UNIVERSIDADE CATÓLICA PORTUGUESA

Benchmarking international performance on climate change mitigation: an application of Data Envelopment Analysis (DEA)

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Benchmarking international performance on climate change mitigation: an application of Data Envelopment Analysis (DEA)

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Abstract

Since the Industrial Revolution, large amounts of greenhouse gases (GHGs) have been released to the atmosphere which led to global warming and climate change. Despite the efforts from nations to limit the temperature rise to 1.5 °C, as defined in the Paris Agreement (2015), if emissions do not half until 2030, it is likely to achieve a global warming of 2.7 °C by the end of the century.

Thus, the assessment of environmental performance become crucial. The objective of this thesis is, then, to measure and compare the environmental efficiency at the country level, over the period 2000-2018, being its main contribution to overcome the lack of literature studies with a global scope.

To answer the research questions (How can countries be ranked in terms of their performance? What have been the best and worst performing over time?), a DEA methodology (additive model) was employed. DEA has become a well-established tool to judge the relative efficiency in the environmental field. A clustering analysis was also carried out to distinguish countries based on their proximity-to-target value (%), in 2018. The DEA model includes three inputs (population, energy use and GHGs emissions) and two outputs (GDP and renewables). The population and GDP are non-discretionary variables.

Regarding the main findings, globally, countries have become more efficient over time. Bhutan, Kiribati, Norway, Nepal and Iceland have been the efficient countries that appear more times in the reference set of other countries, being an example of best practices. In 2018, the poorest 5 performing countries were Russia, followed by Iran, Saudi Korea, Saudi Arabia, and South Africa, being all inefficient since 2000. Despite being inefficient during most of the years, China, United States and India significantly improved their performance which was mainly explained by their higher consumption of renewables.

Key words: climate change; environmental performance; data envelopment analysis (DEA); additive models; efficiency analysis; benchmarking; clustering analysis

Resumo

Desde a Revolução Industrial, elevadas quantidades de gases de efeito de estufa (GEE) têm sido libertados para a atmosfera, levando ao aquecimento global e às alterações climáticas. Apesar dos esforços das nações para limitar o aumento das temperaturas em 1.5 °C, como definido no acordo de Paris (2015), se as emissões não forem reduzidas para metade até 2030, é provável atingir um aquecimento global de 2.7 °C até ao final do século.

Assim, a avaliação do desempenho ambiental tornou-se crucial. O objetivo desta tese é, desta forma, medir e comparar a eficiência ambiental ao nível dos países, durante o período 2000-2018, sendo a sua principal contribuição ultrapassar a falta de estudos na literatura com um foco global.

Para responder às questões de pesquisa (Como é que os países podem ser ordenados em termo do seu desempenho? Quais têm sido os países com melhores e piores desempenhos, ao longo do tempo?), a metodologia DEA (modelo aditivo) foi aplicada. O DEA tornou-se numa ferramenta bem estabelecida em avaliar a eficiência relativa no campo ambiental. A análise de clusters foi, também, desenvolvida para distinguir os países em termos da sua proximidade ao target (%), em 2018. O modelo DEA inclui três inputs (população, uso de energia, emissões GEE) e dois outputs (PIB e renováveis). A população e o PIB são variáveis não discricionárias.

Face aos principais resultados, globalmente, os países têm-se tornado mais eficientes ao longo do tempo. Butão, Kiribati, Noruega, Nepal e Islândia têm sido os países eficientes que mais vezes têm aparecido como referência para os outros, sendo exemplos de melhores práticas. Em 2018, os 5 países com pior desempenho foram a Rússia, seguida pelo Irão, Coreia do Sul, Arábia Saudita e Africa do Sul, sendo todos ineficientes desde 2000. Apesar de terem sido ineficientes na maioria dos anos, a China, os Estados Unidos e a India melhoraram significativamente o seu desempenho, explicado sobretudo pelo maior consumo de renováveis.

Palavras-chave: alterações climáticas, desempenho ambiental, data envelopment analysis (DEA), modelo aditivo, análise de eficiência, benchmarking, análise de clusters.

Table of Contents

Figure Index

Graph Index

Table Index

List of Abbreviations

CCPI – Climate Change Performance Index

CH_4 – Methane

CI – Cooperation Index

CI – 3 – Climate Change Cooperation Index

CO_2 – Carbon Dioxide

COP – Conference of the Parties

DEA – Data Envelopment Analysis

EPI – Environmental Performance Index

GHG – Greenhouse gas emissions

IPCC – Intergovernmental Panel on Climate Change

NDC – Nationally Determined Contributions

N_2O – Nitrous Oxide

UNEP – United Nations Environment Programme

UNFCCC – United Nations Framework Convention on Climate Change

WMO – World Meteorological Organization

WWA – World Weather Attribution

Chapter 1: Introduction

As a global problem, the impacts of climate change, term used by scientists "(…) to describe the complex shifts, driven by greenhouse gas concentrations (…)" (Nunez, 2019) are already felt in communities across the world (Codal et al., 2021).

Defined as a "(…) long-term change in the average weather patterns that have come to define Earth's local, regional and global climates", the extension of climate change effects will depend on the capacity of countries to mitigate and to adapt to those adverse effects[1] (NASA, n.d.-a). This way, "climate change encompasses not only the rising average temperatures", known as global warming, "but also extreme weather events" (Nunez, 2019).

Since the Industrial Revolution, large amounts of greenhouse gases (GHGs) have been released to the atmosphere. As a result, the last decade (2011-2020), was 1.09°C warmer than pre-industrial times (IPCC, 2021).

Despite the efforts from nations to limit the temperature rise to 1.5 °C compared to pre-industrial levels, GHG emissions continue to grow, being recommended a reduction by half of CO_2 emissions until 2030 to be on track with this limit (UNFCCC, 2021). Otherwise, it is likely to achieve a global warming of 2.7 °C by the end of the century, based on the updated Nationally Determined Contributions (NDCs) for 2030 (UNEP, 2021), which will cause disastrous impacts on climate and natural systems.

[1] Higher frequency of wildfires, longer periods of droughts, floods, more intense heat waves, melting of the ice mass at the poles, rising sea levels and the extinction of animal and plant species.

1.1 Objective and Research Question Definition

A growing interest from economies regarding the importance of assessing and monitoring environmental performance has emerged (Matsumoto et al., 2020). Proposed by Charnes et al. (1978), Data Envelopment Analysis (DEA) has been a widely employed tool in measuring environmental performance (Suzuki & Nijkamp, 2016). However, up to this point, as stated by Matsumoto (2020), "many studies that used the DEA approach for environmental assessment focused on a particular period of time and geographical zone".

Under this context, the objective of this master thesis is to measure and compare the environmental efficiency at the macro level in a worldwide context (138 to 169 countries under analysis), over the period 2000-2018, respectively, based on DEA methodology. Thus, the main contribution of this thesis is to overcome the lack of studies in the literature that assess the environmental efficiency on a global scale. Another contribution is the long-term panel data which covers 19 years.

The DEA model was constructed based on socioeconomic (population and GDP) and on climate change mitigation variables[2] (GHG emissions, renewables[3], energy use). As most literature studies only incorporate CO_2, another contribution is to consider a larger scope of greenhouse gases[4].

Based on this method, a benchmarking analysis on the performance of countries regarding their climate change mitigation efforts will be carried out, allowing the identification of the most (less) efficient, and thus, best (worst) performing countries, over the period in analysis. This analysis would be, then, the foundation to recommend some actions that could be implemented by lower performers countries to improve their performance.

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[2] Indicators used in the construction of the Climate Change Performance Index (CCPI, 2021).

[3] Renewable energy consumption.

[4] CO_2, methane, nitrous oxide, and F-gases

At the second stage, the clustering analysis will be applied to group countries based on their 2018's profile, that is, based on their proximity-to-target value (%).

The final purpose of this analysis is to answer the following research questions:

1. How can countries be ranked in terms of their climate change mitigation performance, based on benchmarking principles?
2. What have been the best and worst performing countries, over time?

1.2 Document Structure

This thesis is made up of five chapters, being organized as follows:

The **chapter 1 (Introduction)** contains a brief exposition of the climate change problem and an explanation of the relevance of assessing environmental performance at a national scale. It also presents the objective and the research questions that this study aims to answer as well as its contribution to the literature.

The **chapter 2 (Literature Review)** includes an explanation of the causes and the impacts of climate change, and an overview of the politics related with this matter. This section also includes a summary of the literature studies which assessed the environmental performance at national and regional levels, using the DEA methodology (with focus on efficiency analysis).

The **chapter 3 (Method and Data)** comprises the explanation of the DEA methodology with focus on additive models and the description of the variables included in the model.

The **chapter 4 (Results and Discussion)** summarizes the main results in terms of the evolution of global inefficiency over time, the introduction of the most efficient and inefficient countries and respective characteristics and targets. It also contains a brief explanation of the clustering analysis and its results.

The **chapter 5 (Conclusion)** highlights the main findings and the practical interest of this thesis. It also includes the limitations faced and some recommendations for future academic research.

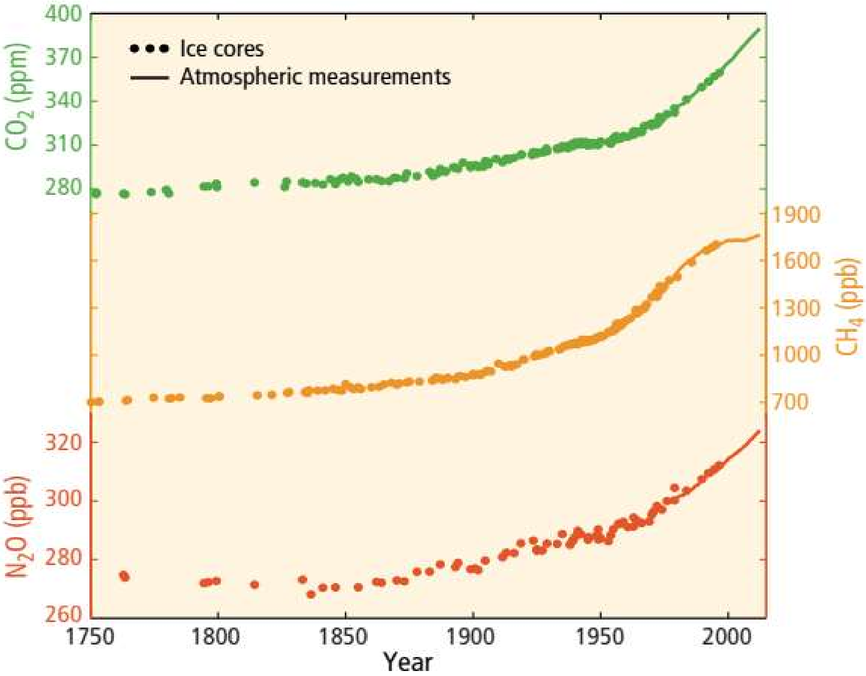
Chapter 2: Literature Review

2.1 Climate Change – the causes

Scientific research indicates that climate change has been caused by anthropogenic activities dating back to the period of the Industrial Revolution (Codal et al., 2021). Despite having strongly improved the welfare and standard of living of societies, due to the higher levels of production that allowed a higher consumption, the Industrial Revolution resulted in a massive increase of energy usage, namely by the burning of fossil fuels (coal, oil and gas) (Codal et al., 2021), which release large amounts of carbon dioxide and other GHGs into the atmosphere. The atmospheric concentration of GHG directly impacts the average global temperature on Earth as they absorb and block heat radiating from Earth toward space.

Since the pre-industrial era, the atmospheric GHGs concentrations (carbon dioxide (CO_2), methane (CH4), and nitrous oxide(N_2O) have increased (Figure 2.1). The atmospheric levels of carbon dioxide, the most abundant GHG (76% - in 2010) (Figure 2.2), amounted to 412 ppm, in 2020, which represents an increase of 47% (130 ppm) compared to the pre-industrial levels (280 ppm) (European Environment Agency, 2021).

The concentrations of methane (CH_4) and nitrous oxide (N_2O) have also been increasing (Figure 2.1). Despite having a smaller share of global GHG (16%), methane (CH_4), the main component of natural gas, has a “global warming potential over 80 times greater than CO_2 during the 20 years after it is released” (Nunez, 2019). The nitrous oxide (N_2O) has a share of 6% and it is 264 times more powerful than carbon dioxide over 20 years, and it remains in the atmosphere for over a century (Nunez, 2019).



[5]

Figure 2.1– The evolution (1750-2010) of atmospheric GHG concentrations in parts per million (ppm) (IPCC., 2014.).

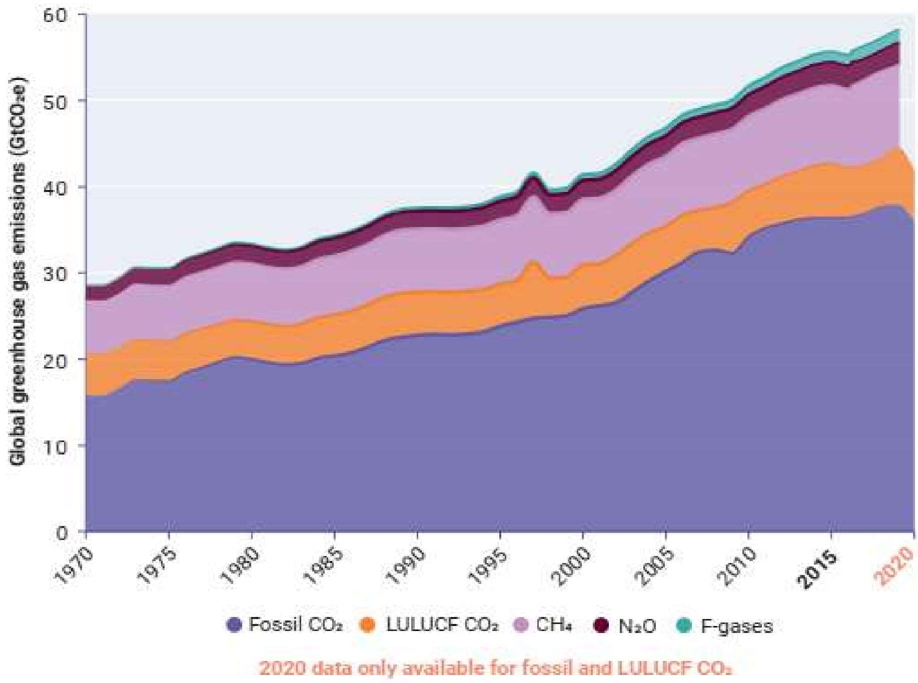


Figure 2.2 – The evolution (1970-2020) of GHG emissions by gases (UNEP, 2021).

[5] Until 1958, the GHG concentrations were estimated through ice cores. After 1958, estimates are obtained through direct observation (atmospheric measurements).

2.2 Climate Change - the current state

Due to the high levels of GHGs in the atmosphere, from 2011 to 2020, it was registered an increase of 1.09°C, in comparison to the mean of 1850-1900[6] (IPCC, 2021).

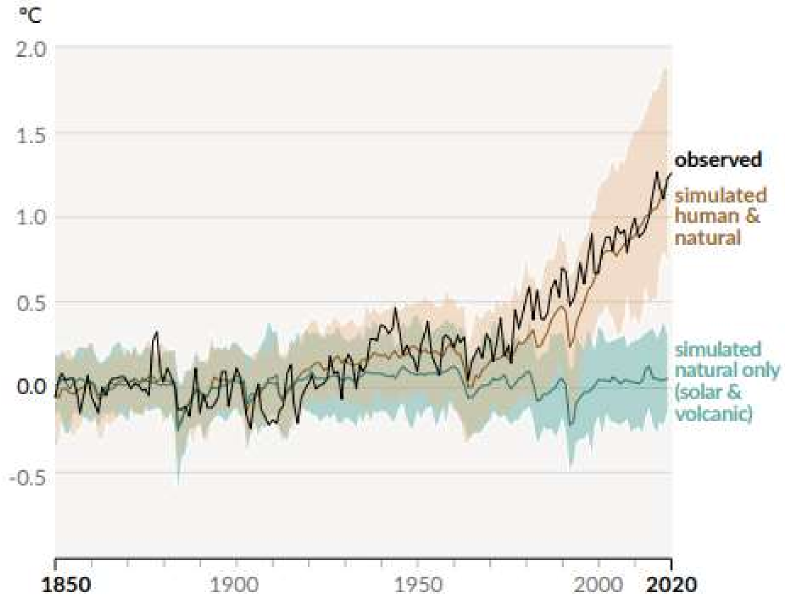


Figure 2.3 – The evolution (1850-2020) of global surface temperature: observed and simulated using human & natural and only natural factors (IPCC, 2021).

As a result of warmer temperatures, the amounts of snow and ice have been decreasing (Figure 2.4) and therefore, the sea level has been rising (Figure 2.5): between 1901 and 2018, it increased by 0.20 meters (IPCC, 2021).

[6] "The period 1850–1900 represents the earliest period of sufficiently globally complete observations to estimate global surface temperature". This period "is used as an approximation for pre-industrial conditions (IPCC, 2021).

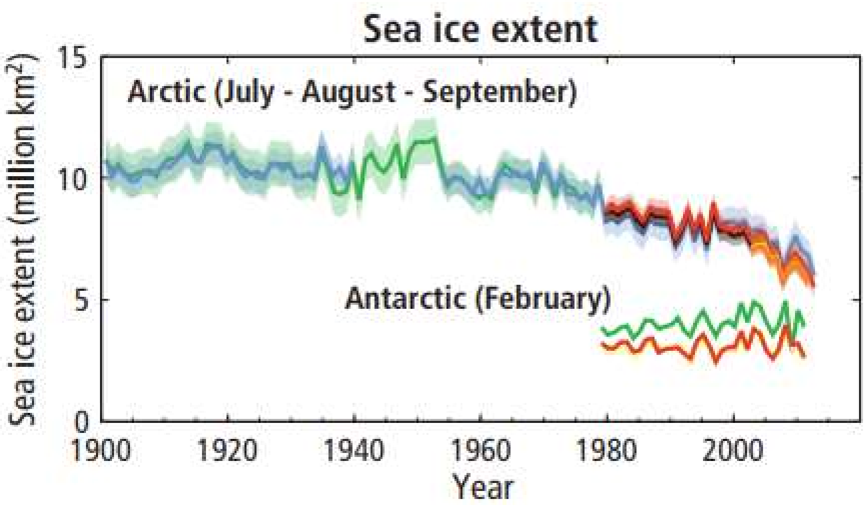


Figure 2.4 - The evolution (1900-2012) of sea ice extent (million km2) (IPCC, 2014).

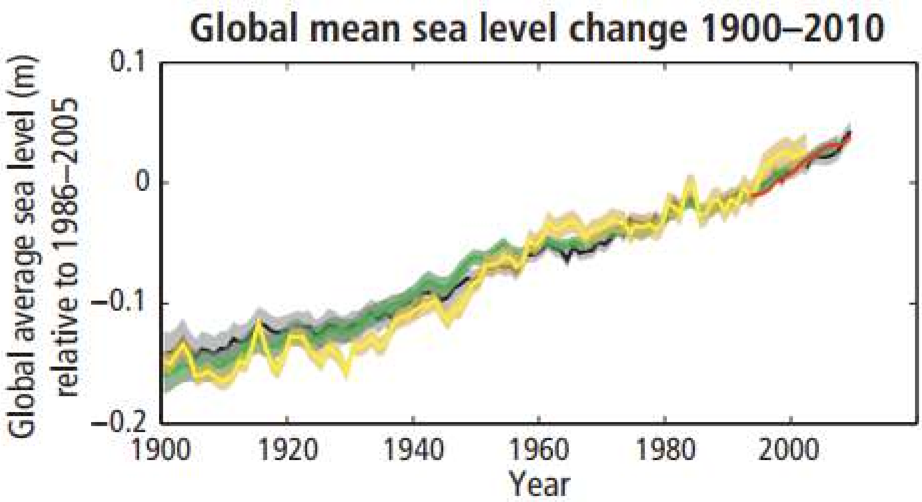


Figure 2.5 – The evolution (1900-2010) of the sea level change relative to the period (1986-2005) (IPCC, 2014)

2.3 The politics of Climate Change

The recognition of climate change as one of the major threats to the planet's sustainability, led as early as 1988 "governments, intergovernmental and non-governmental organizations to collaborate in a concerted effort to prepare, as a matter of urgency, a framework convention on climate change" (Sands, 1992). During this year, the Intergovernmental Panel on Climate Change (IPCC), established by the United Nations Environment Programme (UNEP) and by the

World Meteorological Organization (WMO), was endorsed by the UN general assembly with the objective of providing scientific guidance to policymakers about the "current state of knowledge" of climate change, namely its impacts and future risks, and adaptation and mitigation options (IPCC, n.d.-b). Since its creation, it has already produced five Assessment Reports (AR) and it is currently preparing the sixth, which is expected to be completed in September 2022 (IPCC, n.d.-a). The first report (FAR) was released in 1990 and emphasized the urgency to address the challenge of climate change through international cooperation, having "played a decisive role in the creation" of the United Nations Framework Convention on Climate Change (UNFCCC) (IPCC, n.d.-b), signed at the Rio Summit in 1992.

"The UNFCCC entered into force on 21 March 1994. Today, it has near-universal membership": 197 countries have ratified the Convention, being also referred as Parties to the Convention (UNFCCC, n.d.-d).

As stated in article 2 of the Convention, "the ultimate objective of this Convention (...) is (…)" the "stabilization of greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system ", allowing "ecosystems to adapt naturally" and enabling the sustainable "economic development", without compromising "food production" (UNFCCC, 1992).

Parties meet annually at the Conference of the Parties (COP), since 1995, unless they decide otherwise. The Conference of the Parties is described as the "supreme decision-making body of the Convention" (UNFCCC, n.d.-a), being responsible for monitoring and guaranteeing its effective implementation as well as any other legal instrument that the COP may adopt. One of the objectives of the COP is to "review the national communications and emission inventories submitted by Parties" and, relying on this information, assess the progress and effectiveness of the measures implemented by each country (UNFCCC, n.d.-a).

An important milestone was COP21 held in Paris in 2015. The outcome of the Conference was the signature of the Paris Agreement, the first ever universal legally binding global climate deal, effectively replacing the Kyoto Protocol (COP3). Given the fact that global temperature is increasing by 0.2ºC ((±0.1°C)) per decade, scientists predict that, if this pace of warming continues, the global temperature would, then reach, 1.5ºC, by 2040, in comparison with pre-industrial times (Allen et al., 2018). With the objective of "holding the increase in the global average temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels" (Allen et al., 2018), 196 parties adopted the Paris Agreement, in 2015 (UNFCCC, n.d.-c).

To address the Paris Agreement temperature goals, every 5 years (starting in 2020), countries must submit in their Nationally Determined Contributions (NDCs) the targets, policies and measures for reducing their GHG emissions as well as for adapting to the impacts of climate change (UNFCCC, n.d.-c). Each successive NDC should represent a success compared to the previous one and encompasses the highest possible ambition (UNFCCC, 2016).

The NDC Synthesis Report, published on September 17, 2021, synthetizes the information from the 165 latest available NDCs communicated by the 192[7] Parties to the Paris Agreement, which encompasses the post-2020 climate actions "being or planned to be undertaken by the governments and how these actions impact greenhouse gas emissions in 2025 and 2030" (UNFCCC, n.d.-b). The key findings of this report were prepared in advance for the COP 26 (Glasgow) so that the latest information was available. Among the main key findings, the following stand out (UNFCCC, 2021):

- Possibility of reaching the emissions peaking up to 2030.

[7] The Parties cover 94.1 per cent of total global emissions in 2019 (52.4 Gt CO2 eq without and around 56.0 Gt CO2 eq with LULUCF) (UNFCCC, 2021).

- To be on track with the temperature limit rise of 1.5 °C, global CO_2 emissions should decrease by 45% from the 2010 level until 2030 and reach net zero by the mid-century.
- To be aligned with the 2 °C pathway, emissions must decline by 25% from the 2010 level by 2030 and reach net zero around 2070.
- The renewable energy generation[8] was the most frequently mitigation measure pointed out.

According to the UNEP's emission report gap (2021), the global warming is likely to achieve 2.7 °C by the end of the century if only unconditional[9] NDCs are implemented (Figure 2.6). The implementation of net-zero pledges could reduce 0.5°C off global warming. This indicates that despite being more ambitious than the previous, the updated mitigation pledges for 2030 are insufficient to reduce emissions below the carbon budget (400; 1 150 Gt CO_2 eq), estimated with 66% of probability to limit warming by 1.5 °C/2 °C, respectively.[10]

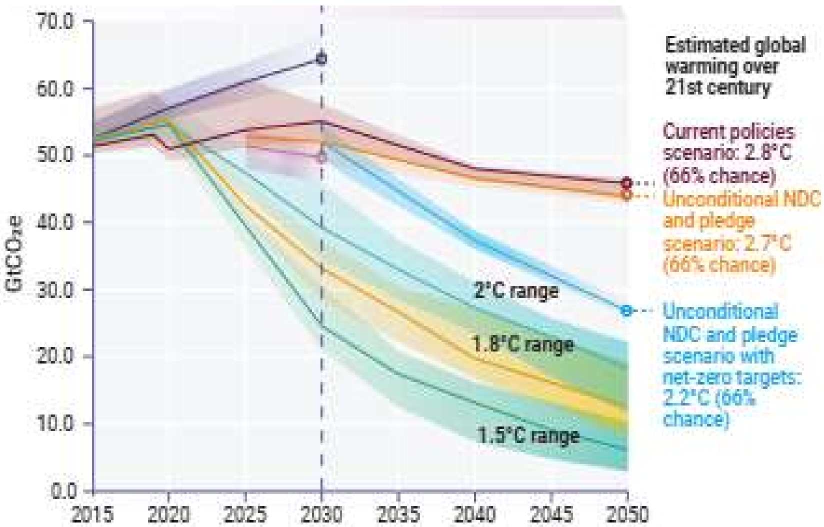


Figure 2.6 - Global GHG emissions for different temperature rise scenarios (1.5 °C; 2°C; 3°C) (UNEP, 2021).

[8] Quantitative measured by the weight of renewables in electricity generation, for example.

[9] "Conditionality: Some parties have submitted NDCs that are entirely or partially conditional on factors such as international support (e.g. finance or technology transfer), while others have submitted NDCs that are not conditional" (UNEP, 2021).

[10] Before the Paris Agreement, it was estimated an increase of global temperatures of 4 °C, by the end of the century (UNEP, 2021).

- During the Glasgow Conference, the most recent COP, held in 2021, nations took a range of decisions to limit global warming by 1.5 °C. Considering the need of reducing emissions by half until 2030, it was defined that countries should return by the end of 2022 with more ambitious targets to close the emissions gap (Annex I). The main outcomes are summarized below:

Table 2.1 – The main outcomes of the Glasgow Climate Conference (2021) (Mountford et al., 2021)

Areas	Actions
Adaptation	o Adoption of the Glasgow-Sharm el-Sheikh work programme for the Global Goal on Adaptation (GGA) in order to improve the assessment of progress in terms of the adaptation goal and to foster its implementation.
Finance	o End of the international financing for fossil fuels; o Recognition of the failure of developed countries in mobilizing 100 billion dollars in 2020 to support developing countries in their climate actions. o Commitment from developed countries to double the funds for adaptation actions by 2025. o The Adaptation Fund registered the highest level of contributions. o Identification of the need for developed countries to provide more resources to countries vulnerable to extreme weather events.
Mitigation	o 109 countries signed the Global Methane Pledge to decrease emissions by 30% until 2030. o Commitment from India to achieve net-zero emissions until 2070. o A pledge to "halt and reverse forest loss and land degradation

Loss and Damage[11]	o	Fund the Santiago Network, part of the Warsaw International Mechanism, established in COP25, "to catalyze the technical assistance" to address loss and damage, especially in developing countries that are more vulnerable to the adverse effects of climate change.
Others	o	Conclusion of the Paris rulebook.

Source: (Mountford et al., 2021)

Apart from the mitigation strategy, which involves reducing and stabilizing the emission of GHGs, it is essential for the future, the implementation of a climate adaptation strategy[12] even if the Paris Agreement targets are achieved, as many regions have already suffered with the impact of warmer temperatures and more frequent extreme events (Donatti et al., 2020). The adaptation should occur at international, national and local levels (Allen et al., 2018).

2.4 Measurement of Climate Mitigation Efforts

The process of evaluating countries' performance is often performed based on environmental indicators (Zanella et al., 2013).

Regarding the mitigation of climate change, there are some composite indices that allow the comparison between countries: the most well-known are the Climate Change Performance Index (CCPI), the Cooperation Index on Climate Change (CI) and the Climate Change Cooperation Index (C3–I) (Codal et al., 2021). In addition to these, despite having a broader scope that goes beyond climate change (only represents 24% of the indicator), the Environmental

[11] Encompasses destructive ravages, caused by climate change, that countries cannot prevent or adapt to (Mountford et al., 2021).

[12] According to the IPCC (Allen et al., 2018), climate adaptation comprises a set of actions that must be taken both to reduce the exposure and vulnerability of localities to the harmful effects of climate change, as well as to increase potential benefits.

Performance Index (EPI) is also a well-established composite indicator for environmental performance evaluation[13].

The use of composite indicators is becoming increasingly popular in benchmarking countries' performance in several fields, namely, the environment, as it is easier for the public to interpret them (OECD, 2008).

However, despite providing important insights for environmental debates, there are some drawbacks in relying on composite indicators, namely, the inherent subjectivity of the definition of the weights of each sub-indicator (Morais & Camanho, 2011) and the lack of information about how countries can improve their performance (Zanella et al., 2013).

Proposed by Charnes et al. (1978), Data Envelopment Analysis (DEA) has been a widely employed tool in measuring environmental performance (Suzuki & Nijkamp, 2016) among countries or regions. The implementation of DEA models can provide quantitative information about environmental performance and trends which can support policymakers in defining national/regional sustainability policies and objectives. In this context, this methodology can be used for two different purposes: to measure environmental efficiency (ability to transform inputs into outputs) or to construct a composite indicator (CI) based on an optimal definition of the sub-indicators' weights (Zanella et al., 2013). A more detailed explanation of the DEA methodology is available in section 3.1.

Contrasting both methods, the construction of the CI only considers the "achievements, without taking into account the resources used" (Morais & Camanho, 2011).

As stated by Suzuki (2016), the comparative efficiency analysis in the sustainability context, "has increasingly become an important research topic in recent years". As a result, there are several literature studies that have already employed DEA models to measure the "(…) aggregate energy-environment-

[13] More details about these composite indicators are available in the annex section.

economic efficiency among countries or regions (…)", being part of them referred in the next section.

One of the advantages of using DEA compared to other techniques, is that DEA allows the identification of the best performing peers whose practices can help other countries to improve their performance (Zanella et al., 2013).

There are other studies in the literature that benchmark countries by carrying out different methodologies such as clustering analysis (Puertas & Marti, 2021) and balance scorecard methodology (Codal et al., 2021).

2.5 Literature Review on studies based on DEA

As a global problem, addressing climate change is urgent so that it does not compromise countries' future sustainable development. For that reason, a growing interest from economies regarding the importance of assessing and monitoring environmental performance has emerged (Matsumoto et al., 2020).

The table below synthetizes some of the main studies of the literature which have applied DEA to assess and rank the environmental performance of different regions/countries (EU, ASEAN and APEC countries, Chinese provinces, global cities) over time, based on their economic performance (GDP was a common variable in all studies) and climate change mitigation, from the perspective of efficiency analysis. Apart from the efficiency method, it is also referred a study which used the DEA to construct a composite indicator (Zanella et al., 2013).[14] Being the major GHGs emitter, there is a vast literature studies with focus on Chinese territory. One of the differences among the following studies is the variability of the DEA methodologies applied.

[14] The focus of the literature review was the studies which used DEA to assess environmental performance from the perspective of efficiency analysis.

Table 2.2 - Published research literature on international environmental efficiency.

ARTICLE	SCOPE	METODOLOGY	VARIABLES	TIME - PERIOD	OBJECTIVE	STRENGHTS/ LIMITATIONS
Matsumoto et al., 2020	Country level. 27 European countries.	DEA window approach – assess countries' environmental performance. Malmquist-Luenberger index - evaluate the changes in environmental performance over time.	**Inputs:** Labor, Capital, Energy consumption **Outputs:** GDP, CO_2 emissions from energy consumption $PM_{2.5}$ emissions (models 1, 3) Waste (models 2, 3)	2000-2017	Assess the environmental performance and trends, providing quantitative data which will contribute to a more effective policy making.	**Strengths:** Provided an evaluation and comparison between countries over time. The panel data has more observations than previous studies in this field.
Wang et al., 2020	Regional level. Study developed for 39 global cities (obtained from the C40 Cities Climate Leadership Group).	Two methodologies were applied: Regular DEA model (two models were developed based on natural and managerial disposability). Super Efficiency DEA model (SEDEA)	**One input:** Population. **Outputs:** GDP (desirable) GHG emissions (undesirable) .	2012-2015	Ranking global cities based on their economic and climate change mitigation performance.	**Strengths:** Focused on critical variables related to climate change rather than on wide range of sustainability indicators. Considered the undesirable outputs on the SEDEA framework. Filled a literature gap by applying the concepts of natural and managerial disposability in city ranking. Incorporate GHG emissions directly. **Limitations:** Short period of analysis.

Suzuki & Nijkamp, 2016	Country level. The report analyzed 27 EU countries and 20 ASEAN and APEC (A&A) countries.	Super - efficiency DEA (CCR – I model) for the efficiency evaluation. CCR-I, DFM and TO-DFM-FF models were implemented to make efficiency improvement projections.	**Two inputs**: primary energy consumption population **Two outputs**: CO_2 and GDP	2003-2012	Comparative study on the energy-environment-economic efficiency for each country.	**Strengths:** Focus on critical variables that are common to all countries. Provides a cross-regional comparison between EU and A&A countries. Suggests efficiency-improvement energy plan. **Limitations:** Low number of inputs and outputs. The article does not take into account other GHGs apart from CO_2.
Chen et al., 2015	Regional level. 30 provinces of China.	Output-oriented DEA model. The undesirable outputs were converted into desirable based on a linear monotonic decreasing transformation approach. Use of a statistical hypothesis test to analyze the efficiency results, assuming VRS.	**Two inputs**: energy consumption and social fixed assets investment. **Four outputs**: GDP (desirable); waste water, solid and gas (undesirable)	2001-2010	Evaluate the environmental efficiency of 30 provinces in China to support a more adequate policy design for each of these areas.	**Limitations:** Do not focus on climate change mitigation.
Yang et al., 2015	Regional level. 30 provinces in China.	Super-efficiency DEA.	**Four Inputs:** energy consumption ; nº employees' depreciation of fixed	2000-2010	Measures de environmental efficiency of 30 Chinese regions. Analyze the efforts made	**Limitations**: The article does not take into account CH_4 and NH_2 emissions.

			capital, CO_2 and SO_2 emissions. **One Output**: GDP		over time regarding environment protection. Understand the disparities across regions.	
Zanella et al., 2013		Construction of a composite indicator of environmental performance (relying on the sub-indicators of EPI) based on DEA.			Benchmarking countries. Allows the comparison with countries with similar features and better performance, which should be seen as an example.	**Strengths:** Indicator weights results from an optimization process. The scope of this thesis is beyond climate change mitigation; Relies on a wide range of environmental indicators.

*TO-DF-FF (Target Oriented Distance Friction Minimization in combination with a Fixed-Factor Model.

After the literature review, and as stated by Matsumoto (2020), it was possible to conclude that "many studies that used the DEA approach for environmental assessment focused on a particular period of time and geographical zone". Under these circumstances, one of the contributions of this thesis is to overcome the lack of studies in the literature that assess the environmental efficiency on a global scale. The method and the model constructed are explained in the following chapter.

Chapter 3: Method and Data

3.1 Data Envelopment Analysis

3.1.1 DEA: the method

Proposed by Charnes et al. (1978), the DEA has become a well-established tool to judge the relative efficiency "of a set of comparable entities called decision making units (DMUs)" (Peng Zhou,2006), through a mathematical programming model. The DMUs (homogeneous entities) can be organizations (schools, banks, hospitals, courts), countries, for example, which are responsible for transforming the same multiple inputs into the same multiple outputs[15].

Figure 3.1 – Transformation process of inputs into outputs (DEA).

The DEA is a non-parametric frontier technique: on one hand, one of the advantages of this methodology is that it does not require "any prior assumption on the underlying functional relationships between inputs and outputs" (Zhou

[15] In DEA, one of the assumptions is that each DMU under assessment is "have control over the process they deploy to convert their inputs into outputs" (Thanassoulis et al., n.d.)

et al., 2008), being for that reason non-parametric, contrasting with other frontier techniques that are constructed econometrically (specify a functional form for the frontier).

The DEA is based on a mathematical procedure that calculates the efficiency frontiers relying only on observed data. This tool provides an efficiency score which corresponds to the distance of each DMU to that frontier, i.e., "a DMU that is located on the frontier is efficient, whereas a DMU that is off on the frontier is inefficient" (Suzuki & Nijkamp, 2016). In other words, the method determines the relative efficiency of a DMU by comparing it with similar DMUs in producing a certain level of output based on the amount of inputs used (Mardani et al., 2017). Based on the graph below[16], we can conclude that the DMUs A, B, and C are located on the frontier, being technically efficient as there is not any other DMU that produces the same level of output without increasing inputs. The DMUs F and D, on the other hand, are inefficient.

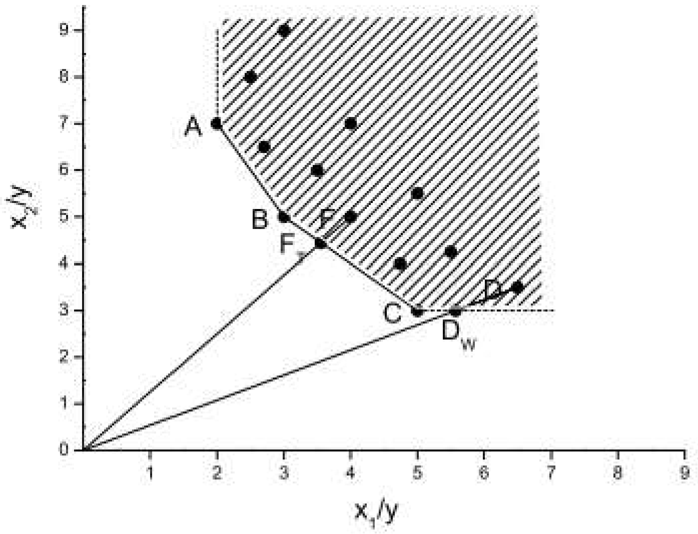


Figure 3.2 – Graphical representation of DMUs under the DEA methodology (Vaz, M. 2007).

[16] In the graph it is represented two inputs (x_1, x_2) which will be transformed in one output (y) (Vaz, M. 2007).

In the literature, there are a wide number of extensions to the traditional DEA models (Zhou et al., 2008) that distinguish among them in terms of a set of technical characteristics:

- **Model Orientation**
  - **Input/Output**→ increase the efficiency by decreasing inputs/outputs while the level of outputs/inputs remains at the same level, respectively.
  - **Non-oriented** (e.g., additive model)→ both inputs and outputs are targeted for improvement.
- **Model Metrics**
  - **Radial** (e.g., CCR model (1978), developed by Charnes, Cooper and Rhodes)
  - **Non-radial** (SBM (slacks-based measure) model developed by Tone)
- **Technology**
  - **constant returns to scale** (CRS) - handles proportional changes in inputs and outputs: benchmarks are obtained through linear combination (Figure 3.3).
  - **variable returns to scale** (VRS) – benchmarks are obtained through linear convex combinations (Figure 3.3).

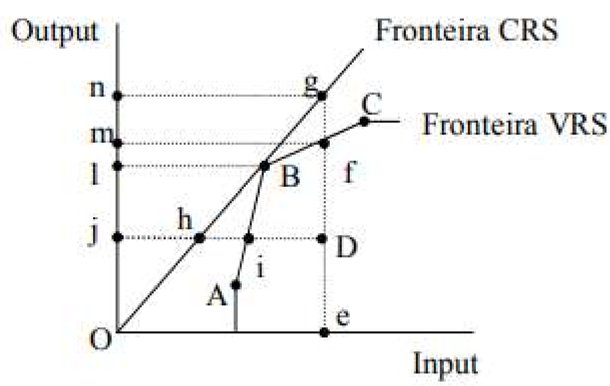


Figure 3.3 – Graphical representation of the CRS and VRS frontiers (Vaz, M. 2007).

The concept of efficiency depends on the orientation being described as the ratio between observed output and maximum output that can be produced from a given set of inputs or the ratio between the minimum input which can be used to produce a certain volume of outputs and the observed input.

Regarding the applications of DEA, it can, then, highlighted:

- Analysis of the relative efficiency among DMUs.
- Discrimination between efficient and inefficient DMUs.
- Definition of targets that would enable inefficient DMUs to become efficient.
- Definition of benchmarks, also designed as peers, through the notion of dominance: if one DMU dominates another, that is, if it is more efficient then it should be considered as a reference of better practice.

3.1.2 Additive Models

Charnes et al. develop an additive DEA model (1985), a non-oriented model, being among the first introduced in the literature. The difference comparing with input or output-oriented models is that it considers possible and simultaneous decreases of inputs and increases of outputs. Apart from this, another important aspect of this model is that it enables finding the Pareto - efficient units, i.e., the DMUs that the observed value equals its target having, for this reason, a slack equal to zero (Thanassoulis et al., n.d.).

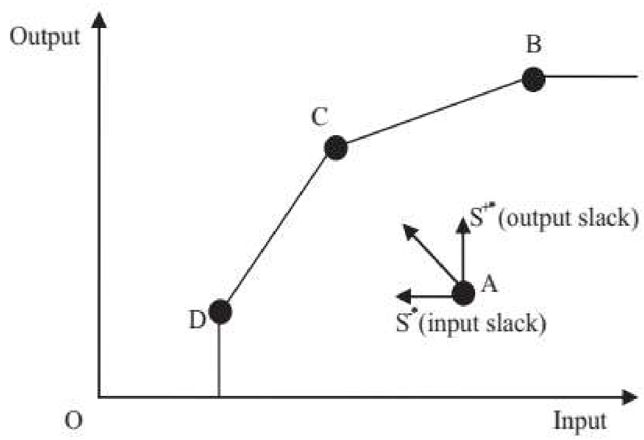


Figure 3.4 - Graphical representation of a non-radial model (Suzuki & Nijkamp, 2016)

The objective function is the sum of the slacks that is sought to be maximized (Figure 3.5). One of the drawbacks of additive models is that they do not provide a final efficiency score (Thanassoulis et al., n.d.).

$$\mathrm{Add}_o = \max \left\{ \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \;\middle|\; \begin{array}{l} \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro}, \quad r = 1, \ldots, s, \\ \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{io}, \quad i = 1, \ldots, m, \\ \lambda_j \in S \end{array} \right\}$$

Figure 3.5 – Additive model objective function (Thanassoulis et al., n.d.).

3.2 Data

This thesis aims to assess the environmental efficiency in a worldwide context, analyzing 138 to 169 countries over the period 2000-2018. For that purpose, it was employed an additive DEA model to evaluate and compare countries' environmental efficiency by considering socioeconomic and environmental variables. Three inputs (population, energy use and GHGs emissions[17]) and two outputs (GDP and renewables[18]) were considered. The population and GDP are considered non-discretionary variables, i.e., fixed factors as they cannot be flexibly adjusted in a short/medium time horizon. The variables and respective source are summarized below:

[17] The GHG emissions are considered an undesirable output and for that reason they should be reduced. Thus, this variable was treated as an input of the model.

[18] It corresponds to the consumption of energy through renewables.

Table 3.1 – Inputs and Outputs of the DEA model.

Type	Variables (Units)	Data Source
Inputs	Population (thousands)	World Bank[20]
	GHGs emissions (kilotons of CO_2 equivalent)	U.S. Energy Information Administration (EIA)[21]
	Energy Use (kilotons BTU)[19]	U.S. Energy Information Administration (EIA)
Outputs	GDP, PPP (constant 2017 international $) (millions)	World Bank
	Renewables (kilotons BTU)	U.S. Energy Information Administration (EIA)

Under the DEA framework, a country is viewed as a production unit that consumes inputs (population and energy use), i.e., uses energy in order to boost economic growth (GDP, desirable output), releasing GHGs (undesirable output). Being emissions an undesirable output, they were treated as an input as they should be minimized to achieve higher efficiency. At the same time, countries are continuously consuming more energy from renewable sources (desirable output) that should increase in order to achieve higher efficiency (lower pollution).

In this study, there are three variables (Energy Use, GHG Emissions and Renewables[22]) that can be acted upon, being the efficiency measured with reference to these factors. The analysis was restricted to technical efficiency: in order to improve it, each unit was allowed to move in all directions so that inputs (Energy Use; GHG Emissions) were not increased and outputs (Renewables) were not decreased. In this sense, it was implemented an additive model as both inputs and outputs are targeted for improvement. The principle of the methodology is to rank countries based on their relative efficiency.

[19] Energy use includes the consumption of coal, natural gas, petroleum, net nuclear, hydroelectric, and non-hydroelectric renewable energy.

[20] World Development Indicators (https://data.worldbank.org/indicator)

[21] International Data (https://www.eia.gov/international/data/world)

[22] Renewables consumption.

One country is more efficient compared to another, in the same period, when:

- The population and/or emissions and/or energy use are lower for the same value of GDP/renewables.
- GDP/renewables are greater for the same value of population/ emissions/energy use.
- Production increases and GHG emissions shrink.

3.2.1 Descriptive Analysis

Previously to the typo of the DEA model, to overcome possible bias in the analysis, for each year, the countries that had missing data for one or more variables were removed from the dataset. For that reason, countries such as Andorra, America Samoa, Eritrea, French Polynesian, Democratic People's Republic of Korea (North Korea), Liechtenstein, Monaco, Venezuela, and Yemen were excluded from the analysis during the entire period (2000-2018)[23]. Since 2013, more than 160 countries were assessed (Table 3.2).

Table 3.2 – Number of countries analyzed in each year (2000-2018). [24]

2000	138	**2010**	154
2001	137	**2011**	156
2002	138	**2012**	159
2003	138	**2013**	164
2004	138	**2014**	167
2005	142	**2015**	169
2006	146	**2016**	169
2007	146	**2017**	169
2008	145	**2018**	169
2009	148		

From 2000 to 2018, the global population has expanded in 24% (5,7 billion; 7.1 billion; respectively). China is the most populated country with 1.4 billion people; in 2018, St. Kitts and Nevis was the least populous country with only 52 thousand citizens.

[23] These countries didn't have information about their GDP in World Bank database from 2000-2018.

[24] The list of the countries under analysis in 2018 is included in the appendix.

The global GDP at purchasing power parity (PPP) increased by 86% between 2000 and 2018, being China the country that contributed the most for this growth. With an annual GDP (PPP) five times greater in 2018 than at the beginning of the first decade, China took the first position with a share of 17% of the global GDP (PPP), in 2018, outperforming the United States (16%), which occupied the second place[25]. In addition to these countries, India has become the third most important country (7%). Together, these three countries were responsible for half of GDP growth from 2000-2018. As a result, in 2018, on average, the average national GDP (PPP) reached 726 thousand million dollars (Table 3.3). The standard deviation has also increased, indicating more dispersion of the data points, that is, a higher GDP heterogeneity among countries.

Meanwhile, as countries gained economic growth, total energy use has expanded (49%), which was mainly (57%) explained by China that consumed almost 3.5 times more energy in 2018 than in 2000. As a result, China has become the country that consumes more energy ($37 * 10^6$ Kt BTU), representing a quarter of 2018's global energy use, followed by the United States (17%) and Russia (6%), respectively. As a result of the higher energy use, the GHG emissions have also increased, although at a lower rate (40%) due to China's economic growth, which was the world's largest emitter of GHG (27%) followed by United States (13%) and India (8%), in 2018[26]. Despite the generalized increase, 29 countries (predominantly European countries) reduced their emissions from 2000 to 2018, without compromising their economic growth[27] (Appendix III).

This indicates there has been a higher consumption of sustainable sources of energy:

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[25] China outperformed the United States considering the PPP GDP. However, in terms of nominal GDP, the United States was the largest economy with a 24% share, in 2018 (Amoros, 2019)

[26] In 2005, China released more GHG emissions than the United States being, since then, the biggest GHGs emitter.

[27] Only Greece registered an insignificant decrease (-1%) of GDP.

- In 2018, more than one-tenth (11%) of the world's energy use was obtained from renewable sources (+ 3 pp than 2000).
- The global amount of renewables more than doubled (110%) between 2000-2018. The countries that led the effort were China (43%), United States (16%), European Union (15%), India (5%) and Brazil (4%).

Table 3.3 – Summary statistics (2000, 2009, 2012, 2018).

Variable	Year	Mean	SD	Min	Max
Population (thousands)	2000	41 507	143 091	70	1 262 645
	2009	43 397	151 853	10	1 331 260
	2012	42 158	150 915	10	1 354 190
	2018	**43 029**	**154 323**	**52**	**1 402 760**
GDP (PPP const. 2017 international $) (millions)	2000	461 792	1 409 294	184	14 143 360
	2009	580 714	1 765 667	60	16 381 405
	2012	620 778	1 941 736	82	17 445 764
	2018	**726 330**	**2 436 908**	**265**	**21 229 364**
Energy Use (Kt BTU)	2000	686 167	2 454 258	125	24 889 188
	2009	787 233	2 969 177	194	25 368 820
	2012	839 385	3 348 240	206	33 008 315
	2018	**869 474**	**3 589 162**	**276**	**37 074 330**
GHG emissions (Kt of CO2 eq.)	2000	222 791	747 456	50	6 861 150
	2009	253 158	963 224	50	9 377 660
	2012	263 888	1 063 665	50	11 399 830
	2018	**266 333**	**1 104 534**	**110**	**12 355 240**
Renewables (Kt BTU)	2000	56 178	178 119	0	1 539 271
	2009	68 932	237 705	0	1 918 548
	2012	76 064	285 757	0	2 378 236
	2018	**96 588**	**406 567**	**1**	**4 130 927**

Furthermore, to better understand the relation among variables, it was computed the Pearson's correlation coefficient[28]. Both in 2000 and 2018, the

[28] Pearson's correlation coefficient values vary between [-1; 1]. The signal indicates if the variables are positive (>0) or negative correlated (<1), that is, if one variable increases, the other also increases or if one variable increase the other decrease. The number expresses the intensity of the correlation: the nearest to 1, the most variables are correlated, the nearest to 0, the weakest correlated variables are.

variables that are more strongly correlated (positive) are consumption (energy use) and GHG emissions with a relation of 0.98 (almost a linear correlation). From 2000 to 2018, the correlation between GDP and renewables increased from 0.82 to 0.94, indicating that in 2018, as GDP increases, the highest the investment that countries are making in renewables, compared to 2000.

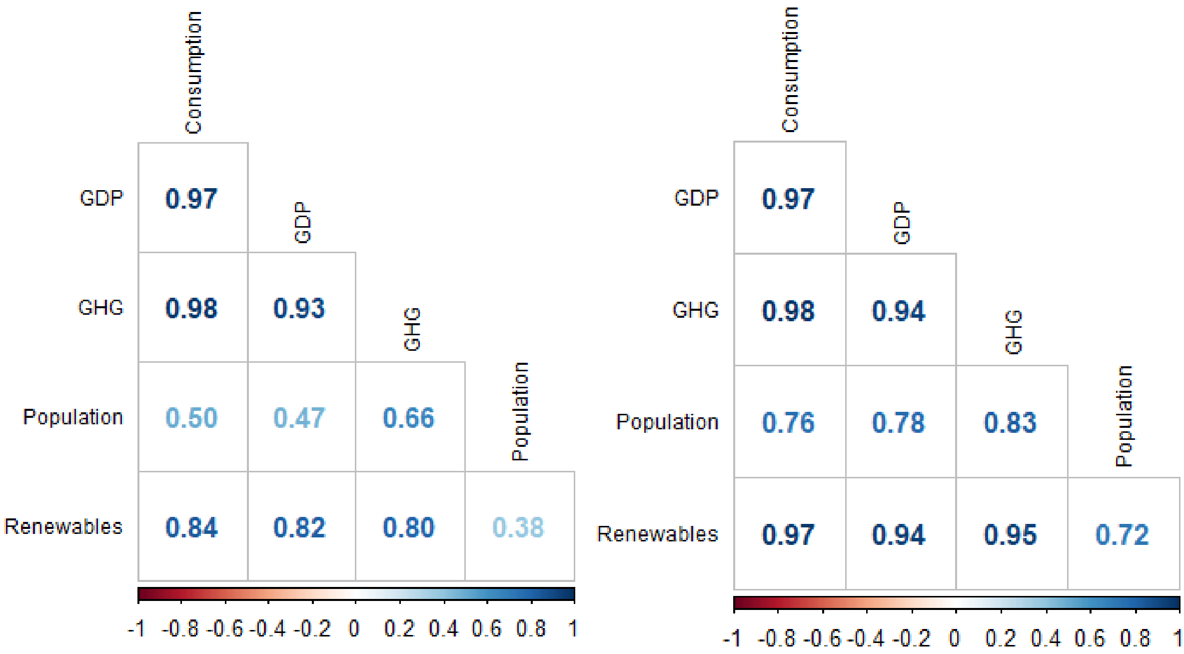


Figure 3.6 – Correlation between the variables in 2000 (left) and 2018 (right).

Chapter 4: Results and Discussion

4.1 Overall Results

The mathematical formulation of the additive model can be written as follows, where x_ij is the amount of input i consumed by unit j, y_rj is the amount of output r produced by unit j and we assume that a subset of the m inputs is discretionary (Id), and a subset of the s outputs are discretionary (Od):

$$\text{OF} = Max\left(\textstyle\sum_{i\ in\ Id} s_i^- + \textstyle\sum_{r\ in\ Od} s_r^+ \right)$$

$$s.t. \sum_{j=1}^{n} \lambda_j x_{ij} + S_i^- = x_{ij_0}, \quad i = 1, \dots, m,$$

$$s.t. \sum_{j=1}^{n} \lambda_j y_{rj} - S_i^+ = y_{rj_0}, \quad r = 1, \dots, s,$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \in S$$

$$S_i^+ \geq 0, S_i^- \geq 0, \lambda_j \geq 0$$

To solve this linear programming problem, it was used the GAMS software.

The objective function corresponds to the sum of slacks (just for the discretionary inputs and outputs) that is sought to be maximized. As the additive model does not provide an efficiency score, the objective function does not have great interpretation. The only conclusions that can be pointed out are:

- any value equal to zero means that the DMU is efficient.
- values greater than zero can be interpreted as the sum of the percentage changes to be made in inputs and outputs to reach the frontier.

In this sense, in order to obtain an inefficiency measure for each DMU, it was computed, at a later stage, the Euclidian Distance[29] that measures the distance between each observed value from the respective target, for each variable. Thus, the highest the Euclidian Distance the greatest the inefficient of the DMU; on the other hand, the closer the targets to a unit, the less the change is required to achieve those targets, so more efficient the DMU is. The formula can be written as follows, where both target and observed values have been normalized:

$$\text{DMU Inefficiency} = \sqrt{(target - obs.)^2_{Energy\ Use} + (target - obs.)^2_{GHG\ emissions} + (target - obs.)^2_{Renewables}}$$

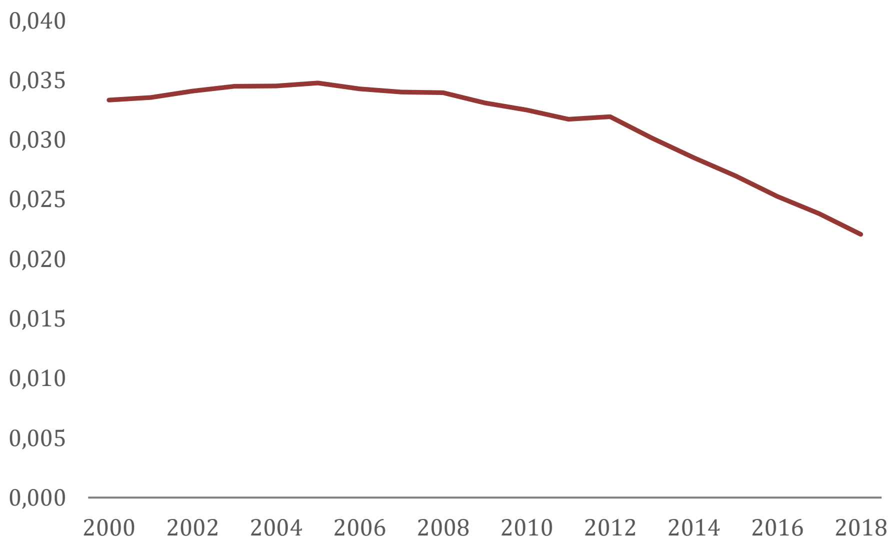
The Graph 4.1 exhibits how the global average inefficiency evolved between 2000 and 2018, making possible to identify three trends:

[2000 – 2005]: average increase of annual inefficiency.

[2005 – 2012]: countries slowly started becoming less inefficient.

[2012 – 2018]: sharply improvement in efficiency.

Graph 4.1 – Evolution of global inefficiency over time (2000-2018).



The improvement of efficiency between 2000 and 2018 is explained by the higher growth rates of outputs compared to the inputs: in fact, during this period, although each country consumed, on average, more 27% of energy and released

[29] As the variables (Energy Use, GHG emissions, Renewables) are measured in different scales, it was carried out a min-max normalization which represents each observation in a scale of 0 to 1.

more 20% of GHG emissions, they've registered a higher economic growth (57%) and consumed more 72% of renewable energy.

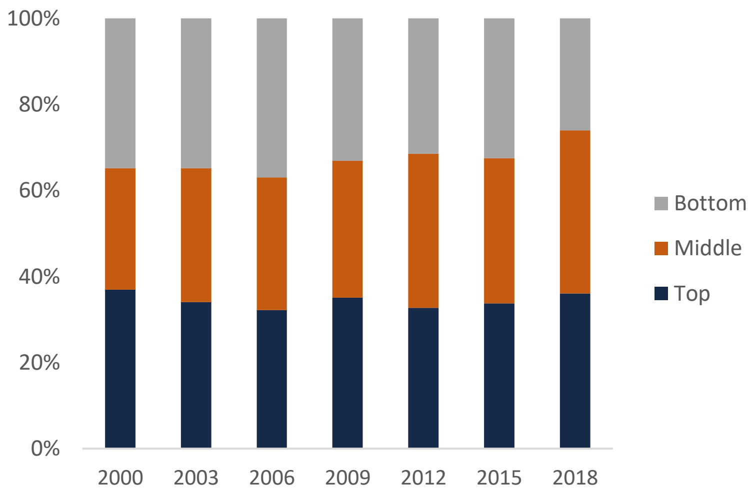
Table 4.1 – Global average growth rate between 2000 and 2018, for the variables of the DEA model (Population, Energy Use, GHG emissions, GDP and Renewables)

	INPUTS			OUTPUTS	
	Population	Energy Use	GHG emissions	GDP	Renewables
Growth (2000-2018)	**4%**	**27%**	**20%**	**57%**	**72%**

In order to differentiate DMUs' performance, these were grouped in three categories (top, middle and bottom performers), based on their percentile[30]. In this sense, in 2018, more than one third (38%) of countries (64 out of 169) was considered as having a medium level of efficiency, followed, with a small difference, by the 61 countries considered as efficient.

The notorious improvement of efficiency is reflected in the growing decrease of bottom performance' countries weight: for example, in 2000, 35% of countries were inefficient compared to 25%, in 2018. However, this analysis indicates that there is still room for improvement as most countries continue having a medium/low level of efficiency (Graph 4.2).

Graph 4.2 – Weight of each category (top, middle and bottom) in the total number of countries.



[30] The percentile was computed based on the Euclidean distance: the highest (lowest) the efficiency of the DMU, the lowest (highest) the distance and the highest (lowest) the percentile.

Top performers were the ones belonging to the percentile >= 66%; bottom performers <33%; middle performers >=33% and <66%.

Regarding the characteristics of each category, the countries ranked as top performers were smaller compared to the ones with bottom performance: on average (2000-2018), top performers countries had 11 million population compared with the average 99 million population of bottom performers. In terms of the other variables, bottom performers consume on average more 12 times energy and release 12 more GHG to the atmosphere; on the other hand, their GDP is only 10 times higher and invest only 4 times more in renewables, on average (Table 4.2).

Table 4.2– Characteristics of the top, middle and bottom efficient countries.

	Avg Population	**Avg Energy Use**	**Avg GHG Emissions**	**Avg GDP**	**Avg Renewables**
Top	11 405	173 268	52 092	141 963	36 057
Middle	18 305	185 936	69 279	192 658	45 759
Bottom	98 791	2 045 512	641 344	1 454 065	135 354

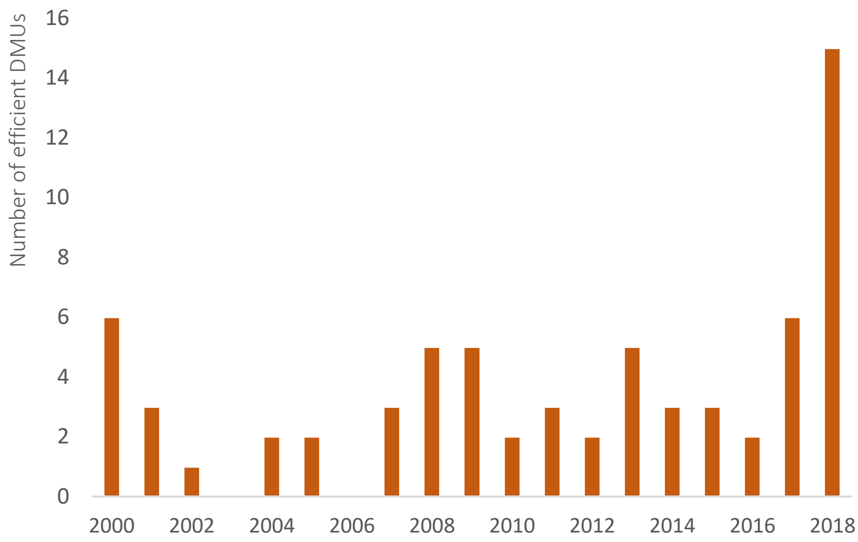
4.2 Efficient Countries

With the objective of studying the efficient countries, two approaches were conducted: it was analyzed the peers and the countries that have been consistently ranked as top performers (are not necessarily peers). In this sense, it will be possible to study which countries are examples of good performance and to conclude about the countries that despite not being a peer, have shown a consistent and efficient performance over the years.

The peers are the efficient units for which the sum of the slacks of the objective function is zero, not existing any other country that produces more, i.e., that has a higher GDP and renewables with the same or less use of inputs.

From 2000 to 2018, 68 peers were identified, 15 of them regarding 2018 performance (Graph 4.3).

Graph 4.3 – Number of efficient DMUs per year.



Only 33 countries were classified as peer at least one year: the countries that have shown more consistency in terms of their environmental efficiency are Canada, Iceland, Luxembourg, Nauru, Norway, and Paraguay.

Table 4.3 - List of the efficient countries and respective year.

Afghanistan	2002; 2004
Bhutan	2008; 2009
Brazil	2009; 2011
Burundi	2005; 2009
Canada	2000; 2008; 2013; 2017
Chad	2005; 2010
China	2018
Comoros	2007; 2008
Costa Rica	2015
Equatorial Guinea	2001; 2004
France	2018
Germany	2018
Iceland	2011; 2012; 2013; 2017; 2018
India	2018
Indonesia	2017
Ireland	2018
Italy	2014; 2018
Kiribati	2000; 2001
Luxembourg	2007; 2016; 2018
Nauru	2009; 2011; 2012; 2013; 2014; 2015; 2016
Nepal	2007; 2015
Nigeria	2009; 2010
Norway	2000; 2008; 2017

Paraguay	2000; 2008; 2013; 2014
Rwanda	2018
Singapore	2018
Sri Lanka	2013; 2018
Sudan	2000; 2001
Sweden	2018
Switzerland	2017; 2018
United Arab Emirates	2000
United Kingdom	2018
United States	2017; 2018

To differentiate between efficient DMUs it was analyzed the number of times they appeared in the reference set of other countries:

Table 4.4 - Characterization of peers.

Bhutan2009	1093	Afghanistan2004	141	India2018	17
Kiribati2001	1043	Paraguay2013	130	Paraguay2014	16
Norway2017	708	Afghanistan2002	123	Chad2010	15
Nepal2015	591	Bhutan2008	113	Sudan2001	11
Iceland2012	578	Paraguay2008	97	Nauru2016	11
Sri Lanka2013	507	Nauru2009	86	Sweden2018	8
Equatorial Guinea2001	410	United Kingdom2018	80	United States2018	6
Nigeria2009	401	Norway2008	72	Luxembourg2007	5
Switzerland2017	335	United States2017	71	Ireland2018	4
Paraguay2000	307	United Arab Emirates2000	70	Nauru2011	4
Costa Rica2015	300	Italy2018	66	Nauru2014	4
Nepal2007	299	Burundi2005	34	Nauru2015	4
Norway2000	253	Canada2000	32	China2018	3
Germany2018	246	Italy2014	32	Kiribati2000	3
Brazil2011	240	Singapore2018	31	Comoros2007	2
Comoros2008	234	Iceland2018	30	Sri Lanka2018	2
Rwanda2018	197	Canada2013	27	Indonesia2017	1
Canada2008	183	Nauru2013	23	Iceland2017	1
Canada2017	162	France2018	22	Luxembourg2018	1
Brazil2009	156	Nigeria2010	21	Sudan2000	1
Switzerland2018	153	Luxembourg2016	19	Equatorial Guinea2004	1
Iceland2013	145	Chad2005	19		

From 2000 to 2018, 92 countries achieved, at least once the top ranking. However, only 51 countries had a consistent performance during this period. These countries are listed in Table 4.5.

As already stated, the top efficient countries (islands) have a low population (only 10 countries had more than 10 million people).

Regarding the efficient countries (Table 4.5), even though they are already among the best performers, there is still space for improvement (given by their targets), namely in what concerns the reduction of emissions and specially a greater consumption of renewable energy. For each country, it was identified the main peer, that is, the country with best practices: the peers who appeared the most were Bhutan (8 times), Kiribati (13) and Nauru (6) (Table 4.5). It should also be highlighted that there are 4 countries that were never dominated by others, that is, have always been a reference of best practices which are: Iceland, Luxembourg, Norway, and Sri Lanka.

Table 4.5 - List of the best performing countries over time (2000-2018)

	Inef.	times	Pop	Ener. Use	GHG em.	GDP	Renew.	Ener.Use	GHG em.	Renew.	Ener.Use	GHG em.	Renew.	PEER 1	Lambda 1
Albania	0,002	19	2 953	28 842	9 257	28 760	13 898	28 842	4 093	20 118	0%	-56%	48%	Bhutan	0,70
Antigua and Barbuda	0,000	8	93	2 551	1 136	1 747	9	2 551	1 123	1 884	0%	-1%	99683%	Nauru	0,86
Barbados	0,001	9	285	6 085	3 950	4 399	34	6 085	3 317	4 869	0%	-15%	39197%	Nauru	0,54
Belize	0,000	19	315	2 614	1 257	2 277	758	2 614	437	1 996	0%	-64%	199%	Kiribati	0,80
Bhutan	0,000	19	678	11 465	1 722	5 232	9 838	11 465	1 214	9 838	0%	-31%	0%	Bhutan	0,85
Botswana	0,002	15	1 873	15 157	15 819	23 952	1 925	15 157	8 304	9 371	0%	-49%	450%	Equatorial Guinea (1)	0,76
Burkina Faso	0,001	18	15 096	7 649	23 329	25 606	512	7 649	18 611	4 822	0%	-18%	842%	Nepal (2)	0,43
Burundi	0,000	19	8 522	1 552	3 774	7 029	383	1 552	3 651	806	0%	-3%	103%	Burundi	0,82
Cabo Verde	0,000	19	487	2 649	661	2 798	84	2 649	617	1 948	0%	-6%	6554%	Comoros	0,90
Comoros	0,000	19	679	588	434	1 972	8	588	434	157	0%	0%	6415%	Comoros	0,91
Costa Rica	0,001	19	4 507	45 936	13 373	74 942	21 429	45 936	9 429	23 882	0%	-31%	13%	Bhutan (3)	0,56
Dominica	0,000	19	71	621	255	786	70	621	140	261	0%	-48%	287%	Kiribati	0,57
Eswatini	0,000	19	1 062	5 211	3 002	7 702	1 661	5 211	1 242	3 331	0%	-59%	103%	Comoros	0,57
Fiji	0,001	19	846	6 649	2 446	9 440	1 301	6 649	1 343	4 118	0%	-45%	222%	Kiribati	0,70
Gabon	0,001	19	1 617	13 580	6 803	24 686	2 284	13 580	3 528	6 742	0%	-49%	194%	Kiribati	0,64
Ghana	0,002	11	21 907	37 208	23 924	71 160	14 194	37 208	9 408	19 039	0%	-61%	35%	Sri Lanka (4)	0,51
Grenada	0,000	9	109	1 060	2 312	1 594	8	1 060	1 580	632	0%	-32%	9262%	Nauru	0,84
Guinea	0,002	19	10 080	9 560	20 586	19 930	1 448	9 560	10 185	6 977	0%	-50%	411%	Bhutan	0,44
Guyana	0,001	19	754	6 456	4 085	7 338	87	6 456	4 085	4 908	0%	0%	7368%	Bhutan (5)	0,42
Haiti	0,001	19	9 797	8 914	8 412	29 367	474	8 914	8 412	3 758	0%	0%	990%	Rwanda	0,52
Iceland	0,000	19	313	44 037	3 386	15 459	34 397	42 803	2 717	34 595	-4%	-19%	1%	Iceland	0,72
Kiribati	0,000	16	102	219	85	214	4	219	65	101	0%	-22%	5431%	Kiribati	0,99
Lao PDR	0,001	15	5 962	19 730	10 694	25 635	12 235	19 730	3 921	12 830	0%	-63%	8%	Bhutan (6)	0,56
Lesotho	0,000	19	2 026	3 202	4 772	4 592	1 316	3 202	1 177	2 343	0%	-75%	81%	Kiribati and Comoros	(0,70; 0,64)
Luxembourg	0,001	13	535	47 618	11 150	61 253	5 109	47 236	10 027	8 507	-1%	-10%	77%	Luxembourg	1,00
Madagascar	0,002	19	20 729	10 264	28 688	32 500	1 784	10 264	17 790	6 612	0%	-38%	265%	Afghanistan	0,57
Malawi	0,001	19	14 326	7 304	12 431	18 669	3 845	7 304	5 120	4 345	0%	-60%	15%	Rwanda	0,62
Maldives	0,001	12	414	5 209	1 523	7 145	5	5 209	1 523	3 100	0%	0%	57776%	Kiribati	0,77
Mali	0,001	16	13 992	7 797	28 864	27 734	1 641	7 797	16 123	4 485	0%	-43%	164%	Nepal	0,46
Mauritania	0,001	18	3 388	7 340	10 837	15 993	303	7 340	10 837	4 787	0%	0%	2128%	Mauritania	0,48
Montenegro	0,001	13	620	12 159	3 827	10 901	4 933	12 159	1 568	8 709	0%	-59%	78%	Bhutan	0,61
Mozambique	0,002	12	20 840	39 845	25 203	18 096	31 661	39 845	3 362	32 458	0%	-87%	3%	Iceland	0,78
Namibia	0,002	19	2 095	15 814	12 479	18 777	5 385	15 814	3 048	11 172	0%	-75%	107%	Bhutan	0,79

Nauru	0,000	7	10	247	56	107	0	247	56	0	0%	0%	0%	Nauru	1,00
Nepal	0,000	16	26 071	18 051	35 486	66 839	7 381	18 051	31 458	8 572	0%	-11%	20%	Nepal (7)	0,86
Norway	0,001	19	4 862	482 073	48 564	299 910	316 378	463 784	44 763	316 378	-4%	-8%	0%	Norway	0,84
Paraguay	0,001	19	6 160	112 766	39 783	62 812	95 290	112 766	32 901	95 290	0%	-16%	0%	Kiribati	0,64
Rwanda	0,000	19	9 915	3 161	4 919	14 863	461	3 161	4 904	1 113	0%	0%	204%	Rwanda (8)	0,71
Samoa	0,000	19	185	1 038	536	1 096	111	1 038	232	712	0%	-57%	600%	Kiribati	0,91
Sao Tome and Principe	0,000	18	177	444	145	594	16	444	143	250	0%	-2%	1531%	Kiribati	0,88
Sierra Leone	0,000	19	6 212	2 844	5 922	9 040	189	2 844	5 478	1 825	0%	-8%	2332%	Kiribati	0,64
Solomon Islands	0,000	13	560	1 266	798	1 394	10	1 266	798	977	0%	0%	13090%	Kiribati	0,89
Sri Lanka	0,001	11	20 589	71 995	29 253	214 398	12 127	71 995	26 973	17 575	0%	-8%	51%	Sri Lanka	0,74
St. Kitts and Nevis	0,000	9	51	913	362	1 234	18	913	362	374	0%	0%	2090%	Nauru	0,90
St. Vincent and the Grenadines	0,000	19	109	862	371	1 212	55	862	240	414	0%	-41%	682%	Kiribati	0,92
Suriname	0,001	19	523	9 167	3 305	9 146	2 159	9 167	1 268	6 282	0%	-61%	197%	Rwanda	0,52
Tajikistan	0,001	19	7 475	54 420	9 578	18 012	39 658	50 961	3 311	41 427	-6%	-64%	5%	Iceland	0,93
The Bahamas	0,002	9	371	11 323	2 902	13 388	4	11 323	2 902	6 752	0%	0%	284737%	Nauru	0,61
Togo	0,001	19	6 311	6 496	6 871	11 059	813	6 496	4 799	4 943	0%	-30%	512%	Bhutan	0,52
Uganda	0,001	19	32 023	16 735	38 510	57 849	5 352	16 735	29 344	8 991	0%	-23%	71%	Nepal (9)	0,81
Vanuatu	0,000	9	264	634	803	800	21	634	535	434	0%	-33%	2157%	Kiribati	0,94

31

(1) main peer during 9 year: 2000-2002; 2011; 2014-2018;

(2) main peer during 16 years.

(3) main peer during 15 years.

(4) the most recent peer: 2009-2010; 2013-2018

(5) the most recent peer (since 2012)

(6) main peer during 12 years

(7) main peer during 16 years

(8) the most recent peer (since 2011)

(9) the most recent peer (since 2007)

[31] Vanuatu, Barbados, St. Kitts and Nevis, Grenada, The Bahamas, Antigua and Barbuda and Nauru were considered top efficient in all the years for which there was observations.

4.3 Inefficient Countries

The Table 4.6 lists the countries that have been over the years consistently among the worst performers. For that reason, it was chosen the top 20 countries with the highest inefficiency values for each year.

In 2000, China and United States were the most inefficient (inefficiency = 0.34, for both), followed by Russia (inefficiency = 0.22). However, while China started becoming increasingly more inefficient up to 2011, the US have made a continuous progress and stop being classified as one of the worst performing countries in 2015. Despite later, after 2011, China started to make noteworthy positive evolution and achieved efficiency in the last year (2018).

In 2018, the poorest 5 performing countries were Russia, followed by Iran, Saudi Korea, Saudi Arabia, and South Africa, all having a consistent inefficient behavior as they were always in top 20 worst performing countries in all years.

Table 4.6 – List of the worst performing countries over time (2000-2018)

[32][33]

Countries	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Nºtimes
Russia	0,22	0,22	0,23	0,24	0,23	0,23	0,23	0,23	0,24	0,22	0,24	0,24	0,24	0,23	0,24	0,24	0,23	0,24	0,24	**19**
Iran	0,15	0,15	0,15	0,15	0,16	0,16	0,17	0,17	0,18	0,19	0,19	0,19	0,20	0,20	0,21	0,21	0,21	0,22	0,23	**19**
South Korea	0,17	0,17	0,17	0,18	0,18	0,18	0,18	0,18	0,18	0,18	0,19	0,19	0,19	0,19	0,18	0,19	0,19	0,18	0,18	**19**
Saudi Arabia													0,17	0,17	0,18	0,18	0,17	0,18	0,17	**7**
South Africa	0,13	0,13	0,13	0,14	0,14	0,14	0,14	0,14	0,15	0,14	0,15	0,15	0,15	0,15	0,15	0,15	0,14	0,15	0,14	**19**
Thailand	0,08	0,09	0,09	0,10	0,11	0,11	0,11	0,11	0,11	0,12	0,13	0,13	0,13	0,14	0,14	0,14	0,13	0,13	0,13	**19**
Ukraine	0,15	0,14	0,15	0,15	0,15	0,14	0,14	0,15	0,15	0,13	0,13	0,14	0,14	0,13	0,13	0,12	0,12	0,11	0,11	**19**
Mexico	0,13	0,13	0,14	0,15	0,14	0,15	0,15	0,15	0,15	0,17	0,15	0,15	0,14	0,15	0,13	0,13	0,13	0,12	0,10	**19**
Kazakhstan	0,08	0,08	0,08	0,08	0,09	0,09	0,09	0,10	0,10	0,10	0,10	0,10	0,10	0,10	0,10	0,10	0,10	0,10	0,10	**18**
Egypt	0,06	0,07	0,07	0,08	0,08	0,08	0,09	0,09	0,09	0,10	0,10	0,10	0,11	0,10	0,10	0,10	0,10	0,10	0,10	**13**
Australia	0,11	0,11	0,11	0,11	0,11	0,11	0,11	0,11	0,11	0,11	0,11	0,11	0,11	0,10	0,10	0,10	0,10	0,10	0,09	**19**
Malaysia	0,07	0,07	0,08	0,08	0,08	0,09	0,09	0,09	0,09	0,10	0,10	0,10	0,10	0,10	0,10	0,09	0,09	0,09	0,09	**13**
Uzbekistan	0,08	0,08	0,08	0,08	0,08	0,08	0,09	0,09	0,09	0,08	0,08	0,09	0,08	0,08	0,08	0,08	0,07	0,08	0,08	**11**
Netherlands	0,09	0,09	0,09	0,10	0,10	0,09	0,09	0,09	0,09	0,09	0,09	0,09	0,08	0,08	0,08	0,08	0,08	0,08	0,07	**17**
United Arab Emirates	0,00	0,01	0,01	0,01	0,01	0,02	0,03	0,05	0,07	0,09	0,10	0,10	0,10	0,10	0,09	0,08	0,08	0,07	0,07	**9**
Japan	0,17	0,17	0,18	0,16	0,16	0,16	0,14	0,16	0,14	0,15	0,14	0,15	0,15	0,14	0,12	0,10	0,10	0,07	0,06	**17**
Indonesia	0,10	0,09	0,09	0,10	0,10	0,10	0,10	0,10	0,10	0,10	0,11	0,09	0,08	0,07	0,07	0,05	0,02	0,00	0,01	**13**
China	0,34	0,36	0,37	0,38	0,39	0,52	0,56	0,58	0,57	0,60	0,65	0,70	0,67	0,62	0,46	0,37	0,23	0,11	0,00	**18**
India	0,24	0,24	0,24	0,24	0,24	0,23	0,22	0,22	0,23	0,24	0,23	0,21	0,21	0,17	0,16	0,12	0,07	0,03	0,00	**16**
United States	0,34	0,36	0,33	0,32	0,31	0,30	0,27	0,28	0,24	0,19	0,18	0,13	0,12	0,10	0,09	0,08	0,04	0,00	0,00	**15**
United Kingdom	0,14	0,14	0,14	0,13	0,13	0,12	0,12	0,11	0,11	0,11	0,11	0,09	0,09	0,07	0,04	0,03	0,02	0,01	0,00	**13**
Germany	0,14	0,14	0,13	0,14	0,13	0,12	0,12	0,09	0,09	0,09	0,09	0,06	0,05	0,05	0,03	0,03	0,02	0,01	0,00	**10**

[32] The column nº times corresponds to the number of times each country was ranked in top 20 worst performers, during the period 2000-2018.

[33] Countries are ranked by their 2018's inefficiency value in descending order.
Cells colored with pink means that the country was not among the 20 worst performers of that year.
There was no data for Saudi Arabi from 2000-2011.

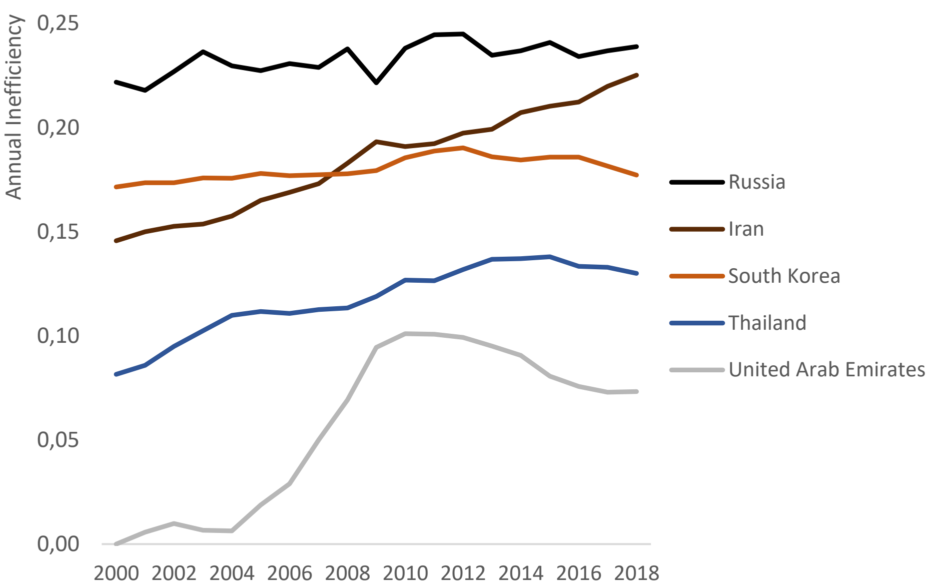
Of the countries listed as inefficient, it is analyzed in the Table 4.7 the countries that have aggravated their inefficiency or not made significant improvement, namely (Graph 4.4):

Table 4.7 – Inefficient countries: reasons for their worst performance.

Country	Reasons for worst performance	Main Peers (lambda)
Russia (5th largest GHGs emitter)	Oscillating inefficiency. Residual growth in renewable energy consumption (+ only 3%), considering the global average (+72%).	**[2000-2018]** 1st Brazil2011 (avg 59%) 2nd Canada2013 (avg 37%)
Iran	Increasingly more inefficient since 2000. This is explained mostly by the renewable's consumption: despite the increase in 3.5 times, from 2000-2018, this growth was not enough to keep up with their renewables' target growth.	**[2000-2008]** 1st Norway2000 (avg 53%) **[2009-2018]** 1st Canada2000 (avg 49%) **[2000-2018]** 2nd Brazil 2011 (avg 31%)
South Korea	Registered approximately the same level of inefficiency (2000-2018), despite the small improvement in the last 3 years of the period which was explained by the higher renewables use. In 2018, the renewables consumption represented only 8% of their annual target, indicating that this country has a high margin to improve its performance.	**[2000-2018]** 1st Canada2000 (avg 54%) **[2000-2014]** 2nd Norway2000 (avg 29%) **[2014-2018]** 2nd Germany2018 (avg 19%)
Thailand	Has become increasingly more inefficient since 2000. Should also consume more renewables energy.	**[2000-2009]** 1st Norway2017 (avg 76%) **[2010-2018]** 1st Norway2000 (avg 68%)

UAE	[2004-2010] - it was registered a peak in the annual inefficiency, which is explained by the fact that inputs increased above the targets' growth, while the output/renewables stayed far behind it. **Inputs (2004-2010):** + 41% vs 36% (target) Energy Use + 41% vs 36% (target) GHG emissions **Outputs (2004-2010):** + 161% vs 2113% (target) Renewables	**[2004]** 1st UAE2000 (avg 60%) **[2005-2006]** 1st Singapore (avg 49%) **[2007-2018]** 1st Norway (avg 82%)

Graph 4.4 – Evolution over time (2000-2018) of 5 of the worst performing countries (Russia Iran, South Korea, Thailand, United Arab Emirates).



Focusing on 2018's results, to become efficient, the top 15 worst performing countries should particularly consume more renewable energy followed by a reduction in their emissions. Russia and United Arab Emirates are the only countries that need to consume less energy. In terms of emissions, Uzbekistan is the country that must reduce their emissions the most.

For each of the inefficient countries, it was identified the peers with similar environmental profile as also the degree of similarity among them (given by lambda[34]). In this sense, as seen throughout the entire period, Brazil is the best practice example for Russia, followed by Canada: to close the gap to its targets (Table 4.8), Russia should consume less 38% of energy, cut its emissions in half and almost triple renewables. For two thirds (10) of these countries, Norway is referred as the main peer being its environmental practices an example to be followed. Besides, Canada (3) is the main benchmark for Iran, South Korea and Saudi Arabia; Italy (1) is also mentioned for Mexico.

[34] Represents the contribution of each peer: no country can contribute more than 100%; the sum of all the contributions must equal 100%.

Table 4.8 - Summary of the characteristics, targets, % change and peers of the top 15 worst performing countries (2018).

	Characteristics						Targets			% Change			Peers			
	Inef.	Pop.	Ener. Use	GHG em.	GDP	Renew.	Ener. Use	GHG em.	Renew	Ener. Use	GHG em.	Renew.	Peer 1		Peer 2	
Russia	0,24	144 478	8 383 003	2 543 400	3 913 976	413 668	5 161 316	1 307 081	1 234 124	-38%	-49%	198%	Brazil2011	52%	Canada2013	39%
Iran	0,23	81 800	2 997 668	828 280	1 102 001	36 608	2 997 668	749 880	966 100	0%	-9%	2539%	Canada2000	65%	Brazil2011	31%
South Korea	0,18	51 607	3 136 456	718 880	2 164 813	61 554	3 136 456	680 229	793 054	0%	-5%	1188%	Canada2008	62%	Germany2018	23%
Saudi Arabia	0,17	33 703	2 565 770	638 120	1 604 007	367	2 565 770	525 697	698 199	0%	-18%	190145%	Canada2008	55%	Norway2000	29%
South Africa	0,14	57 793	1 384 767	513 440	801 925	25 391	1 384 767	353 127	613 810	0%	-31%	2317%	Norway2000	65%	Brazil2011	26%
Thailand	0,13	69 428	1 406 343	416 950	1 256 359	91 014	1 406 343	381 307	627 388	0%	-9%	589%	Norway2000	64%	Brazil2011	33%
Ukraine	0,11	44 623	944 069	274 510	521 479	30 148	944 069	217 261	495 422	0%	-21%	1543%	Norway2000	82%	Brazil2011	18%
Mexico	0,10	126 191	1 993 430	679 880	2 514 780	162 062	1 993 430	585 670	579 085	0%	-14%	257%	Italy2018	56%	Brazil2009	39%
Kazakhstan	0,10	18 276	857 581	274 220	466 860	28 231	857 581	153 750	442 494	0%	-44%	1467%	Norway2000	86%	Canada2000	8%
Egypt	0,10	98 424	1 019 203	329 220	1 118 716	39 776	1 019 203	329 220	450 935	0%	0%	1034%	Norway2017	43%	Brazil2009	29%
Australia	0,09	24 983	1 497 202	615 380	1 224 879	99 722	1 497 202	290 545	472 734	0%	-53%	374%	Norway2000	66%	Germany2018	18%
Malaysia	0,09	31 528	967 653	306 670	869 460	72 817	967 653	204 860	443 870	0%	-33%	510%	Norway2008	67%	Norway2000	16%
Uzbekistan	0,08	32 956	458 874	235 510	233 426	13 079	458 874	45 544	322 576	0%	-81%	2366%	Norway2000	89%	Paraguay2000	11%
Netherlands	0,07	17 232	965 319	178 640	966 021	54 828	965 319	168 165	360 470	0%	-6%	557%	Norway2008	50%	Norway2017	34%
United Arab Emirates	0,07	9 631	1 159 321	263 240	644 969	3 003	950 132	138 862	301 672	-18%	-47%	9946%	Norway2008	77%	Singapore2018	22%

Despite being listed as inefficient in Table 4.8, the countries below significantly improved their performance (Graph 4.5) being relevant to understand the reasons behind their progress:

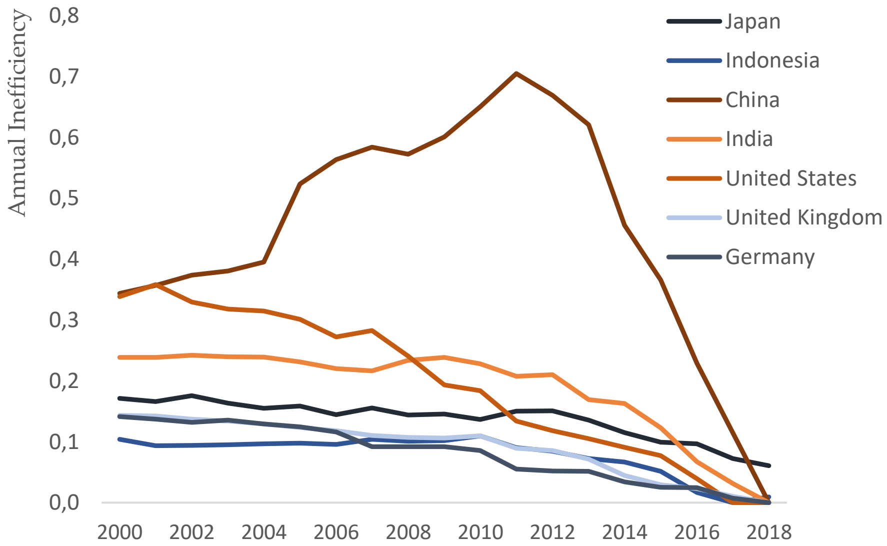
Table 4.9 – Cases of Success: China, United States, India, and Japan.[35]

Country	Reasons for improvement	Main Peers (lambda)
China (1st largest GHGs emitter)	Substantial drop of inefficiency after 2011. Supported its economic growth without deteriorating its environmental performance by investing in renewables: **Inputs (2011-2018):** + 20% Energy Use + 12% GHG emissions **Outputs (2011-2018):** + 63% GDP + renewables more than doubled (+116%)	**[2011-2015]** United States (avg 76%) **[2016-2018]** China (avg 76%)
United States (2nd largest GHGs emitter)	More gradual improvement over time. Gain of efficiency explained by the reduction of emissions and by the increase in the consumption of renewables, while increasing economic growth. **Inputs (2000-2018):** + 3% Energy Use - 12% GHG emissions **Outputs (2000-2018):** + 42% GDP + 86% renewables	**[2000-2017]** United States2017 (83%) **[2018]** United States2018 (100%) During this period there weren't any countries with better performance.

35 Being GHG emissions the main driver of climate change, it was only analyzed the evolution of China, United States, India, and Japan, as they are among the major emitters. The information about the world's largest emitters countries is relative to CO_2 released in 2017 (Richie. H, 2020).

India 4th largest GHGs emitter)	Performance improvement after 2009. **Inputs (2009-2018):** + 50% Energy Use + 38% GHG emissions **Outputs (2009-2018):** + 83% GDP + 77% renewables	**[2015 – 2014]** Brazil2011 (avg 71%) **[2015-2019]** India2018 (avg 81%)
Japan 6th largest GHGs emitter)	Performance improvement after 2012. **Inputs (2012-2018):** - 7% Energy Use - 11% GHG emissions **Outputs (2012-2018):** + 7% GDP + 46% renewables	**[2012-2018]** Germany2018 (avg 63%) The main peer since 2000, has always been Germany.

Graph 4.5 – Evolution over time (2000-2018) of 7 successful countries (Japan, Indonesia, China, India, United States, United Kingdom, Germany).



4.4 Countries Profile: 2018

4.4.1 The method: clustering analysis

Countries exhibit different profiles in what concerns the magnitude of change that is required in order to achieve their targets. Apart from the magnitude, it is also relevant to understand what variables each country should improve the most to become efficient.

Under this context, a clustering analysis was carried out and countries were divided in homogeneous groups. This methodology underlines in two assumptions: the similarity within the same group (intra-cluster distance) should be maximized; for observations belonging to different clusters, the difference (inter-cluster distance) should be maximized.

This analysis was performed in R software based on k-means[36] algorithm, a partitioning method that considers that the center of each cluster could be a random point. The process of defining clusters is iterative:

- the algorithm picks a number k of random cluster centers and assign each observation to the closest one
- it moves each cluster center to the mean of the assigned items
- then, it reassigns the points that are nearest to a different cluster center
- the procedure finishes "until all the objects are well allocated in their groups without requiring a new iteration (Zanella et al., 2013)

The choice of the optimal number of clusters (pre-requisite of the algorithm) was based on two technical approaches: the Elbow and the Davies-Bouldin methods. The Elbow curve shows the sum of square errors (SSE)[37] for each number of clusters, being the optimal choice the one that minimizes the errors. The Davies-Bouldin (DB) index was used as a complementary method because it

[36] Only works with numeric data.

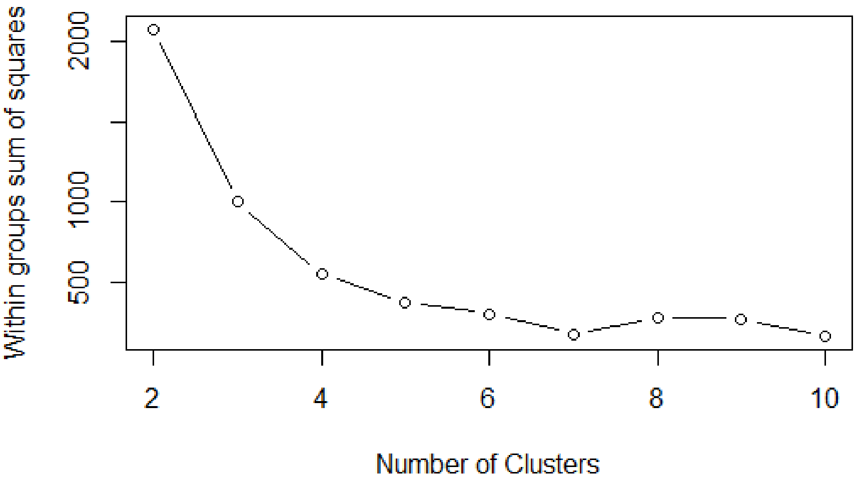
[37] SSE is a measure of the quality of each cluster. It is the sum of the differences between the centroid and each observation.

was not obvious the identification of the elbow (the point in which the behavior changes dramatically) in the Elbow curve. The Davies-Bouldin (DB)[38] method assesses the variability between clusters, so it should be chosen the number of clusters with the lowest DB value.

The clustering analysis was firstly applied to the dataset with the 169 countries analyzed in 2018. However, after plotting the clusters, 28 outliers[39] (Appendix IV) were identified and removed from the dataset. These countries registered very high % change in their renewables as their observed values are very close to zero, indicating that they have an unlimited potential to increase their investment in renewable energy.

After removing the outliers, the k-means algorithm was applied to the subgroup with 141 countries[40]. The following Elbow curve allows the visualization of the change in SSE that falls rapidly until the optimal k. However, there is no strong evidence of an "elbow", that is, whether the optimal number of clusters is 4 or 5.

Graph 4.6 – Elbow curve obtained for 2018 subgroup of countries (141).



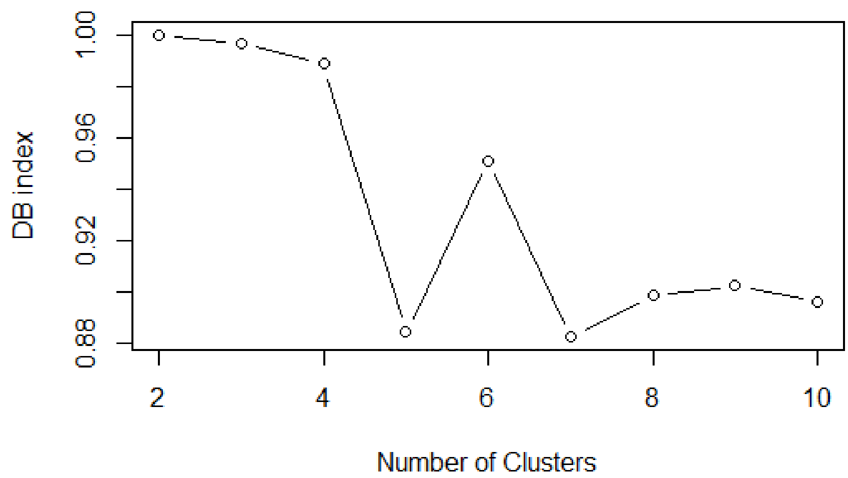
[38] The numerator of DB formula is the standard deviation of each cluster, and the denominator is the distance between different clusters.

[39] The outliers registered a % of change in renewables > Q3 (=1594,21%) + 1,5 * IQR (=1519,88%).

[40] As stated by Zanella (2013), it is necessary to define the initial seeds, that is, the k random cluster centers (centroid) to initiate the first iteration. As the clustering process is affected by this choice, after trying different seeds, it was selected the one that originated the lowest error. For that reason, it was used a seed (7).

Based on the graph below, it can be concluded that the optimal number of clusters is 5 as it minimizes the DB index value.

Graph 4.7 – Davies-Bouldin curve results for 2018 subgroup of countries (141).



4.4.2 Countries profile: clustering results

The 5 clusters created have different dimensions: cluster 2 is the biggest one comprising 90 countries (64%), followed by cluster 1 (24 – 17%) and 5 (15 – 11%) (Figure 4.1).

```
K-means clustering with 5 clusters of sizes 24, 90, 9, 3, 15

Cluster means:
  % change CONS % change GHG % change RENEW
1    0.00000000   -0.3074961       6.607732
2   -0.00492842   -0.3814634       1.102464
3    0.00000000   -0.2314505      21.901979
4    0.00000000   -0.4343689      34.248603
5   -0.02490156   -0.1822698      13.787094
```

Figure 4.1 – Size and characteristics (average % value for each of the 3 variables) of each cluster.

Each cluster aggregates countries that share similarities, that are described in (Table 4.10). The distinction between clusters is mostly related to the average % change of GHGs and Renewables.

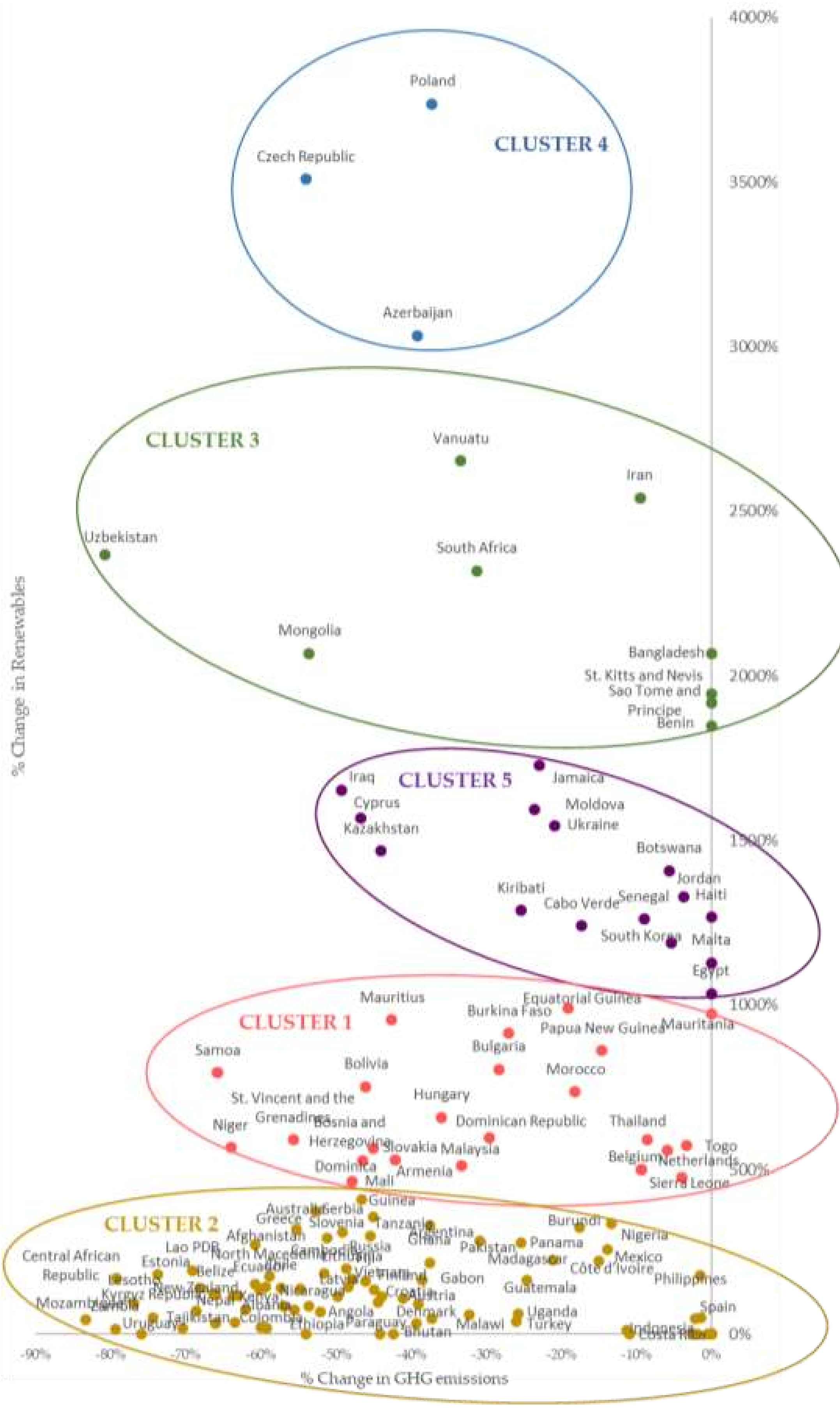
Table 4.10 – Comparison of the characteristics of each cluster[41].

Cluster	Characteristics
C1 (24 countries) – mainly from Africa (9) and Europe (7); three countries of Latin American and Caribe; three from Asia and two located in Oceania.	**% Change GHG emissions -** most countries should reduce their GHG emissions by **10% to 46%** (Appendix VIII). **% Change in renewables -** should increase the renewables by **4 to 10 times** to achieve their targets.
C2 (90 countries) – contains countries from all parts of the world: the highest number are from Europe (27), followed by Sub-Saharan African (23); Latin & Caribbean (19) and Asian countries (19). From North America (United States and Canada), Oceania (Australia and New Zealand) and Middle East (Afghanistan and Turkey) were registered only 2 countries.	**2nd highest % change in GHG emissions** – most countries should decrease their GHG emissions by **10% to 60%;** 25% of countries should cut their emissions more than 60% and up to 83% (Appendix IX). **Lowest % change in renewables –** these countries have the lowest magnitude of change: on average, countries need to double (110%) their renewables. The highest % change required was 374 % (4 times higher). This cluster includes the peers.
C3 (9 countries) – the majority is located in Asia (4) and Sub-Saharan Africa (3). 1 country from	**% Change GHG emissions -** 4 of these countries don’t need to

[41] The list of the countries comprised in each cluster is available in the appendix section (Appendix VII).

the Middle East (Iran) and other from Latin America & Caribbean (St. Kitts and Nevis).	change their GHGs. For the others, it is suggested a reduction of 31% to 81%**.** **% Change in renewables** –increase on average, **18 - 27 times.** 4 of these countries only need to invest in renewables to become efficient.
C4 (3 countries) – Azerbaijan (Eastern Europe), Czech Republic (Central Europe), Poland (Eastern Europe).	**Highest % change GHG emissions** – should emit less **37% to 54%** GHGs. **Highest % change in renewables** – countries that need to increase (on average, **30 - 37 times**) more in renewables to become efficient.
C5 (15 countries) – Most of Middle East (6) and of Eastern Europe (4); 2 Asian countries (Kazakhstan; South Korea); 2 Sub-Saharan Africa countries (Botswana; Cabo Verde); 2 of Latin America & Caribbean (Jamaica; Haiti), 1 of Oceania (Kiribati).	**% Change in GHG emissions –** most countries should reduce their emissions by **4% to 25%** (Appendix X). **% Change in renewables** – should increase the renewables by **10 to 17 times**.

Graph 4.8 – Cluster plot (excel).



Chapter 5: Conclusion

In this thesis, a DEA model was designed to evaluate the environmental efficiency performance of countries between 2000-2018. To define the model, the variables that underlie the construction of the CCPI (Climate Change Performance Index), one of the most well know composite indexes for benchmarking purposes, were used. The variables chosen were also the most commonly used in the literature studies, indicating its relevance in assessing climate change.

The application of the model and the later calculation of an inefficiency measure (the Euclidian Distance) allowed the comparison among countries. Globally, they have become more efficient over time. Besides, the variable that most needs to be improved is the renewables consumption for countries become more efficient.

It was also identified the most and less efficient countries, that is, the ones that are examples of good performance and the ones that need to improve it. This analysis can, then, help countries in designing their environmental policies and targets with the support of benchmarks. At the same, it will allow countries to study the policies of their peers that are leading to a higher climate change effort.

The clustering analysis allowed the definition of countries profile, in 2018. One of the practical implications is that it will allow policy makers to have a perception of the % of change in renewables and energy use required to improve efficiency.

Regarding the limitations, it can be highlighted the lack of information about some countries which ended up by not being analyzed. However, it was covered almost all the world countries.

For future research, it is recommended continuing with this evaluation to monitor the performance of countries.

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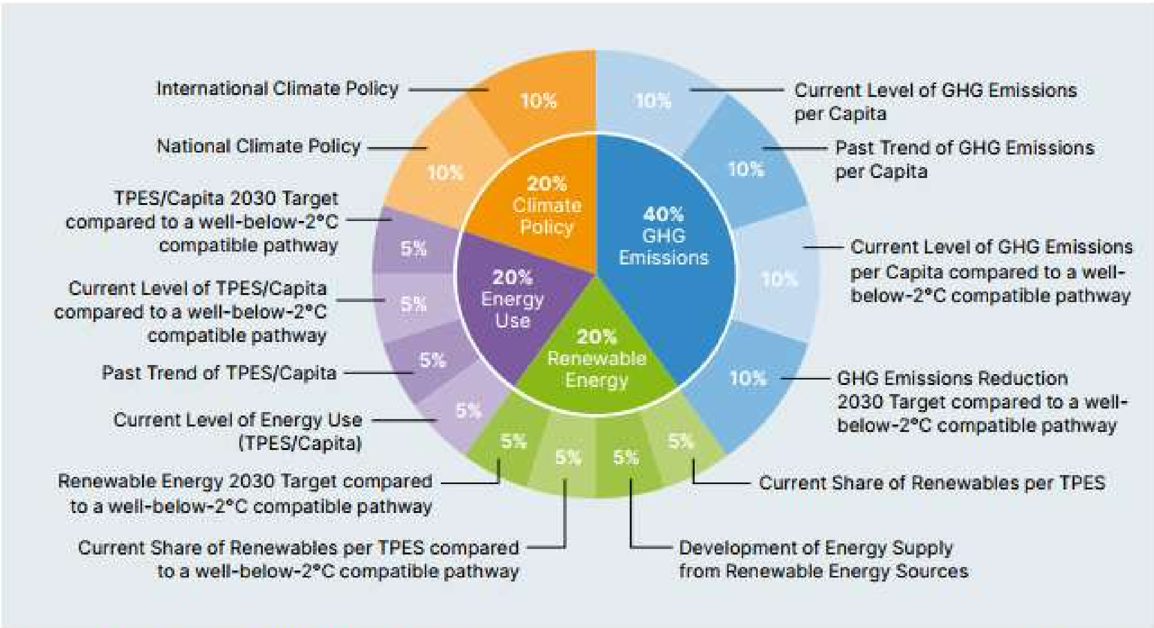
Annex

Annex I - Emissions gap to keep global warming below 2.0 °C, 1.8 °C and 1.5 °C.

Scenario (rounded to the nearest gigaton)	Number of scenarios in set	Global total emissions in 2030 [$GtCO_2e$]	Estimated temperature outcomes			Closest corresponding IPCC SR1.5 scenario class	Emissions gap in 2030 [$GtCO_2e$]		
			50% chance	66% chance	90% chance		Below 2.0°C	Below 1.8°C	Below 1.5°C
Year 2010 policies	6	64 (60–68)							
Current policies	9	55 (52–58)					15 (12–18)	22 (19–25)	30 (28–33)
Unconditional NDCs (updated NDCs and announcements)	8	52 (49–55)					13 (10–16)	19 (16–22)	28 (25–30)
Conditional NDCs (updated NDCs and announcements)	8	50 (46–52)					11 (7–13)	17 (13–19)	25 (22–28)
Below 2.0°C (66% chance)	71	39 (33–49)	Peak: 1.7–1.8°C In 2100: 1.3–1.7°C	Peak: 1.8–2.0°C In 2100: 1.5–1.9°C	Peak: 2.2–2.4°C In 2100: 1.9–2.4°C	Higher-2°C pathways			
Below 1.8°C (66% chance)	23	33 (27–41)	Peak: 1.6–1.7°C In 2100: 1.2–1.6°C	Peak: 1.7–1.8°C In 2100: 1.4–1.8°C	Peak: 2.0–2.2°C In 2100: 1.8–2.2°C	Lower-2°C pathways			
Below 1.5°C (66% chance in 2100 with no or limited overshoot)	26	25 (17–33)	Peak: 1.5–1.6°C In 2100: 1.0–1.3°C	Peak: 1.6–1.7°C In 2100: 1.2–1.5°C	Peak: 1.9–2.1°C In 2100: 1.5–1.9°C	1.5°C with no or limited overshoot			

Source: (UNEP, 2021)

Annex II - CCPI Index: indicators and respective weights.



GHG = Greenhouse Gases | TPES = Total Primary Energy Supply

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Annex III - Cooperation Index (CI): indicators and scale.

Table 1 – Description of the indicators and their scales

Individual indicator	Scale
UNFCCC Indicator I_U	
The indicator is composed of two equally weighted parts:	
1. Has the country ratified the UNFCCC?	Yes/no
2. How fast has the country ratified the UNFCCC?	Declining scale from 1992 through 1997
Kyoto-Protocol Indicator I_K	
The indicator is composed of two equally weighted parts:	
1. Has the country ratified the Kyoto-Protocol?	Yes/no
2. How fast has the country ratified the Kyoto-Protocol?	Declining scale from 1998 through 2005
Reporting Indicator I_R	
The indicator is composed of two equally weighted parts:	
1. Has the country submitted the latest NC report?	Yes/no
2. Has the country submitted its latest required NC report in time?	Declining scale until a delay of 6 month (AI) and 3 years (NAI) respectively
Finance Indicator I_F	
How often has the country made its financial contributions to the UNFCCC secretariat in time between 1996 and 2005?	Linear scale according to the number of contributions in time
Emission Indicator I_E	
The indicator is composed of two parts:	
1. On what level are the 1990 per capita CO_2 emissions in relation to the per capita GDP?	Assessment of the level and trend compared to the Environmental Kuznets Curve of the EU13-countries
2. How have the country's per capita CO_2 emissions developed in relation to the per capita GDP between 1990 and 2002?	

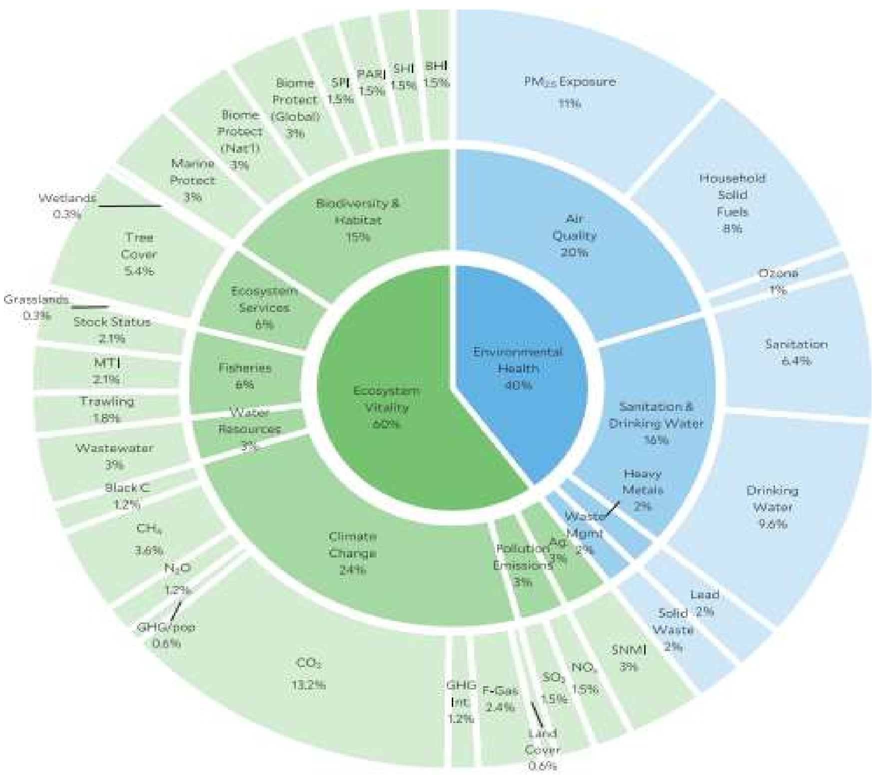
Source: (Baettig et al., 2008)

Annex IV - Policy components of the CI.

Table 1 – Policy components of the CI (C3-I).	
(1)	Two equally weighted indicators capturing whether a country ratified the UNFCCC (yes/no) and how fast it did so (declining scale from 1992 on)
(2)	Two equally weighted indicators capturing whether a country ratified the Kyoto Protocol (yes/no) and how fast it did so (declining scale from 1998 on)
(3)	Two equally weighted indicators capturing whether a country submitted the latest national climate report (yes/no) and whether it did so in time (declining scale until a delay of 6 month (AI countries) or three years (non-AI countries)
(4)	One indicator measuring how often a country made its financial contributions to the UNFCCC secretariat on time between 1996 and 2005 (linear scale according to the number of contributions)

Source: (Bernauer & Böhmelt, 2013)

Annex V - EPI index: indicators and scale.



The 2020 EPI Framework. The framework organizes 32 indicators into 11 issue categories and two policy objectives, with weights shown at each level as a percentage of the total score.

Appendix

Appendix I - Summarized information of CCPI, CI C3 -I and EPI indexes (detailed information about the sub indicators that underlie each indicator).

	CCPI [a]	CI	C3 - I	EPI
Country Coverage	87 (92% of the global GHG emissions)	198	172	180
Time period	Since 2005	1990–2005	1996-2008	Since 2002
Periodicity	Annual	Published once	Published once.	Annual
Indicators (weight)	GHG emissions (40%) Renewable Energy (20%) Energy Use (20%) Climate Policy (20%) Total of 14 different indicators (Annex II) Index final score = weighted average of the scores achieved in the individual indicator (Puertas & Marti, 2021).	Emissions Component and Policy Component (weight 2:1)	Policy and emissions components are aggregated with equal weight (50%/50%)	Ecosystem vitality (60%) and environmental health (40%) 7 + 4 categories 32 performance indicators (Annex V) weighted average
Scale	0 – 100 (less - more “climate friendly)	0 – 6 (least - most cooperative)	0 – 100 (less – more cooperative behavior)	0 – 100 (worst - best performance)
Data	Quantitative (80%) and qualitative (20%) data (climate policy information) >50% of the ranking indicators are expressed in relative terms (better/worse)	Based on aggregate average data (1990-2005)	It was built on the measurement concept of the CI	The data come from trusted third-party sources

Quantitative Component	Current levels, past trend, well-below-2°C compatibility of the current Level and well-below-2°C compatibility of the countries' 2030 target of GHG emissions per capita (also applied to renewable energy and energy use). Only production-based emissions are considered.	Compares emissions against an emissions trajectory, i.e., a fitted environmental Kuznets curve (benchmark) Two indicators: CO2 emissions per capita in relation to GDP per capita (1990); the trend of CO2 emissions per capita in relation to GDP per capita (1990 – 2002)[b].	Trends, levels, relative to income Weights emission levels and emission trends by the corresponding GDP per capita (i.e., income) level.	
Policy Component	Climate and energy policy experts from the evaluated countries (third-party sources)	4 indicators (equally weighted) - states' ratification behavior (UNFCCC and Kyoto Protocol), financial contributions to the UNFCCC, and countries' reporting behavior under the UNFCCC (Figure 2.9)	Observed behavior	
Limitations	Limited comparability between versions (the indicators, and their weights, changed between some versions) Causal relationship between indicators It's not clear how the index incorporates the economic development of each country. Outlier problems	Lower popularity in comparison with CCPI and EPI. It was published once, the information has not been updated. Cross-sectional nature.	Lower popularity in comparison with CCPI and EPI. It was published once, the information has not been updated.	Limited comparability between versions (the indicators, and their weights, changed between some versions). Severe data gaps that limit the analytic scope. It's not clear how the index

	incorporates the economic development of each country. Inability to capture transboundary environmental impacts (it does not account for “exported” impacts associated with imported products)

[a] Based on the latest published report (2022 results)

[b] CI’S methodology assumes that per capita emissions should be allowed to vary depending on the economic situation of that country (Bernauer & Böhmelt, 2013)

Appendix II - List of the countries included in the data model (2018).

Afghanistan	Dominica	Lesotho	Sao Tome and Principe
Albania	Dominican Rep.	Liberia	Saudi Arabia
Algeria	Ecuador	Libya	Senegal
Angola	Egypt	Lithuania	Serbia
Antigua and Barbuda	El Salvador	Luxembourg	Seychelles
Argentina	Equatorial Guinea	Madagascar	Sierra Leone
Armenia	Estonia	Malawi	Singapore
Australia	Eswatini	Malaysia	Slovakia
Austria	Ethiopia	Maldives	Slovenia
Azerbaijan	Fiji	Mali	Solomon Islands
Bahrain	Finland	Malta	Somalia
Bangladesh	France	Mauritania	South Africa
Barbados	Gabon	Mauritius	South Korea
Belarus	Georgia	Mexico	Spain
Belgium	Germany	Moldova	Sri Lanka
Belize	Ghana	Mongolia	St. Kitts and Nevis
Benin	Greece	Montenegro	St. Lucia
Bhutan	Grenada	Morocco	St. Vincent and Grenadines
Bolivia	Guatemala	Mozambique	Sudan
Bosnia and Herzegovina	Guinea	Namibia	Suriname
Botswana	Guinea-Bissau	Nepal	Sweden
Brazil	Guyana	Netherlands	Switzerland
Brunei Darussalam	Haiti	New Zealand	Tajikistan
Bulgaria	Honduras	Nicaragua	Tanzania

Burkina Faso	Hungary	Niger	Thailand
Burundi	Iceland	Nigeria	The Bahamas
Cabo Verde	India	North Macedonia	Togo
Cambodia	Indonesia	Norway	Trinidad and Tobago
Cameroon	Iran	Oman	Tunisia
Canada	Iraq	Pakistan	Turkey
Central African Rep.	Ireland	Panama	Uganda
Chad	Italy	Papua New Guinea	Ukraine
Chile	Jamaica	Paraguay	United Arab Emirates
China	Japan	Peru	United Kingdom
Colombia	Jordan	Philippines	United States
Comoros	Kazakhstan	Poland	Uruguay
Costa Rica	Kenya	Portugal	Uzbekistan
Côte d'Ivoire	Kiribati	Qatar	Vanuatu
Croatia	Kuwait	Romania	Vietnam
Cyprus	Kyrgyz Republic	Russia	Zambia
Czech Republic	Lao PDR	Rwanda	Zimbabwe
Denmark	Latvia	Samoa	
Djibouti	Lebanon		

Appendix III – List of the countries with lower GHG emissions in 2018, compared to 2000, and the correspondent variation in the other variables. [42]

	Population	GDP	Energy Use	GHG emissions	Renewables
Austria	10%	31%	8%	-4%	8%
Belgium	11%	32%	-1%	-21%	304%
Bulgaria	-14%	82%	0%	-8%	260%
Côte d'Ivoire	52%	85%	56%	-29%	75%
Croatia	-9%	40%	1%	-11%	47%
Denmark	9%	25%	-16%	-33%	223%
Finland	7%	28%	-1%	-20%	27%
France	10%	26%	-5%	-17%	70%
Germany	1%	26%	-4%	-17%	234%
Greece	-1%	-1%	-12%	-28%	270%
Hungary	-4%	53%	5%	-14%	834%
Ireland	28%	123%	11%	-9%	664%
Italy	6%	4%	-10%	-24%	77%
Jamaica	11%	15%	-20%	-15%	124%
Japan	0%	15%	-14%	-7%	51%
Lithuania	-20%	105%	0%	-4%	4682%
Netherlands	8%	28%	-3%	-14%	101%

[42] Countries with negative variation of energy use and GHG emissions are colored in green as it has a positive environmental impact. For the same reason, positive variation of renewables is also colored in green.

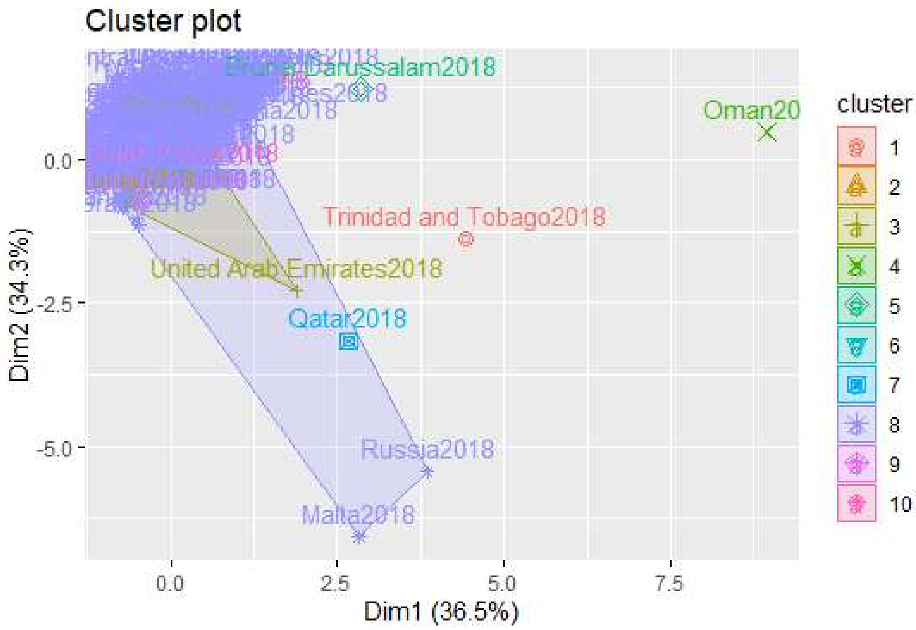
North Macedonia	**2%**	**62%**	**3%**	-11%	69%
Portugal	**0%**	**12%**	**0%**	-15%	94%
Romania	**-13%**	**104%**	**-9%**	-19%	59%
Slovakia	**1%**	**101%**	**-9%**	-14%	84%
Slovenia	**4%**	**51%**	**6%**	-5%	25%
Spain	**15%**	**34%**	**7%**	-12%	173%
Sweden	**15%**	**48%**	**-6%**	-31%	-9%
Switzerland	**19%**	**41%**	**-7%**	-12%	-3%
Ukraine	**-9%**	**41%**	**-37%**	-37%	48%
United Kingdom	**13%**	**36%**	**-16%**	-34%	618%
United States	**16%**	**42%**	**3%**	-12%	86%
Zimbabwe	**22%**	**10%**	**-18%**	-1%	11%

Appendix IV – List of the 28 outliers removed from the dataset.

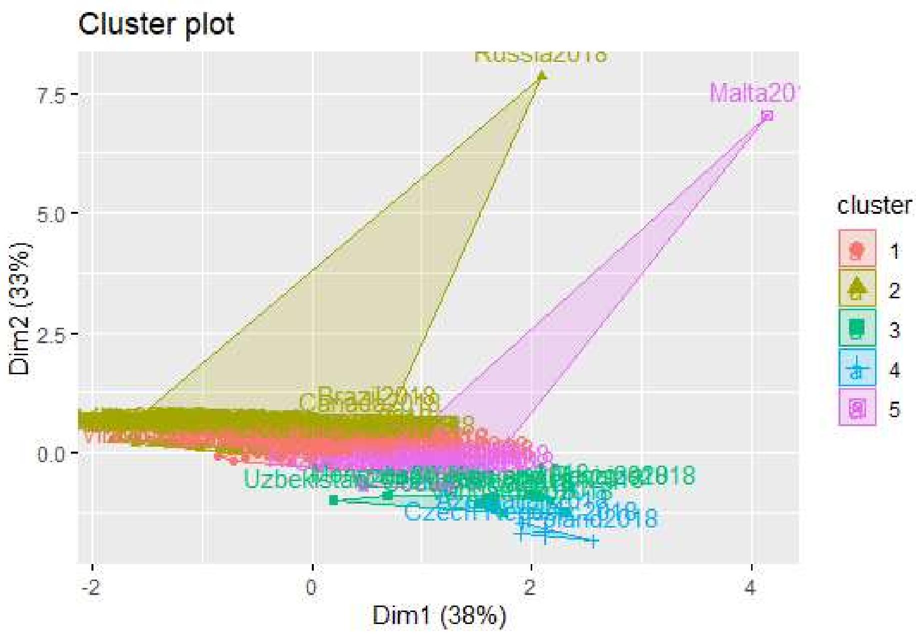
	Observed Value	% Change Renewables
Algeria	2 146	17 623%
Antigua and Barbuda	30	6 095%
Bahrain	198	66 707%
Barbados	86	5 505%
Belarus	1 396	12 884%
Brunei Darussalam	5	693 042%
Chad	21	18 890%
Comoros	1	51 709%
Djibouti	2	65 354%
Grenada	8	7 775%
Guinea-Bissau	5	14 182%
Guyana	54	10 971%
Kuwait	140	208 690%
Lebanon	1 035	5 795%
Liberia	9	42 722%
Libya	418	29 950%
Maldives	6	71 398%
Oman	9	2 727 291%
Qatar	19	335 061%
Saudi Arabia	367	190 145%
Seychelles	11	26 165%
Solomon Islands	13	6 510%
Somalia	39	5 188%
St. Lucia	7	10 446%
The Bahamas	8	109 989%
Trinidad and Tobago	11	1 106 794%
Tunisia	1 401	5 043%

United Arab Emirates	3 003	9 946%

Appendix V – Cluster plot considering 169 countries (before the elimination of outliers).



Appendix VI - Cluster plot considering 141 countries (after removing outliers).[43]



[43] Dimensions 1 and 2 explain 38% and 33% of the point volatility.

Appendix VII – List of countries grouped by clusters.

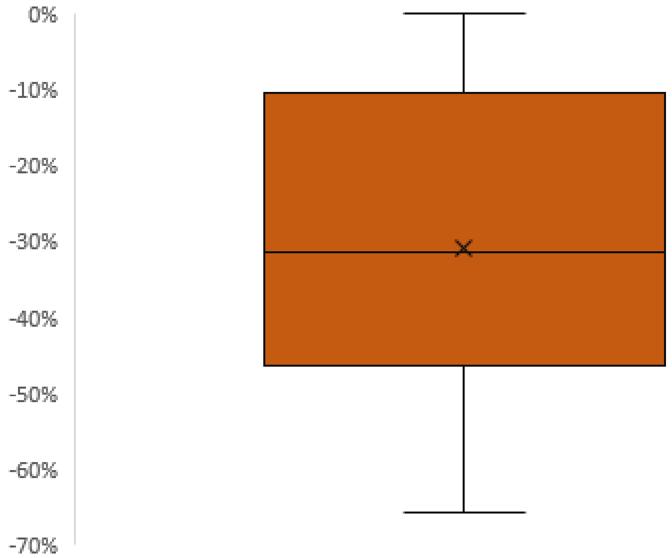
Cluster	Country	% Change Energy Use	% Change GHG emissions	% Change Renewables
1	Armenia	0%	-42%	529%
1	Belgium	0%	-9%	497%
1	Bolivia	0%	-46%	751%
1	Bosnia and Herzegovina	0%	-45%	562%
1	Bulgaria	0%	-28%	802%
1	Burkina Faso	0%	-27%	913%
1	Dominica	0%	-48%	462%
1	Dominican Republic	0%	-30%	596%
1	Equatorial Guinea	0%	-19%	988%
1	Hungary	0%	-36%	657%
1	Malaysia	0%	-33%	510%
1	Mali	0%	-47%	409%
1	Mauritania	0%	0%	972%
1	Mauritius	0%	-43%	954%
1	Morocco	0%	-18%	734%
1	Netherlands	0%	-6%	557%
1	Niger	0%	-64%	564%
1	Papua New Guinea	0%	-14%	859%
1	Samoa	0%	-66%	792%
1	Sierra Leone	0%	-4%	475%
1	Slovakia	0%	-46%	526%
1	St. Vincent and the Grenadines	0%	-56%	588%
1	Thailand	0%	-9%	589%
1	Togo	0%	-3%	571%
2	Afghanistan	0%	-61%	272%
2	Albania	0%	-59%	19%
2	Angola	0%	-52%	67%
2	Argentina	0%	-38%	330%
2	Australia	0%	-53%	374%
2	Austria	0%	-37%	47%
2	Belize	0%	-66%	121%
2	Bhutan	0%	-42%	0%
2	Brazil	-3%	-2%	0%
2	Burundi	0%	-18%	324%
2	Cambodia	0%	-52%	185%
2	Cameroon	0%	-50%	114%
2	Canada	-2%	-3%	0%
2	Central African Republic	0%	-79%	171%
2	Chile	0%	-57%	141%
2	China	0%	0%	0%

2	Colombia	0%	-60%	22%
2	Costa Rica	0%	-11%	0%
2	Côte d'Ivoire	0%	-15%	222%
2	Croatia	0%	-44%	97%
2	Denmark	0%	-39%	32%
2	Ecuador	0%	-60%	135%
2	El Salvador	0%	-39%	93%
2	Estonia	0%	-74%	182%
2	Eswatini	0%	-54%	86%
2	Ethiopia	0%	-54%	2%
2	Fiji	0%	-46%	162%
2	Finland	0%	-41%	109%
2	France	0%	0%	0%
2	Gabon	0%	-39%	164%
2	Georgia	0%	-62%	74%
2	Germany	0%	0%	0%
2	Ghana	0%	-38%	216%
2	Greece	0%	-55%	320%
2	Guatemala	0%	-25%	165%
2	Guinea	0%	-45%	356%
2	Honduras	0%	-66%	123%
2	Iceland	0%	0%	0%
2	India	0%	0%	0%
2	Indonesia	0%	-11%	12%
2	Ireland	0%	0%	0%
2	Italy	0%	0%	0%
2	Japan	0%	-1%	51%
2	Kenya	0%	-63%	36%
2	Kyrgyz Republic	0%	-74%	50%
2	Lao PDR	0%	-69%	194%
2	Latvia	0%	-48%	144%
2	Lesotho	0%	-77%	95%
2	Lithuania	0%	-48%	169%
2	Luxembourg	0%	0%	0%
2	Madagascar	0%	-25%	277%
2	Malawi	0%	-32%	58%
2	Mexico	0%	-14%	257%
2	Montenegro	0%	-55%	74%
2	Mozambique	0%	-83%	46%
2	Namibia	0%	-68%	141%
2	Nepal	0%	-66%	32%
2	New Zealand	0%	-69%	72%
2	Nicaragua	0%	-59%	144%
2	Nigeria	0%	-13%	336%

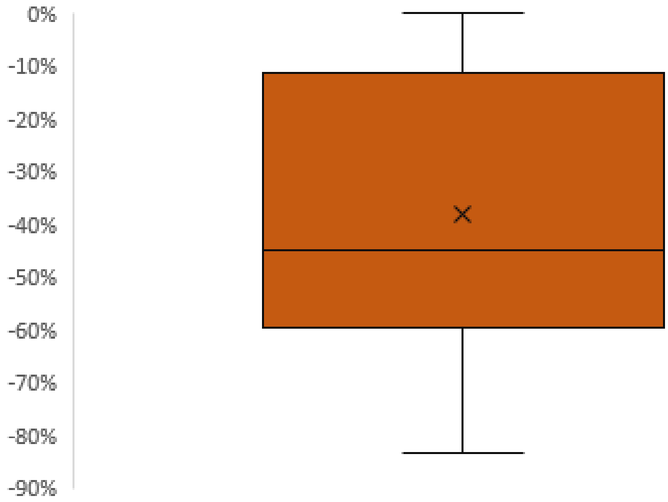
2	North Macedonia	0%	-59%	175%
2	Norway	-1%	-1%	0%
2	Pakistan	0%	-31%	283%
2	Panama	0%	-21%	225%
2	Paraguay	0%	-44%	0%
2	Peru	0%	-57%	84%
2	Philippines	0%	-2%	180%
2	Portugal	0%	-44%	115%
2	Romania	0%	-55%	138%
2	Russia	-38%	-49%	198%
2	Rwanda	0%	0%	0%
2	Serbia	0%	-49%	312%
2	Singapore	0%	0%	0%
2	Slovenia	0%	-51%	292%
2	Spain	0%	-2%	49%
2	Sri Lanka	0%	0%	0%
2	Sudan	0%	-64%	118%
2	Suriname	0%	-61%	152%
2	Sweden	0%	0%	0%
2	Switzerland	0%	0%	0%
2	Tajikistan	0%	-70%	19%
2	Tanzania	0%	-45%	298%
2	Turkey	0%	-26%	38%
2	Uganda	0%	-26%	62%
2	United Kingdom	0%	0%	0%
2	United States	0%	0%	0%
2	Uruguay	0%	-76%	1%
2	Vietnam	0%	-45%	136%
2	Zambia	0%	-79%	16%
2	Zimbabwe	0%	-63%	116%
3	Bangladesh	0%	0%	2065%
3	Benin	0%	0%	1846%
3	Iran	0%	-9%	2539%
3	Mongolia	0%	-54%	2066%
3	Sao Tome and Principe	0%	0%	1918%
3	South Africa	0%	-31%	2317%
3	St. Kitts and Nevis	0%	0%	1942%
3	Uzbekistan	0%	-81%	2366%
3	Vanuatu	0%	-33%	2652%
4	Azerbaijan	0%	-39%	3032%
4	Czech Republic	0%	-54%	3507%
4	Poland	0%	-37%	3735%
5	Botswana	0%	-6%	1407%
5	Cabo Verde	0%	-17%	1240%

5	Cyprus	0%	-47%	1565%
5	Egypt	0%	0%	1034%
5	Haiti	0%	0%	1266%
5	Iraq	0%	-49%	1650%
5	Jamaica	0%	-23%	1726%
5	Jordan	0%	-4%	1326%
5	Kazakhstan	0%	-44%	1467%
5	Kiribati	0%	-25%	1286%
5	Malta	-37%	0%	1127%
5	Moldova	0%	-24%	1594%
5	Senegal	0%	-9%	1259%
5	South Korea	0%	-5%	1188%
5	Ukraine	0%	-21%	1543%

Appendix VIII - Box plot with the distribution of the % change in GHG emissions values (Cluster 1).



Appendix IX – Box plot with the distribution of the % change in GHG emissions values (Cluster 2).



Appendix X - Box plot with the distribution of the % change in GHG emissions values (Cluster 5).