

Multivariate Analysis of CO₂ Emissions by Energy Generation in IEA Member Countries

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ABSTRACT

The concentration of carbon dioxide (CO₂), the main catalyst for global warming, reached an average of 414.7 parts per million in 2021 and 2.3 ppm more than in 2020. This concentration of CO₂ is the highest recorded in at least 800,000 years, according to the International Energy Agency. The increase in the concentration of CO₂ is a growing concern in the scientific community and environmental organizations since the increase in global temperature resulting from this phenomenon can lead to serious and irreversible effects. This topic has gained space in global analyse and has become increasingly recurrent. This research aimed to deal with and analysed essential points in this discussion. With the study, it was possible to point out evidence that Brazil is a country that has been significantly reducing its CO₂ emissions, being in the cluster along with IEA member countries that least issue CO₂. With this article, it was possible to point out similar characteristics between the CO₂ emissions of the countries, making it possible to highlight three latent variables: countries that have a constant tall or low trend in CO₂ emissions, Grouping of countries that showed an upward trend at the beginning of the analysed period, but with a significant reduction CO₂ over time, and countries that have had more discrepant behaviour from the others, these being the countries that have a structural breakdown in their time series of CO₂ emissions by power generation.

Keywords. Cluster, Factor Analysis, CO₂ emissions, Renewable Energy, Multivariate Statistics

INTRODUCTION

Carbon dioxide concentrations are responsible for the greenhouse effect and increased global temperature. Excessive CO₂ in the atmosphere is responsible for overheating the planet, which generates severe environmental imbalances. The high concentration of this gas results in air pollution and acid rain, among other negative points. One of the main sources of CO₂ in Brazil and worldwide is burning fossil fuels (PARASCHIV et al. 2020, and ANDREW, et al. 2022). Investing in renewable energy can help prevent greenhouse gas emissions and protect communities from climate change effects.

There is great concern about changes in atmospheric gas concentrations due to anthropogenic activities. This was observed more intensely from 1750 onwards, with the advent of the first Industrial Revolution. Electric power generation, improvement, transportation system expansion, and indoor heating, among others. It is based essentially on the consumption of energy obtained by burning fossil fuels, the leading energy resource used until today. This is the most significant anthropogenic source of greenhouse gases, such as carbon dioxide (XAVIER 2013).

Carbon dioxide (CO_2) emissions from power generation are a significant environmental problem. Investing in renewable energy can help prevent greenhouse gas emissions and protect communities from the effects of climate change. According to the International Renewable Energy Agency's Global Renewable Energy Report (IRENA, 2021), renewable energy could provide more than a third of global energy needs by 2030 and reduce greenhouse gas emissions by more than a third compared to current fuel energy use trends in fossil fuels. Jacobson and Delucchi (2011) point out that the transition to renewable energy can reduce premature deaths related to air consumption by up to 4.6 million per year by 2030. Finally, the World Bank states that investing in renewable energy can also bring psychological benefits, potentially generating jobs and stimulating economic growth (2019).

To enable energy cooperation focusing on energy security, The International Energy Agency (IEA) was conceived after the oil crisis of 1973-1974, focusing on energy security. The Agency operates within the financial framework of the OECD, and the OECD Council appoints the Supreme Audit Institution of a member country, which performs an audit externally independent of the accounts and financial management of the IEA. It is at the centre of the global energy dialogue. It has become a key player in environmental discussions, providing reliable statistics and analysis on energy production, transmission, and consumption worldwide.

IEA analysis shapes policy to enable the world to meet climate, energy access, and air quality goals while maintaining a strong focus on the reliability and affordability of energy for all. According to Hannam, 2018, p. 36, the IEA is considered the world's leading authority on energy, providing authoritative analysis and data to governments, businesses, and civil society worldwide. The IEA is also recognized for its energy market assessments and forecasts. According to Jablonski and Kuczyńska (2019), the IEA has been an important oil market forecaster and instrumental in understanding changes in the world energy market. The IEA is crucial in transitioning to cleaner, renewable energy sources. A Scopus article highlights that "the IEA is committed to helping to develop policies and strategies that accelerate the transition to cleaner and more sustainable energy" (Lewis & Keirstead, 2020, p. 262). The agency works with governments and other stakeholders to identify best practices and policies for transitioning to renewable energy and achieving global climate goals. In 2017, Brazil joined the International Energy Agency (IEA). In 2022 Brazil and the International Energy Agency signed a technical cooperation agreement. The plan provides for Brazilian participation in reviewing the organization's reports on matters related to the energy transition for the 2022-2023 biennium.

The partnership between Brazil and the IEA aims to support the country in developing renewable energy sources, improving energy efficiency, strengthening energy security, and

reducing greenhouse gas emissions. The technical cooperation agreement between Brazil and the IEA is an important milestone in the country's relationship with the agency. It reinforces the Brazilian commitment to the energy transition and the reduction of greenhouse gas emissions. In addition, the partnership will allow Brazil access to important analysis and information about the global energy market, as well as the agency's expertise in energy and environmental policies (IEA,2022).

Large emitters of greenhouse gases greenhouse effect, like Brazil and the other G20 countries, have the most significant responsibility for the substantial reduction of emissions required to comply with the Paris Agreement's goal of stabilizing Earth's warming at 1.5°C this century. The IEA (International Energy Agency), in its World Energy Outlook 2021¹, estimated 14 billion tons of CO₂ equivalent to the total emissions they need to be shot down by 2030 to get the world on track of 1.5°C. Currently, the national targets on the table are at 2.7°C (CLIMATE, 2021).

This article aims to conduct an exploratory analysis, highlighting the importance of investments in renewable energy generation to reduce CO₂ per energy generation. In this work, we seek to apply multivariate statistical methods, which allow the grouping by the similarity of the variables of interest (CO₂ emissions of the IEA member countries and the associated country Brazil), with this, the objective is to find latent variables that significantly characterize the groups.

Grouping countries by similarity in CO₂ emissions can be a useful approach to better understanding climate change's global dynamics. Countries with similar emissions levels may have similar challenges and opportunities when transitioning to a low-carbon economy. This can allow these countries to share best practices and policies for achieving common climate and environmental goals. By grouping countries according to their CO₂ emissions, it is also possible to identify which regions have the highest emissions concentrations. Peters et al. (2012) suggest that this approach can help identify regions with similar challenges and opportunities in transitioning to a low-carbon economy. These data can provide valuable information for the design of regional climate policies, which can significantly impact reducing emissions and mitigating the effects of climate change.

The intended article is divided into four sections. The first addresses a brief introduction to the subject, and section two presents the implemented methodology. Section three brings the analysis and results, followed by section 4, where the results achieved in the study are concluded.

METHODOLOGY

According to Johnson (2002), multivariate statistical analysis refers to a set of methods implemented simultaneously, enabling the analysis of multiple measures on the variable of interest. Vicinni (2005), points out that multivariate statistics is more than treating a more significant number of variables. Still, in multiple analyses of the data, the variables considered

¹ IEA, World Energy Outlook 2021. Available in <https://www.iea.org/reports/world-energy-outlook-2021/executive-summary>

in the research must be random and interrelated, in which the effect of each one is interpreted simultaneously, that is, jointly. To develop an efficient multivariate analysis, an exploratory study of the observed data must be carried out in the first instance to examine and adequately treat them.

Principal Components

The primary component technique used in this article seeks to extract the most relevant information from the set of variables that have been selected. The primary component technique (PCA) is a statistical approach to reduce data complexity.

PCA has proven to be an effective tool for reducing data dimensionality and identifying the most important variables in a multivariate analysis (Worley & Powers, 2013). According to Gowen et al., 2011 PCA can help identify the most relevant information from the data, remove interferences, and improve the accuracy of the results.

The primary components technique (PCA) has been applied in several studies related to renewable energy and CO^2 emissions. One example is a study published in the journal Renewable Energy, in which the authors used PCA to identify the main sources of CO^2 emissions in a wind power generation system (Du et al., 2020). Through the analysis of CO^2 emission data at different stages of the energy generation process, the authors identified the main sources of emission and proposed measures to reduce the emission of greenhouse gases. Another study, published by Peng et al., 2019, used the PCA technique to analyze the relationship between renewable energy development and CO^2 emissions in different countries. The authors used data from 22 countries and identified three main components that explain the variation in CO^2 emissions and the development of renewable energy. The results showed that the adoption of renewable energy incentive policies can lead to a significant reduction in CO^2 emissions.

Once the principal components technique is used, the dataset can be represented as a set of new orthogonal variables named after the principal components. This way, the data are reduced, and the features that reduce them are interpreted. The database is first verified to be adequate to use the principal component technique, i.e., if the variables in question are correlated. Bartlett's sphericity test is implemented to verify this suitability. The test is based on the correlation matrix (σ) of the variables under study, with the following hypotheses.

$$\begin{cases} H_0: \Sigma \text{ is a diagonal matrix} \\ H_1: \Sigma \text{ not a diagonal matrix} \end{cases}$$

If H_0 is not rejected, applying the primary component technique becomes inadequate, as the variables under study are decorated.

This method is sample-based, so obtaining the actual correlation matrix from the data is impossible. Therefore, it is necessary to get the estimate of Σ , which can be obtained through the equation:

$$S_x = \frac{1}{n-1} X^T H X \quad (1)$$

To determine the principal components, we need to calculate the eigenvalues (λ) and eigenvectors (γ) of matrix (S). An array is defined $Y = P^T X_i$, being $i = 1, \dots, p$, in which p it is an orthogonal matrix whose components are the p eigenvectors of S . With this, the i -th principal component is given by:

$$Y_i = a_{i1}X_1 + \dots + a_{ip}X_p \quad (2)$$

Where, a_{ip} represents the i -th element of the eigenvector of characteristic p .

Therefore, each variable's loadings (loads) in each principal component are calculated; that is, each variable's weight equals the i -th element of the eigenvector. The score of each principal component is given by the linear combination of the loading of each variable multiplied by its value. An efficient way to verify the number of components to be used is by observing the Scree Plot, which is the graph that contains the eigenvalues of each element.

Factor Analysis

According to Santos (2015), factor analysis consists of a statistical technique where it is possible to represent a multivariate process by creating new variables derived from the original variables and, generally, in smaller numbers, representing the process's commonalities. Factor analysis describes the variability of correlated variables observed in a smaller number of unobserved variables, which are linearly related to the original variables. The observed variables are modelled as a linear combination of common factors plus a random error.

The factorial analysis technique has also been used in several studies related to renewable energy and CO₂ emissions. the study by Ayoub et al., 2020 uses factor analysis to assess the main factors that influence the adoption of renewable energy technologies in developing countries. Through the analysis of data from 51 countries, the authors identified four main factors that influence the adoption of renewable energy technologies: government policies, availability of financial resources, capacity to absorb technology, and social and cultural barriers. Jiang et al., 2017 used factor analysis to analyze the relationship between renewable energy and CO₂ emissions in different countries. The authors used data from 31 countries and identified two main factors that explain the variation in CO₂ emissions and the development of renewable energy. The results showed that expanding renewable energy can be an effective strategy to reduce CO₂ emissions in energy-intensive countries.

Factor Analysis assumes the existence of a statistical model that uses regression techniques to test hypotheses and is related to the principal component (MINGOTI, 2007). In short, the factor analysis is considered an extension of the aforementioned principal component analysis; both seek to approximate the covariance matrix Σ ;

The suitability of data for factor analysis can be analyzed using the Kaiser-Meyer-Olkin (KMO) and Barlett's Sphericity tests. The KMO test provides a value in the range [0,1] and closer to 1 means that the factor analysis will be adequate. Value 0 indicates inadequate for factorial analysis, acceptable if greater than 0.5, recommended above 0.8. To start interpreting the factor analysis results, it is necessary to verify the loading matrix. It is essential to point out that if this matrix presents similar numerical magnitude values, the difficulty of interpreting the original

factors increases; that is, when the original variable is highly correlated with more than one factor, its interpretation becomes difficult. There are numerous criteria for applying factor rotation, allowing a better understanding. In this work, the VARIMAX criterion will be used, which consists of trying to find, for a fixed factor, a group of variables highly correlated with it and another group of variables that have little or moderate correlation with the element.

Once the axes have been rotated, the next step is to analyze the new load matrix, obtaining which variables are part of each factor, interpreting them to highlight their main characteristics.

Cluster Analysis

Cluster analysis consists of multivariate techniques that separate objects into groups. This analysis is a statistical procedure that aims to partition the elements into two or more groups called clusters, considering their similarity according to pre-established criteria. According to [7], these criteria are usually based on a dissimilarity function that receives two objects and returns the distance between them.

After implementing a quality metric, the groups must present a high internal homogeneity and external heterogeneity, that is, the elements of a set must be mutually similar and different from the elements of other locations (LINDEN, 2009).

Clustering can be said as an auxiliary tool, it can be used as a set of procedures to organize time series based on similarity or dissimilarity data. The dissimilarity between objects is measured by a distance matrix whose components resemble the distance between two points. The technique above can be described as a two-step process: (i) the choice of a distance measure and (ii) the choice of the clustering algorithm. These two steps together define the complete clustering result.

Cluster analysis is divided into two methods for grouping variables, hierarchical and non-hierarchical. In this work, the non-hierarchical K-means method will be used. K-means is a non-hierarchical clustering heuristic that aims to minimize the distance of objects to a set of k centers. The distance between a point p_i and a group of clusters is given by $d(p_i, \chi)$, defined as the distance from the point to the center closest to it. The function to be minimized is then given by:

$$d(P, \chi) = \frac{1}{n} \sum_{i=1}^n d(p_i, \chi)^2 \quad (3)$$

There are two clustering techniques for building clusters, known as the hierarchical method, which consists of identifying clusters and the probable number g of groups, by a series of successive mergers, or a series of consecutive divisions, with the results observed in the dendrogram, which illustrates mergers or divisions made at successive levels. The other method is non-hierarchical, where the number g of groups is pre-established, this technique consists of directly finding a partition of n items in k clusters by two requirements, such as, internal similarity and isolation of the formed clusters.

According to Mingoti (2007), defining the optimal number of clusters for se is subjective, but criteria make it possible to determine this number more efficiently. These criteria are the behavior of the level of fusion, the behavior of the level of similarity, the R^2 coefficient, the Pseudo F statistic, the semipartial correlation and the Pseudo T^2 statistic. That said, there are adequate clusters for a more accurate and efficient analysis.

ANALYSIS AND RESULTS

To carry out the analysis, carbon dioxide emission *per capita* data by power generation and population of the 30 member countries of the International Energy Agency (IEA) (IEA, 2021) were used, namely: Austria, Czech Republic, France, Ireland, Lithuania, Norway, Spain, Turkey, Belgium, Estonia, Greece, Japan, Mexico, Portugal, Switzerland, Australia, Denmark, Germany, Italy, Luxembourg, Poland, Sweden, United Kingdom, Canada, Finland, Hungary, Korea, New Zealand, Slovak Republic and Netherlands and the associated country Brazil. Population data from these countries were also used, and the period selected for the analysis was from 1990 to 2021. It should be noted that data regarding CO_2 emissions were collected through the British Petroleum (bp) (BP, 2021) database, and data on country populations in each reference year are taken from the Research Federal Reserve Bank of st: Louis (2022), the Statistical Review of World Energy (jun 2022)² and, The World Bank.

Seeking to start an exploratory analysis of the data, in table 1, it is possible to observe the descriptive statistics of CO_2 emission by energy generation and population of the 30 member countries of the IEA, and of the associated country Brazil, figure 1 presents the minimum, median, average, maximum and standard deviation of the variable of interest in this study.

Countries	Min	Median	Average	Max	SD	Countries	Min	Median	Average	Max	SD
Australia	14.31	17.43	17.48	19.57	0.62	Hungary	1.06	1.26	1.44	3.76	0.59
Austria	0.11	7.64	7.1	9.17	0.66	Ireland	1.81	2.5	2.54	3.13	0.37
Belgium	9.1	12.68	12.01	13.66	1.37	Italy	4.69	6.61	6.57	7.91	1.06
Brazil	1.31	1.77	1.84	2.49	0.29	Japan	1.38	1.67	1.66	1.81	0.1
Canada	13.7	15.96	16.14	17.71	1.00	Lithuania	7.00	10.92	10.43	13.94	1.97
Switzerland	10.16	16.68	15.85	23.5	3.21	Luxembourg	52.18	74.73	72.78	85.68	9.77
Czech Republic	2.5	5.43	5.02	7.64	1.31	Mexico	2.2	2.89	3.05	4.44	0.61
Germany	0.18	0.26	0.27	0.51	0.06	Netherlands	2.31	3.2	3.26	3.94	0.43
Denmark	6.34	10.92	10.4	13.9	1.93	Norway	5.13	8.04	7.9	12.91	1.82
South Korea	4.9	7.77	7.32	9.07	1.04	New Zealand	69.28	119.93	117.13	138.93	18.79
Spain	12.84	18.82	19.05	25.7	3.37	Poland	5.65	7.64	7.58	9.92	1.22
Estonia	41.3	64.8	64.29	83.87	12.21	Portugal	3.94	4.61	5.45	6.8	0.82
Finland	7.56	10.69	10.13	14.19	1.68	Slovakia	5.98	7.99	7.73	8.56	0.63
France	0.48	0.59	0.62	0.75	0.08	Sweden	15.9	26.07	27.01	40.09	7.87
United Kingdom	4.17	7.02	6.44	7.82	1.11	Turkey	3.74	8.94	7.78	11.04	2.08
Greece	98.76	110.62	110.54	120.01	4.79						

Fig. 1: Descriptive statistics

Source: Elaborated by the authors.

Figure 2 presents the correlation matrix between the countries; the blue color represents the positive correlation, and the stronger the positive correlation between the countries, the more

² The Stats Review has been published by bp since 1952 and from this year onwards it will continue as The Energy Institute Statistical Review of World Energy. <https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html>

intense the shade of blue; in this way, the countries that present a positive correlation walk together in periods reduction and more CO^2 emissions, that is when a country reduces emissions the other also presents a reduction. The same goes for the increase in emissions. The red color represents the negative correlation between the countries, that is, when a country is in the CO^2 emission reduction period, the other is emitting more emission reduction period, the other is emitting more.

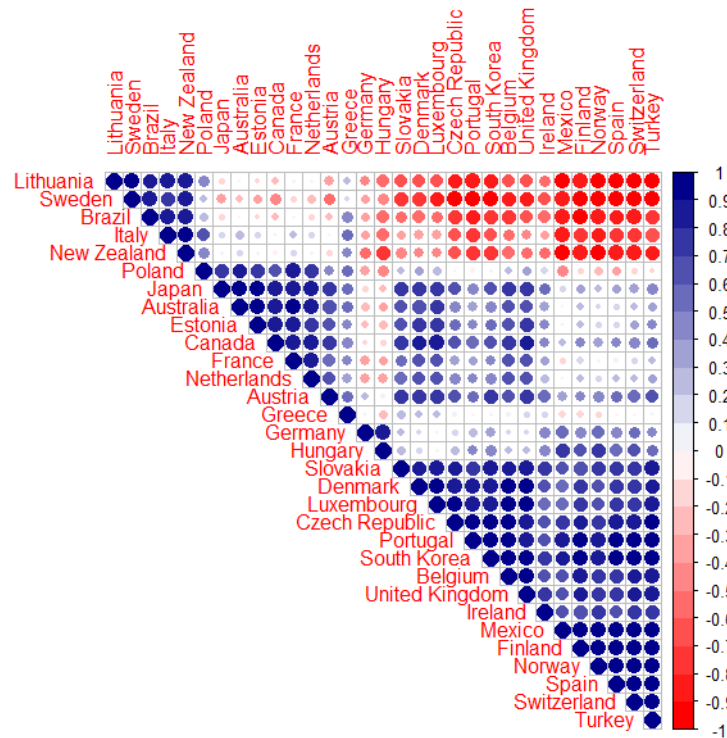


Fig. 2: Correlation Matrix

Source: Elaborated by the authors.

After the initial analyses, Bartlett's Sphericity Test was performed to check the correlations between the variables. The test result showed a significantly small p-value, less than 5% (chosen significance level), so we have evidence to reject the null hypothesis. With that, there are some relationships between the variables. The component analysis main will be valid.

After estimating the S matrix, according to the methodology above, the eigenvalues and eigenvectors are calculated to obtain the components, the explained variation per component, and the accumulated explained variation, which can be seen in figure 3.

Components	Eigen Value	Explained Variation	Acumulated Explained Variation
1	4.27	0.58	0.58
2	2.86	0.26	0.85
3	1.32	0.05	0.91
4	0.94	0.02	0.93
5	0.65	0.01	0.95
6	0.54	0.009	0.96
7	0.52	0.008	0.971
8	0.46	0.006	0.978
9	0.37	0.004	0.979

Fig. 3: Components and Explained variation.
Source: Elaborated by the authors.

As seen in Table 2, two components will be necessary to follow the criterion of using the components that explain at least 70% of the total variation. Still, considering the standard of selecting all the details with an eigenvalue greater than 1, it would result in 3 three components. To decide efficiently and more accurately, the Scree Plot is used, Figure 4, where it is noted that after the 4th component, the distance between the components remains constant. This result corroborates the second criterion that three components are sufficient, thus explaining 91% of the total variance.

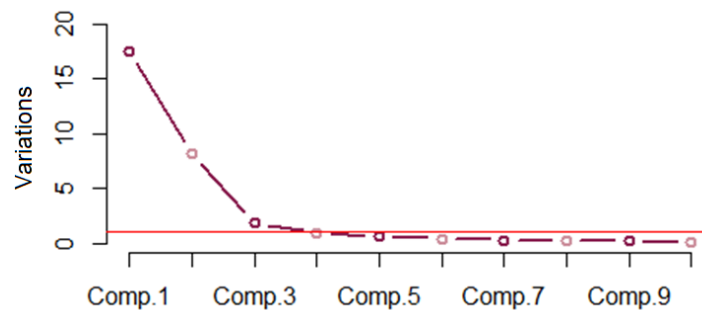


Fig. 4: Scree Plot
Source: Elaborated by the authors.

It is important to emphasize that the commonalities were analysed, and no country had a commonality below 0.72, so none of the countries needed to be removed from the sample. That said, the KMO test (Kaiser-Meyer-Olkin) was applied to assess the adequacy of the sample size, the result of this test varies between 0 and 1, with results above 0.5 being acceptable for factor analysis. In this test, KMO = 0.61 was obtained, so the sample is suitable for factor analysis. Considering the study already carried out in Principal Components, three factors will explain 91% of the total variance.

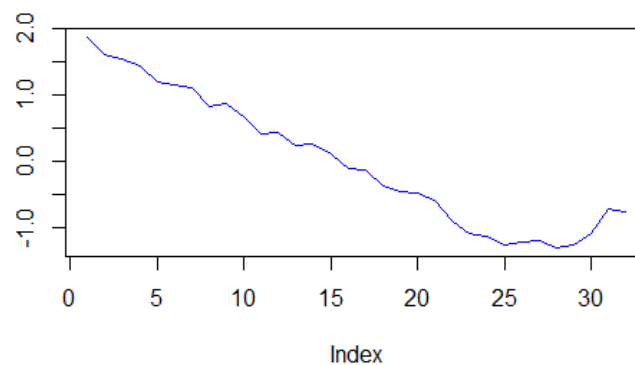
As previously mentioned, there are numerous criteria to apply factor rotation; in this work, the orthogonal factor rotation method used was VARIMAX, proposed by Kaiser in 1958, which makes it possible to find the rotation matrix that maximizes the variance of the loadings of each factor on all variables (FIGURE 5).

Countries	Factor 1	Factor 2	Factor 3	Countries	Factor 1	Factor 2	Factor 3
Australia		0.971		Hungary	0.608		
Austria		0.739		Ireland	0.574		
Belgium	0.756			Italy	-0.921		
Brazil	-0.987			Japan		0.951	
Canada		0.907		Lithuania	-0.959		
Switzerland	0.924			Luxembourg		0.719	
Czech Republic	0.826			Mexico	0.944		
Germany			-0.840	Netherlands		0.897	
Denmark		0.702		Norway	0.945		
South Korea	0.849			New Zealand	-0.942		
Spain	0.935			Poland		0.840	
Estonia		0.937		Portugal	0.901		
Finland	0.944			Slovakia	0.625		
France		0.939		Sweden	-0.946		
United Kingdom	0.705			Turkey	0.905		
Greece			0.5098				

Fig. 5: Factor loadings with rotation

Source: Elaborated by the authors.

From the correlation matrix between the variables and the latent factors, after the rotation, given in figure 6, one can observe the presence of three latent factors, which, due to their form of association with the original variables, can be interpreted in the same way. Following way: Factor 1: Factor 1 represents the countries that show downward or upward trends in the analysed period; that is, in this factor are the countries that have significantly and constantly reduced their ideal CO_2 emissions by the generation of energy and population in the observed period, in it too this is the country that only showed an upward trend over the years, that is, the one that at no time reduced its CO_2 emissions, with Lithuania being the only country in this factor that did not present a reduction in the period studied (Figure 6).

**Fig. 6: Factor 1 and its belonging series.**

Source: Elaborated by the authors.

Factor 2: Factor 2 comprises countries that show an upward trend in the first years analysed, but with a significant drop in CO_2 emissions per energy generation and population over time. The striking characteristic of this factor is that all the countries that comprise it reached the year 2021 with an excellent reduction in CO_2 . It is noteworthy that the countries that invested

in renewable energy over the period separated for analysis reduced the emission of polluting gases (FIGURE 7).

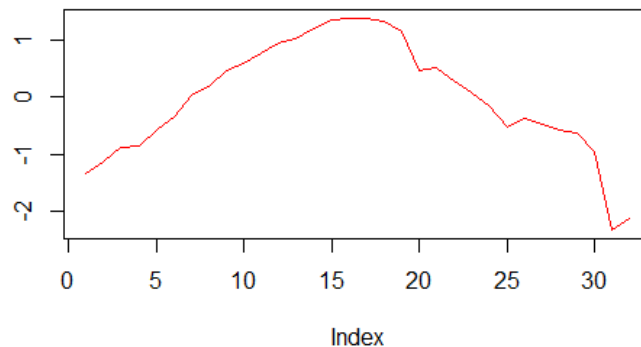


Fig. 7: Factor 2 and its belonging series.

Source: Elaborated by the authors.

Factor 3: Factor 3 is composed of only two countries, those with different characteristics from the countries contained in Factor 1 and 2. In this Factor, the striking feature is that the two countries do not show an upward or downward trend, but a structural break. Germany presents a significant drop in the year 1993, emphasizing that the analysis deals with the emission of CO^2 by energy generation, this result corroborates the data presented by Bicalho (2015), since the beginning of the 90s, Germany has been making significant changes to its energy matrix, which justifies the reduction in CO^2 emissions during this period. In summary, the two countries in this Factor 3 achieved their greatest CO^2 reduction in the period between 2019 and 2020 (Figure 8).

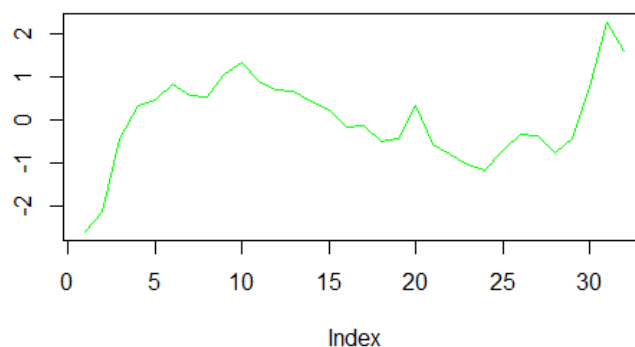


Fig. 8: Factor 3 and its belonging series.

Source: Elaborated by the authors.

Figure 9 shows the organization of the factors mentioned above. Green lines represent positive correlations between variables and clusters; red lines correspond to negative correlations.

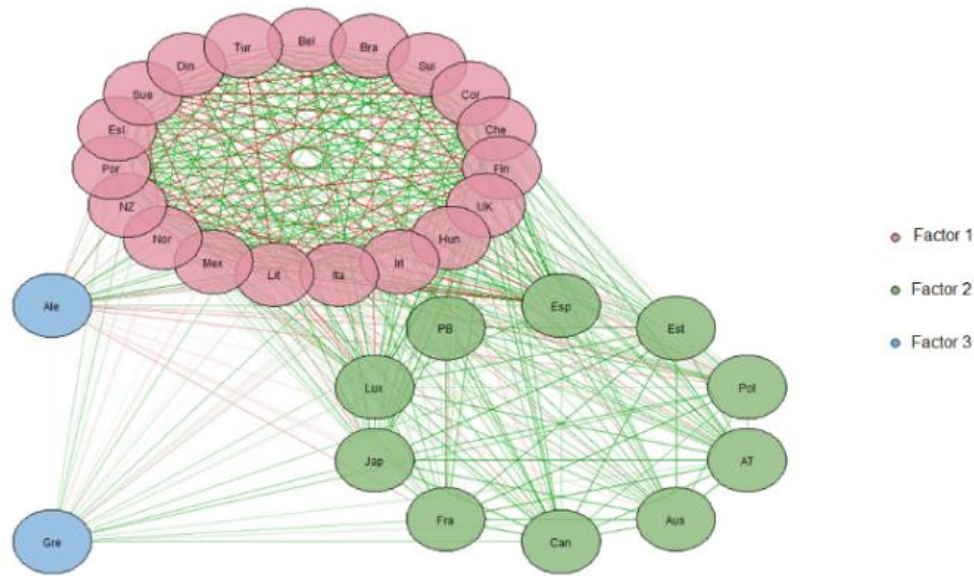


Fig. 9: Visualization of Clusters.

Source: Elaborated by the authors.

To start the cluster analysis, hierarchical methods with Euclidean distance were used. To analyse the optimal number of clusters, it is not feasible to use the dendrogram, as there are many observations, so the Scree Plot will be used again, which can be seen in Figure 10, so it is noted that the distances between objects become constant, defining thus choosing 4 clusters for analysis.

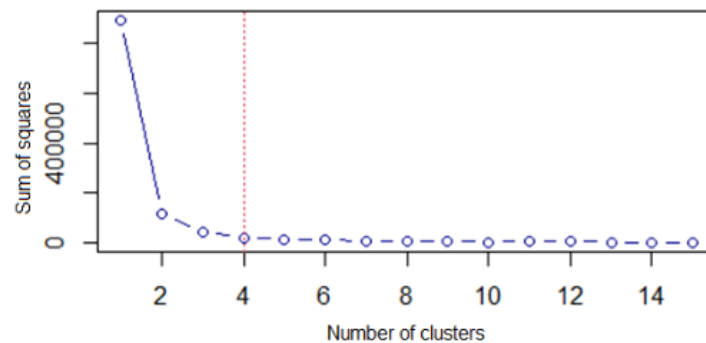


Fig. 10: Scree Plot - Clusters

Source: Elaborated by the authors.

Through the analyses previously presented, it was defined that the ideal number of clusters is $K=4$. After determining the number of sets to be used, the non-hierarchical K-means method is applied. The k-means method is a partition method that measures the proximity between groups using the Euclidean distance between the centroids of the groups, which is the case of this study.

Figure 11 illustrates the clusters grouped using the K-means method. The green lines represent the positive correlation between the observed variables, and the red ones show a negative correlation.

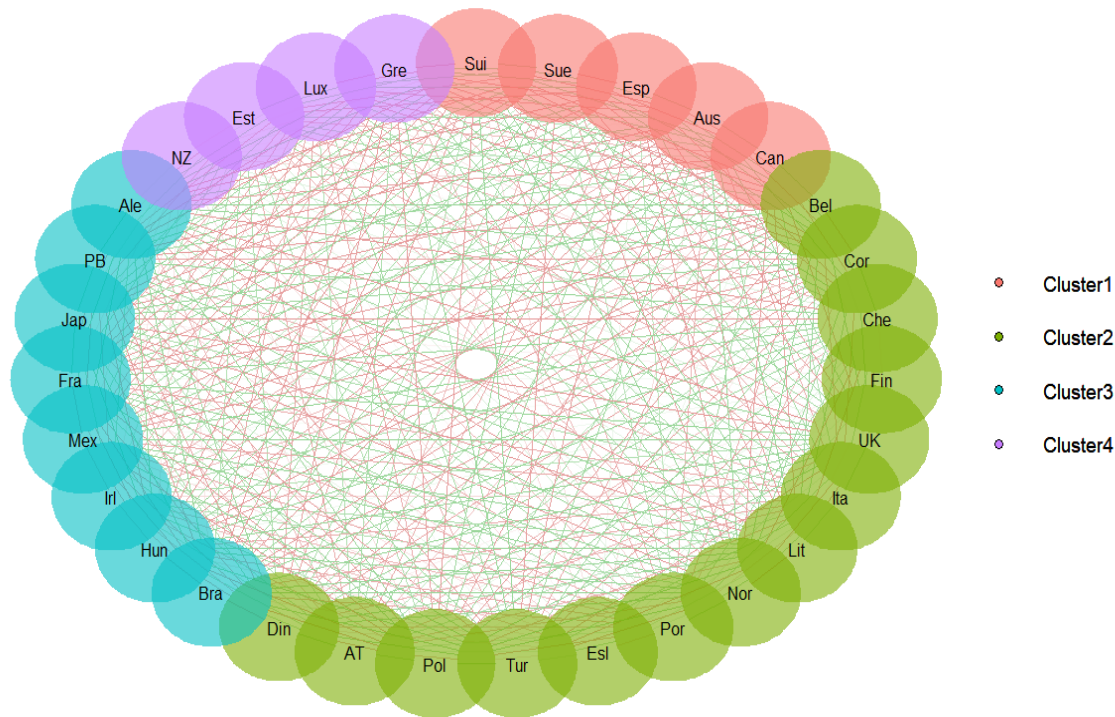


Fig. 11: Clusters - K-means method
Source: Elaborated by the authors.

Figure 12 presents the result of the 4 clusters. It can be noted that cluster 4 contains the countries that emit the most CO₂ per generation of energy in the period analyzed, with an average of 91,185 emissions, these countries showed a little decrease over the years compared to the others. In Cluster 3, there are the countries that emit the least CO₂ per generation of energy and population, which emit an average of around 1,839 CO₂. It should be noted that Brazil is in this cluster, and that the country has been investing heavily in renewable energy over the period analyzed.

Cluster 1		Cluster 2		Cluster 3		Cluster 4	
Countries	Average	Countries	Average	Countries	Average	Countries	Average
Switzerland (Sui)	15.854	Belgium (Bel)	12.011	Brazil (Bra)	1.846	New Zealand (NZ)	117.131
Sweden (Sue)	27.007	South Korea (Cor)	7.322	Hungary (Hum)	1.442	Estonia (Est)	64.287
Spain (Esp)	19.049	Czech Republic (Che)	5.028	Ireland (Irl)	2.542	Luxembourg (Lux)	72.782
Australia (Aus)	7.800	Finland (Fin)	10.139	Mexico (Mex)	3.057	Greece (Gre)	110.539
Canada (Can)	16.143	United Kingdom (UK)	6.445	France (Fra)	0.628		
		Italy (Ita)	6.578	Japan (Jap)	1.661		
		Lithuania (Lit)	10.438	Netherlands (PB)	3.260		
		Norway (Nor)	7.908	Germany (Ale)	0.274		
		Portugal (Por)	5.455				
		Slovakia (Esl)	7.733				
		Turkey (Tur)	7.783				
		Poland (Pol)	7.581				
		Austria (AT)	7.759				
		Denmark (Din)	10.401				
Total Average	17.171		8.042		1.839		91.185
Variance	55.031		5.749		1.159		683.268
SD	7.418		2.390		1.077		26.139

Fig. 12: Principal Components
Source: Elaborated by the authors.

With regard to the CO^2 emission trajectory of the countries that make up cluster 1, it should be noted that: According to data from the Research Federal Reserve Bank of St. Louis, Spain's CO^2 emissions showed an upward trend between 1990 and 2005, peaking in 2007 at 377.5 million tons of private CO^2 metrics. Since then, CO^2 emission has dropped significantly, reaching its lowest point in 2014, with 271.9 million metric tons of CO^2 privately owned. However, since then the trend has returned to an increase, with a drop in 2020, due to the COVID-19 pandemic. These data indicate that Spain has made efforts to reduce its CO^2 emissions in recent decades, but it still has a long way to go to reach the targets set by the Paris Agreement.

According to data from the Research Federal Reserve Bank of St. Louis, Canada's CO^2 emission showed an upward trend between 1990 and 2005, reaching a peak in 2007 with 558.9 million metric tons of CO^2 emitted. Since then, CO^2 emission has dropped significantly, reaching its lowest point in 2014. In this year, CO^2 emission dropped to 536.2 million metric tons, which represented a decrease of approximately 4% compared to 2005. In 2021, Canada's CO^2 emission was 565.2 million metric tons. According to data from the Research Federal Reserve Bank of St. Louis, Australia's CO^2 emission showed an upward trend between 1990 and 2007, peaking in 2007 with 406.7 million metric tons of CO^2 emitted. Since then, CO^2 emissions have varied, but in general have remained at high levels. More specifically, in 1990, Australia emitted around 278.2 million metric tons of CO^2 . In 2007, that number rose to 406.7 million metric tons of CO^2 , representing an increase of approximately 46.2% over 1990. In 2021, Australia's CO^2 emission was 397.9 million metric tons.

Figure 13 shows CO^2 Emissions (tons per capita) - Canada, Australia, Spain, Sweden, Switzerland Germany. As can be seen, the countries had similar levels of CO^2 *per capita* emission in 2019.

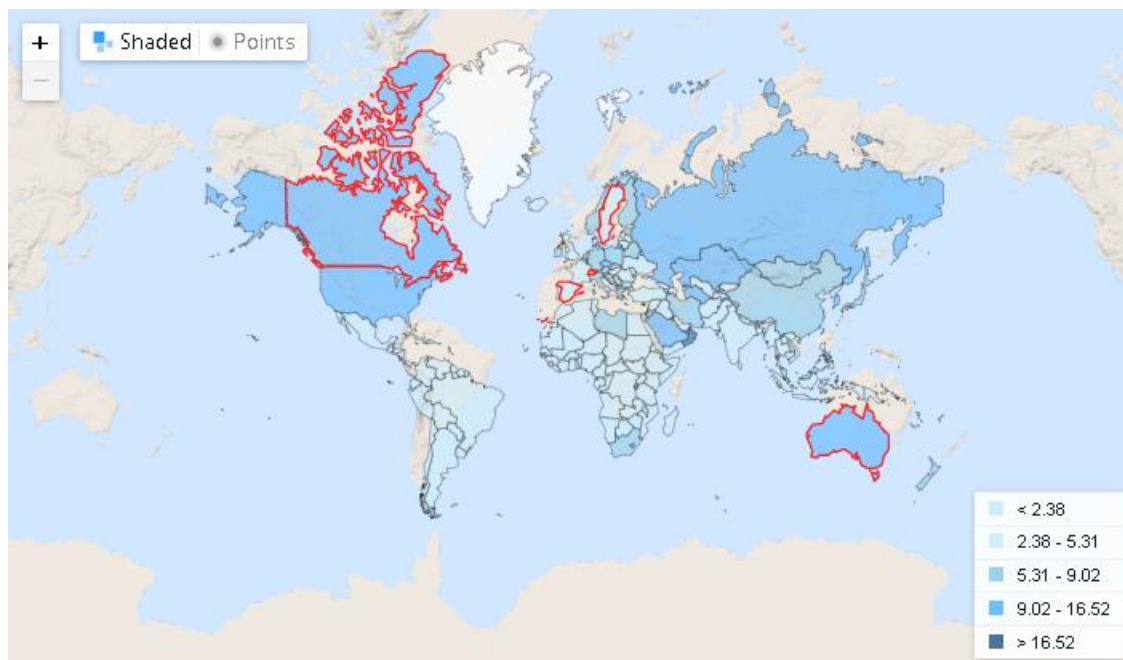


Fig. 13: CO^2 emissions (metric tons per capita) - Canada, Australia, Spain, Sweden, Switzerland Germany, in 2019.

Source: The world Bank

As can be seen in Figure 12, Portugal, Italy, and Turkey are part of the same cluster. Louis, *CO₂* emissions in Portugal increased from around 32.5 million tons in 1990 to around 44.4million tons in 2005, after this period showed a gradual decline. In 2021, Portugal's *CO₂* emissions were around 36.7 million tons. This reduction can be attributed to investments in renewable energy sources, such as wind and solar, and implementation of public policies to reduce greenhouse gas emissions. In parallel, the emission of *CO₂* in Italy increased from around 406 million tons in 1990 to around 470 million tons in 2004 but then started to decrease. In 2021, Italy's *CO₂* emissions were around 327 million tons. This reduction can be attributed to public policies to promote renewable energy sources, such as solar and wind, and tax incentives to improve energy efficiency. Turkey's *CO₂* emissions increased from 202 million tons in 1990 to around 365 million tons in 2018 but gradually declined. In 2021, Turkey's *CO₂* emissions were around 324 million tons. Turkey has been working to increase the share of renewable energy sources in its energy matrices, such as wind and solar energy, and has implemented public policies to reduce greenhouse gas emissions. In 2017, Turkey launched incentive programs for the generation of renewable energy, such as the Incentive Program for the Production of Electricity from Renewable Sources (YEKA). The Program was launched by the Turkish Ministry of Energy and Natural Resources in 2017, with the aim of increasing the share of renewable sources in the country's energy matrix. Another program was the implementation of public policies to improve energy efficiency in buildings, transport, and industries, such as the Energy Efficiency Program for Public Buildings (BÖLÜK et al. 2023, and Yilmaz, Pelin, et al., 2017). Figure 14 shows *CO₂* Emissions (tons per capita) -Belgium, Korea, Rep., Czechia, Finland, United Kingdom, Italy, Lithuania, Norway, Portugal, Slovenia, Türkiye, Poland, Austria, Denmark, in 2019. As can be seen, countries had *per capita CO₂* emission levels in 2019 between 2.38 and 9.02.

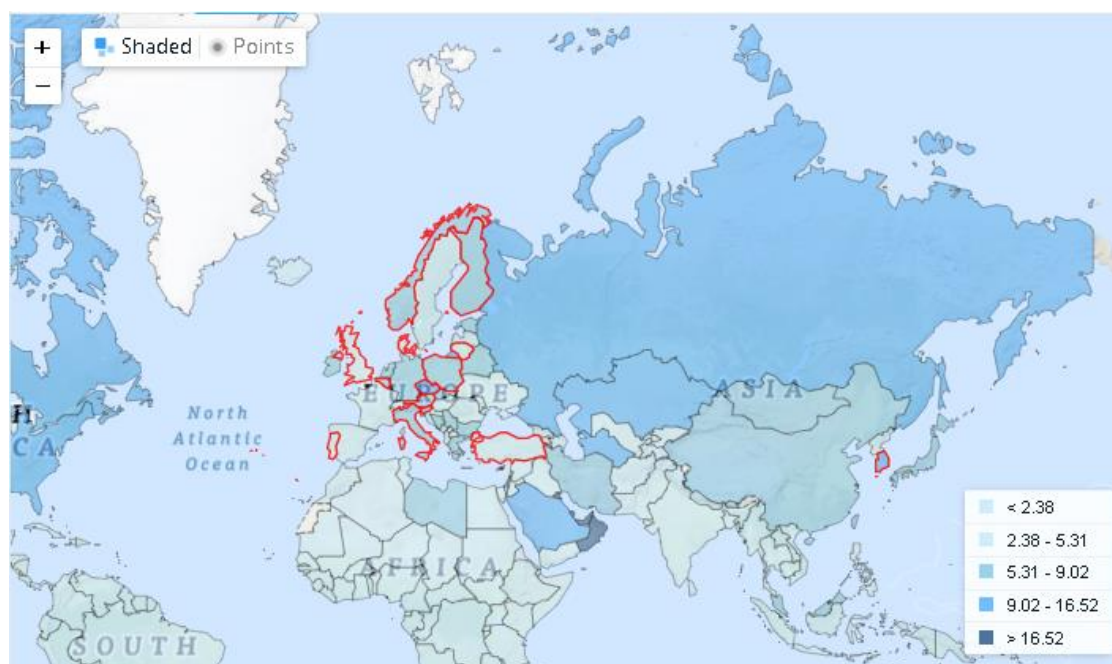


Fig 14: *CO₂* emissions (metric tons per capita) - Belgium, Korea, Rep., Czechia, Finland, United Kingdom, Italy, Lithuania, Norway, Portugal, Slovenia, Türkiye, Poland, Austria, Denmark, in 2019.

Source: The world Bank

Japan, Brazil, and France are part of cluster three, as can be seen in Figure 12. According to World Bank data, Japan's CO_2 emissions increased significantly between 1990 and 2013, rising from 1.08 billion CO_2 emissions to 1.31 billion metric tons of CO_2 . However, the country has invested in measures to reduce its emissions, such as the adoption of renewable energy sources and the improvement of energy efficiency. According to Arora, V., and Bansal, N. (2017), Japan has encouraged using solar, wind, and hydroelectric energy through debt and preferential tariffs. The country has also adopted measures to increase energy efficiency in buildings, transport, and hydrogen, such as promoting hybrid cars and implementing cogeneration systems in autonomous vehicles.

In the case of Brazil, CO_2 emissions, according to World Bank data, increased between 1990 and 2018, but the growth rate was lower than in other developing countries, such as China and India. The country has sought to reduce its emissions by adopting renewable energy sources, such as hydroelectric power, and implementing public policies to reduce deforestation and the burning of fossil fuels. According to Faria, R. A., & Pires, Faria, R. A., & Pires, (2017), Brazil has the potential to increase the share of renewable energies in its energy matrices, such as wind and solar energy. On the other hand, France showed a reduction in its CO_2 emissions between 1990 and 2013, from 412.2 million tons of CO_2 emissions to 353.8 million tons of CO_2 emissions. This is largely due to the adoption of nuclear energy as a source of electricity in the country. However, France has also invested in other renewable energy sources, such as solar and wind. According to a study published in the journal Renewable and Sustainable Energy Reviews by Giannakidis et al. in 2017, France has the potential to further increase the share of renewable energies in its energy matrix. Figure 15 shows CO_2 Emissions (tons per capita) - Japan, Brazil, France, Mexico, Hungary, Ireland, Holland, Germany. As can be seen, the countries had similar levels of CO_2 per capita emission in 2019.

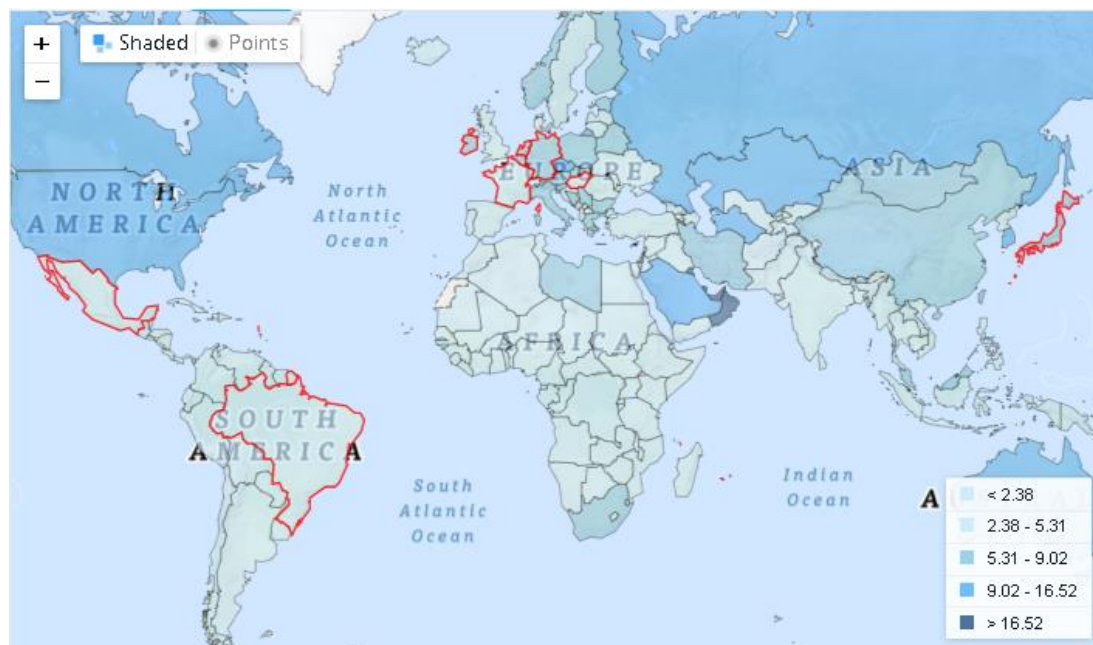


Fig. 15: CO_2 emissions (metric tons per capita) - Japan, Brazil, France, Mexico, Hungary, Ireland, Netherlands, Germany, in 2019.

Source: The world Bank

Greece and New Zealand are part of cluster three, as can be seen in Figure 12. According to World Bank data, Greece, between 1990 and 2019, Greece showed an upward trend in CO₂ emissions, with a peak in 2008 and a decline after the 2009 financial crisis. According to data from the Global Carbon Atlas, in 1990, Greece emitted about 65 million metric tons of CO₂, while in 2019, this emission reached almost 83 million metric tons. Greece has taken steps to reduce its greenhouse gas emissions, especially in relation to power generation. In 2019, the country showed a significant increase in renewable energy production, mainly with the installation of new wind and solar power plants. According to Gkoumas et al. (2019), the country has sought to increase the share of renewable energy sources in its energy matrices, such as wind and solar. It has also implemented policies for energy efficiency in buildings and transport. Papaioannou et al. (2018) highlight the importance of the civil construction sector in reducing CO₂ emissions in the country by implementing energy efficiency measures in buildings. On the other hand, New Zealand showed an increase until 2005, but since then, it has shown a downward trend in emissions. Muri, K., and Boland, J. (2020) highlight the public policies implemented by the government to reduce greenhouse gas emissions, including establishing emission reduction targets, implementing an emissions trading system, and promoting renewable energy sources. In addition, the country has invested in technologies to reduce emissions in the agricultural sector, which is one of the country's main emitters of greenhouse gases.

Figure 16 shows CO₂ Emissions (tons per capita) - New Zealand, Estonia, Luxembourg, Greece (Cluster 4). As can be seen, countries had *per capita* CO₂ emission levels in 2019 between 5,6 (Greece) and 15,3.02 (Luxembourg).

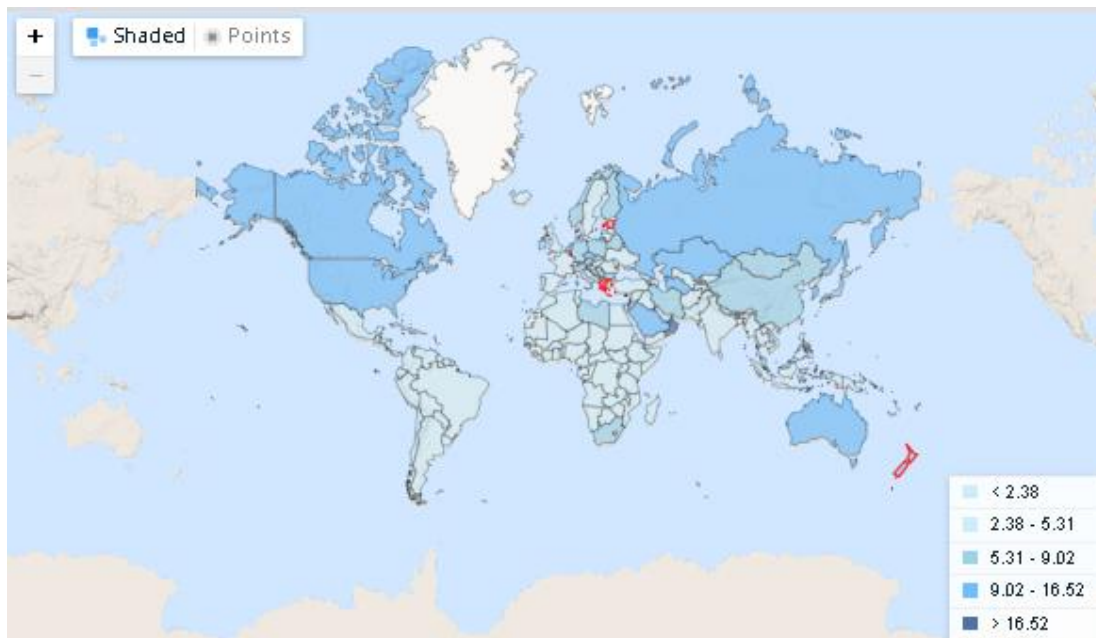


Fig. 16: CO₂ emissions (metric tons per capita) - New Zealand, Estonia, Luxembourg, Greece, in 2019.

Source: The world Bank

It should be noted that we selected some countries from each cluster to discuss the temporal evolution of CO^2 emissions, not mitigating the vast literature on the subject. This was an exercise to show some similarities of the countries that belong to different clusters.

Focusing on Brazil, an important point that can be seen in Figure 17 is that Brazil has been showing a downward trend over the analyzed period, except in 2015, when the country went through a period of drought, reducing energy production by hydroelectric plants, making it necessary to activate thermoelectric plants, which significantly increased the emission CO^2 in the country. With this fact, there is strong evidence that investment in renewable energy is of paramount importance for the reduction of CO^2 , countries that invest in sustainable sources manage to significantly reduce CO^2 emissions.

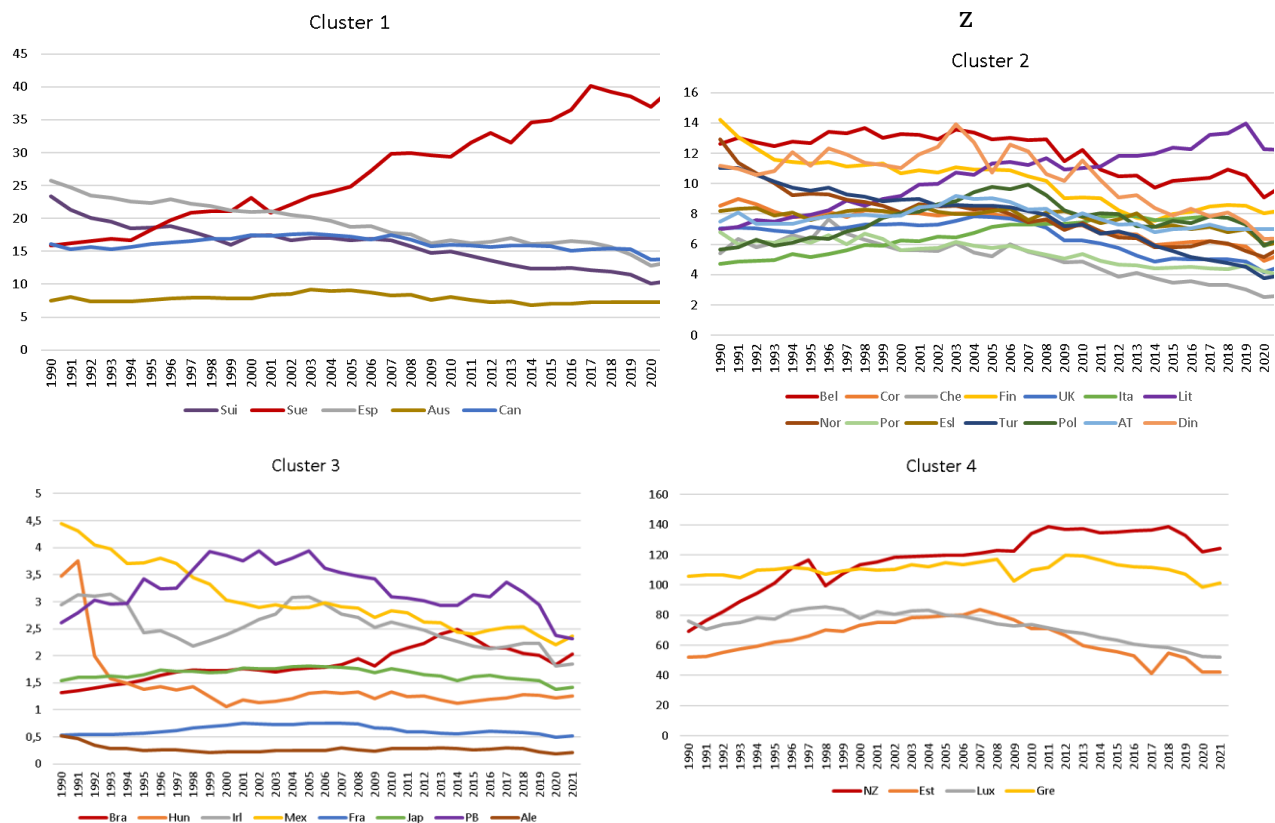


Fig. 17: Clusters by countries
Source: Elaborated by the authors.

CONCLUSION

The high concentration of carbon dioxide is responsible for the greenhouse effect and increased global temperatures. Excess CO^2 in the atmosphere is responsible for overheating the planet. One of the main sources of CO^2 is the burning of fossil fuels. Investing in renewable energy has become a priority for many countries. Given the global pollution problem, IEA has taken on an essential proportion worldwide. The agency has become essential in environmental discussions, providing reliable statistics and worldwide analysis of energy production, transmission, and consumption. IEA analysis shapes policy to allow the world to achieve climate, access to energy, and air quality, maintaining a strong focus on the reliability and

accessibility of energy for all. This article aimed at the multivariate analysis of CO₂ emissions by power generation in IEA member countries verifying standards in the redemptions and the existence of clusters. Additionally, the verification of Brazil fits the agency member countries in this regard. The research achieved its primary objective: verify and validate the importance of investments in renewable energy generation, to reduce CO₂ emissions. With the research it was possible to point out evidence that Brazil is a country that has been significantly reducing its CO₂ emissions, being in the cluster together with the IEA member countries that emit less CO₂.

Another relevant result in the research is the analysis of the Factors, where it was possible to point out characteristics of similarity between the CO₂ emissions of the countries, making it possible to highlight 3 latent variables, being factor 1 composed of countries that present a constant tendency of high or low in the emission of CO₂, whereas Factor 2 allowed the grouping of countries that showed an upward trend at the beginning of the analysed period, but with a significant reduction over time, with this, all countries that make up this factor arrived in 2021 with a decreasing their CO₂ emissions CO₂. Factor 3, on the other hand, grouped the two countries that presented the most discrepant behaviour from the others, these being the countries that have a structural break in their time series of CO₂ emissions per energy generation, Germany presents this drop at the beginning of the period and has been remaining constant over the years, but the two countries Germany and Greece had their lowest CO₂ emissions in the year 2020. With the study it was possible to delve deeper into the importance of renewable energy generation and the behaviour of countries over the years regarding CO₂ emissions caused by energy generation. For future works it is intended to analyse the CO₂ emission by type of energy.

Statement of Novelty and Industrial Relevance

Concern about global warming and pollution has increased interest and investments in developing renewable energy sources that are less harmful to health and the environment. Countries are striving to implement promising sources of renewable energy so that it is possible to replace fossil fuels. Using clean energy eliminates unwanted and harmful waste from other sources, such as coal and nuclear power plants (radioactive waste), one of the primary sources of CO₂ emissions. After the Paris agreement was signed by 195 countries, whose objective is to contain the increase in global warming, countries sought to reduce their emissions of greenhouse gases, such as carbon dioxide, responsible for approximately 60% of the greenhouse effect on earth, whose permanence in the atmosphere is at least 100 years. Thus, it becomes relevant studies that point out the historical evolution of countries in terms of their CO₂ emissions per energy generation. It is important to highlight whether the countries that make up the summit of members of the IEA (International Energy Agency), which acts as a policy guide and seeks that its member countries are access to clean energy for their citizens, are managing to evolve positively in the reduction of CO₂ emissions by energy generation, and what is the similarity of their energy characteristics and carbon dioxide emissions.

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