontal axis represents the production-based percentage contribution of a given environmental load (with respect to the world's total environmental load), while the vertical axis represents its consumption-based percentage contribution. Each figure contains a set of series representing an environmental indicator, and each point represents the environmental performance of a country assessed from the two approaches. Countries scoring the same environmental loads from the two approaches lie in the diagonal line.

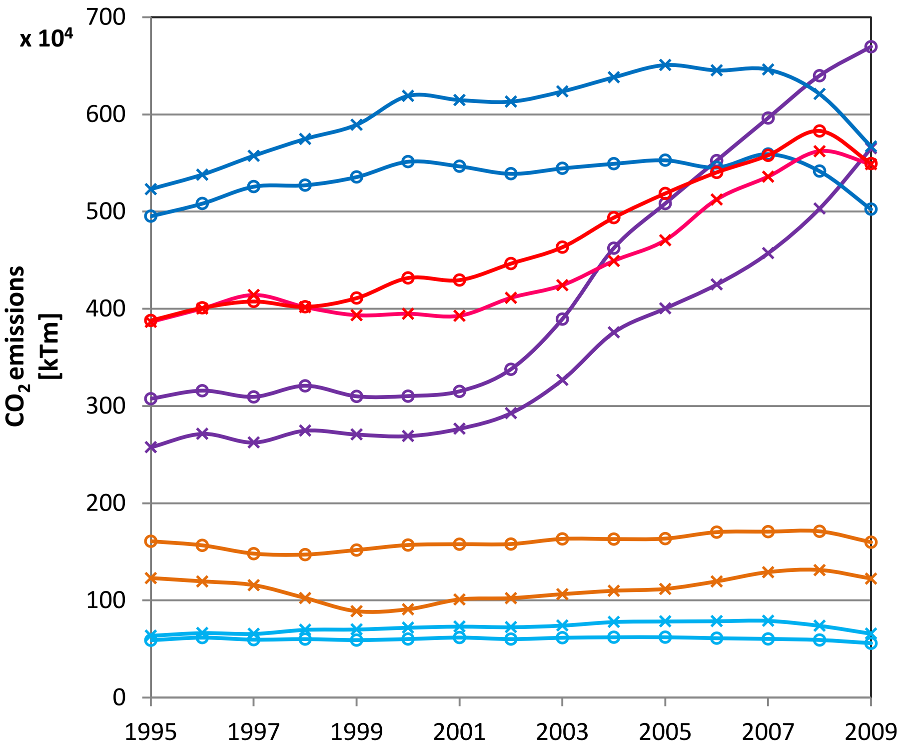
We studied next the evolution of the environmental pressure from 1995 to 2009 for a set of 40 representative countries. To summarize the results, we focus on five of the indicators: the CO_2 emissions, total energy expenditure, total use of water, total land occupation and total consumption of materials.

Figure 2.3 shows the temporal curves of the countries with the highest differences between the two approaches. We adopt the three-letter country codes defined in the ISO 3166 [101] to refer to the countries. We observe that USA shows significant differences in the 5 indicators, with the consumption-based approach yielding larger impacts. Germany, Great Britain, and Japan lead also to larger impacts in the consumption-based approach. In the remaining countries, (and the rest of the world, RoW) the production-based curves lie always above the consumption-based ones, indicating that part of their production is sent to external consumers.

In Figure 2.3a, for example, USA (from the production-based viewpoint) reduced its CO_2 emissions, keeping them almost constant after 2000. However, from a consumption-based viewpoint, the CO_2 emissions increased during that period. Remarkably, the CO_2 emissions of China and RoW have recently increased drastically, which might be due to the displacement of the manufacturing tasks of USA to emerging economies.

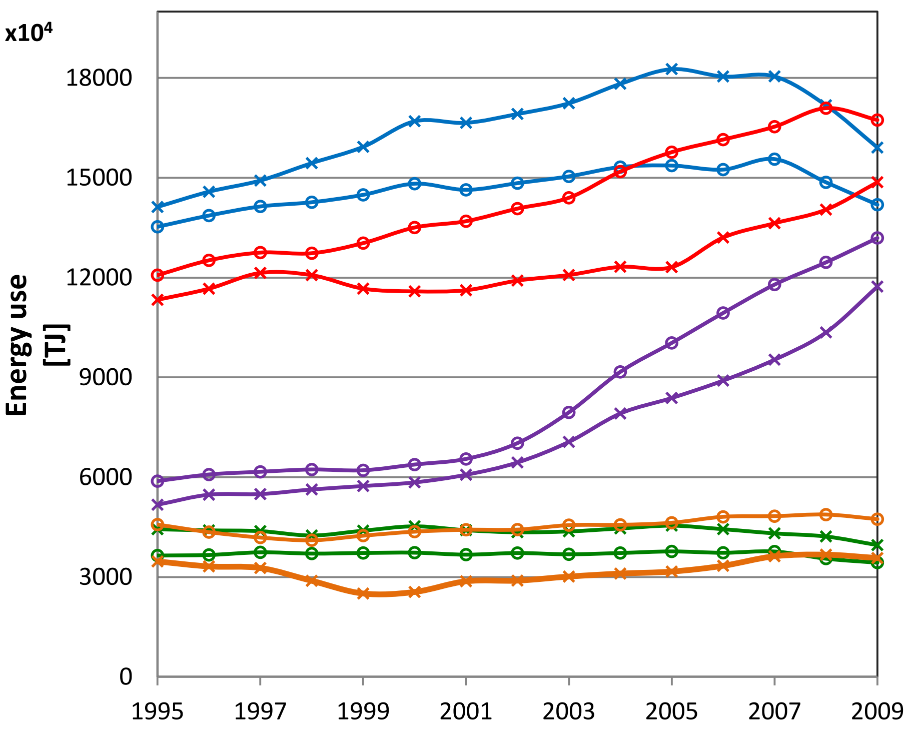
In the next sections of this chapter we focus our attention on the use of nuclear and solar energy in some of the wealthiest economies in the period 1995-2009.

a)



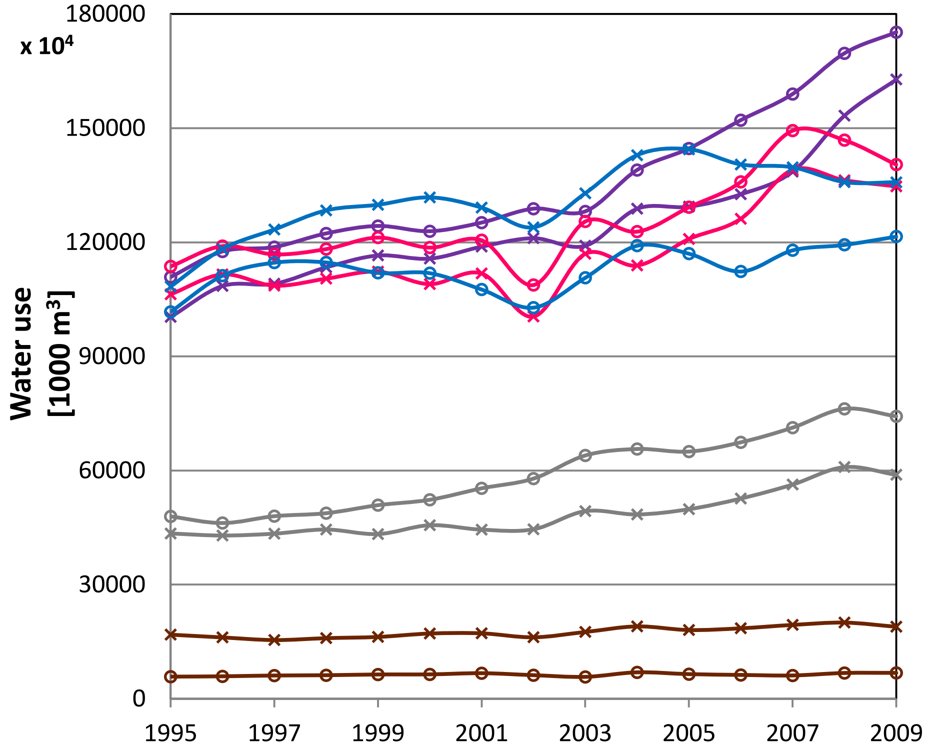
x 10^4
700
600
500
400
300
200
100
0
CO2 emissions [kTm]
1995
1997
1999
2001
2003
2005
2007
2009

b)



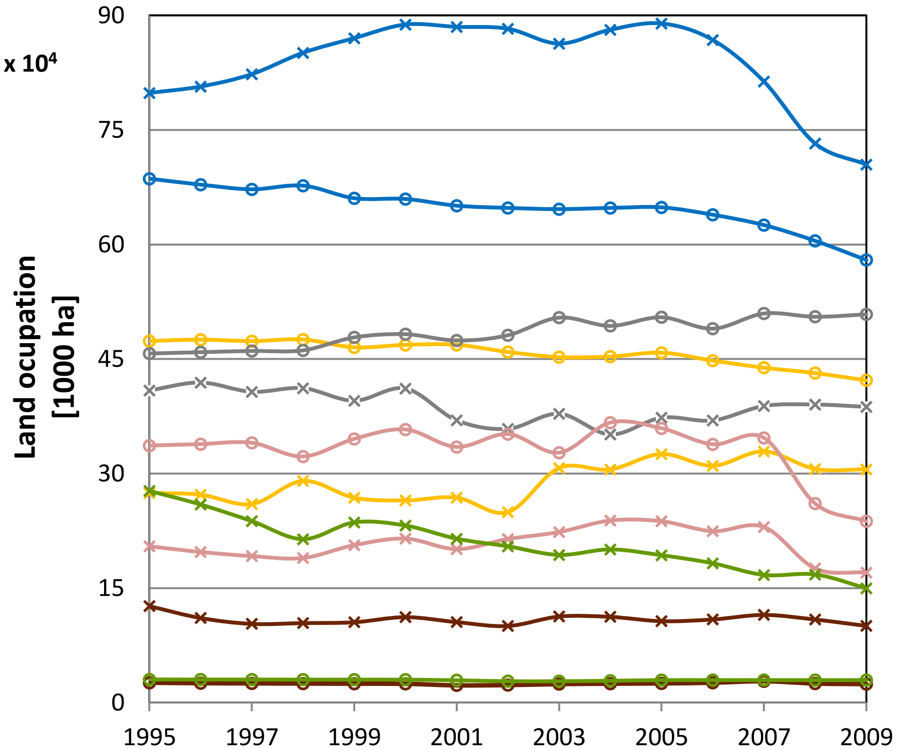
x10^4
18000
15000
12000
9000
6000
3000
0
Energy use [TJ]
1995
1997
1999
2001
2003
2005
2007
2009

c)



x 10^4
Water use [1000 m³]
180000
150000
120000
90000
60000
30000
0
1995
1997
1999
2001
2003
2005
2007
2009

d)



x 10^4
Land ocupation [1000 ha]
90
75
60
45
30
15
0
1995
1997
1999
2001
2003
2005
2007
2009

e)

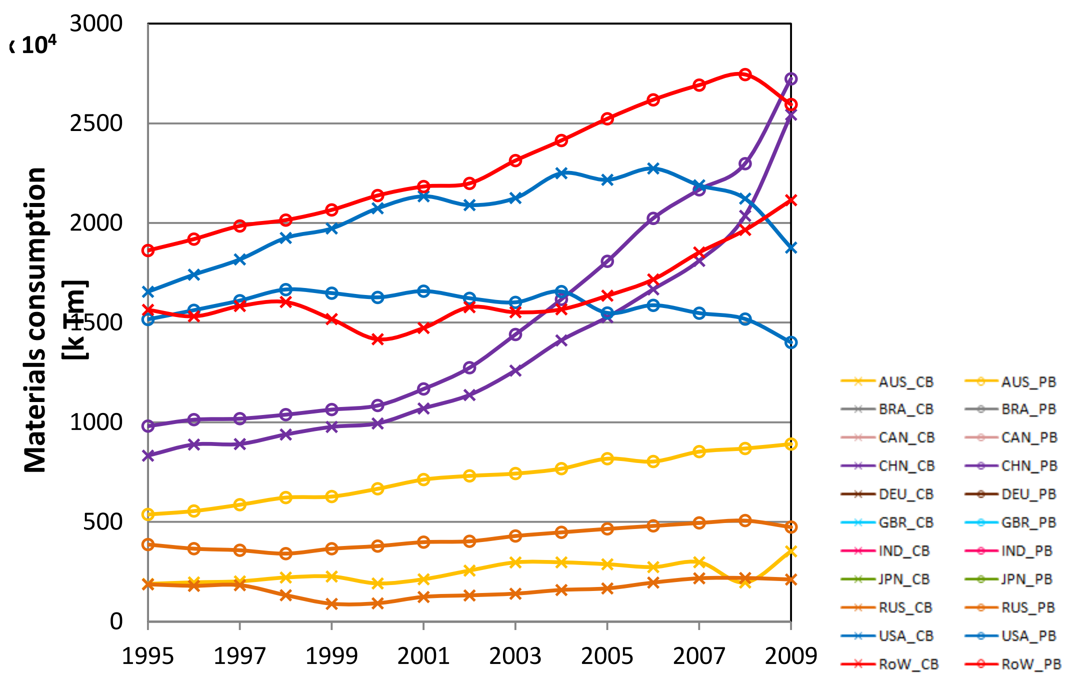


Figure 2.3: Time evolution of the CO_2 emissions (Figure 2.3a), total energy use (Figure 2.3b), total water use (Figure 2.3c), total land occupation (Figure 2.3d) and total materials consumption (Figure 2.3e); assessed from the two viewpoints, in the period 1999-2005. The countries are differentiated by the colors of the lines. The consumption-based lines are marked with crosses and the production based ones are marked with circles.

2.3.1.1 Consumption-based vs. production-based assessment in nuclear energy

Global warming has recently become a world priority, and strong efforts are being undertaken to mitigate it. In this context, we need to be aware that alternative technologies that reduce the impact in global warming might increase other negative effects. Many environmental studies of energy systems have restricted the analysis to combustion-related emissions [102], thereby ignoring the negative effects in other categories. This is the case, for instance, of nuclear energy, which shows a good performance in terms of global warming but negative impacts in other categories such as ionizing radiations. In this section of the thesis, we will analyze the role of nuclear energy from the production and consumption based perspectives.

Nuclear energy production differs from one country to another. In addition, local and imported products are manufactured with different energy portfolios, which might include nuclear power. Moreover, each country has different energy intensity (and, in turn, different environmental performance). Production-based assessments of nuclear energy use could be questionable, since a country might indirectly consume nuclear power embodied in the life cycle of the goods and services demanded from other countries. Countries consuming nuclear power from foreign sources via trade are externalizing the environmental impacts of this energy source.

In this section we focus our attention on the top 10 producers of nuclear energy (*i.e.* those countries with the highest nuclear power production on average in the period 1995-2009). In Figure 2.4 we compare, for the top 10 producers, the average nuclear power assessed from the production-based and consumption-based approaches. Results indicate that the amount of nuclear energy produced changes considerably between countries, being United States by far the largest nuclear power producer (and consumer), followed by France and Japan. However, there are no significant differences between the production-based and consumption-based assessments in the top 10 nuclear energy producers, and there is no generalized trend in the differences between the approaches. That is, in countries like Spain, Great Britain and USA, the consumption-based nuclear energy is greater than that assessed with the production-based approach; while in the remaining countries the opposite situation occurs. In addition, we observe evident differences between the assessment approaches (in absolute values) in France, Russia and USA.

Figure 2.5 compares the per-capita energy use from the production-based and consumption-based assessments. The first thing that comes out into evidence is that, in the per-capita assessment, the differences between countries are not as marked as in the overall values (in Figure 2.4). This is because each country’s nuclear energy production (or consumption) is “normalized” by its own population. In Figure 2.5a, there are two countries that significantly differ from the others: Sweden and France. Sweden shows the highest per-capita nuclear energy use, followed by France. Regarding the differences between the assessment approaches (Figure 2.5b), the highest differences are observed in Sweden and France, which are between 10 MJ/inhabitant-year. This means that conducting production-based assessments would misallocate up to such amount of energy, per country and year.

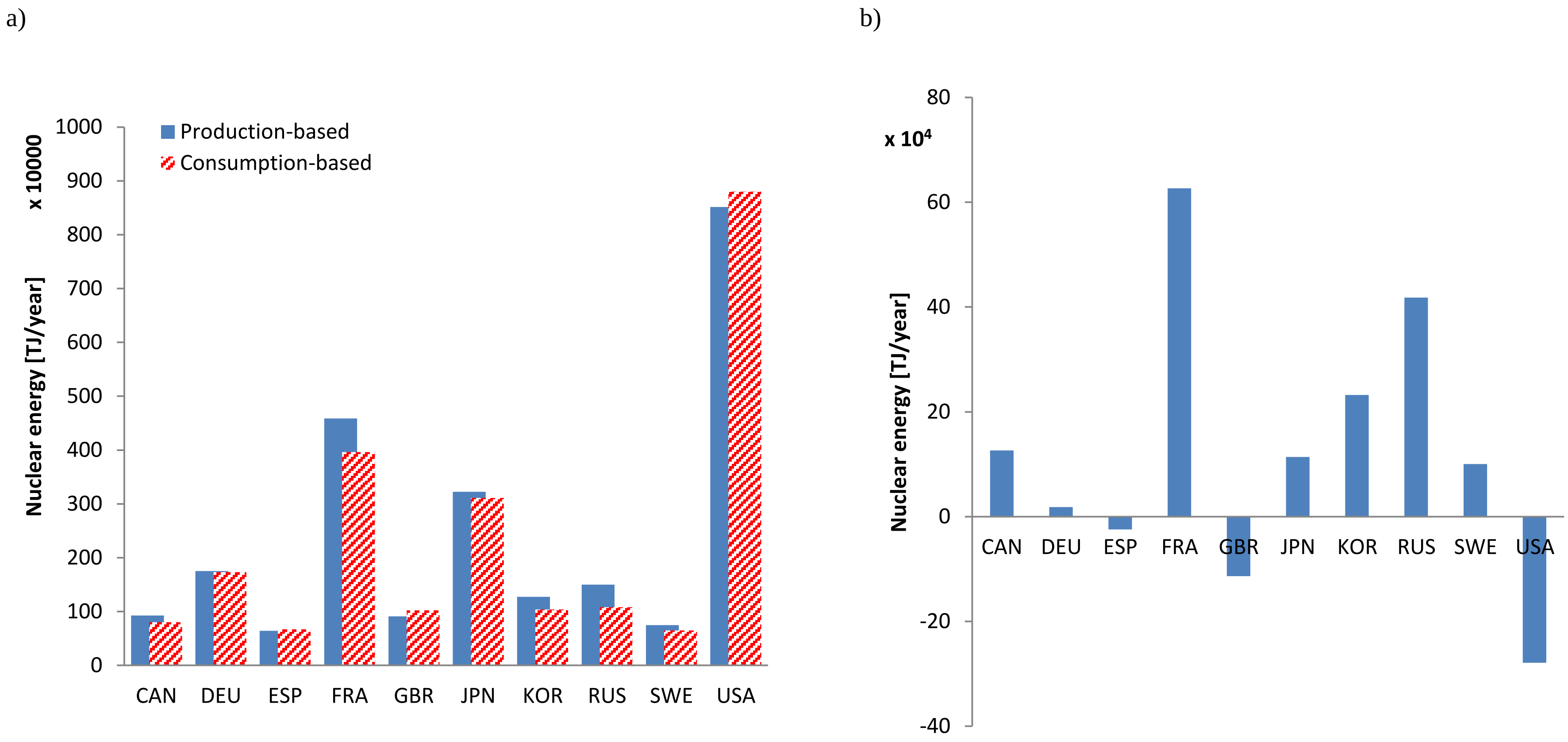


Figure 2.4: Comparison of the nuclear energy share of the top 10 nuclear energy producers following two different approaches: consumption-based and production-based. Figure 2.4a shows the average of nuclear energy estimated from each approach, in period 1995-2009; while Figure 2.4b shows the difference between production-based and consumption-based nuclear energy in average, in the same period.

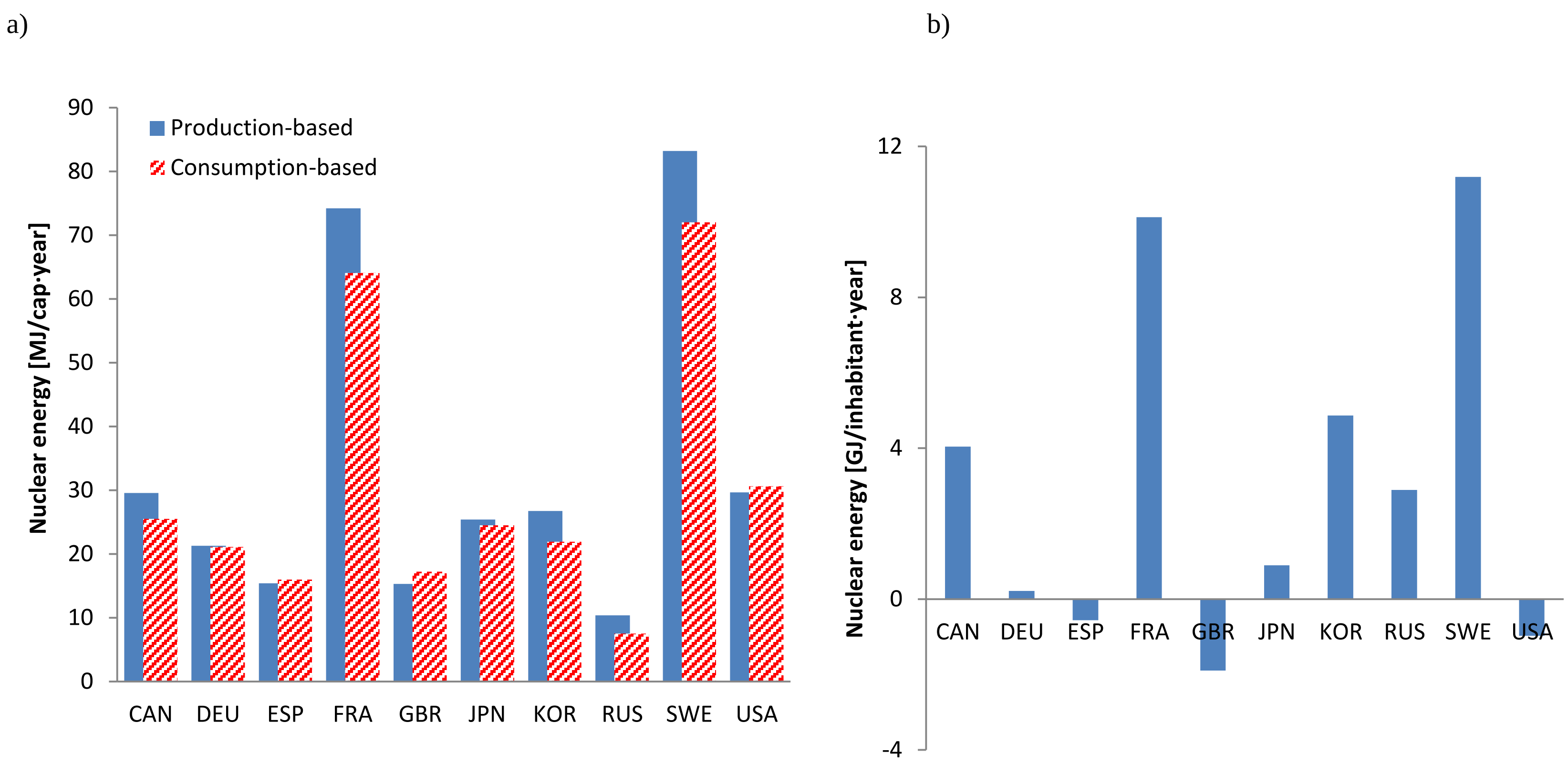


Figure 2.5: Comparison of the per-capita nuclear energy share of the top 10 nuclear energy producers following two different approaches: consumption-based and production-based. Figure 2.5a shows the average of nuclear energy estimated from each approach, in period 1995-2009; while Figure 2.5b shows the per-capita difference between production-based and consumption-based nuclear energy in average, in the same period.

Figure 2.6 shows the top 10 countries with the greatest differences (in absolute values) between the production-based and consumption-based nuclear power.

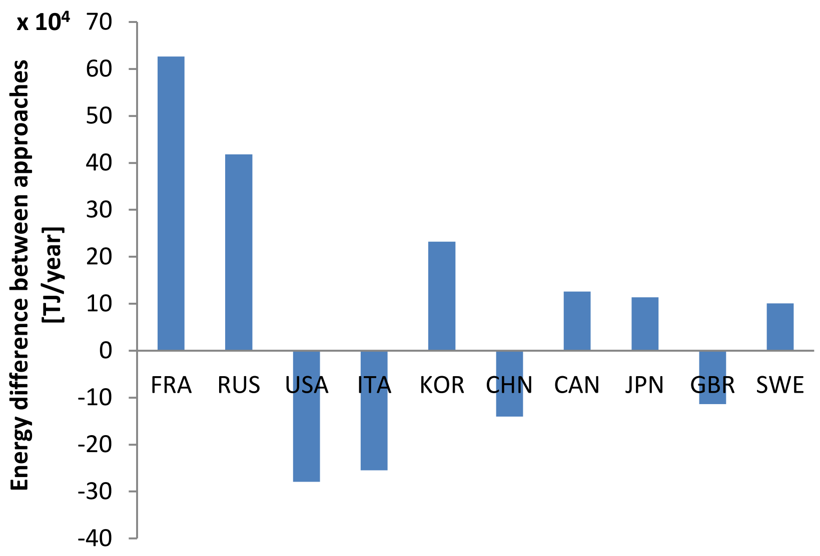


Figure 2.6: Average yearly difference between production-based and consumption-based nuclear energy in the 10 countries with the greatest difference (1995-2009).

Figure 2.6 shows that 6 out of the 10 countries produce more nuclear power than the amount consumed, which implies that part of it is intended to meet the demand from other countries. We find that France, the second worldwide producer of nuclear power, has the highest positive difference between production and consumption-based nuclear energy. In contrast, United States is by far the largest nuclear power producer at a global scale and also the country with the highest negative difference. Furthermore, the case of Italy is interesting since it does not produce nuclear power within its national territory, but consumes large amount of nuclear energy via trade, finally being among the countries with major differences between the two different approaches. We should note that a positive difference between production based and consumption based energy use does not imply, in general, that a country is a net exporter of such type of energy (the concept of net importers and net exporters will be explained later, in the international trade section, 2.3.2).

Figure 2.7 shows the per-capita differences between both approaches for the aforementioned countries. Luxembourg has the highest per-capita (negative) difference between the approaches. In other words, every year, every inhabitant of Luxembourg is "externalizing" 25 GJ of Nuclear power to other countries.

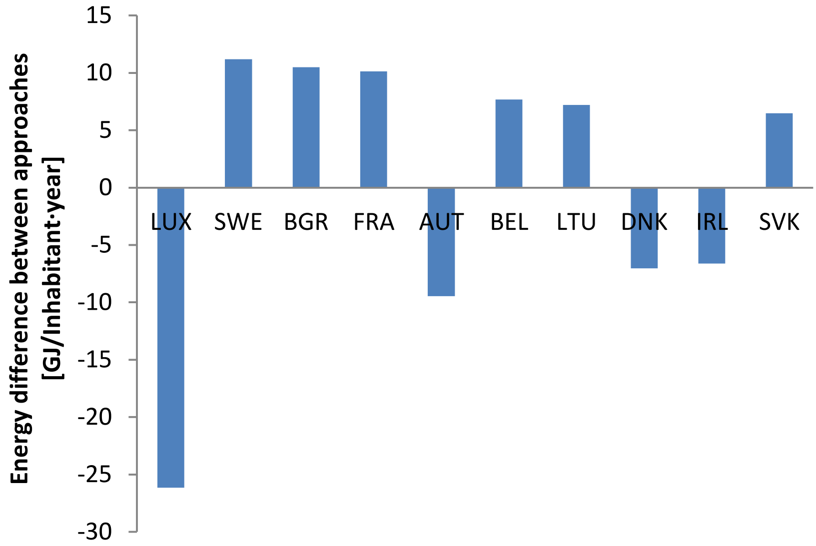


Figure 2.7: Per-capita average yearly difference between production-based and consumption-based nuclear energy in the 10 countries with the greatest difference (1995-2009).

We next studied the temporal evolution of the nuclear energy use in each country, through the two assessment approaches. Figures 2.8a and 2.8b depict a bar chart for each assessment approach, in which the length of the bars represent the average nuclear energy use in the period of study, and the color of the bars follow a color-scale which represents the slope with which nuclear power increases (or decreases) per year. We appreciate that, from a production-based assessment, there are countries that do not generate nuclear energy (15 of the 40 countries do not produce nuclear energy), but they do indeed consume nuclear energy indirectly through imports of goods/services produced in countries with nuclear energy. In fact, from the consumption-based point of view, all the countries consume nuclear energy (although in some cases the amount consumed is very low). Regarding the temporal evolution of nuclear energy use, we find that, as a general trend, the use of nuclear sources has increased among countries in both cases (production-based and consumption-based). Only 7 countries are reducing their nuclear energy use (from a production-based approach), and 8 from a consumption-based standpoint. Moreover, the reductions in nuclear energy consumption in such countries do not compensate for the increase taking place in the remaining countries. Regarding the assessment approach, we found that the temporal trends of nuclear energy use, calculated following the two different approaches are very similar.

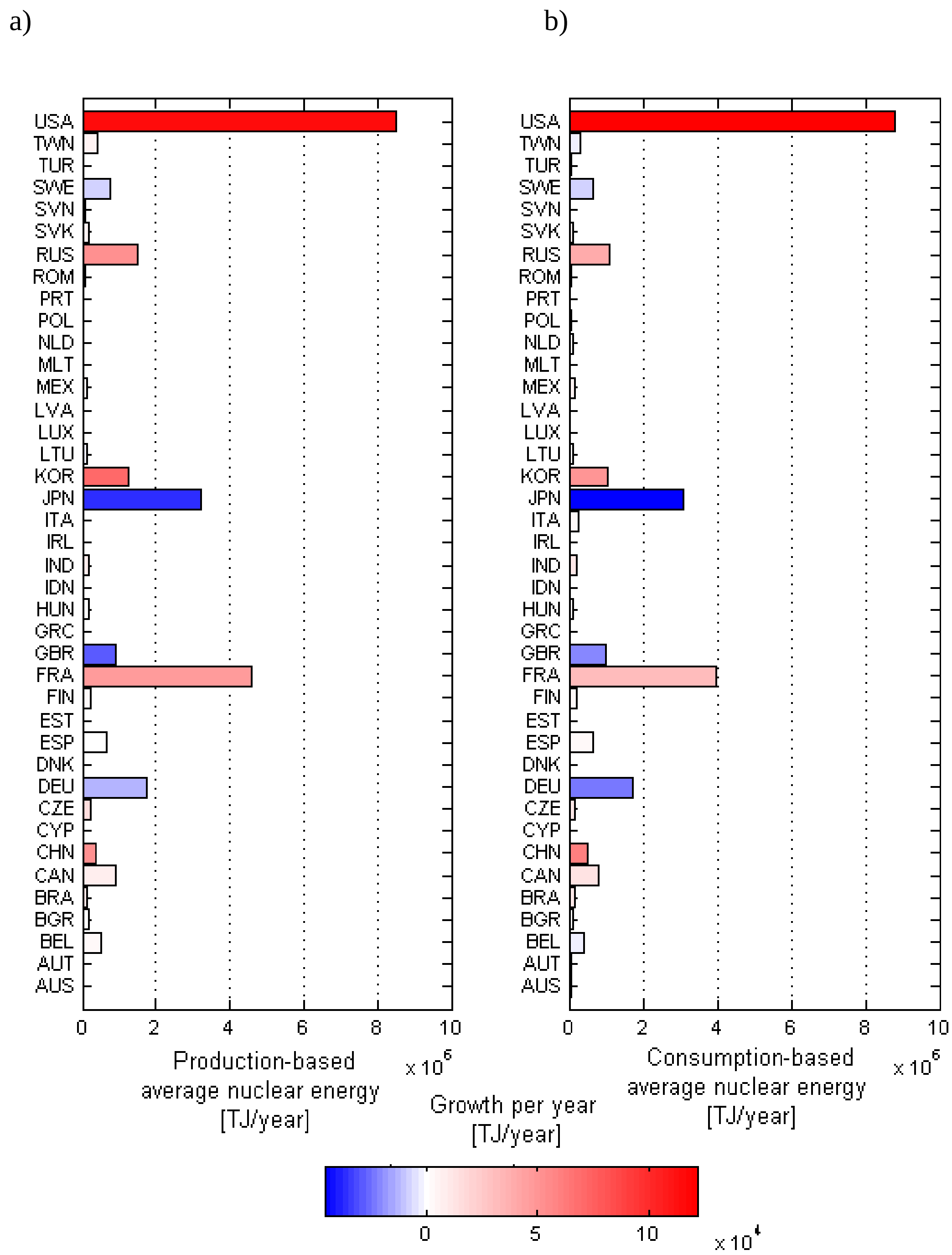


Figure 2.8: Temporal evolution of the nuclear energy in the 40 countries that appear in the WIOD. The length of the bars represents the average nuclear energy use (1995-2009), and the color of the bars indicates the slope of the increase (or decrease) of nuclear energy used. Figure 2.8a shows the results of the production-based assessment, while Figure 2.8b is based on the consumption-based assessment.

Figure 2.9 shows the yearly per capita nuclear power use in the last 15 years according to the two approaches. As expected, the per-capita nuclear energy use is more homogeneous between countries than the overall nuclear energy use (in Figure 2.8). This is particularly true when adopting the consumption-based viewpoint (Figure 2.9b). This happens because there are countries without nuclear energy production that import goods/services produced with nuclear energy.

The highest per-capita nuclear energy use is observed in Sweden and France Sweden shows in turn the highest reduction tendency (in both approaches), while France keeps a slight growth in the per-capita nuclear energy use, especially in the production-based approach. We also notice that countries like Korea and Czech republic tend to increase their per-capita nuclear energy use, especially in the production based approach.

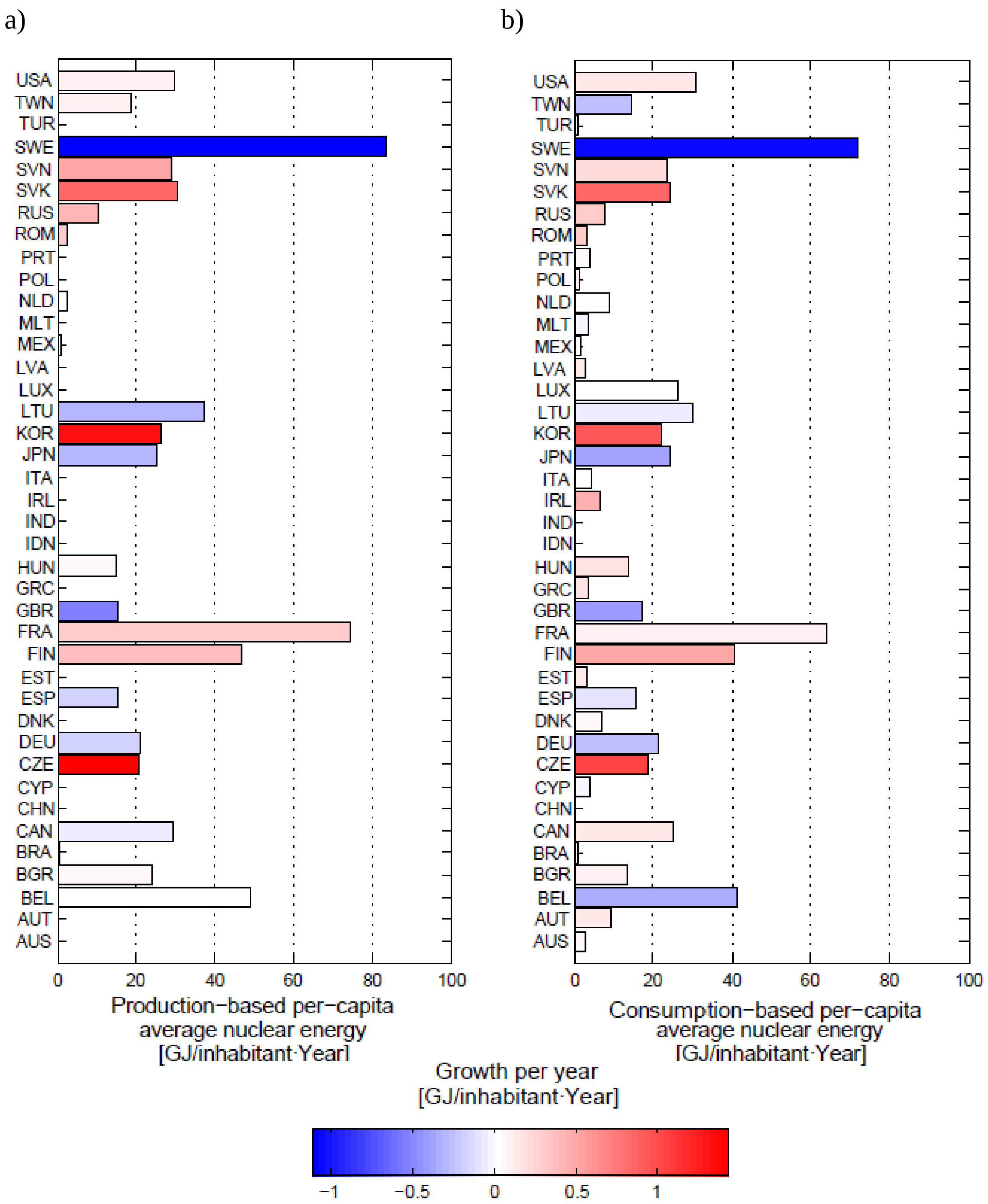


Figure 2.9: Temporal evolution of the per-capita nuclear energy in the 40 countries that appear in the WIOD. The length of the bars represents the per-capita average nuclear energy use (1995-2009), and the color of the bars indicates the slope of the increase (or decrease) of per-capita nuclear energy used. Figure 2.9a shows the results of the production-based assessment, while Figure 2.9b is based on the consumption-based assessment.

2.3.1.2 *Consumption-based vs. production-based assessment in solar energy*

In this section we turn our attention to the amount of solar energy embodied in trade. In a globalized market, part of the goods and services consumed in a country might be produced abroad using diverse energy generation technologies. Hence, to properly assess the extent to which a country is moving towards a more sustainable energy system (*e.g.* by implementing renewable energy sources in their economic structure), it is imperative to consider both, the amount of renewable energy used within its geographical limits and that embodied in the imported goods/services (which are generated overseas with another energy portfolio). We next analyze such issue by the use of multi-regional environmentally extended input-output models. The analysis of the production-based and consumption-based amount of solar energy consumed by a country provides valuable insight on the extent to which the country is moving towards a more sustainable energy system. This information can be used to develop regulations that will establish targets on solar energy shares from the viewpoints of both, production and consumption.

We first determine the amount of solar energy consumed by the 10 wealthiest economies in the world following the two approaches (*i.e.* production-based and consumption-based), and then study their temporal evolution during period 1995-2009. Figure 2.10a compares the average solar energy share quantified according to each of the approaches, during period 1995-2009.

As observed, the amount of solar energy used varies significantly from one country to another, being China, USA and Japan the countries with the largest use of solar energy in their energy systems during the past two decades. Figure 2.10b depicts the difference between the solar energy estimated through the two approaches (consumption-based values appear in the minuend, so a negative difference indicates that the solar energy embodied in the products demanded by a country is greater than that produced within its boundaries). China has the highest (positive) difference between both approaches. This is because a significant portion of the solar energy generated internally is used to produce items that are exported overseas instead of domestically consumed. As opposed to China, in USA the consumption-based solar energy is higher than the production-based. This is a generalized trend in other top economies, but in minor proportion. The reason for this is that these economies have a negative balance of import/exports of goods with China, which uses larger amounts of solar energy. We should recall that positive differences between production based and consumption based energy use do not necessarily imply that a country is a net exporter of such type of energy. Later in section 2.3.2 we will discuss in wider detail the concept of net imports/net exports and their environmental implications.

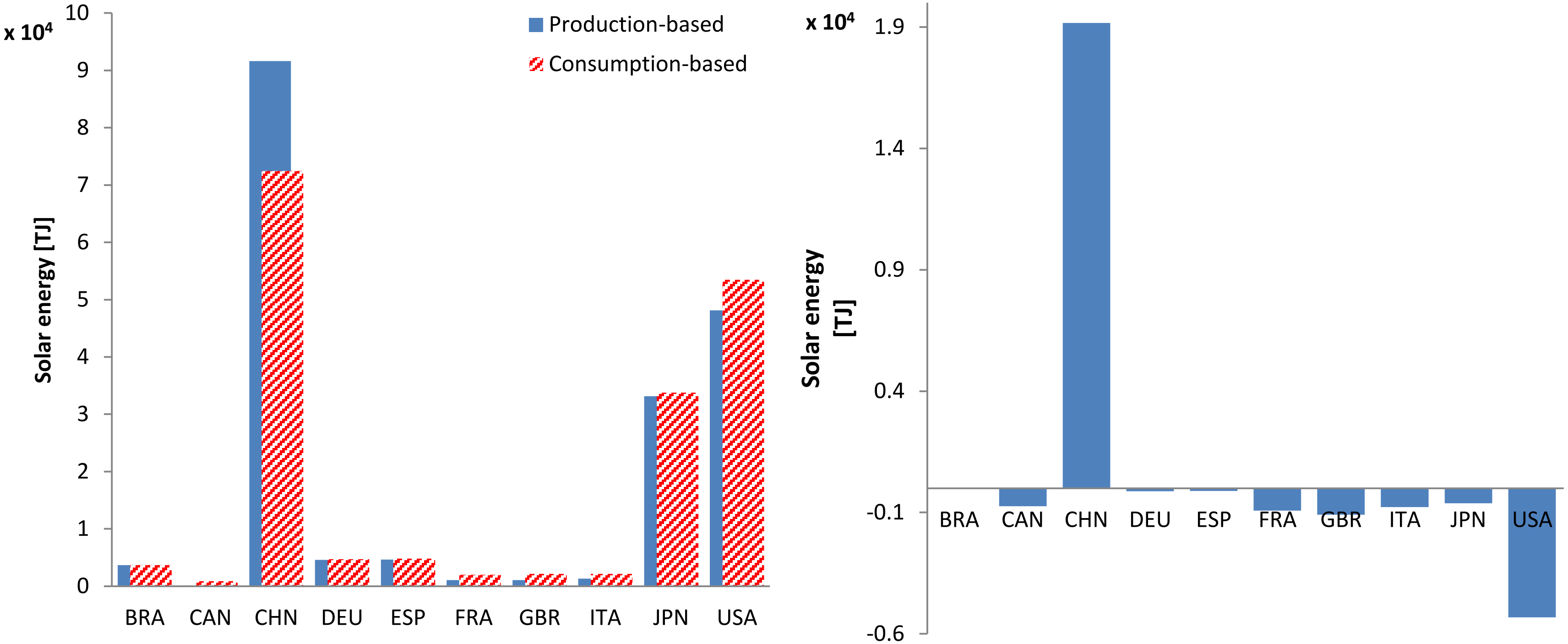
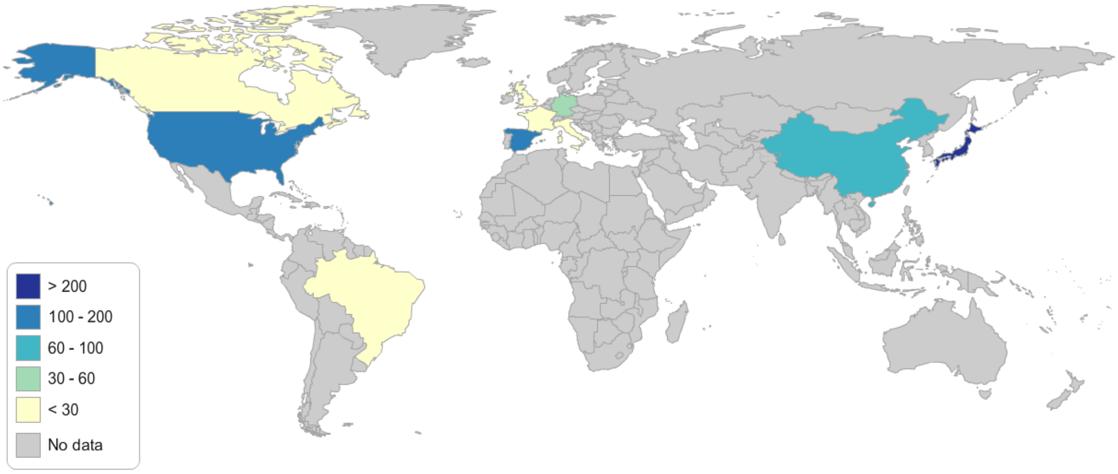


Figure 2.10: Comparison of the solar energy share of the top 10 economies according to the two different perspectives: production-based and consumption-based approaches. Figure 2.10a shows the average of solar energy estimated from each approach, in period 1995-2009; while Figure 2.10b shows the average difference between production-based and consumption-based solar energy use in the period of study.

Figure 2.11 shows a color-scale world map of the consumption-based and production-based solar energy per capita. Japan has the highest per-capita solar energy use according to both approaches; while on the contrary, Brazil and Canada show the lowest per-capita solar energy use in both approaches. China shows higher per-capita solar energy use in the production-based assessment, unlike Italy, France and Great Britain, in which the consumption-based solar energy is larger. Germany, Spain, and USA yield similar per-capita values regardless of the assessment approach followed.

a)



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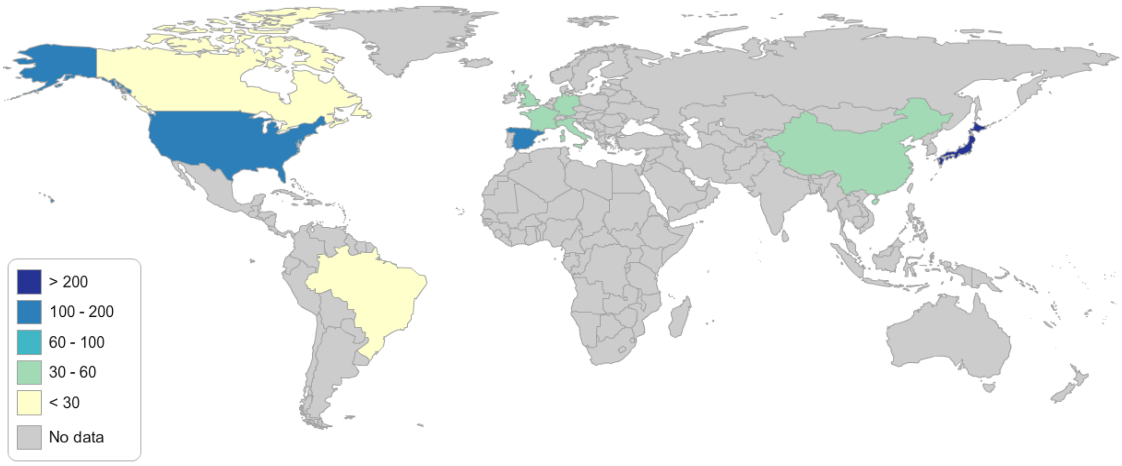


Figure 2.11: Average solar energy use per-capita, in the top 10 economies during the past two decades. The units of the color scale are expressed in MJ/year-inhabitant. Figure 2.11a: production-based approach; Figure 2.11b: consumption-based approach. Some EU countries show larger solar energy per capita in the consumption based approach, since they import products from other nations (*e.g.* China) with large solar energy use. On the contrary, countries like China show better ratios in the production

based approach, since most of the solar energy generated internally is used to produce goods that are exported to third countries.

Figure 2.12 shows the temporal evolution of the amount of solar energy and its percentage in the total energy produced by a country quantified according to the production-based perspective. Similarly, Figure 2.13 shows the evolution of solar energy use (in magnitude and percentage) following a consumption-based approach.

In general could be observed that, in the past two decades, the use of solar energy has increased significantly in most of the top economies from both viewpoints: production-based and consumption-based (see Figures 2.12a and 2.13a). This significant increase in solar energy use, which started after 1998, shows different intensity in each of the top countries. Japan is an exception to this trend. In 1995 it was the top producer (and consumer) of solar energy, followed by China and USA; but since then, the Japanese solar energy quota has decreased insomuch that China and USA have surpassed its production. We clarify that the solar energy production in Brazil was zero before 1999. For this reason, the curves associated to Brazil in Figure 2.12 start after 1999 and not in 1995, like in the rest of the countries.

The analysis of the temporal evolution of the solar energy use percentage with respect to the total energy consumption reveals also that the share of solar energy in the top 10 economies has increased since 1995 (see Figures 2.12b and 2.13b). The solar energy use has grown more than the total energy consumption, resulting in increasing solar energy ratios (what is not surprising, as its commercial exploitation took place during the period studied). We note that, regardless of the assessment approach, China has experienced the greatest growth of solar energy in magnitude, which significantly exceeds that taking place in the other countries.

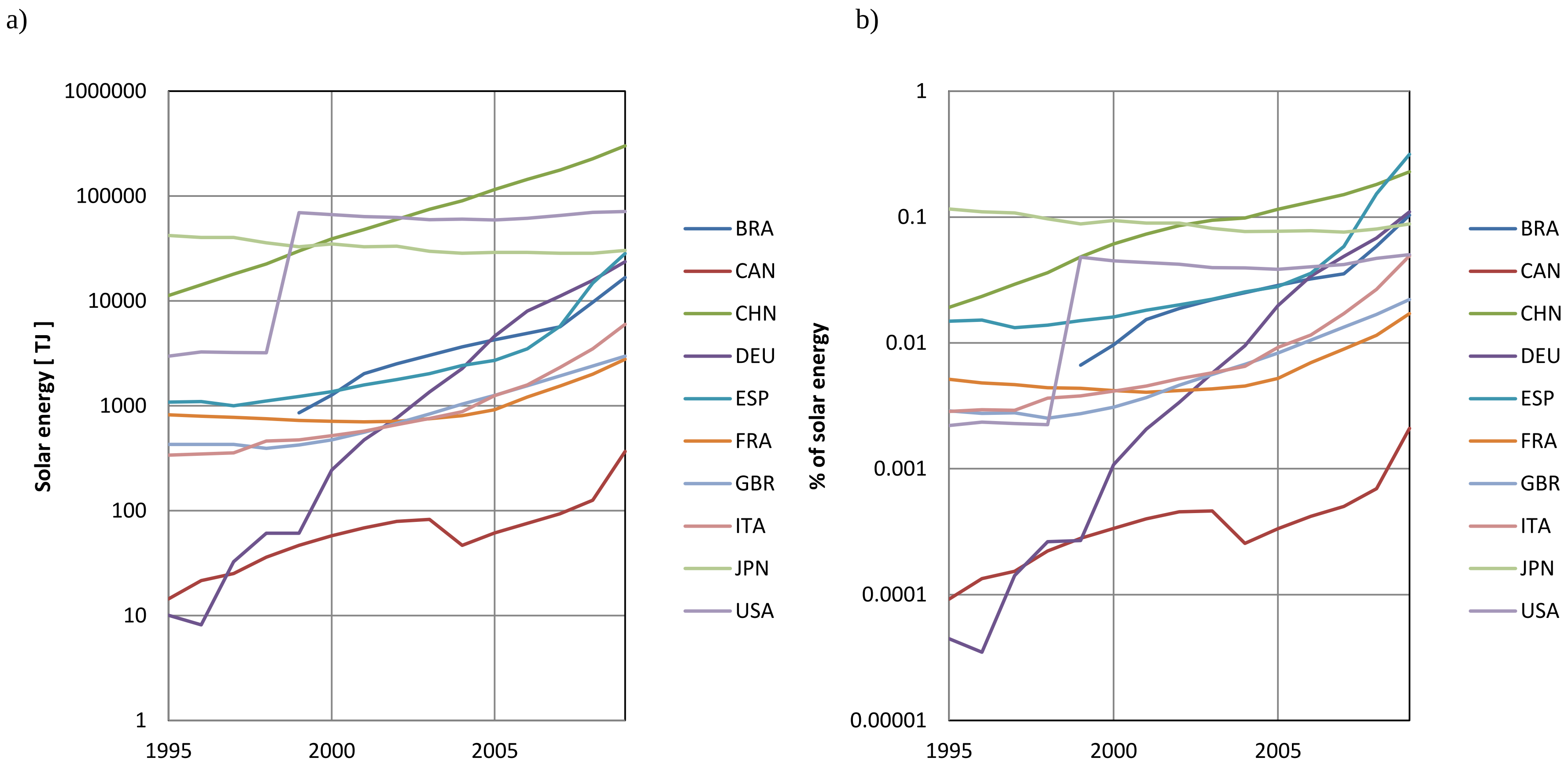


Figure 2.12: Production-based temporal evolution of the solar energy in the top 10 world economies. Figure 2.12a: Evolution of the solar energy use. Figure 2.12b: evolution of the percentage of solar energy with respect to the total energy use (the latter includes all energy sources and types).

a) b)

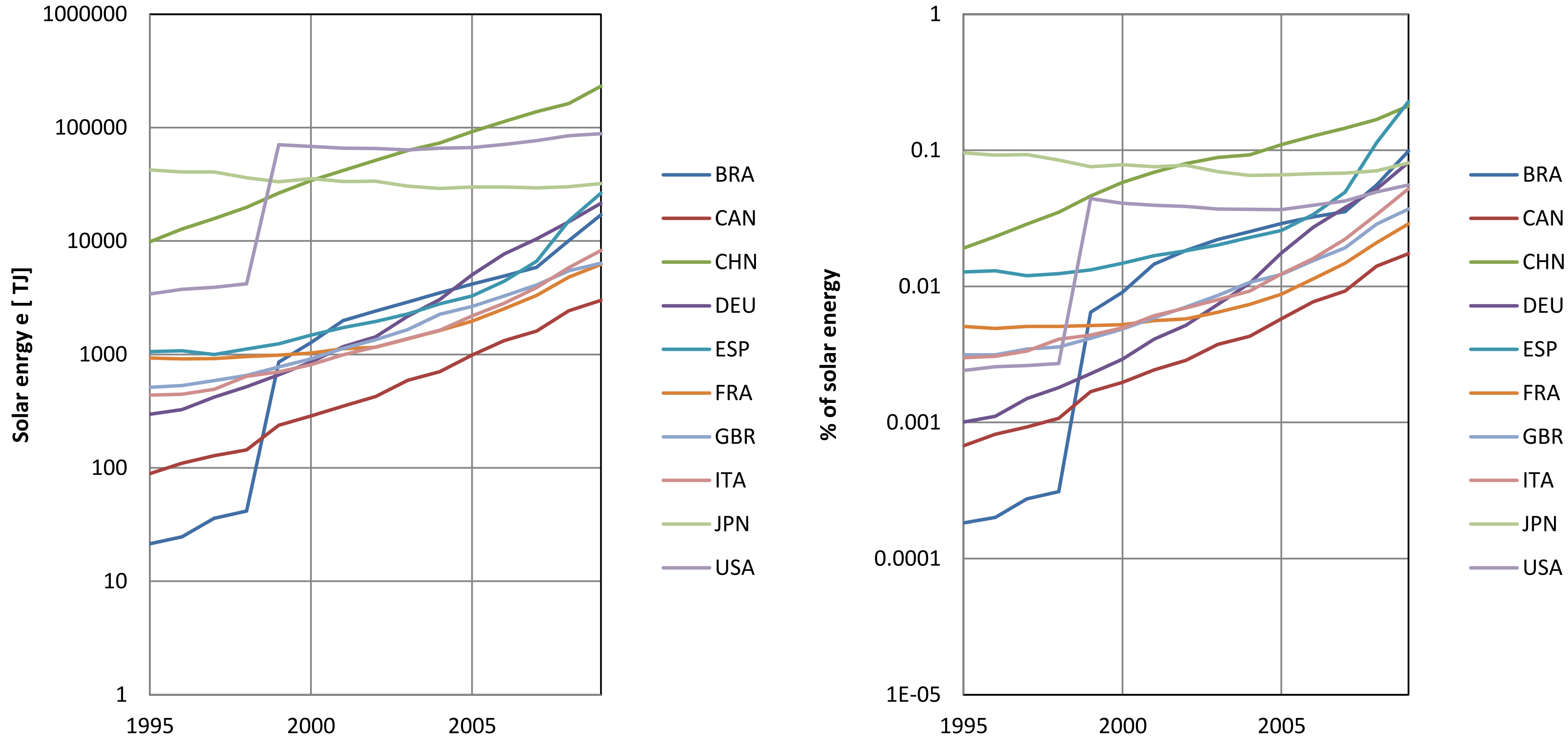


Figure 2.13: Consumption-based temporal evolution of the solar energy in the top 10 world economies Figure 2.13a: Evolution of the solar energy use. Figure 2.13b: evolution of the percentage of solar energy with respect to the total energy use (the latter includes all energy sources and types).

2.3.2 *Environmental repercussions of international trade*

The results of the previous section suggest that international trade plays a key role in the assessment of environmental impacts, since production-based studies could misallocate the corresponding responsibility. The extent to which trade is important depends strongly on the indicator under consideration. To get further insight into this issue we investigate the percentage of environmental loads embodied in trade for each of the 69 indicators in the database (Figure 2.14). We use Eq. (2.25) to estimate the amount of environmental loads embodied in international trade. We found that indicators related to fossil resources depletion (under the materials category) are the ones for which trade plays a major role. Indeed, before 2006, 29.32-49.17% of the total impact in each of the subcategories of fossil resources (except fossil coal) was embodied in trade. To a lesser extent, the indicators of the materials category related to mineral extraction (including fossil coal) are also highly embodied in trade (15.07-32.20%). In contrast, only 10.72% of the total CO_2 emissions are embodied in trade, and other impacts related to water and land use and biomass consumption are, in general, less embodied in trade (<13%). Regarding the indicators related to the use of energy, the percentage embodied in trade ranges from 1.49% to 31.65%.

To investigate the evolution of the importance of trade, and given the significant change in trends that was triggered by the financial crisis in 2006, we separate our data in two blocks: 1995 to 2006 and 2007 to 2009. From 1995 to 2006, the amount of environmental loads embodied in trade grow annually for most of the indicators (66 out of 69). During this period, growth was fastest for those that were already highly embodied in trade, which suggests an accelerating increase in the importance of trade. In contrast, from 2007 to 2009, the amount of environmental loads embodied in trade increases just for a few indicators (7 out of 69). Growth also changes dramatically, with the importance of trade growing even faster for some indicators (such as CO emissions) while being totally reversed for others (such as those related to fossil resources).

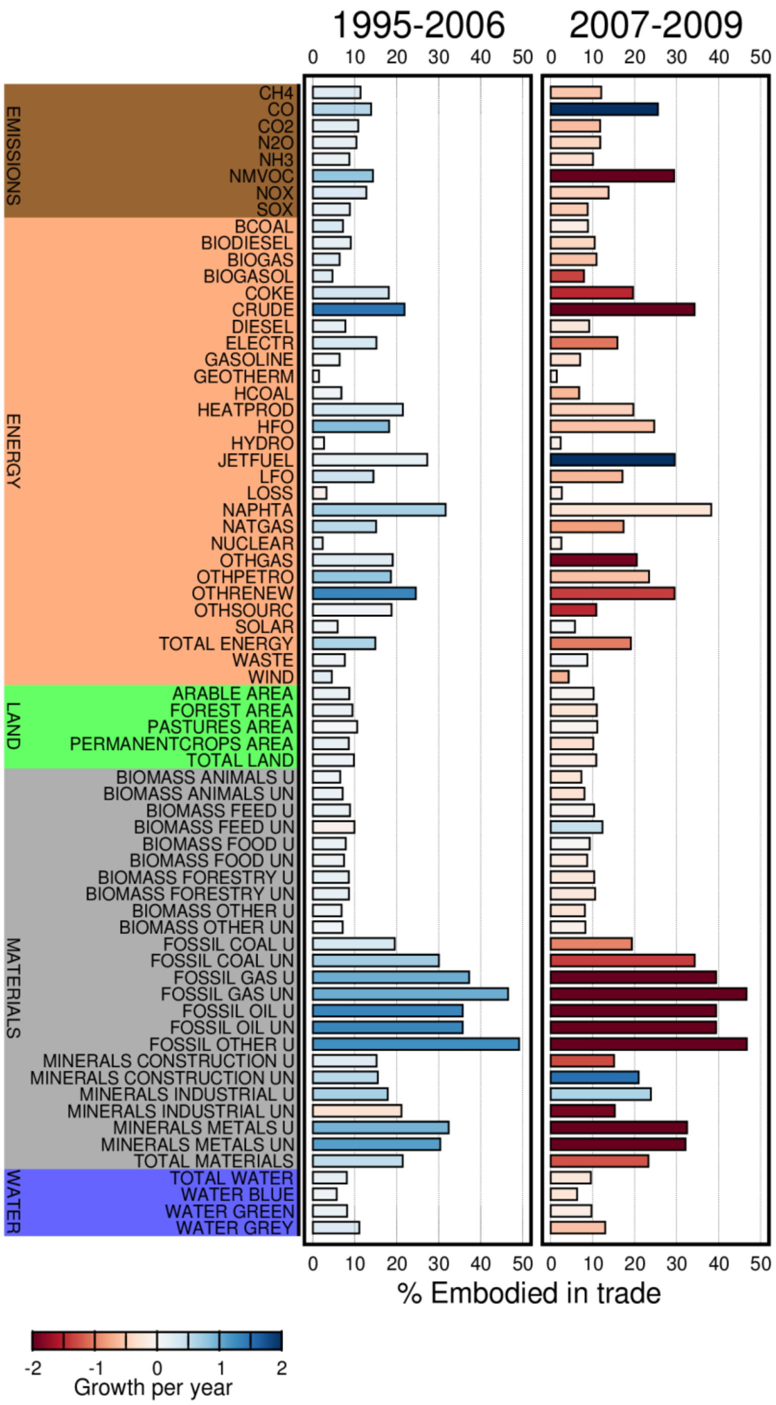


Figure 2.14: Percentage of environmental loads embodied in trade before and after the global crisis. For all of the 69 indicators (grouped by type), we show the percentage embodied in trade with respect to the world's total impact values for each indicator. We show two bar charts corresponding to the periods 1995-2006 and 2007-2009. Each bar represents the average of the percentage of a specific impact embodied in trade during the corresponding period. The color indicates the annual growth of trade-embodied percentages obtained from a linear fit to the data for that period following the scale in the color bar. For example, the consumption of crude oil in the period 1995-

2006 was on average 21% embodied in trade and showed a positive increase, while in the period 2007-2009 it was on average 34% embodied in trade, and showed a decreasing trend.

We next identify the main sources and destinations of environmental loads at a global scale by analyzing the net exporters and importers for each environmental indicator. We use Eq. (2.29) to identify the net importers and net exporters of environmental loads. Due to the large amount of indicators, we represent in Figure 2.15 the results for CO_2 emissions and fossil oil. As expected, we found that developed countries are often net importers, which indicates that the impact of the goods and services consumed are masked by displacing production to emerging countries with softer environmental regulations [3]. Results suggest that the extent to which trade is important depends strongly on the indicator under consideration. For example, USA is the largest net importer of both CO_2 emissions and fossil oil used (which includes all fossil oil used to produce goods and services that are ultimately consumed in the USA); while its net imports of CO_2 emissions account for 0.81% of total world emissions, its net imports of fossil oil account for as much as 7.10% of the total world consumption.

In the following two subsections we examine in wider detail two of the energy indicators: the use of nuclear and solar energy.

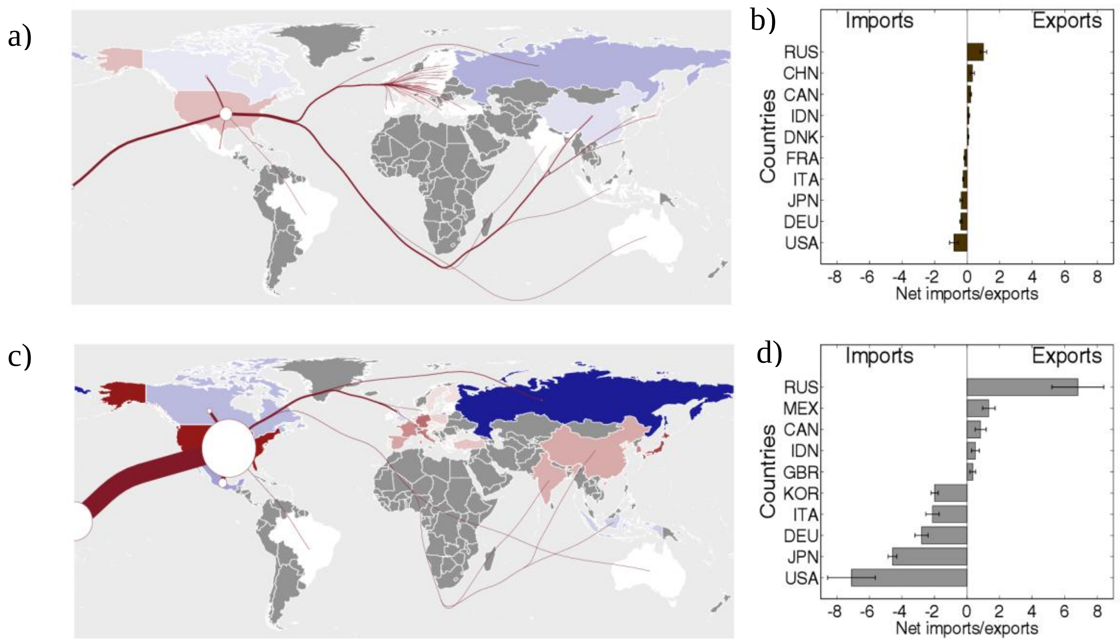


Figure 2.15: Differential importance of trade in environmental indicators. For two environmental indicators (a-b, CO_2 emissions; c-d, Fossil oil) we display the spatial distribution of net exports/imports (a and c), along with the values of the net exports/imports corresponding to the largest exporters/importers (expressed as a fraction of the total world consumption) (b and d). In (a) and (c), countries colored in blue are net exporters and countries colored in red are net importers. For each environmental load, we show as well the total net impact imported by the top net importer. b, d show the top five net exporters/importers, and their average net exports/imports as a percentage of the total world consumption during the period 1995-2006 for each impact. Positive values correspond to net exports, while negative values correspond to net imports. For example, USA net imports account for over 7% of the total world consumption of fossil oil. Error bars indicate one standard deviation over the period considered.

2.3.2.1 Environmental effects of nuclear energy embodied in trade

Deepening on the nuclear energy indicator, we present in Figure 2.16 the temporal evolution of the world's nuclear energy production in the period 1995-2009, along with the share of it that is embodied in international trade. It is observed that the total nuclear energy production has, in general terms, increased, with a small drop taking place during the world-wide crisis (2007). However, after 2006 it tends to decrease. Regarding the share of nuclear that is internationally traded, its temporal evolution is similar to that of the total nuclear energy production. Note that there is a very low portion of nuclear energy embodied in international trade (the highest value of the temporal series is 3.5% in 2006). This is because nuclear energy is mainly consumed internally in all the countries that generate it.

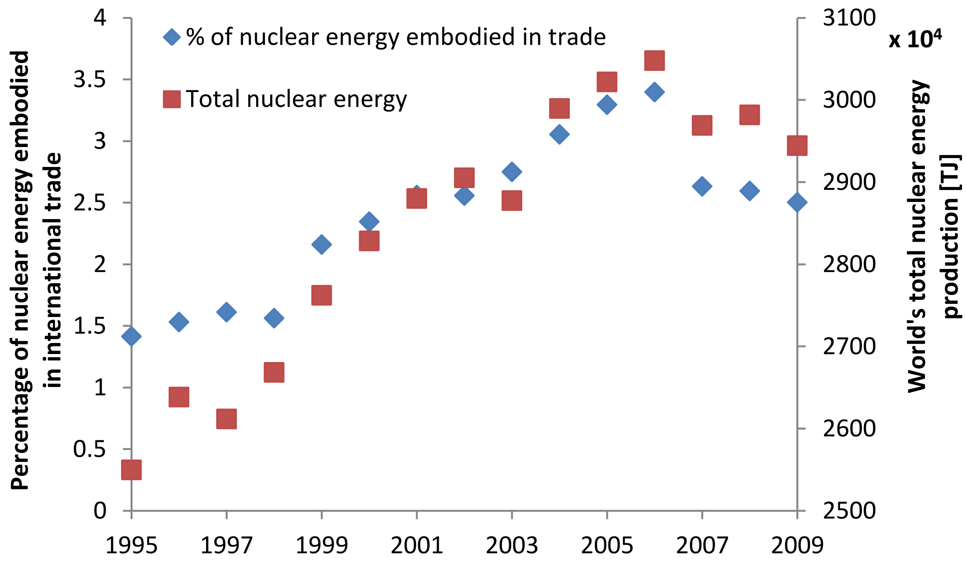


Figure 2.16: Temporal evolution of the world's total nuclear energy, and its percentage embodied in international trade.

We next study whether a country is net importer or net exporter of nuclear energy. In Figure 2.17, we further compare the most representative net imports/exports with the total world's nuclear energy production. In other words, Figure 2.17 shows the percentage of net nuclear energy imported/exported with respect to the world's nuclear energy production (*i.e.* the average of the 15-year period). We found that, from the top 5 net importers and top 5 net exporters, the highest amount of net imports/exports corresponds to the net exports from France, which is 3 times higher than the net imports of Italy (which has the following highest absolute value). However, the net imports/exports of nuclear energy are not particularly high, since France; whose net exports are the highest, barely reaches the 0.6% of the total nuclear energy produced worldwide. Then, it could be argued that the countries with nuclear power production use it mostly for domestic use (*e.g.* electricity in households).

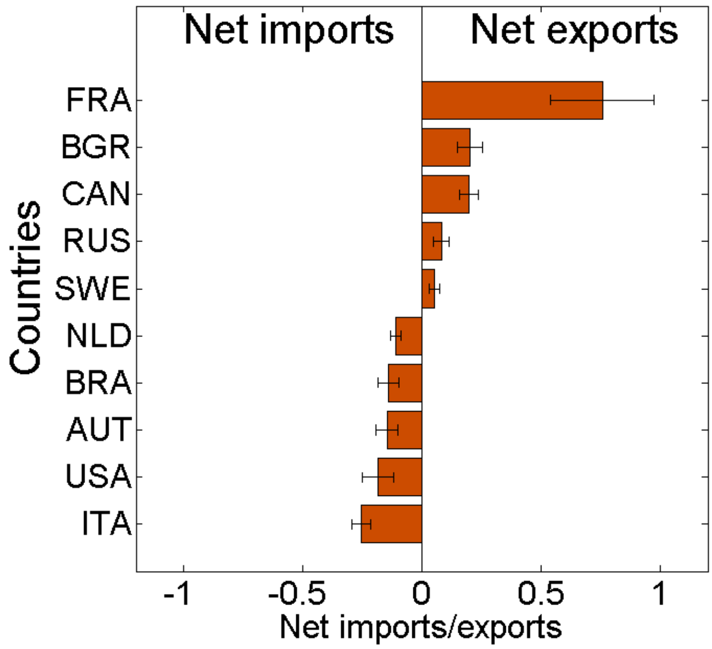


Figure 2.17: Average net imports/exports of nuclear energy embodied in international trade of the top 5 net importers and top 5 net exporters (1995-2009). The scale represents the percentage of nuclear energy that is embodied in the net imports/exports, with respect to the world's nuclear energy production.

We should recall that the assessment of the net imports/exports of a given impact should not be mistaken with the consumption-based and production-based impact assessments. That is, the net imports (or exports) represent the environmental loads embodied in the net difference between the direct sales of goods made by one country to the others, and the direct purchases made by the country of goods produced by other nations. Note that the environmental loads embodied in the life cycle of the demanded products (*i.e.* the indirect purchases), are not considered in this analysis (but are in contrast included in the consumption-based assessment). Thereby, a positive difference between production based and consumption based energy use does not necessarily imply that a country is a net exporter of such type of energy. It is true, however, that in net exporters of nuclear energy the production-based nuclear energy will very likely exceed the consumption-based one.

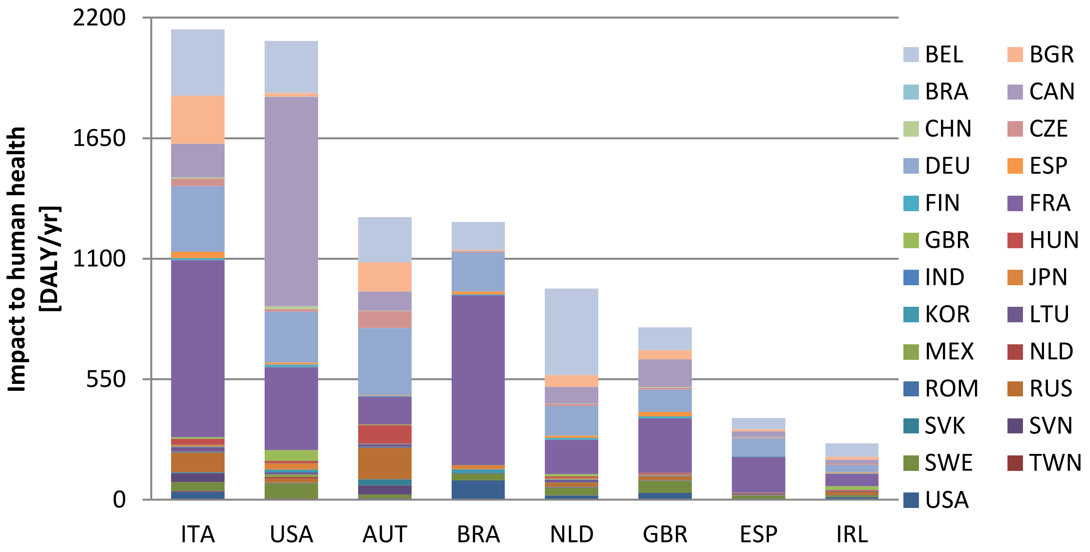
Numerical results confirm the observation made before, that countries with higher production-based nuclear power (*e.g.* France and Sweden) appear among the top 5 net exporters. Similarly, USA and Italy (in which the consumption-based nuclear energy exceeds the production-based on) appear among the top 5 net importers of nuclear energy.

Note that net importers of nuclear power externalize the environmental impacts associated with nuclear energy generation. That is, they consume goods that were produced with nuclear energy, but the negative effects of using this energy source takes place in the exporting country, not in the importing one. We analyze next the countries where this occurs.

Nuclear energy causes different negative impacts in human health, ecosystem quality and depletion of resources. In this thesis, we focus our attention on the first damage category. The impact on human health is measured in disability-adjusted life years (DALYs). To translate nuclear energy generation into the associated impact, we make use of the Eco-invent database v 2.0 [103], which stores information on a wide variety of impacts associated with the most widely used industrial technologies, including those employed for generating energy. To determine the human health impact of nuclear energy, we follow the Eco-indicator 99 methodology [82] and adopt the hierarchical average (H, A) perspective. This methodology is based on life cycle assessment principles, and considers the impact associated with all the steps in the life cycle of nuclear energy generation.

Consider the matrix IMP^k introduced in Eq. (2.23), where in this particular case, k is referred to the impact to human health associated with nuclear energy generation. Hence, each element of the matrix IMP^k represents the amount impact traded between the countries in the rows and the countries in the columns (the impact associated to the nuclear energy embodied in the intermediate sales and the final demand). To quantify the impact, we multiply each of the rows (which represent the nuclear energy generated by a country), with its corresponding impact factor (which is retrieved from the Eco-invent database). This allows translating the nuclear energy that each country sells (via trade of goods/services) into the associated impact on human health. Figure 2.18 shows the damage to human health externalized by the net-importers of nuclear energy, indicating the country where the impacts take place. We want to emphasize that in Figure 2.18 we are not considering the impact that one country causes to itself (for those with nuclear power production). Hence, we are only considering in the figure the impact that one region displaces (externalizes) to the countries from which the former imports goods/services that are produced using nuclear energy in the foreign exporting countries. In other words, we do not consider the main diagonal of matrix S in the calculation of the impact. Since the impact externalized changes considerably from one country to other, we divide Figure 2.18 into 3 parts (a, b and c), each one with a different scale on the vertical axis.

a)



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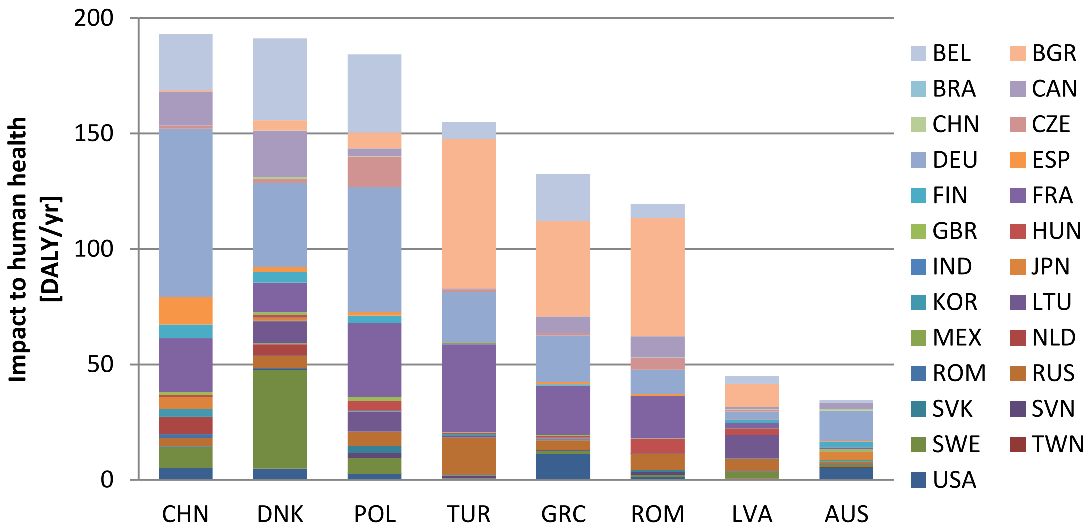

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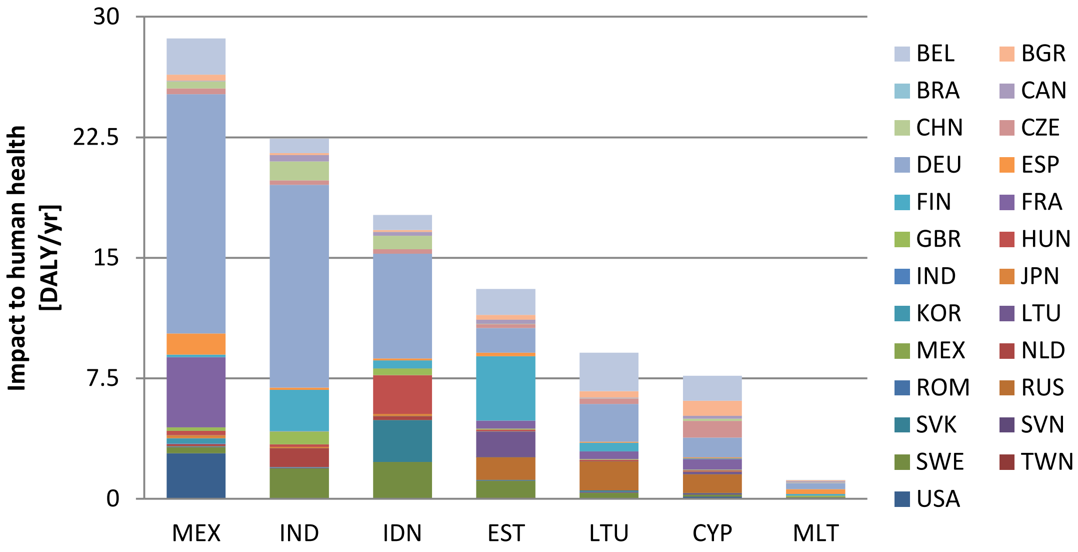

Figure 2.18: Average externalization of the impact to human health associated with the production of nuclear energy, in the period 1995-2009. The height of the bars represents the cumulative impact to human health (in DALYs) that the countries on the horizontal axis externalize to others. The color of the bars represents the countries to which the impact is externalized from the countries on the horizontal axis (the colors corresponding to each country are given in the legend of the figures).

Figure 2.18 (a, b and c) shows in the horizontal axis the countries that are externalizing the impact. The bars are ordered in descending order of externalized impact. Hence, Italy is the country that externalizes the largest amount of DALYs. On the contrary, Malta is the net-importer with the least externalization of impact to human health. In each bar we specify the amount of impact caused in each producing country (see the legend). Belgium, Canada, France and Germany are the most impacted countries by the foreign demands. In particular, in Figure 2.18a we observe that the largest externalities are caused by United Sates in Canada (around 1000 DALYs per year), followed by those caused by Italy in France (around 800 DALYs per year). We notice that the largest externalities occur mainly between nearby countries. In other cases, like Brazil and France, (externalities of approximately 770 DALYs per year), large externalities take place because the net import-export balance between the countries is high.

Quantifying the impact that one country transfers to others through its demand is valuable for the exporting countries, since this impact taking place in their national territory ultimately leads to more investments in health and social security [19]. With this information at hand, such countries could evaluate in a better manner the economic profit of the internationally traded goods, and the need to define special taxes on them if required. This analysis identifies if an economic activity is in line with the sustainability principles, by contrasting the economic benefit with environmental and social welfare.

2.3.2.2 Environmental effects of solar energy embodied in trade

In this section we perform an analysis similar to the previous one but this time applied to the amount of solar energy embodied in trade. Note that, as oppose to nuclear power, the impact of solar energy is rather low. Figure 2.19 shows the temporal evolution of the world's total solar energy use and its share embodied in international trade. The total solar energy production has drastically increased (from $2.4\cdot10^4$ TJ in 1995, to $4.3\cdot10^5$ TJ in 2009), while its fraction embodied in trade has remained relatively constant. In addition, the share of solar energy that is internationally traded is relatively low (from 4.6% in 1995 to 7.02% in 2008 of the world's total solar energy generation).

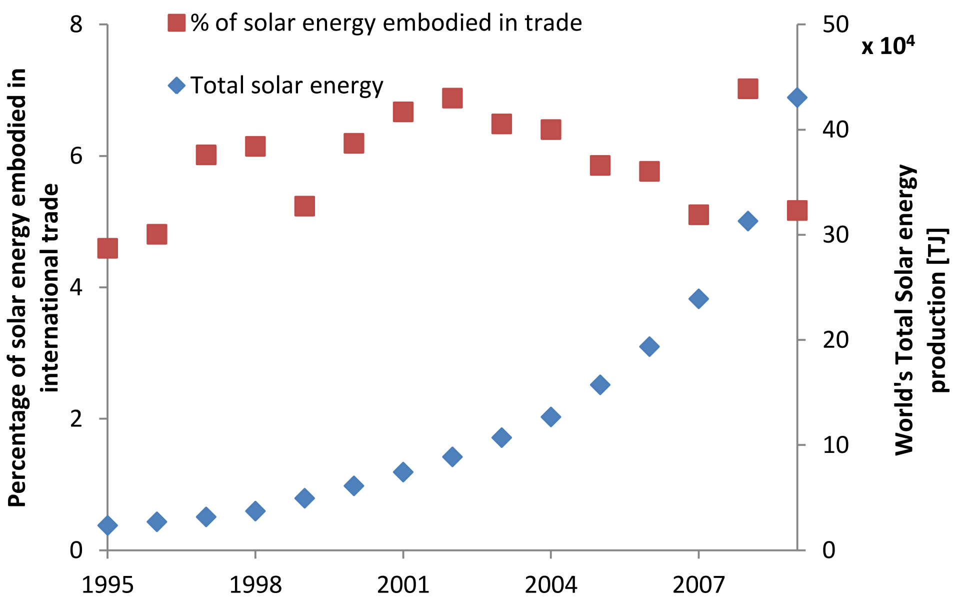

Figure 2.19: Temporal evolution of the world's total solar energy, and its fraction embodied in trade.

We study next whether a country is a net importer or net exporter of solar energy. We calculate the net exports/imports of solar energy in a country (difference between sales and purchases multiplied with the corresponding solar energy intensity) from 1995 to 2009, and compare this information with the total world's production of solar energy.

Figure 2.20 shows the average percentage of net solar energy imported/exported (with respect to the world's solar energy production). There are only 2 out of the 10 top economies that are net exporters of solar energy, namely China and Japan. The other 8 countries are net importers of solar energy, being USA the one with the highest average imports. China has a large number of solar facilities that produce electricity. Part of this electricity is ultimately used to produce goods that are exported [104]. Because of this, China has become the world's largest exporter of solar energy embodied in trade. Hence, efforts to promote solar energy in China have a positive effect in the remaining importing countries, as it helps increasing the share of this renewable energy in the total energy required to satisfy their demand of goods and services. It is important to note that most of the solar energy embodied in trade at the global scale is exported by China. Its net exports embody approximately 2.9% of the world's solar energy production (in average, during 1995-2009), which is very close to the total amount of solar energy embodied in international trade (*i.e.* 5.9 % in average in the period 1995-2009).

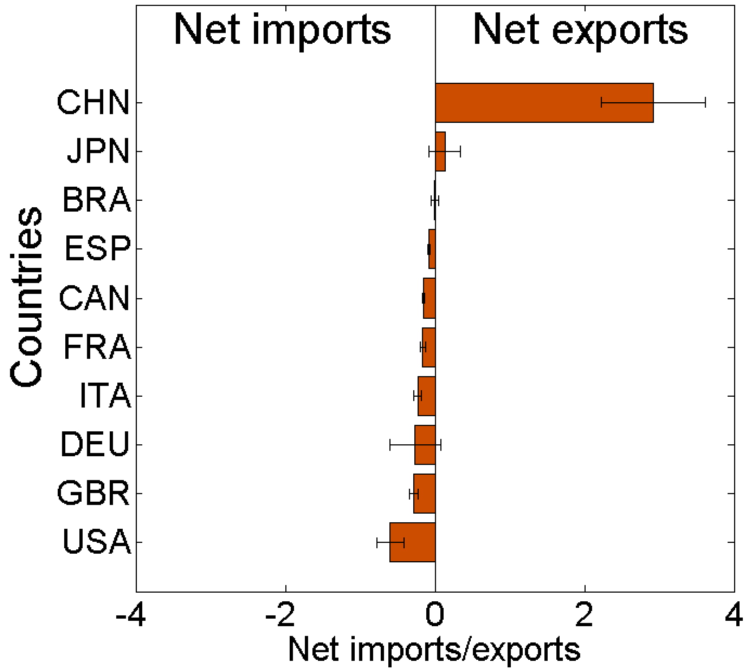

Figure 2.20: Average net imports/exports of solar energy embodied in international trade of the top 10 wealthiest economies. The scale represents the percentage of solar energy that is embodied in the net imports/exports, with respect to the world's solar energy production.

Note that, as previously mentioned, in a net exporter the production-based solar energy does not necessarily exceed the consumption-based one. This is the case of Japan, which in Figure 2.20 appears as a net exporter of solar energy (in very small proportion), but Figure 2.10 shows that the consumption-based solar energy use exceeds the production-based one. This occurs because the direct purchases of the Japanese economy embody less solar energy than the one embodied in their direct sales.

We finally investigate the amount of solar energy exported from China to the remaining countries via international trade (see Figure 2.21). We observe that the main flow of solar energy embodied in the trade of goods from China goes to Japan (139 TJ per year in average in the period 1995-2009), followed by Australia, Turkey and Germany, (48, 13 y 12 TJ respectively). By purchasing products made in China, the main economies are indirectly consuming solar energy. Note, however, that China implements also other technologies apart from solar energy, like coal combustion, that lead to significant negative impacts.

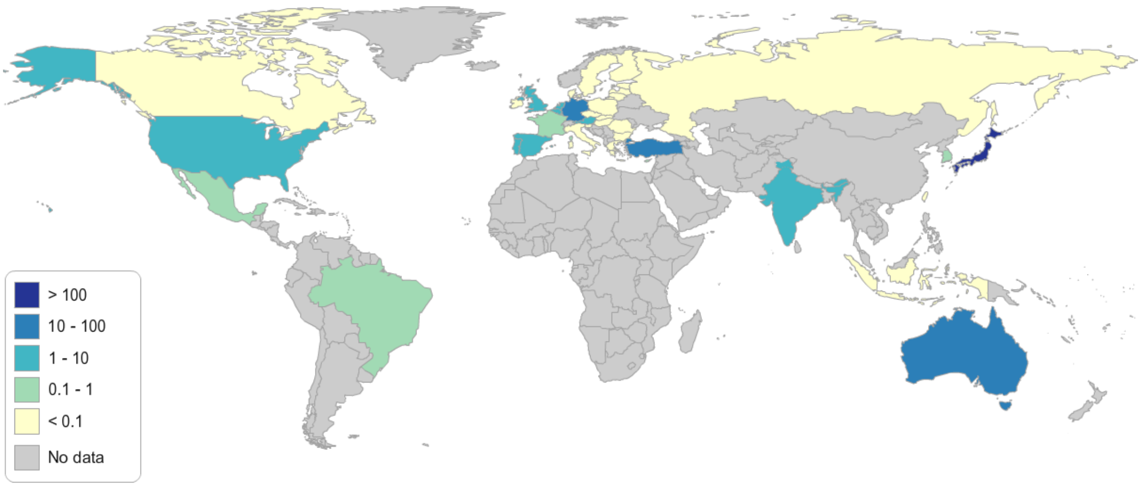

Figure 2.21: Average solar energy embodied in exports from China in period 1995-2009. The units of the color scale are expressed in TJ/year.

2.3.3 Environmental equity

International trade has an important and (at least before the financial crisis and subsequent global recession) increasingly relevant role in global environmental loads. To get further insight into this, we next study its effect on the global environmental equity of the world. We obtain environmental Gini coefficients using consumption-based yearly environmental loads according to Eq. (2.34). The idea is to account for the environmental loads embodied in trade so as to properly assign responsibilities to the countries where consumption (as opposed to production) takes place. To calculate global Gini coefficients, we assume that there is an even distribution of consumption or pollution within each country.

Our results indicate that there is a large variability among the environmental indicators considered in the analysis concerning how equitably they are distributed worldwide (Figure 2.22). Some environmental loads are very equitably distributed, including those related to water use, biomass, and some air emissions like NH_3 and N_2O (Gini coefficients between 0.14 and 0.3; Figure 2.22a). Conversely, the distribution of others is highly inequitable even relative to income inequality, like for example, biodiesel, biogasoline and nuclear power (Gini coefficients between 0.79 and 0.92; Figure 2.22b). In general terms (Figure 2.22c), we observe that the indicators related to satisfying basic needs (water and land use and biomass related to food) are distributed more equitably (Gini coefficients between 0.23 and 0.53); whereas, energy-related indicators are less equitably distributed (Gini coefficients between 0.47 and 0.80).

To get further insight into the importance of imports and exports of environmental loads in equity, we compare consumption-based Gini coefficients to those obtained with traditional production-based accounting (Figure 2.22d). We found that production-based accounting can overestimate the Gini coefficient by as much as 37% and underestimate it by as much as 16%. Although, overall, the consumption-based approach overestimates inequality more often than the reverse (44 out of 69 indicators), inequality is systematically underestimated for most of the emissions and, to a lesser extent, for indicators related to water use.

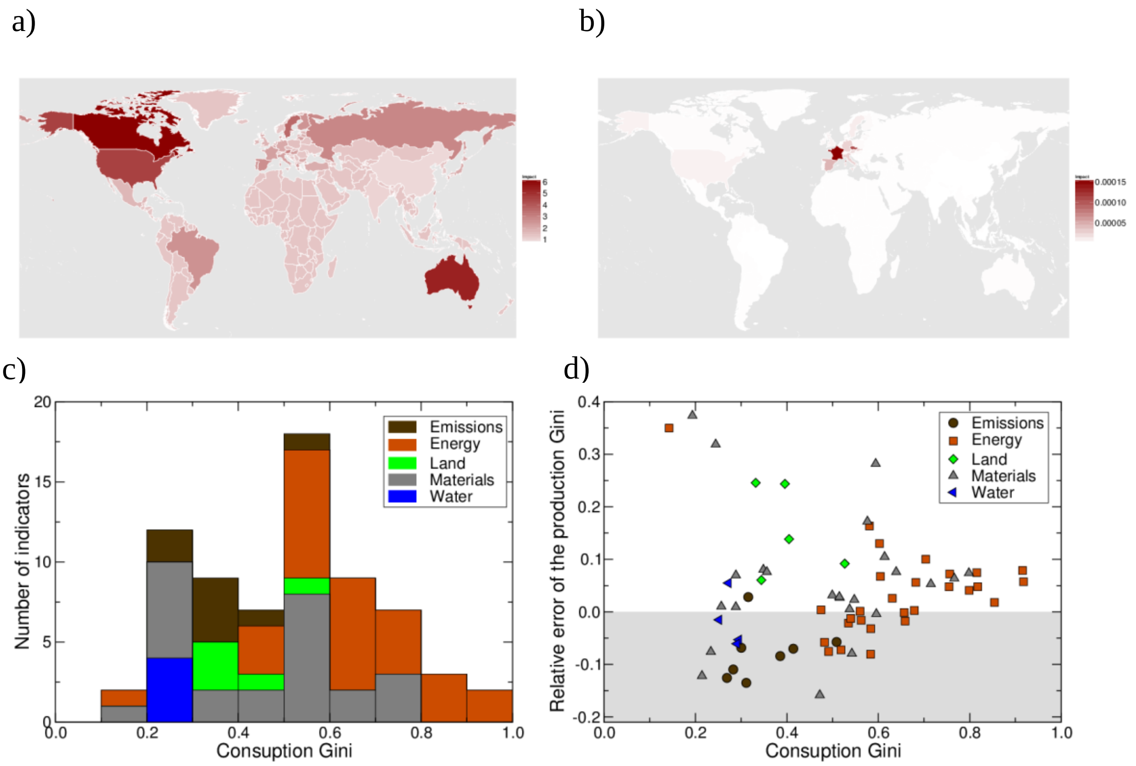

Figure 2.22: Environmental equity at global scale. We depict as well the global distribution of two indicators (with low and high Gini values). The world map in the left (a) corresponds to the use of water (Gini=0.25), and the world map in the right (b) corresponds to the use of biodiesel (Gini=0.91). The color-scale represents the amount of environmental loads associated to countries (in 1000 m^3 and TJ respectively). For the period 1995-2006, we show the distribution of average consumption-based Gini values (c) within equi-spaced ranges between 0 and 1. The height of the bars represents the number of Gini coefficients found in each range, while the color indicates the category

to which such coefficients belong (water, materials, land, energy and emissions). Furthermore, we compare the consumption and production-based accounting approaches (d), in which each point of the scatter plot represents one indicator.

Finally, we study the evolution of environmental inequality before and after 2007 (Figure 2.23). Our analysis reveals a number of noteworthy patterns. Before 2007, environmental inequality remained relatively constant, with most (59 of 69) of the Gini coefficients changing by less than ±0.005 per year. Despite these relatively small variations, we observe that very high Gini coefficients tended to decrease over time, whereas very small Gini coefficients tended to grow. This suggests that inequality related to different environmental indicators may converge to some intermediate value. In any case, the relatively slow trends observed before 2007 break after the spread of the global recession after 2007. Indeed, we observe that most of the Gini coefficients decrease rapidly in the period 2007-2009, with 24 out of 69 Gini coefficients dropping by more than 0.02 per year, and 43 of them decreasing by more than 0.01 per year. Before 2007, 39 out of 69 Gini coefficients are between 0.5 and 1; while after 2007, 41 of them lie between 0.1 and 0.5, and none of them is greater than 0.9. In particular, energy-related Gini coefficients, as well as those related to fossil fuels, have experience the most significant decreases, probably driven by the fall in consumption in the wealthiest countries.

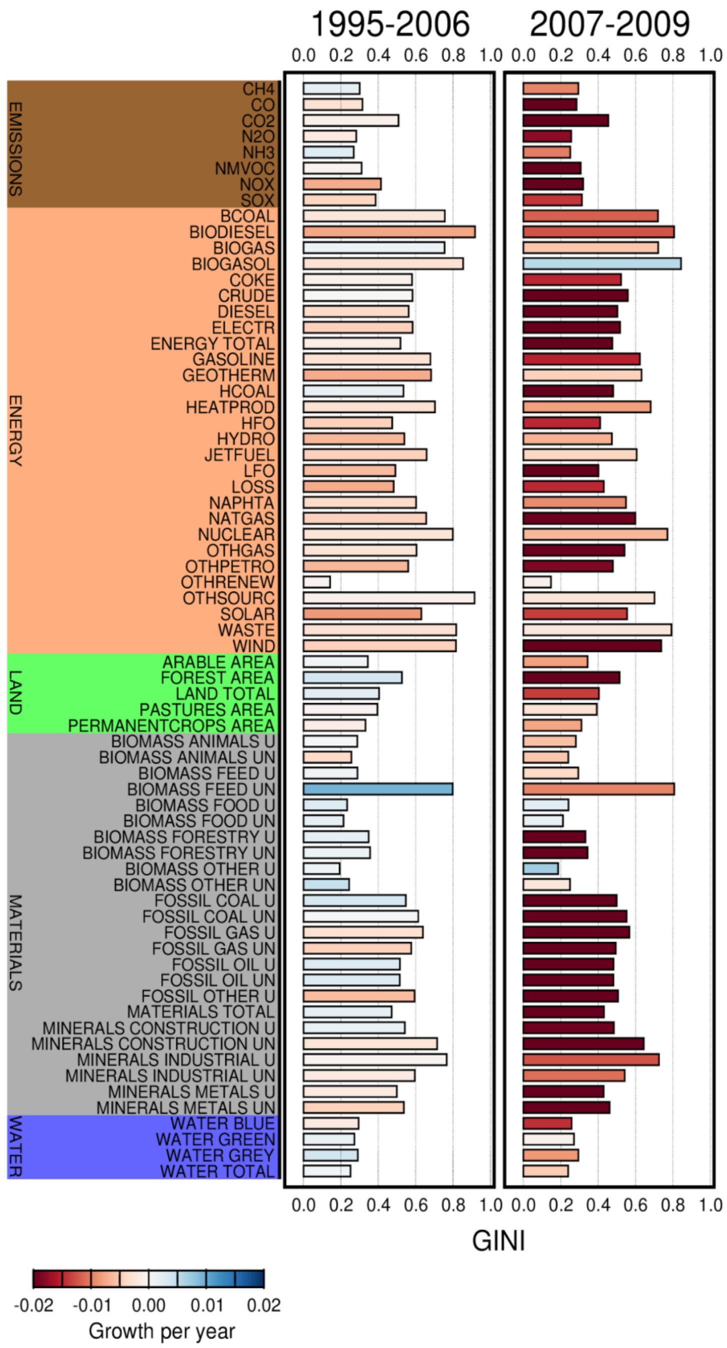

Figure 2.23: Environmental Gini coefficients and their trend over time. We show the Gini coefficients for the 69 environmental indicators in two bar charts corresponding to the periods 1995-2006 and 2007-2009. The length of each bar represents, for one indicator, the average Gini coefficient of the corresponding period. The color of the bars indicates the trend over time of the Gini values (average growth per year).

2.4 Conclusions

In this chapter we used EEIO models to assess the environmental impacts generated worldwide following two different approaches: production-based and consumption-based. We studied 69 environmental indicators related to emissions to air, consumption of natural resources (water, energy, materials) and land occupation; paying special attention to nuclear and solar energy use. We applied this approach to a multi-regional EEIO model that covers 40 of the main economies, representing 85% of the world's gross domestic product.

Our analysis based on the life cycle assessment of international supply chains of goods/services sheds light on the international channels through which the environmental loads are traded between countries via imports and exports. This information can facilitate the design of more effective policies that transparently allocate the environmental responsibility of impacts to the consuming countries.

We conclude that, international trade plays a major role in environmental impact assessment, and should be taken into account in the formulation of sustainability policies in order to avoid undesired effects (*e.g.* carbon leakage) that do not lead to true environmental improvements. That is, policies aiming to lower a given environmental load should target the consumers rather than the producers, since part of the impacts are externalized to other countries.

International trade could lead to unfair scenarios in which countries externalize the environmental pressures by displacing their manufacturing tasks to other regions. The effect of international trade highly depends on the environmental loads being assessed. For example, the indicators related to mineral extraction and fossil resources are much more embodied in trade than indicators related to water and biomass consumption. Nevertheless, the growing globalization of markets makes the effect of trade-embodied environmental loads increasingly meaningful.

In general, the percentage of trade-embodied loads decreased after 2006, probably due to the crisis. Two well defined patterns are identified: from 1995 to 2006, where (in most of the indicators) the trade-embodied environmental loads tend to grow; and from 2006 to 2009, wherein they increase in some indicators and decreases in others. Indicators related to water and biomass consumption have a small variation over time, while those related to mineral extraction and fossil resources change significantly before and after 2006.

We found that wealthier economies are in general net importers of environmental loads, evidencing that the impact of the goods/services consumed therein is masked by displacing the manufacturing tasks to emerging countries with softer environmental and social regulations. Identifying the ultimate source of environmental loads helps to take actions in the correct countries and sectors, both by imposing economic penalties to the consumers (*e.g.* taxation); or encouraging the adoption of sustainable habits (such as the implementation of large scale solar energy in China).

Gini coefficient revealed that the most basic necessities (*e.g.* the use of water, land and biomass related to food) are distributed in a rather equitable manner, while in contrast, energy-related indicators are less equally distributed (*e.g.* fossil fuels). As a generalized trend, the environmental inequality has decreased after 2006. Particularly, energy-related Gini coefficients have moved towards equity in the recent years, while in contrast, Gini coefficients corresponding to land and water do not substantially change before and after 2006. Moreover, the general downward trend of Gini values could be related to a widespread cause, for example the global recession.

2.5 Nomenclature

2.5.1 Abbreviations

EEIO	*Environmentally extended input-output*
LCA	*Life cycle assessment*
RoW	*Rest of the world*
WIOD	*World input-output database*

2.5.2 Equations

α	*Area below the Lorenz curve*
β	*Area between the Lorenz curve and the perfect equality line*
A	*Technical coefficients matrix*
$A^{rr'}$	*Technical coefficients between regions r and r'*
a_{ij}	*Technical coefficient*
$a_{ij}^{rr'}$	*Technical coefficients between i region r and sector j region r'*

EX^k *Vector of environmental loads (type k) exported from each country*

$Gini^k$ *Vector of environmental Gini coefficients of environmental indicator k*

I *Identity matrix*

i *Selling sector*

$\hat{\imath}$ *Summation vector*

$\hat{\imath}'$ *Transposed summation vector*

IM^k *Vector of environmental loads (type k) imported from by country*

IMP^k *Matrix of environmental loads transferred between regions*

Imp_P^k *Production-based environmental loads of environmental indicator k*

Imp_P^{kr} *Production-based environmental loads of region r, indicator k*

Imp_C^k *Consumption-based environmental loads of environmental indicator k*

Imp_C^{kr} *Consumption-based environmental loads of region r, indicator k*

$Imp^{rr'k}$ *Environmental loads of type k exported from r to r'*

Imp_N^k *Environmental loads (k) of the goods consumed in the country of origin*

Imp_T^k *Environmental loads (k) of the goods that are internationally traded*

j *Purchasing sector*

k *Type of environmental indicator*

L *Leontief inverse matrix*

n Number of sectors

NET^k *Vector of net imports or exports*

p *Number of regions*

PI^k *Pollution intensity vector of the k environmental indicator*

$PI^{r\,k}$ *Pollution intensity vector of region r and of the k environmental indicator*

$pi_i^{r\,k}$ *Pollution intensity of sector i, region r of the k environmental indicator*

$Population_r$ *Population of region r*

r *Selling region*

r' *Purchasing region*

$ratio^{rk}$ *Ratio between the percentage of environmental load k of country r and the percentage of population of country r*

X *Total output vector*

X^r *Total economic output of region r*

$X^{*r'}$ *Output of all countries and sectors required to meet the demand of r'*

x_i *Total economic output of sector i*

x_i^r *Total economic output of region r sector i*

Y *Final demand vector*

$\hat{Y}$ *World's total final demand vector*

y_i *Final demand from final of sector i*

$Y^{r'}$ *Final demand vector from region r' to all countries and sectors*

$Y^{rr'}$ *Final demand vector from region r' to all sectors from region r*

Y_mr *Multi-regional final demand matrix*

$\hat{y}_i^r$ *Final demand from all the world to country r sector i*

Z *Intermediate sales matrix*

$Z^{rr'}$ *Matrix of intermediate sales from region r to r'*

$z_{ij}^{rr'}$ *Intermediate sales from sector i region r to sector j region r'*

z_{ij} *Intermediate sales from sector i to sector j*

$\%Imp\_C^{r\,k}$ *Percentage of consumption-based environmental loads of country r, indicator k with respect to the world's total environmental loads k*

$\%Imp\_P^{r\,k}$ *Percentage of production-based environmental loads of country r, indicator k with respect to the world's total environmental loads k*

$\%net^{r\,k}$ *Percentage of net environmental loads of country r, indicator k with respect to the world's total environmental loads k*

$\%Population_r$ *Percentage of population or region r with respect to the world's population*

3 IDENTIFYING STRATEGIES FOR MITIGATING THE GLOBAL WARMING IMPACT OF THE EU-25 ECONOMY USING A MULTI-OBJECTIVE INPUT-OUTPUT APPROACH

3.1 Introduction

The CO_2 atmospheric concentration, which is increasing at a rate of around 2 ppmv every year [105], has become a major global environmental problem over the last decades [106]. This high CO_2 concentration has led to severe dangers for Earth's climates and ecosystems such as global warming, sea level rise and ocean acidification. Many national governments have placed greenhouse gas emissions mitigation as a priority, and have started to implement stringent measures based on the reorganization of the way in which society develops (work, transport, leisure, city planning, housing, electricity production) [107]. A large body of literature has studied different technological alternatives to mitigate global warming by adopting an engineering approach. However, less work has been devoted to the analysis of global warming mitigation at a wider scale, that is, to the study of how to reduce greenhouse gas emissions from a macro-economic level.

In this chapter, we present a systematic multi-objective optimization approach for simultaneously minimizing the global warming potential (assessed through a life cycle assessment methodology) and maximizing the total economic output of the European Union (EU-25). The calculations are performed using an environmentally extended input-output (EEIO) model based on a Comprehensive Environmental Data Archive—EU25 ($CEDA_{EU25}$) database [108, 109], which considers 487 sectors (including household activities) for the EU-25 economy in 2006. The use of a highly disaggregated EEIO model allows identifying specific economic activities that are ultimately responsible for the overall environmental impact.

To the best of our knowledge, this is the first contribution that applies multi-objective optimization to input output models of the European Union economy. There are few approaches similar to the one proposed here (*i.e.* multi-objective optimization applied to EEIO models), but they typically restrict the analysis to single countries or small regions, and in addition to this, they tend to employ highly aggregated data that provides little information on the ultimate source of impact. Furthermore, in this chapter we present a detailed study of the extent to which the satisfaction of the demand of a single sector (rather than the economic activities performed by the single sector itself) contribute to the total impact. Through this study, we identify sectors with low direct emissions but large indirect ones, which could be used to define more effective environmental policies.

3.2 Method description

3.2.1 Standard EEIO model of the EU-25: Comparison of the alternatives

We consider the European economy in 2006 as described in the environmentally extended input output table $CEDA_{EU25}$, which covers 25 nations within the European Union. This database provides a high resolution EEIO table that covers the environmental effects of household consumption in the European Union. The database considers 487 sectors and 10 different environmental impacts. It covers productive sectors and a series of household consumption activities with direct emissions, such as automobile driving, cooking and heating, and a number of postconsumer waste management sectors (for details on the data provided in the $CEDA_{EU25}$ database, please refer to Huppes *et al.*, 2006 and Heijungs *et al.*, 2006 [108, 109]). The EEIO table covers in turn final private household consumption using data from the statistical office of the European Union.

In its basic form, a quantity oriented input-output model consists of a system of linear equations, each of which describes the distribution of the production of an economic sector among the remaining sectors of the economy [6]. Previously in Chapter 2, we have described some examples of such equations (see Eq. (2.2)). Following the nomenclature introduced in chapter 2, the total output of the *i* sector of an economy is given by Eq. (3.1).

$$x_i = \sum_{j=1}^{n} z_{ij} + y_i \tag{3.1}$$

The output of one sector could be reformulated as a function of the technical coefficients (see Eq. 2.5), as given in Eq. (3.2).

$$x_i = \sum_{j=1}^{n} a_{ij} \cdot x_j + y_i \qquad (3.2)$$

The technical coefficients (a_{ij}) denote the output of sector *i* required to produce one unit of output in sector *j* (*i.e.* the amount of goods produced by sector *j* purchased by sector *i* in order to produce one unit of *i*). Input-output models often assume a direct proportionality between the total output of a sector and the inputs that this sector acquires from its supplying sectors. Under this premise, the technical coefficients a_{ij} can be considered constant in a given time period (assuming that the technological conditions of an economy remain unchanged).

Environmentally extended input-output models can be obtained from standard input-output tables by adding the pollution intensities of each sector. The pollution intensity is the amount of a given environmental load that emerges when generating one unit of economic output. We denote the pollution intensity by *PI*, which represents the environmental load per Euro of output in each sector. In this chapter, we focus on the global warming potential for a 100-years time horizon (GWP_{100}), which is expressed in CO_2 equivalent emissions (amount of CO_2 that would have the same global warming potential than a given amount of other greenhouse gases like CH_4 or N_2O). Then, for a given economy, the GWP_{100} associated to the production technologies of a sector *i* is given by Eq. (3.3).

$$GWP_{100\,i} = x_i \cdot PI_i \qquad (3.3)$$

And the total GWP_{100} of the economy is given by Eq. (3.4)

$$GWP_{100} = \sum_{i=1}^{n} x_i \cdot PI_i \qquad (3.4)$$

3.2.2 Multi-objective optimization problem

3.2.2.1 Problem statement

The optimization problem we aim to solve, which is based on the information contained in the EEIO tables described before, can be formally stated as follows. Given are the economic and environmental data of the EU-25 in 2006, including the transactions taking place between economic sectors and the associated environmental impact (this information is retrieved from the $CEDA_{EU\text{-}25}$ database). We assume that the final demand of each economic sector can vary within lower and upper bounds defined beforehand (in practice, the demand can be controlled by imposing taxes on goods/services). The goal is to identify the economic sectors that should be regulated in order to minimize the environmental impact and maximize the total output.

3.2.2.2 Mathematical formulation

Our approach is based on a multi objective linear program that contains an EEIO model. The linear programming model takes the following form:

$$min\left\{-\sum_{i} x_i, GWP_{100}\right\} \tag{3.5}$$

S.t:

$$x_i = \sum_{j=1}^{n} a_{ij} \cdot x_j + y_i \qquad \forall i \tag{3.6}$$

$$GWP_{100} = \sum_{i=1}^{n} x_i \cdot PI_i \qquad \forall i \tag{3.7}$$

$$\underline{y_i} \le y_i \le \overline{y_i} \tag{3.8}$$

As observed, the model contains three main blocs of equations: the basic input-output equations, the equations that determines the environmental impact (*i.e.* global warming potential), and an inequality constraints that imposes lower and upper bounds on the demand. Hence, the key assumption of the model is that the demand can be changed so as to decrease the environmental impact. By defining the demand as a variable (constrained within realistic lower and upper bounds represented by $\underline{y_i}$ and $\overline{y_i}$ respectively) rather than as a parameter, the model has the flexibility to leave part of it unsatisfied, reflecting the application of environmental policies that would define taxes on sectors so as to reduce the corresponding demand.

3.2.2.3 Pareto optimality

Since tradeoffs will naturally exist between both objectives, the solution of the problem will consist of a set of Pareto optimal points (for details on Pareto optimality see for instance Ehrgott, 2005 [67]), each achieving a unique combination of total output and global warming potential. These so called Pareto solutions feature the property that it is impossible to improve them in one objective without necessarily worsening the other. Figure 3.1 shows an example of a Pareto front.

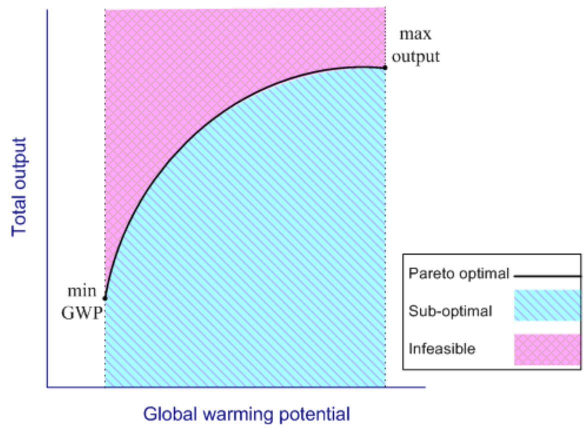

Figure 3.1: Example of a bi-criteria Pareto optimal frontier for two conflictive objectives (*i.e.* total economic output vs. global warming potential).

We apply the epsilon constraint method [68] to solve the aforementioned model, which is based on calculating a series of single objective sub-problems, where one criterion is kept as main objective while the others are transferred to auxiliary constraints that impose limits on them. Our multi-objective formulation contains around 1940 variables and 970 equations. It was implemented in the modeling system GAMS v 24.0 [110], and solved with CPLEX 12.2.0.2. We generated 10 Pareto optimal solutions using the epsilon constraint method. Once the Pareto solutions are calculated, it is possible to choose the most appropriate one by modulating our goals and bearing always in mind the applicable legislation as well as the stakeholders' preferences. Our final goal is to identify solutions that mitigate the environmental impact at a marginal decrease in economic performance.

3.3 Results

3.3.1 Analysis of the direct and indirect contribution to global warming potential of each economic sector

Before presenting the optimization results, we analyze the direct (production based) and indirect (consumption based) environmental impacts of the sectors of the EU economy. The direct contribution to global warming potential is obtained by multiplying the total economic output of each sector by its corresponding pollution intensity according to Eq. (3.3). In contrast, to estimate the indirect impact of a sector we assume that the whole EU-25’s economy works entirely and solely to cover the demand of that sector. Hence, in the latter case, we consider all the intermediate economic transactions associated with the supply chain of the sector of interest.

The consumption based (indirect) approach calculates the impact as follows. We first fix the demand of sector *i* and set the demand of the remaining sectors to zero. This creates a column vector whose values are all zero except for the *i* sector. Let us denote this consumption based demand vector of sector *i* as y_i^C. It is important to note that there are a total of *n* y_i^C vectors (one for each sector). We then solve Eq. (3.2) repeatedly for each of these vectors, obtaining the consumption based output for each sector *i*, denoted as x_i^C. The consumption based global warming potential of sector *i* is then given by Eq. (3.9). Note that these calculations take into account all the inter sector economic transactions required to satisfy the demand of sector *i* (regardless of the sector where these take place).

$$GWP_{100} = \sum_{i=1}^{n} x_i^C \cdot PI_i \tag{3.9}$$

In terms of direct emissions, we found that 4% of the sectors are responsible for 49% of the EU-25’s global warming potential, while the remaining 51% of the impact is produced by 96% of the sectors. Table 3.1, obtained from Eq. (3.3), shows the percentage breakdown of output contribution and CO_2 equivalent emissions to the EU-25's economy for the sectors responsible for more than 1% of the European GWP_{100}.

Table 3.1.: Breakdown of the sectors contributing in more than 1% to the GWP_{100} of the EU-25 in 2006, and their corresponding contribution of output from a production-based viewpoint.

Sectors	CO_2e emissions contribution	Output contribution
Motor vehicles and passenger car bodies (driving with)	6.95%	4.28%
Electric services (utilities)	6.10%	1.37%
Eating and drinking places	3.39%	4.01%
Meat packing plants	3.12%	1.30%
Blast furnaces and steel mills	2.95%	1.01%
Industrial inorganic and organic chemicals	2.10%	0.98%
Meat animals	2.03%	1.01%
Poultry slaughtering and processing	1.99%	0.98%
New residential 1 unit structures, nonfarm	1.83%	3.82%
Heating equipment, except electric and warm air furnaces	1.63%	0.57%
Feed grains	1.41%	0.72%
Petroleum refining	1.34%	1.15%
Crude petroleum and natural gas	1.23%	1.63%
Natural, processed, and imitation cheese	1.18%	0.62%
Wholesale trade	1.17%	3.03%
Sausages and other prepared meat products	1.15%	0.47%
Fluid milk	1.15%	0.63%
Miscellaneous plastics products	1.13%	0.96%
Household laundry equipment	1.04%	0.34%
Poultry and eggs	1.03%	0.56%
Trucking and courier services, except air	1.00%	1.15%

As observed, among the most polluting sectors, there are some with high environmental impact per Euro of output and high demand, and others with low or medium pollution intensity but very high demand. Particularly, Huppes *et al*. (2006) [108] found that meat and derived products, along with household heating represent a large share of the total environmental impact due to their high impact per Euro and high customer expenditure, while in the case of other sectors like bars and restaurants, clothing, residential construction and services such as telecommunications, the impact per Euro is low or medium, but their sales volume is particularly high.

There are sectors that contribute significantly to the total impact, but whose output is used by other sectors. That is, their impact is embodied in the supply chains of other services/goods. To shed light on this issue, we investigate which sectors are ultimately responsible for the total impact. Note that the direct emissions of a sector are those generated by the sector itself, while the indirect ones correspond to the emissions generated by all the activities required to satisfy the demand of the sector (*i.e.* emissions embodied in the supply chain of the sector).

Similarly, Table 3.2, obtained from Eq. (3.5), provides details on the indirect (consumption based) assessment of the European GWP_{100} output contribution and CO_2 equivalent emissions of the sectors responsible for more than 1% of the total GWP_{100}. By comparing Table 3.1 and Table 3.2, we found that the most polluting sectors differ from one approach to another. In particular, out of the 21 “top polluting” sectors according to the direct (production based) assessment, there are only 10 appearing in the “top polluting” sectors list of the consumption based approach. This mismatch is due to the fact that there are sectors that generate large emissions, but whose output is mainly used by other sectors. One clear example of such situation is the sector labeled as *Industrial inorganic and organic chemicals*. From a production based assessment, this sector is the 6th of the list and responsible for 2.1% of the global warming potential of the European Union. However, from a consumption based viewpoint, the products from this sector are addressed to other sectors (as intermediate sales) and not to final consumers, thereby the impact of the sector itself is zero. Hence, the impact of this intermediate sector is transferred proportionally to products and services addressed to final consumers (*e.g.* manufactured foods, clothes, etc.).

Table 3.2: Breakdown of the sectors contributing in more than 1% to the *GWP_{100}* of the EU-25 in 2006, and their corresponding contribution of output, from a consumption-based viewpoint.

Sectors	CO_2e emissions contribution	Output contribution
Motor vehicles and passenger car bodies	12.35%	9.53%
Eating and drinking places	8.84%	9.04%
Meat packing plants	5.40%	3.31%
Poultry slaughtering and processing	4.21%	2.76%
New residential 1 unit structures, nonfarm	3.10%	4.67%
Heating equipment, except electric and warm air furnaces	2.81%	2.16%
Sausages and other prepared meat products	2.60%	1.58%
Household laundry equipment	2.48%	1.15%
Fluid milk	2.35%	1.68%
Natural, processed, and imitation cheese	2.14%	1.50%
Household refrigerators and freezers	1.86%	0.80%
New additions & alterations, nonfarm, construction	1.73%	2.41%
Apparel made from purchased materials	1.63%	2.16%
Beauty and barber shops	1.42%	1.69%
Edible fats and oils	1.40%	0.96%
Telephone, telegraph communications and communications services	1.33%	3.06%
Automotive repair shops and services	1.29%	1.84%
Electric lamp bulbs and tubes	1.29%	0.48%
Household audio and video equipment	1.18%	0.59%
Insurance carriers	1.14%	3.92%
Drugs	1.09%	1.01%
Household appliances	1.03%	0.89%
Bottled and canned soft drinks	1.01%	0.95%
Bread, cake, and related products	1.00%	1.03%
Household cooking equipment	1.00%	0.53%

In Figure 3.2 we compare the *GWP_{100}* assessed through the direct (production based) and indirect (consumption based), where the x axis represents the *GWP_{100}* contribution per sector through a production based assessment, and the y axis the *GWP_{100}* sector contribution from a consumption based viewpoint.

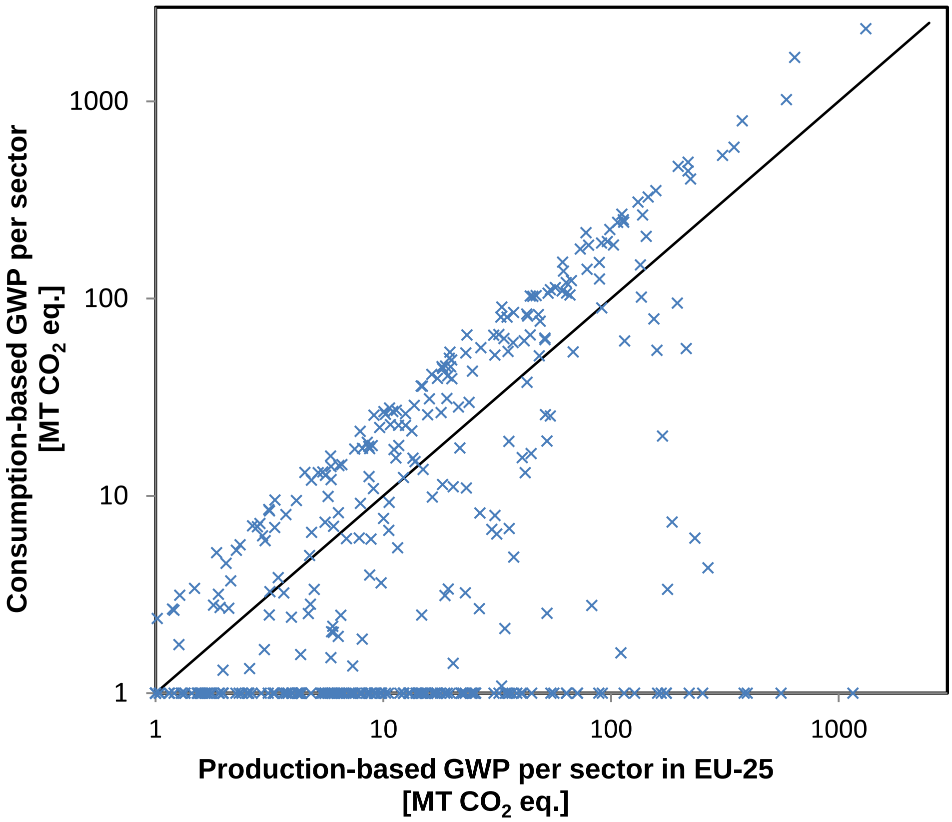

Figure 3.2: Scatter plot contrasting the consumption-based and production-based global warming potential emissions per each sector in the European economy in 2006.

There are 304 out of 487 sectors below the diagonal, indicating that the majority of the sectors show higher global warming potential through the production based approach. Hence, environmental policies devised to control the direct greenhouse gas emissions might wrongly penalize the demand of sectors (*e.g.* by establishing taxes on their products) whose output is largely used by other sectors as intermediate products/services. In other words, production based environmental policies might be ineffective, since they are based on imperfect knowledge on how the impact is generated in a complex logistic network, and therefore might fail to control the ultimate source of impact.

3.3.2 Results of the optimization

Figure 3.3 depicts the Pareto front that trades off the global warming potential and total output. The Pareto solutions are labeled from 1 to 10, being 1 the minimum impact solution and 10 the one with the maximum economic output. Due to the linear nature of the model, the Pareto frontier is concave, implying that the slope increases as we move to the left in the curve. Hence, from the maximum output to the minimum impact point, we gradually need greater reductions of output in order to achieve the same impact reduction.

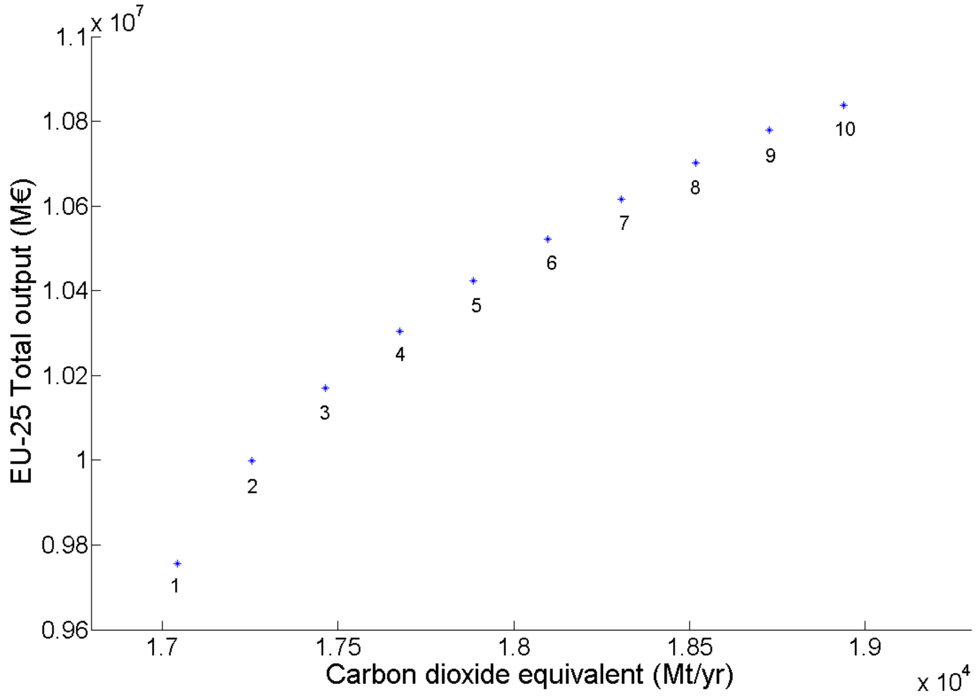

Figure 3.3: Pareto optimal frontier for GWP_{100} vs. the EU-25's total output in the year 2006.

As expected, in the extreme point corresponding to the maximum output, the demand of all of the sectors hit the upper bound; while in the extreme solution with minimum impact, these demands reach the lower bound. Note that the demand of each sector is allowed to vary between a lower bound (90% of the current demand), and an upper bound (the current demand). Hence, the Pareto optimal solutions between the extreme points are unique combinations of totally and partially satisfied demands of sectors.

Particularly, as we reduce the global warming potential, the number of sectors that are regulated increases. Table 3.3 shows, for each Pareto point, the number of sectors that are regulated (*i.e.* whose demand is not totally met) along with the ratio between the variation of the total output and the reduction in GWP_{100} (%GWP_{100} reduction / %

Output reduction). This can be interpreted as an elasticity output of the reduction in emissions. A high value in this elasticity indicates a high sensibility of the emissions for a given decrease in output, whereas a low value indicates that the reduction in emissions is rigid to changes in output.

Table 3.3: Optimal solutions found for the GWP_{100} minimization. The Pareto points correspond to Figure 3.3.

	Pareto points									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
GWP_{100} reduction	10.0%	8.9%	7.8%	6.7%	5.6%	4.4%	3.3%	2.2%	1.1%	0.0%
Output reduction	10.0%	7.7%	6.2%	4.9%	3.8%	2.9%	2.0%	1.2%	0.5%	0.0%
Elasticity-output	1.00	1.15	1.26	1.36	1.46	1.53	1.63	1.79	2.07	-
Number of capped sectors	282	214	175	116	88	46	43	21	11	-

A detailed analysis of the results reveals that the model first identifies the sector that reduces the impact the most for a given drop in total output. Once such sector reaches the lower bound; the algorithm proceeds in a similar manner with the following sectors until the environmental target imposed by the epsilon constraint is reached. The sector that is being reduced when the algorithm meets the epsilon target is not decreased any further, and its demand then falls between its upper and lower bounds. Hence, in each Pareto point, we find three types of sectors: those whose demand is reduced to the lower bound, those whose demand hits the upper bound, and only one of them with a demand lying between its upper and lower bound. The complex interactions between sectors make it difficult to identify at a first glance the sectors to be firstly regulated. For instance, sectors with small production based emissions might consume intermediate goods and services from very polluting sectors. In this context, the input-output model helps uncovering these complex relationships with the aim of identifying the ultimate source of impact.

An important outcome from the optimization problem concerns the number of sectors whose final demand is restricted to reach a given environmental target. This information is quite valuable for governments and public policy makers, as it pinpoints the sectors to be more severely regulated to attain significant environmental benefits. As observed, solution 9 shows the highest elasticity (2.07) of GWP_{100} reduction per output reduction, allowing for a reduction of GWP_{100} of 1.1% at the expense of a drop in the output of 0.5%. In this solution, only 11 sectors are restricted. In point 8, the impact is halved with respect to point 9, at the expense of reducing the output by more than double and restricting 21 sectors. Such trend of reducing more the output than the impact by moving to the left of the curve tends to increase due to the concavity of the curve. Point 9 is for example an appealing solution for policy makers due to its high ratio value. Table 3.4 provides detailed information on the sectors that are capped in the Pareto point 9, and the extent to which their demand should be reduced with respect to the original one.

Table 3.4: Household activities and industrial sectors whose final demand should be restricted in the Pareto optimal solution 9.

Sectors	$\frac{y(i)-y_0(i)}{y_0(i)}$
Household cooking equipment	-10.0%
Household refrigerators and freezers	-10.0%
Household laundry equipment	-10.0%
Electric housewares and fans	-10.0%
Electric lamp bulbs and tubes	-10.0%
Household audio and video equipment	-10.0%
Chemical and fertilizer minerals	-10.0%
Sausages and other prepared meat products	-9.6%
Nonwoven fabrics	-10.0%
Fabricated textile products	-10.0%
Boot and shoe cut stock and findings	-10.0%

Among the sectors that are regulated in solution 9, we found industrial sectors such as *Chemical and fertilizer minerals, sausages and other prepared meat products, Nonwoven fabrics, Fabricated textile products and Boot and shoe cut stock and findings*. Note that the $CEDA_{EU25}$ database considers domestic activities. Hence, solution 9 requires reducing 10% the consumption of energy in domestic appliances (*e.g.* refrigerators, light bulbs, fans, and equipment related to laundry, cooking, video and audio). These activities are the first to be restricted. Reducing energy consumption in households has little impact in the European economy, but leads to significant reductions in CO_2 equivalent emissions. Acting on the energy consumption and alimentary habits in Europe contributes efficiently to global warming mitigation [3].

Results show that the sectors capped in first place by the optimization model are not necessarily the same sectors that appear in the list of top polluting industries (from both approaches, consumption-based and production-based), except for a few of them (*i.e.* sausages and other prepared meat products and household laundry equipment). This happens because the optimization model considers environmental and economic concerns simultaneously, while the aforementioned lists focus only on the environmental performance.

The output of one sector covers the final demand and the intermediate sales. Hence, reductions in the output of a sector can take place without modifying the original demand by simply decreasing the intermediate transactions. Figure 3.4 shows the cumulative distribution of the percentage of economic output reduction in the intermediate Pareto optimal solutions. That is, the y axis of the curve displays the percentage of sectors whose economic output is reduced by a percentage less or equal to the amount shown in the horizontal axis.

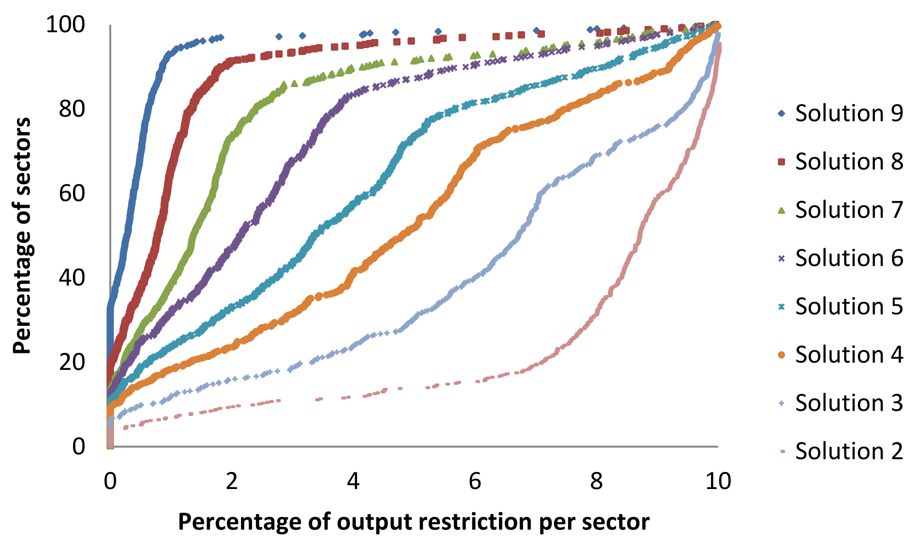

Figure 3.4: Cumulative distribution of the output reduction per-sector in the intermediate Pareto optimal solutions.

As seen, the number of sectors restricted increases from solution 9 to solution 2. In solution 9, the overwhelming majority of sectors have an output reduction of less than 2% (93% of the sectors show a reduction of less than 2%), while in solution 2; only 6.7% of the sectors reduce the output by less than 1%, and 68.5% reduce more than 8%. As an example, Table 3.5 displays the sectors with output reductions above 2% in solution 9.

Table 3.5: Sectors whose total output is reduced by more than 2% in the selected optimal solution (*i.e.* solution 9).

Sectors	$\frac{x(i)-x_0(i)}{x_0(i)}$
Household laundry equipment (washing with)	10.00%
Household refrigerators and freezers (use of)	10.00%
Household cooking equipment (use of)	10.00%
Electric lamp bulbs and tubes (use of)	10.00%
Household audio and video equipment (use of)	8.45%
Sausages and other prepared meat products	8.01%
Electric housewares and fans (use of)	7.90%
Fabricated textile products	7.01%
Wood television and radio cabinets	5.40%
Electric services (utilities)	4.70%
Electron tubes	4.27%
Nonwoven fabrics	4.18%
Turbines and turbine generator sets	4.15%
Coal	3.16%
Power, distribution and specialty transformers	2.78%

Comparing Tables 3.4 and 3.5, we observe that 9 of the 11 sectors in Table 3.4, appear also in Table 3.5 (*i.e.* not only their final demand is reduced, but also their economic output drops by more than 2%). In contrast, 6 of the sectors appearing in Table 3.5 reduce their output without manipulating the demand (*e.g. Wood television and radio cabinets, Electric services (utilities), Electron tubes, Turbines and turbine generator sets, Coal, Power, distribution, and specialty transformers*). As an example, the reduction in the consumption of energy in households affects the output of sectors belonging to the supply chain of energy, such as coal and turbines (which are both used for energy generation).

3.4 Discussion of the results

Our findings suggest that EU-25's public energy policies should take into account simultaneously economic concerns along with environmental priorities to guarantee long term sustainability. Sustainability policies should be integrated in the European Union for simultaneously improving the socioeconomic development and environmental performance. The following three main different strategies can be extracted from the results obtained.

3.4.1 Encouraging technology improvement

One of the main outcomes from the multi-objective optimization is the identification of sectors whose regulation leads to major greenhouse gas savings at a marginal decrease in economic performance. This information is rather valuable for governments and public policy makers when establishing effective sustainability policies, as it pinpoints the sectors with a better potential for reducing the greenhouse gas emissions (larger reductions in emissions at a marginal drop in economic performance). A high disaggregation of sectors facilitates the precise identification of such key economic sectors.

Policy makers have different alternatives to achieve the target reductions specified in the Pareto set. The two main are: (i) implementing policies that reduce the activity of key polluting sectors (*e.g.* through the increase of environmental taxes); and (ii) fostering research on how to improve the technological efficiency of those sectors. Policy makers should in either case concentrate the efforts on the most appealing sectors identified by the optimization model (those showing a better ratio of potential environmental savings per unit of economic drop).

3.4.2 Following optimal paths

Improving simultaneously the socioeconomic development and the environmental quality is very much in line with the principles of sustainability, where a balance is established between such competitive objectives. The Pareto optimal frontier represents the ideal path to be followed when the goals are set in sustainability. Hence, the economic policies adopted by national governments willing to "sacrifice" to some extent its economic output (at the expense of attaining better environmental performance), should follow the guidelines obtained from the analysis of the Pareto front. This would avoid implementing suboptimal solutions.

The main advantage of heeding the path established by the Pareto front that adopts an input-output approach is that policy makers are considering the direct and indirect greenhouse gas emissions in the whole production chain of the demanded products. Consumption-based policies are more effective than those based on production, since they prevent nations from displacing their manufacturing tasks to countries with softer production based regulations [3].

3.4.3 Greening the final demand

According to the optimization results, household utilization of energy is among the first activities to be regulated. In addition, the regulation of other industries such as those producing some meat derived products and clothes and apparels can lead to significant environmental savings. European governments should therefore pay more attention to energy use in household consumption, encouraging lifestyle changes, promoting the consumption of green labeled products, and developing more efficient electric appliances. Implementing green consumption habits will translate into the use of less energy intensive products, which will in turn decrease energy consumption.

3.5 Conclusions and policy implications

Based on EEIO tables, this work addressed the simultaneous optimization of economic and environmental objectives at a macroeconomic scale in the EU-25 in 2006. A preliminary analysis of the data reveals that global warming potential is generated either from direct consumption or through indirect consumption embedded in the supply chain and life cycle of products. Consumption-based and production-based emissions differ substantially, which can lead to misallocation of impacts and concentration of efforts on sectors which are not the ultimate source of impacts.

From the production based assessment, the impact is allocated proportionally to each sector involved in the supply chain of a product; whereas, through the consumption based approach, the environmental responsibility of the whole process from cradle to grave is assigned to the products addressed to final consumers. A consumption based analysis reveals that there are sectors developing everyday activities that show very high global warming potential values (*e.g. bars and restaurants*) because the carry the burdens generated by other intermediate polluting sectors embedded in their supply chains (*e.g.* electric services, food industries, fertilizers, paper, and other sectors involved). Efficient taxes schemes defined on final products that cause significant impacts could make gradual changes in consumption patterns and ensure a more sustainable development.

The present study explores in quantitative terms the way in which the European economy should proceed to optimally reduce the global warming potential without significantly compromise the economic performance. The analysis identifies the sectors (or activities) that lead to major environmental savings with the least economic impact in the economy. This analysis provides as output a Pareto set of alternatives, each of which reduces the global warming potential with respect to the previous one at the expense of restricting progressively the total output of the economy. Numerical results showed that, with the existing technology and current international trade network; the GWP_{100} indicator could be lowered in greater proportion than the economic output by restricting adequately the demand of certain sectors. As an example, the GWP_{100} can be reduced by 1.1% by only reducing the economic output in 0.5%. This could be achieved by reducing 10% the final demand in 11 economic activities out of the 487 studied.

In addition, we found that the economic activities that should be firstly restricted are those with a high ratio amount of greenhouse gases emitted/contribution to the EU-25's total output. Through the application of this methodology, we found that the use of household appliances, the consumption of certain apparels, and the consumption of sausages and other prepared meat products are listed among the activities to regulate with higher priority in order to attain global warming potential reductions with the least impact to the European economy. Minor changes in basic consuming habits in households could lead to significant environmental savings with small changes in the overall economic structure. The integration of multi-objective optimization and EEIO proved to be an efficient tool for pinpointing sectors that should be firstly regulated in order to attain specific environmental targets.

We are aware that some economic sectors are not "elastic", so their demand cannot be reduced easily. This limitation could be overcome by coupling our approach with a detailed economic analysis on the elasticity of each sector's demand in order to set more realistic limits on its bounds.

Another potential improvement of the method consists of accounting for possible changes in consumers' behavior in terms of sector substitution in final consumption. As an example, reducing the demand in bars and restaurants might be traduced in an increase of household cooking. Finally, the input-output quantity oriented model assumes that prices are constant, but these fluctuate and have an impact on the demand. The inclusion of this consideration would also result in a more realistic model.

3.6 Nomenclature

3.6.1 Abbreviations

$CEDA_{EU25}$	*Comprehensive environmental data archive of the EU-25*
CO_2	*Carbon dioxide equivalent emissions*
EEIO	*Environmentally extended input-output*
EU-25	*European Union with 25 countries*
PI	*Pollution intensity*
GWP	*Global warming potential*

3.6.2 Equations

a_{ij}	*Technical coefficients*
GWP_{100}	*Global warming potential measured in 100-years period*
i	*Producing sector*
j	*Consuming sector*
n	*number of sectors*
PIi	*Pollution intensity of sector i*
x_i	*Total economic output of sector i*
x_i^C	*Consumption-based output*
$\overline{y_i}$	*Upper bound of the final demand of sector i*
$\underline{y_i}$	*Lower bound of the final demand of sector i*
y_i	*Final demand of sector i*
Z_{ij}	*Intermediate flows from sector i to sector j*

4 On the use of weighting in life cycle assessment: translating decision-makers' preferences into weights via linear programming

4.1 Introduction

This chapter presents an alternative method to facilitate decision-making in LCA studies consists of addressing the problem backwards. That is, given a solution (or set of solutions) proposed for improving the LCA performance of a system, the problem consists of finding the lower and upper limits of the intervals within which the weights to be attached to a set of LCA impacts should fall to make the selected solution optimal over the rest of alternatives. Hence, decision makers are not required to provide weights beforehand, since they are automatically calculated on the basis of the alternatives available (see details in Cortés-Borda et.al. [113]).

Such approach allows expressing several objectives on a common basis (money per unit of impact), which makes it easier to check whether the alternatives are consistent with the decision-makers' preferences. In other words, these weights represent the economic penalties that decision-makers are willing to pay when choosing a given alternative. This could be understood as the valuation or monetization of the environmental impact [114, 115]. Note that such approach provides an outcome similar to that generated by sensitivity analysis of LCA outcomes [116], but instead of using economic estimations; it relies on a systematic mathematical approach. The information generated by such type of analyses is valuable for decision-makers, as it allows ranking alternatives on a common scoring system based on monetary units. Additionally, approaches based on LP tools can be applied efficiently to problems involving up to thousands of solutions and hundreds of environmental indicators. Furthermore, it allows identifying tendencies in which weights increase and decrease. The solution sought should show a good balance between weights, and therefore a good performance on average in all the indicators.

To the best of our knowledge, this is the first approach that addresses decision-making in LCA following reverse engineering principles in order to calculate the monetary units (*i.e.* economic penalties) that one is willing to pay for the damage caused when a given alternative is chosen.

4.2 Method description

4.2.1 Illustrative example

To motivate our approach, let us consider an illustrative example with 6 solutions (1 to 6) and 2 competitive environmental indicators (I_1 and I_2). The values of I_1 and I_2 are given in Table 4.1. For clarification purposes we will assume in this particular example that I_1 is the cost in USD of a given product and I_2 are the kilograms of CO_2 associated with its production. For example, solution 1 is the cheapest alternative but also the most polluting option. Clearly, choosing this alternative as the "best" implies that I_1 is given more importance than I_2.

Table 4.1: Set of solutions considering two LCA indicators.

Solution	I_1	I_2
1	2	40
2	5	27
3	8	24
4	10	28
5	11	11
6	18	8

Figure 4.1 depicts the solutions in the space of the two environmental indicators. As observed, point 4 is suboptimal since point 3 shows lower values than 4 in both indicators. Further reductions in the set of solutions are not possible, since the remaining alternatives are all Pareto optimal. That is, the Pareto solutions cannot improve the performance of one indicator without reducing the performance of the other (*i.e.* there is no solution that dominates any of the others). Note that we use here the mathematical definition of Pareto optimality (see for instance Ehrgott, 2005 [67]).

According to this, a given solution is said to be Pareto optimal if there is no other solution that performs better than it in at least one objective without necessarily worsening at least any other criterion.

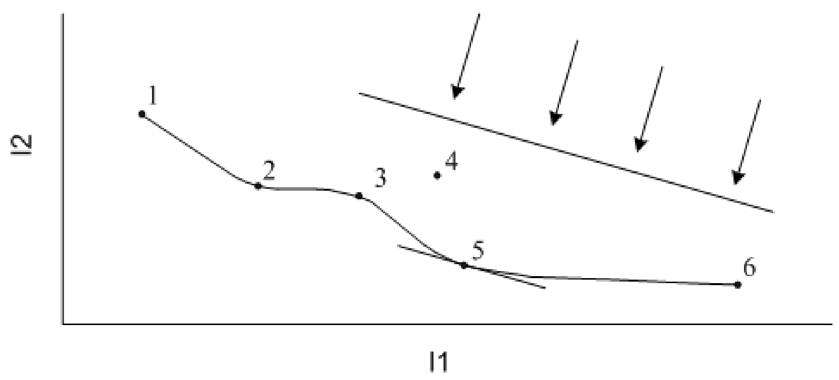

Figure 4.1: Six solutions (dots 1-6), the Pareto front (curved line), and an iso-preference line (straight line) for the case of two environmental indicators.

A common approach to select between the set of Pareto optimal points (*i.e.* all except alternative 4) consists of minimizing a weighted sum of the two indicators, thereby simplifying the associated decision-making process. Aggregated metrics are typically expressed as a linear combination of the individual impacts as follows:

$$AIND = w_1 \cdot I_1 + w_2 \cdot I_2 \quad (4.1)$$

Where *AIND* is the aggregated indicator, *Ii* represents the value of the environmental and economic indicators *i*, and *wi* is their corresponding weight. Figure 4.1 illustrates the graphical meaning of using these weights for optimization purposes. As observed, the solution obtained by optimizing a given weighted combination of impacts is the intersection between the straight line with slope $-w_2/w_1$ and the curve that trades-off both environmental and economic indicators (*i.e.* the Pareto front I_1 vs. I_2). In the figure, the weighted sum is represented by a straight line. The minimization problem seeks to push this line towards the origin until it intersects the convex region on the boundary. Depending on the weighting values, different points can emerge as optimal solutions. This is shown in Table 4.2, in which various $-w_2/w_1$ ratios (R_1 to R_5) are considered.

Table 4.2: Results of the weighted sum for different weighting ratios for the illustrative example (solution with the minimum weighted sum for each combination of weights is underlined).

Solution	**R_1** 0.1	**R_2** 0.3	**R_3** 1	**R_4** 2	**R_5** 3
1	**<u>6</u>**	14	42	82	122
2	7.7	**<u>13.1</u>**	32	59	86
3	10.4	15.2	32	56	80
4	12.8	8.4	38	66	94
5	12.1	14.3	**<u>22</u>**	**<u>33</u>**	44
6	18.8	20.4	26	34	**<u>42</u>**

As observed in Table 4.2, the weighting scheme has a major impact on the decision-making process. The underlined values shown in Table 4.2 represent the solutions that scored the minimum weighted sum for each combination of weights. It can be clearly observed how the optimum solution changes from one point to another according to different weighting values. An important remark is that despite being Pareto optimal, solution 3 cannot be generated by minimizing any aggregated indicator, regardless of the weighting scheme of choice. This is because this point lies in the non-convex region of the trade-off curve (see details in Ehrgott, 2005 [67]). The same holds for solution 4, but in this case the reason is that this solution Pareto suboptimal, so it can be discarded from the pool (solution 2 is better than solution 4 in both metrics simultaneously).

Given a set of alternatives and the corresponding LCA impacts, our goal is to determine the minimum and maximum values of the weights to be attached to each indicator such that within this range the solution can become optimal; while if any of them falls outside this interval, the alternative is guaranteed to be sub-optimal. These bounds provide valuable insight regarding the weights that practitioners implicitly consider when they select a given alternative. Furthermore, when the cost is included in the analysis, these weights represent the economic penalties that decision-makers are willing to pay for a unit of impact.

4.2.2 Linear programming formulation

Our approach is based on LP tools. We are given a set of solutions and the environmental impact associated to each of them (quantified according to some environmental indicators). From now on, we assume that we would like to minimize both indicators simultaneously (the case in which an indicator, like energy saving or recyclability, must be maximized can be easily handled by reversing its sign in the objective function). We further assume that the final solution to be implemented in practice is identified by minimizing a weighted sum of these impacts. The goal of the analysis is then to determine for every solution *j* and impact category *i*, the lower and upper limits of the interval [$\underline{w}_{i,j}$, $\overline{w}_{i,j}$] such that if the weight attached to the category falls outside the interval, then the solution will be guaranteed to be suboptimal (*i.e.* the solution will not be selected if the weight falls outside this interval). The limits of this interval are obtained by solving the following LP models.

Model 1: maximizing w_i

$$\bar{w}_{i,j} = \max w_i$$

$$\sum_i w_i \cdot I_{i,j} \leq \sum_i w_i \cdot I_{i,j'} \qquad \forall\, j \neq j' \tag{4.2}$$

$$w_i^{LO} \leq w_i \leq w_i^{up} \tag{4.3}$$

Model 2: minimizing w_i

$$\bar{w}_{i,j} = \min w_i$$

$$\sum_i w_i \cdot I_{i,j} \leq \sum_i w_i \cdot I_{i,j'} \qquad \forall\, j \neq j' \tag{4.4}$$

$$w_i^{LO} \leq w_i \leq w_i^{up} \tag{4.5}$$

Parameter $I_{i,j}$ denotes the value of impact i in solution j. Eqs. (4.2) and (4.4) ensure that solution j shows better aggregated impact than the remaining alternatives j', while constraints (4.3) and (4.5) force the weights to lie between some lower and upper limits that should be defined according to external restrictions. Note that the lower limit on the weight should be greater than zero, thereby enforcing a positive weight.

A pre-filtering step can be applied prior to the calculation of the LP in order to discard suboptimal solutions (*i.e.* those alternatives improved by at least another one in all of the objectives considered simultaneously). Note, however, that this step can be skipped, since the LP model will render infeasible for such solutions (*i.e.* there will be no combination of weights for which a suboptimal Pareto solution will become optimal).

We rely on the set of solutions previously presented in Table 4.1. To find the minimum and maximum weights that drive this decision, we apply our LP-based approach based on Eqs. (4.3) to (4.5). For this particular example, models 1 and 2 are as follows:

$$
\begin{aligned}
\overline{w}_{i,j} = \quad & \max \quad w_2 \\
& s.t. \quad 1\cdot 2 + w_2\cdot 40 \le 1\cdot 5 + w_2\cdot 27 \\
& \qquad\; 1\cdot 2 + w_2\cdot 40 \le 1\cdot 8 + w_2\cdot 24 \\
& \qquad\; 1\cdot 2 + w_2\cdot 40 \le 1\cdot 10 + w_2\cdot 28 \\
& \qquad\; 1\cdot 2 + w_2\cdot 40 \le 1\cdot 11 + w_2\cdot 11 \\
& \qquad\; 1\cdot 2 + w_2\cdot 40 \le 1\cdot 18 + w_2\cdot 8 \\
& \qquad\; 0 \le w_2 \le 10^6
\end{aligned}
$$

$$
\begin{aligned}
\overline{w}_{i,j} = \quad & \min \quad w_2 \\
& s.t. \quad 1\cdot 2 + w_2\cdot 40 \le 1\cdot 5 + w_2\cdot 27 \\
& \qquad\; 1\cdot 2 + w_2\cdot 40 \le 1\cdot 8 + w_2\cdot 24 \\
& \qquad\; 1\cdot 2 + w_2\cdot 40 \le 1\cdot 10 + w_2\cdot 28 \\
& \qquad\; 1\cdot 2 + w_2\cdot 40 \le 1\cdot 11 + w_2\cdot 11 \\
& \qquad\; 1\cdot 2 + w_2\cdot 40 \le 1\cdot 18 + w_2\cdot 8 \\
& \qquad\; 0 \le w_2 \le 10^6
\end{aligned}
$$

Where the search space for w_2 is between zero and a large number (in this case 10^6). w_1 was set to 1 on purpose so that, after solving the LPs, the w_2/w_1 ratio represent the economic penalty (in USD) that decision-makers are willing to pay per kilogram of CO_2. Bearing this in mind, the results of the LPs (see Table 4.3) are interpreted as follows: if decision-makers would be willing to pay a cost in between 0 and 0,23 USD per kilogram of CO_2, then solution 1 would be optimal. If decision-makers were willing to pay a little bit more for unit of CO_2 polluted, then they should choose solution 2.

Table 4.3: Results of the minimum and maximum weight values (W_2) for the illustrative example.

Solution	**min** w_2	**max** w_2
1	0.00	0.23
2	0.23	0.38
3	-	-
4	-	-
5	0.38	2.33
6	2.33	∞

As observed in Table 4.3, there is no combination of weights for which solutions 3 and 4 are optimal. Furthermore, solutions located on the right hand side of the curve show large weights, while these weights decrease as we move to the left. This is consistent with the fact that these solutions (points 5 and 6) show less I_2 values.

Let us finally note that the LPs introduced before might render infeasible if there is no weighting combination for which a given solution is optimal (*e.g.* solutions 3 and 4 in Figure 4.1). This will happen when the alternative is either sub-optimal in the space of environmental indicators or lies in the non-convex part of the Pareto set.

4.3 Method application

4.3.1 Problem description

As benchmark problem to illustrate the capabilities of our approach, we consider the problem of optimizing hydrogen supply chains for vehicle use. A description of the problem under study is given elsewhere [118], including a detailed life cycle assessment on several production, storage and manufacturing technologies to produce hydrogen. Given are a hydrogen demand, fixed time horizon, set of time periods, production, and storage technologies available, capacity limitations of plants and storage facilities, operating and facility investment costs and interest rate. The goal is to minimize the total cost of the infrastructure and the associated impact, which is quantified according to three environmental indicators. Note that the interest here is on the application of our approach to a set of design alternatives for producing and delivering hydrogen rather than on discussing their main structural features. Details on the latter topic can be found in the publication associated with this topic [119].

A superstructure of alternatives is considered, from which the best ones must be identified. Particularly, we consider three technologies to produce hydrogen (*i.e.* steam methane reforming, coal gasification and water electrolysis), and two storage technologies (*i.e.* compressed hydrogen storage and liquefied hydrogen storage). In this work, we calculate a set of Pareto optimal alternative designs, each achieving a unique combination of environmental indicators, using a simplified version of the mixed-integer linear programming (MILP) model described in detail in [119]. From these solutions, decision-makers should choose the best ones according to their preferences. The aforementioned MILP includes three types of variables: continuous, binary and discrete. Continuous variables are used to model mass flow rates and capacities of plants and warehouses, while binaries are employed to denote the execution of capacity expansions and the establishment of transportation links. Discrete variables denote the number of plants and types of technologies selected. Note that, for the sake of simplicity, we focus on selecting the type of technologies and not their spatial locations.

4.3.2 Solution strategy

We use the epsilon constraint method [68] to generate a set of Pareto solutions (*i.e.* network designs leading to different environmental indicators). These optimal points are then fed into the LP model that determines intervals for the weights. The epsilon constraint method is a multi-objective algorithm that solves a set of single-objective models obtained from the original multi-objective one by keeping one criterion in the objective function and transferring the rest to auxiliary constraints that bound them within some allowable limits. Particularly, we follow here a heuristic that consists of calculating a set of bi-criteria problems using the epsilon method, in each of which the cost is traded-off against each single impact separately. That is, we minimize the cost of the network for different limits on a given environmental impact, and then repeated the same type of calculations for the other impacts. We finally identify 30 Pareto optimal design alternatives (10 solutions in each bi-criteria problem), each showing a unique combination of economic and environmental performance and a specific set of production and storage technologies. With the Pareto solutions at hand, we apply next the LP approach in order to determine the weight intervals within which these solutions can be globally optimal.

The environmental impact of each alternative was quantified according to the Eco-indicator 99 framework. We focus on the impact to human health in three categories (carcinogenic, respiratory effects and climate change), measured in disability-adjusted life years (DALY). The life cycle inventory (LCI) was determined from the production rates of hydrogen and the amount of hydrogen stored using algebraic equations along with information retrieved from Eco-invent [103].

We should remark that it is possible to generate the set of alternatives used for decision-making and employed in our approach by means of different strategies (*e.g.* rules of thumb, heuristics, optimization, etc.). For the purpose of our study, it suffices with an initial set of feasible alternatives, each showing a unique combination of economic and environmental performance. In common environmental assessments, these alternatives should be defined by decision-makers based on previous knowledge on the system. Note that we have used a rigorous optimization model to generate these design alternatives, but in the more general case this model is not really required, as for the application of the LP method it suffices to have a set of available alternatives fully characterized (which can be generated using any type of approach).

4.3.3 Numerical results

4.3.3.1 Application to bi-criteria Pareto optimal sets

We start by applying our method to the bi criteria Pareto fronts. In the minimum cost solution, hydrogen is produced via steam methane reforming and stored as liquid. In the minimum impact solutions (*i.e.* minimum human health, ecosystem quality, and depletion of resources), hydrogen is produced through water electrolysis and stored in gas phase. For the sake of brevity, the reader is referred to the original publication for further details on this solution [119].

Figures 4.2, 4.3 and 4.4 show the projections of the 30 solutions onto a set of two-dimensional sub-spaces (*i.e.* cost vs. each damage category separately). More precisely, each plot depicts the 10 Pareto optimal solutions obtained by optimizing each impact vs. the total cost, plus 20 more points resulting from the calculation of the remaining bi-criteria Pareto sets. As seen, only some of the 20 projections lie above the Pareto curves obtained in the two-dimensional subspace. It can also be observed how some points belonging to different bi-criteria Pareto sets overlap.

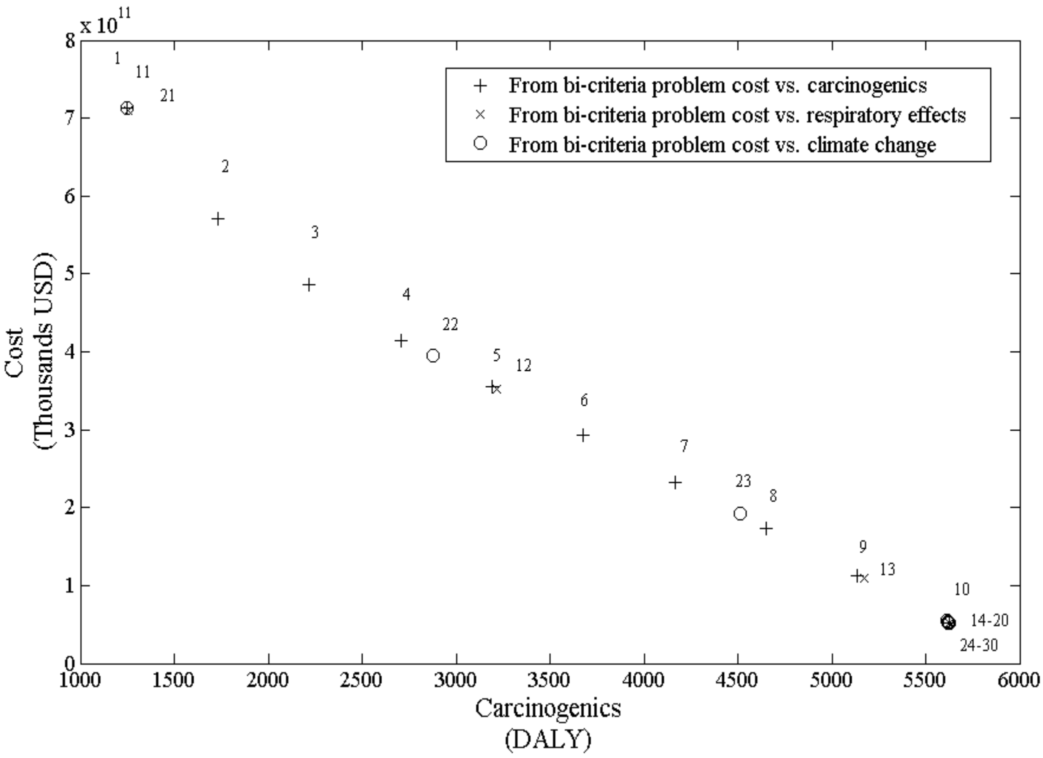

Figure 4.2: Bi-criteria Pareto plot: cost vs. carcinogenic. Numbers on the points correspond to those shown in Table 4.4.

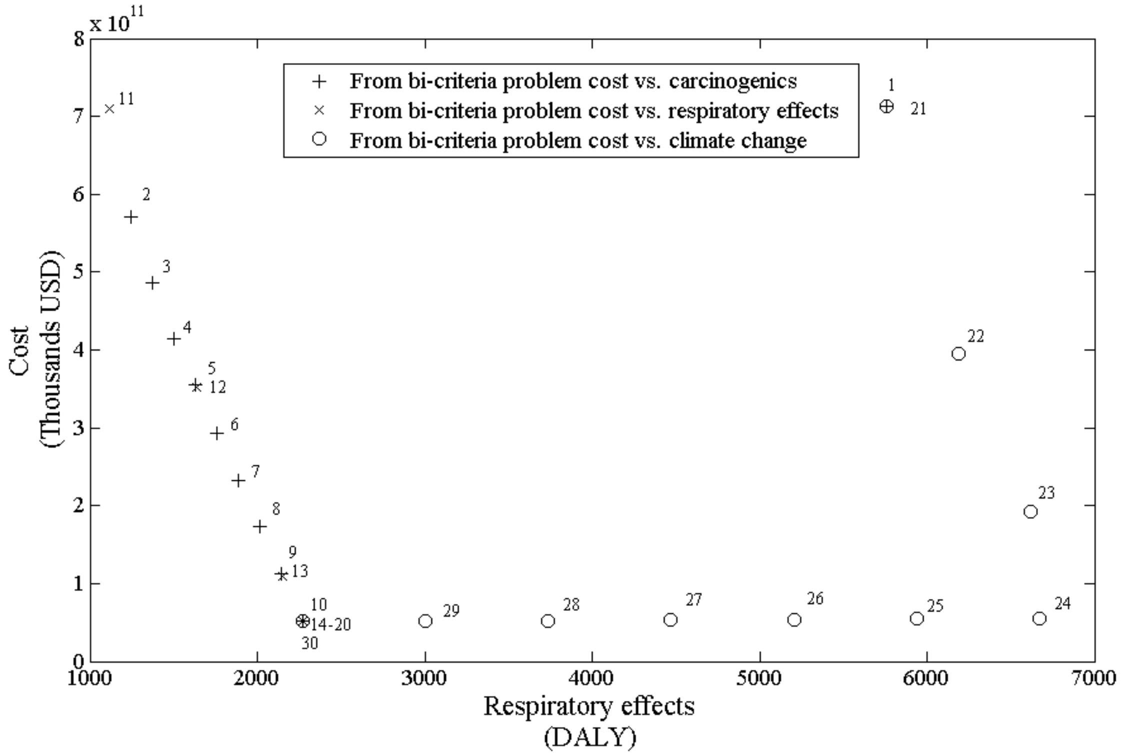

Figure 4.3: Bi-criteria Pareto plot: cost vs. respiratory effects. Numbers on the points correspond to those shown in Table 4.4.

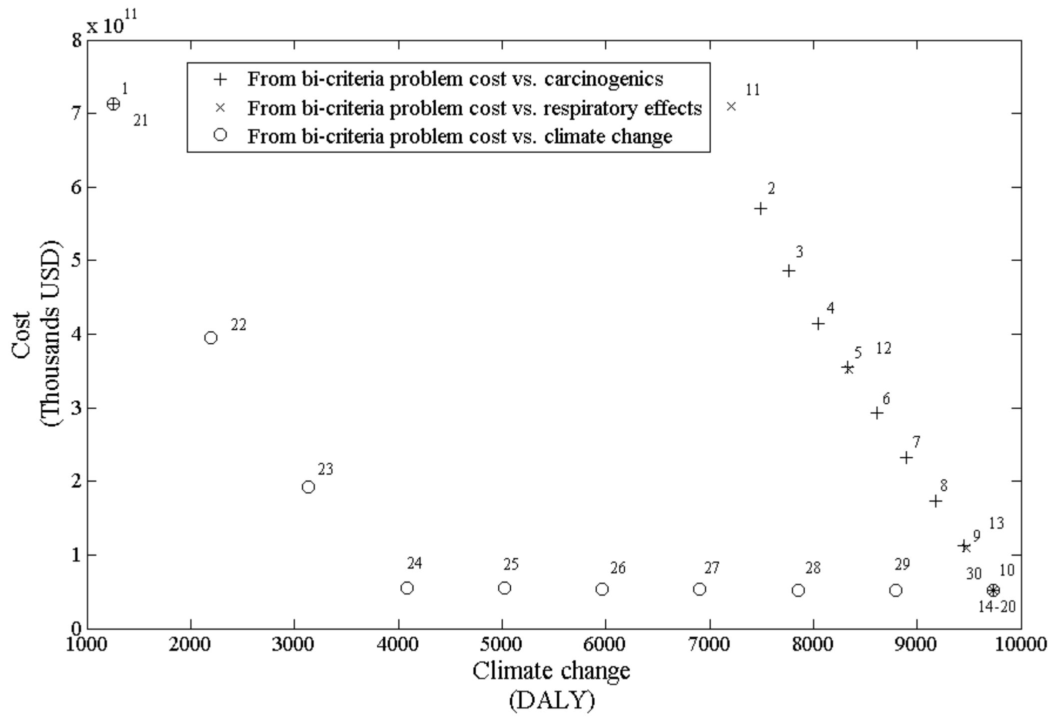

Figure 4.4: Bi-criteria Pareto plot: cost vs. climate change. Numbers on the points correspond to those shown in Table 4.4.

Once obtained the Pareto solutions, we applied our approach to each bi-criteria set of solutions separately (to each Pareto set obtained optimizing one single environmental indicator versus the total cost). In all of the runs, the weight associated with the cost was fixed to one. The LP problems were implemented in GAMS v 24.0 [110] and solved with the solver CPLEX 12.2.0.2. Each LP contains 2 variables (the weights assigned to the economic objective and the environmental metric). It took around 0.015 CPU seconds to solve a single LP instance using an AMD Phenom Triple-core 2.29 GHz processor. Table 4.4 displays the maximum and minimum weights outside which each Pareto solution becomes suboptimal. Note that some solutions which are optimal in one criterion perform significantly worse in the others.

There are some points (*e.g.* solutions 5, 7, 8) in Figures 4.2 to 4.4 that will never become optimal in the simultaneous optimization of the cost and impact regardless of the weights used. This is because these solutions belong to the non-convex part of the Pareto front.

Table 4.4: Results of applying the linear programming approach to each bi-criteria run separately.

		Carcinogenic			Respiratory effects			Climate change		
	Cost (kUSD)	Impact (DALY)	Weights (kUSD/DALY)		Impact (DALY)	Weights (kUSD/DALY)		Impact (DALY)	Weights (kUSD/DALY)	
			Min	Max		Min	Max		Min	Max
1,21	$7.13 \cdot 10^{8}$	1247.583	381992.98	$1.00 \cdot 10^{11}$	5760.537	-	-	1252.42	336517.24	$1.00 \cdot 10^{11}$
2	$5.72 \cdot 10^{8}$	1733.767	174485.47	288915.38	1243.995	66214.37	109638.64	7488.543	-	-
3	$4.87 \cdot 10^{8}$	2219.95	147171.69	174485.47	1372.112	55849.24	66214.37	7769.559	-	-
4	$4.15 \cdot 10^{8}$	2706.133	125362.63	147171.69	1500.23	47573.06	55849.24	8050.574	-	-
6	$2.93 \cdot 10^{8}$	3678.499	124497.82	125362.63	1756.464	47244.88	47573.06	8612.605	-	-
10,14-20,30	$5.11 \cdot 10^{7}$	5623.232	0.00	124497.82	22689.32	0.00	47244.88	9736.67	0.00	745.96
11	$7.09 \cdot 10^{8}$	1256.69	288915.38	381992.98	11182.78	109638.64	$1.00 \cdot 10^{10}$	7212.79	-	-
22	$3.96 \cdot 10^{8}$	2878.533	-	-	61903.18	-	-	2195.11	214735.63	336517.24
23	$1.93 \cdot 10^{8}$	4509.482	-	-	66201	-	-	3137.81	146135.43	214735.63
24	$5.54 \cdot 10^{7}$	5614.59	-	-	66742.58	-	-	4080.50	769.45	146135.43
25	$5.47 \cdot 10^{7}$	5616.031	-	-	59400.37	-	-	5023.20	762.82	769.45
27	$5.32 \cdot 10^{7}$	5618.911	-	-	44715.95	-	-	6908.58	760.89	762.82
28	$5.25 \cdot 10^{7}$	5620.351	-	-	37373.74	-	-	7851.28	745.96	760.89

As mentioned before, our LP-based approach finds the upper and lower bounds of within which an alternative can become optimal among others. These bounds represent the maximum and minimum economic penalties that decision-makers would be willing to pay for each alternative. Some authors refer to this as the environmental valuation or monetization [120]. As observed, these bounds on the weights increase in a single direction over the curves. Thus, in the extreme solutions in which the environmental impact is minimized, the weights take their maximum value. In other words, a very large cost per unit of impact is considered, and such high penalty drives the optimization towards solutions with low impact. In contrast, in the minimum cost solution, the weights are rather low.

4.3.3.2 Application to multi-criteria Pareto optimal sets

We applied our approach to the entire set of alternatives considering simultaneously the cost and the three environmental objectives. The LP problems contain 4 variables (weights for the economic objective and the three environmental objectives). Each LP problem took around 0.047 CPU seconds in the same computer.

In this multi-criteria case-study, there are 22 feasible solutions (considering the repeated solutions) that can be optimal under certain weighting combinations, whereas in the bi-criteria case there were only 17. Thus, discarding alternatives according to optimality principles becomes more difficult as we include more objectives in the multi-criteria analysis. This is because solutions that perform poor in some indicators may perform well in others, so the more indicators we consider, the more chances there are for a solution to show better performance than the rest in certain environmental categories.

Table 4.5 shows the maximum and minimum weights for each alternative considering the four objectives. Similarly to the bi-criteria case-studies, it was found that certain solutions are always suboptimal regardless of the combination of weights. Note that in the multi-criteria approach the boundaries of the “optimal region” become weaker, as they depend as well on the weights attached to other environmental indicators. That is, the weight intervals become wider: the lower bound is decreased and the upper bound is increased. This is because in this second case other impacts and weights come into play, so there are more chances for a solution to become optimal as we consider a larger set of weights. Let us note that the optimality of a solution is not guaranteed even when the weights are within the limits found by the algorithm, as we need to check as well the weights defined for the remaining impact categories. It can be ensured, however, that outside the interval identified by the LP the solution will be suboptimal.

Table 4.5: Results of applying the linear programming approach to the whole set of Pareto solutions simultaneously.

	Carcinogenic (DALY)	Respiratory Effects (DALY)	Climate Change (DALY)	Cost (kUSD)	Carcinogenic weights (kUSD/DALY)		Respiratory effects weights (kUSD/DALY)		Climate change weights (kUSD/DALY)	
					Min	**Max**	**Min**	**Max**	**Min**	**Max**
1,21	1247.583	5760.537	1252.42	$7.13 \cdot 10^{8}$	0.00	$1.00 \cdot 10^{11}$	0.00	$1.00 \cdot 10^{13}$	0.00	$1.00 \cdot 10^{11}$
2	1733.767	1243.995	7488.543	$5.72 \cdot 10^{8}$	0.00	288915.38	0.00	109639.00	0.00	315507.79
3	2219.95	1372.112	7769.559	$4.87 \cdot 10^{8}$	0.00	174485.47	0.00	66214.37	0.00	191989.73
4	2706.133	1500.23	8050.574	$4.15 \cdot 10^{8}$	0.00	147171.69	0.00	55849.24	0.00	161052.56
6	3678.499	1756.464	8612.605	$2.93 \cdot 10^{8}$	0.00	125362.63	0.00	47573.06	0.00	137007.19
10,14-20,30	5623.232	2268.932	9736.667	$5.11 \cdot 10^{7}$	0.00	124497.83	0.00	47244.88	0.00	136105.80
11	1256.69	1118.278	7212.791	$7.09 \cdot 10^{8}$	0.00	$1.00 \cdot 10^{11}$	0.00	$1.00 \cdot 10^{13}$	0.00	$7.79 \cdot 10^{10}$
22	2878.533	6190.318	2195.114	$3.96 \cdot 10^{8}$	0.00	189970.79	0.00	26594.37	348.85	336517.24
23	4509.482	6620.1	3137.808	$1.93 \cdot 10^{8}$	0.00	122981.91	0.00	17216.47	1965.35	214735.63
24	5614.59	6674.258	4080.502	$5.54 \cdot 10^{7}$	0.00	123936.47	0.00	17350.10	580.10	146135.43
25	5616.031	5940.037	5023.197	$5.47 \cdot 10^{7}$	-	-	-	-	-	-
27	5618.911	4471.595	6908.585	$5.32 \cdot 10^{7}$	-	-	-	-	-	-
28	5620.351	3737.374	7851.279	$5.25 \cdot 10^{7}$	0.00	123977.56	0.00	17355.86	556.54	135922.75

4.4 Discussion of results

The weighting intervals for the three bi-criteria case-studies are given in Table 4.4, while Table 4.5 shows the same values for the multi-criteria case. Monetization, and in general the value-laden approaches of life cycle assessments, have been criticized due to the moral implications associated to giving monetary value to the environment and/or biasing the interests of decision-makers. By addressing the problem in an inverse manner, the valuation of impacts is not imposed by decision-makers. Instead, we calculate ranges for the weights attached to the impacts in a systematic manner using an LP model. This approach assesses in a systematic manner the pool of alternatives (from which practitioners should select the best one according to their preferences), providing valuable information for them.

After running the algorithm, it was found that certain solutions are suboptimal independent of the weighting combination. This could be attributed to two reasons: the alternative is Pareto sub-optimal (*i.e.*, there is another alternative that improves it in all the objectives simultaneously) or it lies in the non-convex region of the Pareto front. The range within which the solutions are optimal becomes wider as we increase the number of objectives.

Expressing the alternatives on a common basis (money per unit of impact) simplifies the decision-making procedure, as it allows objective comparisons using a single (and more tangible) indicator. Furthermore, it allows identifying tendencies in the weight values. The final solution sought should show a good balance between weights, and therefore a good performance on average in all of the indicators.

4.5 Conclusions

Life cycle assessment practitioners must choose among several alternatives considering diverse environmental impact indicators, which makes decision-making challenging. While aggregated environmental metrics can simplify decision-making to a large extent, they have been severely criticized for being biased and reflecting the views of a small number of experts. We proposed a systematic LP-based method that supports decision-making in life cycle assessment. Our algorithm systematically provides valid weights ranges within which the solutions are potentially optimal, while at the same time discarding alternatives that are guaranteed to be suboptimal for every possible combination of weights.

This algorithm addresses the weighting problem following a reverse approach. Hence, decision makers are not required to provide weights beforehand, since the intervals within which these weights should fall are automatically calculated by the algorithm on the basis of the alternatives available. Our approach allows expressing several objectives on a common basis (money per unit of impact), which makes it easier to check whether the alternatives are consistent with the decision-makers' preferences. Our final aim is to facilitate decision-making in life cycle assessments, placing particular emphasis on problems with a large number of alternatives and objectives to be considered.

4.6 Nomenclature

4.6.1 Abbreviations

CPU *Central processing unit*

DALY *Disability-adjusted life years*

LCA *Life cycle assessment*

LCI *Life cycle inventory*

LP *Linear programming*

USD *United states dollars*

4.6.2 Equations

AIND *Aggregated indicator*

I_1 *Illustrative indicator 1*

I_2 *Illustrative indicator 2*

i *Impact (or indicator)*

j *Solution*

Ri *Ratios between indicators*

W_1 *Weight of indicator 1*

W_2 *Weight of indicator 2*

$\underline{w}_{i,j}$ *Lower bounds of the weights*

$\overline{w}_{i,j}$ *Upper bounds of the weights*

5 GENERAL CONCLUSIONS AND FUTURE WORK

This doctoral thesis has applied environmentally extended input-output models and multi objective optimization to address the minimization of the environmental impact at a global scale, paying special attention to issues related to sustainability and environmental equity. The following conclusions are drawn:

- Consumption-based policies aiming to lower a given environmental load should target the consumers rather than the producers, since part of the impacts are externalized to other countries with softer production based regulations. As a general trend, the wealthiest economies are net importers of products, and hence of the environmental impacts that they embody. Conversely, the emerging economies have increased their production in the recent past to the point that has become net exporters (*e.g.* China), indicating that the wealthiest economies outsource their demand, which in the end do not lead to true environmental improvements (see section 2.3.1).
- International trade plays a major role in environmental impact assessment, and should be taken into account in the formulation of sustainability policies in order to avoid misallocation of environmental responsibilities. As a generalized trend, the amount of environmental loads embodied in trade decreased after 2006, probably due to the global financial crisis. In particular, two well defined patterns are identified: from 1995 to 2006, in which the percentage of impacts embodied in trade increased in most of the indicators; and from 2006 to 2009, wherein they increase in some indicators and decrease in others (see section 2.3.2). Moreover, the effect of international trade highly depends on the environmental indicators being assessed. As an example, environmental loads associated to mineral extraction and fossil resources are much more trade-embodied and have higher variation over time than those related to water and biomass consumption.
- Environmental Gini coefficients revealed that the most basic necessities (*e.g.* the use of water, land and biomass related to food) are distributed in a rather equitable manner, while in contrast, energy-related indicators are less equally distributed (*e.g.* fossil fuels). However, after 2006 the environmental

inequality has decreased, especially in energy-related indicators (see section 2.3.3). Then, globalization has led to more equitable outcomes.

- A consumption based assessment of the environmental performance of sectors reveals that there are sectors developing everyday activities that show very high environmental impact (*e.g.* bars and restaurants) (see section 3.3.1) because they carry the burdens generated by other intermediate polluting sectors embedded in their supply chains (e.g. electric services, food industries, fertilizers, paper, and other sectors involved). Hence, identifying the ultimate source of impacts helps to take actions in the correct countries and sectors, both by imposing efficient taxes schemes addressed to final products; or encouraging the adoption of sustainable habits.
- The integration of multi-objective optimization with highly disaggregated EEIO models proved to be an efficient tool for identifying precisely the sectors that should be firstly regulated in order to attain specific environmental targets (see section 3.3.2). This hybrid approach provides a Pareto optimal front representing the ideal path to be followed when the goals are set in sustainability by considering the direct and indirect environmental impacts in the whole production chain of the final products.
- Household utilization of energy is among the first activities to be regulated. In addition, the regulation of other industries such as those producing some meat derived products and clothes lead to substantial environmental improvements (see section 3.3.2). Governments should therefore concentrate their efforts on encouraging sustainable lifestyle changes in terms of energy consumption and alimentary habits in households, on promoting the consumption of green labeled products and encouraging the use of more energy efficient electric appliances; which will in turn reduce the life cycle environmental impacts.
- With the current technologies and international trade network, the environmental impact (*i.e.* the global warming potential) could be lowered in greater proportion than the economic output by restricting adequately the demand of certain sectors. As an example, the GWP_{100} can be reduced by 1.1% by only reducing the economic output in 0.5%. This could be achieved by

reducing 10% the final demand in 11 economic activities out of the 487 studied (see section 3.3.2).

- The implementation of systematic tools based on LP has proved useful to provide valid weight ranges for aggregated environmental indicators, while at the same time discarding alternatives that are guaranteed to be suboptimal for every possible combination of weights (see section 4.3.3). This prevents decision makers from proposing biased alternatives since they are no longer required to provide weights beforehand.

Through the application of the methodologies here introduced, policy-makers could take into consideration issues that are usually difficult to assess, like the environmental impacts embodied in international trade and its effects on environmental equity.

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7 APPENDICES

7.1 Publications

7.1.1 Journal articles

7.1.1.1 Manuscripts published

Cortés-Borda D, Guillén-Gosálbez G., Jiménez-Esteller L. On the use of weighting in LCA: translating decision makers' preferences into weights via linear programming. *Int J Life Cycle Assess*. **2013**, 18, 948-957. DOI: 10.1007/s11367-012-0540-6.

Brunet R, Cortés D., Guillén-Gosálbez G., Boer D., Jiménez L. Minimization of the LCA impact of thermodynamic cycles using a combined simulation-optimization approach. *Appl Therm Eng*. **2012**, 48, 367-377. DOI: 10.1016/ j.applthermaleng.2012.04.032.

7.1.1.2 Manuscripts submitted

Cortés-Borda D., Ruiz-Hernandez A., Guillén-Gosálbez G., Guimerá R., Sales-Pardo M. Identifying strategies for mitigating the global warming impact of the EU-25 economy using a multi-objective input-output approach. (Submitted to Energy Policy, May 2014)

Cortés-Borda D., Guillén-Gosálbez G., Jiménez L. Solar energy embodied in international trade of goods and services: A multi-regional input-output approach. (Submitted to Energy, March 2014)

7.1.1.3 Manuscripts in progress

Cortés-Borda, D., Guillén-Gosálbez, G., Jiménez, L. Assessing nuclear energy externalities embodied in international trade via a multi-regional input-output approach.

Cortés-Borda, D., Guillén-Gosálbez, G., Sales-Pardo, M., Guimerà, R. The role of the economic recession in 2006 in trade-embodied environmental loads and environmental equity.

7.1.2 Scientific conference participations

7.1.2.1 Oral communications

Cortés-Borda, D., Ruiz-Hernández, A., Guillén-Gosálbez, G., Llop, M., Guimerá, R., Sales-Pardo, M. Minimization of the GHG Emissions at the Macroeconomic Level Via a Multi-Objective Input-Output Approach: A Case Study of the EU-25 Economy. American Institute of Chemical Engineers (AIChE) Annual Meeting. November 2013. San Francisco, USA.

Pascual, J., Guillén-Gosálbez, G., Jimenez, L., Cortés-Borda, D. Multi-objective optimization of international economies via multi-regional input-output analysis: Application to the US economy. American Institute of Chemical Engineers (AIChE) Annual Meeting. November 2013. San Francisco, USA

7.1.2.2 Poster presentations

Cortés-Borda, D., Ruiz-Hernández, A., Guillén-Gosálbez, G., Llop, M., Guimerá, R., Sales-Pardo, M. Multi-objective optimization method based on input-output models to minimize the life cycle greenhouse gas emissions of the European economy (submitted). 13th Mediterranean Congress of Chemical Engineering (13MCCE). October 2014 Barcelona, Spain.

Cortés-Borda, D., Ruiz-Hernández, A., Guillén-Gosálbez, G., Llop, M., Guimerá, R., Sales-Pardo, M. GHG Emissions Minimization at the Macroeconomic Level via a Multi-objective Optimization / Input-output Approach: A Case Study of the EU-25 Economy. 24th European symposium on computer aided process engineering (ESCAPE24). July 2014, Budapest, Hungary.

Cortés-Borda, D., Ruiz-Hernández, A., Guillén-Gosálbez, G., Llop, M., Guimerá, R., Sales-Pardo, M. Minimizing the European greenhouse gas emissions from a macroeconomic view-point: a multi-objective optimization input-output approach. 4th International congress on green process engineering. April 2014. Seville, Spain.

Brunet, R., Cortés, D., Boer, D., Guillén-Gosálbez, G., Jiménez, L. Combined Use of Simulation Packages, Multi-Objective Optimization and Statistical Tools for the Environmentally Conscious Design of Thermodynamic Cycles. American Institute of Chemical Engineers (AIChE) Annual Meeting 2011. Minneapolis, USA

7.1.3 *Tables*

7.1.4 *Figures*