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Effects of CO_2, N_2O, CH_4 Emissions and Adjusted Net National Income on Food Security in 86 Countries

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ABSTRACT

This paper examines the impact of climate change (measured as carbon dioxide, nitrous oxide, and methane emissions, as well as temperatures), arable land, and sustainable development (measured as Adjusted Net National Income, ANNI) on food security in 86 countries during 2012-2020. To this end, Granger non-causality in heterogeneous panels, static and dynamic panel data models, clusterization with elbow and silhouette analysis, as well as radar plot visualization. The Food Security Index (FSI) comes from Economist Impact (2022) and the rest of the variables from World Bank (2024). The main empirical result from panel data suggest that climate change has a negative effect on FSI, and ANNI measured as Gross National Income minus fixed capital consumption and natural resource depletion, used as a proxy of sustainable development, has a positive impact on FSI. Moreover, the cluster analysis complements the econometric analysis by identifying structural differences among countries that panel data models might overlook. Initially, two clusters are identified: one with only two members, China and the United States, and the other with the remaining countries. Subsequently, a cluster analysis is performed removing China and the United States to identify patterns in the rest of the countries. In this case, eight clusters are identified that share similar characteristics in the dynamics of all the variables under study, allowing for a more in-depth examination. There are now two clusters with only one member, Brazil and Russia. Other cluster contains only G7 countries. The largest cluster includes 31 countries. Finally, radar plots allow the specific characteristics of each of the eight groups to be visualized in relation to all the variables under study. Finally, the cluster analysis also offers important implications for sustainable policy design, suggesting the need for cluster-specific approaches rather than one-size-fits-all solutions.

Keywords: Climate Change, Sustainable Development, Food Security, Panel Data, Cluster Analysis, Radar Plot Visualization
JEL Classifications: C33, Q51, Q53, O13.

1. INTRODUCTION

Recent studies assess the impact of climate change on global food security and crop productivity. Most of these studies explore the consequences of climate change on arable land and agriculture, with a particular focus on the challenges in vulnerable regions in Africa and Asia. These investigations also discusses the complexities of mitigating climate-induced disturbances in crop growth patterns and the implications of climate change on biodiversity, recognizing the interconnectedness of ecological systems and the imperative for innovation; the emphasis is on ensuring the resilience of global agriculture in the face of climate changes (Praveena and Malaisamy, 2024; Chandio et al., 2020; Hertel and de Lima, 2020).

The most common way to quantify and monitor climate change is by measuring carbon dioxide CO_2, nitrous oxide N_2O and methane CH_4 emissions, along with temperatures. In this sense, the carbon footprint includes all these emissions and converts them into CO_2 equivalent, which is a useful indicator for assessing the impact of human activities on climate change. On the other hand, industrial livestock focuses on meat production contributing significantly to

CH_4 emissions. Therefore, the interaction of climate change, food security and sustainable development is an issue relevant importance.

On the other hand, according to the World Food Program (WFP) Global Outlook 2025, 343 million people are acutely food insecure in 74 countries where WFP operates. It should be noted that there has been a 10% increase since 2023, with almost 200 million more people than pre-pandemic levels. Nowadays, food security has become one of the most relevant issues after the COVID-19 pandemic and the conflict between Russia and Ukraine in 2022. Russia being one of the main food producers, it produces around 40% of crops of the total agricultural production, and 60% of livestock including wool, meat and dairy production. Russia is also the third largest producer of potatoes, the fourth largest producer of wheat, and the twelfth largest producer of corn.

Today food security has become a priority on national and international political agendas. It is supposed to be one of the most pressing challenges in most of nations, since food security implies one of the main factors of the well-being of the population. The term food security emerged after the Second World War and the creation of the United Nations. Today there is a wide literature dealing with this topic and its relations with other variables such as sustainable development and climate change (Swaminathan, 2001; Godfray et al., 2010; Lang and Barling, 2012; Berry et al., 2015; Kamruzzaman, 2016; Raymond and Goulet, 2020; Lucatello and Sánchez, 2022; Salazar-Núñez et al., 2022; Rehman et al., 2022; Ivanova and Serrano, 2022; Praveena and Malaisamy, 2024).

Since the 1996 Rome Declaration on World Food Security (RDWFS) were defined two basic dimensions, availability and utilization, with a focus on nutritional well-being. In this sense, the sustainable management of natural resources and the elimination of unsustainable patterns of food consumption and production is becoming an important issue. In this regard, the World Summit on Food Security (2009) added the concept of stability/vulnerability as the short-term time indicator of the capacity of food systems to withstand crises, whether natural or man-made, as part of the Five Rome Principles for Sustainable Global Food Security. More recently, the relevance of sustainability to preserve the environment, natural resources and agroecosystems has been highlighted, as well as the importance of food security as a part of sustainability and vice versa (Patra et al., 2025).

From the previous perspective, the concept of sustainable diets can play a key role as an objective and way of maintaining nutritional well-being and health, while ensuring sustainability for future food security. Sustainability must be integrated as an explicit dimension of food security, to prevent current policies and programs from being the causes of greater food insecurity in the future (Berry et al., 2015). The links between sustainability and food security are becoming increasingly relevant in current research. Hence, the concept of sustainability in the context of food security is gaining importance in recent times. Finally, sustainability must be assumed as part of the long-term temporal dimension in the assessment of food security.

Food security has naturally been associated with food production, hence it is related to the availability of food in the market and linked to the ability to purchase or acquire a basic food basket. Therefore, food security is associated with nutrition, clean water, healthy environment, income, basic health, and educational coverage. In this sense, food security is linked to ecological factors that determine it in the long term (Swaminathan, 2001). Food security is a complex issue, as it is related to a multitude of economic, financial, administrative, technological, innovation, ecological, social, environmental, political, and many other variables. It is worth noting that food security is impacted depending on the time horizon, some variables are affected in the short term and others in the medium and long term. Hence, food security is one of the most important challenges to achieve at the local and international level, given its contribution to the well-being of the population (Wijekoon and Marikar, 2024).

Moreover, there are two general approaches to food security, on the one hand a perspective that is based on the increase in food production and focuses on arable land and agriculture, while on the other hand, a more complex, considers ecological systems. The first approach began after the Second World War, and within a few decades it was replaced by the second one, which is more complex in an ecological context. Lang and Barling (2012) conclude that it is imperative to create a sustainable food system, which demands a more relevant policy framework than the one that currently exists. Finally, the study by Raymond and Goulet (2020) highlight that the interaction between food security and food sustainability with science and technology to be democratized through food policies. In this sense, knowledge infrastructures show the limitations of the models to evaluate and confront the lack of food security.

According to the Sustainable Development Goals (SDGs), one of them is to eradicate extreme poverty for all people around the world by 2030, so the challenge of food security is urgent to contribute to eradicating poverty throughout the planet. In this sense, Kamruzzaman (2016) suggests that to achieve the objectives the world needs to be consistently peaceful, since poor countries require greater commitment and effort to achieve changes in the global economic structure, so the eradication of poverty must be addressed rigorously.

Furthermore, the links between climate change and food security are highlighted by the current variations in the planet's climate affecting the world's population. In this sense, Godfray et al. (2010) state that continued growth in population and consumption will mean that global demand for food will increase for at least another 40 years. Increasing competition for land and water, as well as overexploitation of fisheries, will affect the ability to produce food, as will the urgent need to reduce the impact of the food system on the environment. In this sense, the effects of climate change are another threat, but the world can produce more food and can ensure that it is used more efficiently and equitably. The authors conclude that a multifaceted and linked global strategy is needed to ensure sustainable and equitable food security.

The present investigation also carries out a cluster analysis to complement the proposed econometric analysis by identifying structural differences among the countries in the sample that panel data models might fail to notice. This cluster analysis allows for the identification of groups of countries that share similar characteristics in the dynamics of all the variables under study, allowing for a more in-depth examination. Hence, cluster analysis will be used as an alternative research framework to complement the investigation about the interactions among sustainable development, climate change, and food security in 86 countries. Cluster analysis is commonly used as a fitting multivariate statistic because of its ability to identify inherent groupings among countries based on various simultaneous similarities (Mooi et al., 2018). Mainly, the use of the k-means clustering algorithm has been based on its efficacy in sustainability research regarding pattern identification among countries in terms of environmental and economic indicators (Xu and Wunsch, 2010; Lin et al., 2022).

This research differs from the current literature in the following ways: (1) it focuses on a large sample of 86 economies, (2) it considers greater availability of data compared to the past, allowing for a greater number of countries, variables and periods, (3) it estimates cointegration, Granger non-causality in heterogeneous panels, and dynamic panel data models, (4) it corrects multicollinearity and autocorrelation problems, (5) it carries out a cluster analysis to complement the econometric analysis by identifying structural differences among countries that panel data models might overlook, and (6) it finds patterns in clusters that share similar characteristics in the dynamics of all the variables under study.

The rest of the document is organized as follows: Section 2 provides a short literature review; Section 3 presents the nature of the data, the descriptive statistics and the graphical analysis of the data; Section 4 deals with cointegration, Granger causality and panel data analysis; Section 5 carries out a cluster analysis to complement the econometric analysis by clarifying structural differences among countries; Section 5 presents the analysis and discussion of the main empirical results; finally, Section 6 presents the conclusions, acknowledges the limitations, and offers some policy recommendations.

2. A SHORT LITERATURE REVIEW

The interaction among sustainability, climate change and food security is analyzed in various investigations. For instance, Bongiovanni and Lowenberg-Deboer (2004) study the role of precision agriculture in helping to manage crop production inputs in an environmentally friendly way. By using site-specific knowledge, precision agriculture can determine rates of fertilizers, seeds and chemicals for soil and other conditions. It is worth mentioning that precision agriculture substitutes information and knowledge for physical inputs, it can contribute in many ways to the long-term sustainability of production agriculture. In this sense, precision agriculture should reduce environmental load through optimal application of fertilizers and pesticides, decrease chemical load, and can contribute to better environmental management.

On the other hand, Lobell et al. (2011) analyze the effect of climate change on future food availability, finding that in the cropping regions and growing seasons of most countries and temperature trends exceeded one standard deviation of historical inter-annual variability from 1980 to 2008. Their analysis of linking yields of the four major staple crops to climate indicate that global maize and wheat production declined by 3.8% and 5.5%, respectively, relative to a contractual scenario with no climate trends. For soybeans and rice, the winners and losers were largely balanced. Climate trends were large enough in some countries to offset a significant portion of the increases in average yields arising from technology, carbon dioxide fertilization, and other factors. Likewise, Vermeulen et al. (2012) suggest that food systems contribute between 19% and 29% of global greenhouse gas (GHG) emissions. Agricultural production, including indirect emissions associated with land cover change contributes between 80% and 86% of total food system emissions. The authors warn that the impacts of global climate change on food systems are widespread, complex, geographically and temporally variable, as well as deeply influenced by socioeconomic conditions. These authors also state that climate change will affect agricultural yields and incomes, food prices and, in particular, food security. Also, these authors indicate that low-income food producers and consumers will be more vulnerable to climate change due to their comparatively limited capacity to invest in adaptive technologies and suggest synergies among food security, adaptation and mitigation. Likewise, Wheeler and Braun (2013) study the role of climate change in progress towards a world without hunger, highlighting that the stability of food systems as a whole may be at risk due to climate change and variability in supply in the short term; however, they emphasize that the potential impact is less clear at the regional scale, but climate change may exacerbate food insecurity in areas currently vulnerable to hunger and malnutrition. Finally, the authors suggest the need for considerable investment in adaptation and mitigation actions to achieve a climate-smart food system that is more resilient to the influences of climate change on food security.

On the other hand, Garnett et al. (2013) examine the challenges posed by climate change to agriculture and food security in developing countries, highlight that many current agricultural practices damage the environment and are becoming a major source of GHG, and conclude that food insecurity in a region can have widespread political and economic ramifications worldwide in an increasingly globalized world. Likewise, Lipper et al. (2014) study the role of climate-smart agriculture in transforming and reorienting agricultural systems to support food security in the context of the new realities of climate change, highlighting that climate-smart agriculture promotes coordinated actions by farmers, private sector, civil society and policy makers towards climate-resilient pathways. Finally, reorienting agricultural systems to support food security increases local institutional effectiveness, promotes coherence between climate and agricultural policies, linking climate and agricultural financing.

Similarly, Ebert (2014) investigates the role of underutilized vegetables and leguminous crops in achieving nutritional security, highlighting that significant research, breeding and development efforts are needed. The author finds that underutilized crops such as amaranth, drumstick and mung bean have demonstrated potential for wider adoption and commercial exploitation. Moreover, Vervoort et al. (2014) analyze food security in the context of climate change in East Africa, concluding that long-term viability and sustainability could be ensured if decision-makers took ownership of the process and focused on developing strategic planning capacity within their local organizations. Finally, Dawson et al. (2016) examine the effects of climate change on the United Nations Objectives of eradicating poverty and hunger; however, the rapid growth of the world population, coupled with global climate change have negative effects on food security. The authors estimate food exports, assess diets and malnutrition, determine average calories per capita, and state the degree of inequality in food access. Finally, they determine calorific values of food, asses crop yields and examine population changes under socioeconomic and climate change scenarios for 2050, 2085 and 2100. These authors project that in a scenario without climate change based only on projected changes in population and agricultural land use, the results show that 31% (2.5 billion people in 2050) of the world's population is at risk of malnutrition if no agricultural adaptation or innovation is made in the intervening years. In a second scenario, 21% (1.7 billion people) are at risk of malnutrition in 2050 when climate change is taken into account. However, their modeling does not take into account future trends in technology, improved crop varieties or interventions in agricultural trade, although it is clear that all of these adaptation strategies will need to be adopted on a global scale if society is to ensure an adequate food supply for a projected world population of more than 9 billion people.

On the other hand, Terry et al. (2017) analyze the impact of population growth and climate change on food security in Africa by 2050. They find the prevalence of malnutrition in 44 African countries and population growth as the main cause of food insecurity and malnutrition, they suggest different adaptation alternatives: Increasing yield through sustainable intensification and increasing imports with trade agreements to prevent food insecurity in the future. Later, Mechiche-Alami (2020) studies the role of national large-scale land acquisition policies and agricultural intensification programs in food security in Africa. The author concludes on the risks of prioritizing productivity policies that are incapable of providing accessibility to food in Africa, which only benefits transnational and national elites at the expense of small farmers. Finally, the author suggests agroecology as a potential alternative to sustainably improve food security on the African continent.

Moreover, Guiné et al. (2021) assess the relationship between food security and sustainability, considering statistical information for the various dimensions of food security during the period 2000-2020. The authors conclude that malnutrition is more affected by the availability of food and nutrients than political stability, and that the level of development is not the main explanation for nutrition problems. They suggest that agri-food supply chains should be improved and political stability supported to mitigate malnutrition worldwide and ensure global access to sustainable and healthy diets. In this sense, Laurett et al. (2021) study several determinants of sustainable development in agriculture in Brazil as natural agriculture, innovation and technology and environmental aspects. The authors identify different associated elements of sustainable development in agriculture such as external influencers, commitment to sustainability, concern for future generations, environmental motivators, individual characteristics, socio-environmental benefits and subjective well-being.

Likewise, Wahben et al. (2022) analyze the factors that promote food security and the sustainability of future food production (environmental, social and economic). They carry out an exhaustive study of the literature on food security, its determinants and policies. The authors find that the policies that stand out are those to mitigate food loss and waste. The authors also suggest including environmental indicators and policies, consumer representation and the entire supply chains in the Global Food Security Index (GFSI). Furthermore, they conclude that food security is a complex issue and demands multidisciplinary interventions. Finally, Viana et al. (2022) review the literature on Sustainable Development Goals (SDG 2 – zero hunger) and food security, analyzing many investigations on the topic, revealing that most of these investigations were published between 2015 and 2019 (59%), and most case studies were conducted in Asia (36%) and Africa (20%). Over the past 30 years, most research focused on six main research fields: land use change (28%), agricultural efficiency (27%), climate change (16%), farmer motivation (12%), urban and peri-urban agriculture (11%) and land suitability (7%).

Moreover, Moon (2024) examines the effects of climate change on food security of vulnerable groups in Bangladesh. The author highlights the significant risks that climate change poses to food security in Bangladesh and vulnerable women, including increased susceptibility to food shortages and post-disaster problems. In this case, women in Bangladesh are more susceptible to these problems due to their social, economic and political circumstances, concluding that women are negatively affected by climate change. The author also suggests implementing policies to improve regional agricultural production and strengthen resilience to climate change. More recently, Wijekoon and Marikar (2024) explore the role of the Sri Lankan Army in improving food security influenced by climate change, agricultural practices and social dynamics in the country. The authors also examine the potential contributions of the military in terms of food production, infrastructure development, and technology, highlighting the importance of collaboration, knowledge transfer, and sustainable practices to achieve lasting food security. Hence, through collaborative efforts involving multiple stakeholders, including government agencies, local communities, and agricultural organizations, a more resilient and secure food system for the country can be imagined.

Finally, Cluster analysis is commonly used as a fitting multivariate statistic because of its ability to identify inherent groupings among countries based on various simultaneous similarities (Mooi et al., 2018). Mainly, the use of the k-means clustering algorithm has been based on its efficacy in sustainability research regarding pattern identification among countries in terms of environmental and economic indicators (Xu and Wunsch, 2010). The k-means algorithm works by dividing observations into k groups in an attempt to minimize the within-cluster sum of squares (Lloyd, 1982). In cluster analysis, the elbow method evaluates the relationship between the within-cluster and cluster size, and the silhouette analysis measures how well every country is assigned to its cluster to other clusters, hence giving a measurement of cluster cohesion and separation (Kodinariya and Makwana, 2013; Madhulatha, 2011).

3. NATURE OF THE DATA, DESCRIPTIVE STATISTICS AND GRAPHICAL ANALYSES

The data used in this research is obtained from Economist Impact (2022) and World Bank (2024). The Food Security Index (FSI) is made up of 68 indicators that measure variables that encourage food security in both developed and developing countries and is available on the Economist Impact website. The FSI considers food affordability, food quality and food safety, as well as sustainability. On the other hand, from the World Bank data (2024) is obtained the Adjusted Net National Income (ANNI) measured as Gross National Income minus fixed capital consumption and natural resource depletion in constant 2010 US dollars and is used as a proxy variable for sustainable development. Likewise, carbon dioxide (CO_2), nitrous oxide (N_2O) and methane (CH_4) emissions are given in kt (thousand tons) of CO_2 equivalent. It should be noted that the emission of 1 kg of N_2O equals 298 kg of CO_2 equivalent, and the emission of 1 kg of methane (CH_4) is equal to 25 kg of CO_2 equivalent. Finally, temperature data is given in degrees Celsius, and arable land is expressed as a percentage of total land.

The study period is restricted to the availability of data, so variables correspond to the period 2012-2020. This research uses the same number of observations for all variables for all countries. The panel includes 86 economies: Algeria, Angola, Argentina, Austria, Azerbaijan, Bahrain, Bangladesh, Belarus, Belgium, Benin, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Canada, China, Colombia, Congo (Dem. Rep.), Costa Rica, Côte d'Ivoire, Czech Republic, Denmark, Dominican Rep., Ecuador, Egypt, El Salvador, Ethiopia, Finland, France, Germany, Ghana, Greece, Haiti, Hungary, Indonesia, Israel, Italy, Japan, Kazakhstan, Kenya, Kuwait, Laos, Madagascar, Malaysia, Mali, Mexico, Nepal, Netherlands, New Zealand, Nicaragua, Norway, Oman, Pakistan, Paraguay, Peru, Philippines, Poland, Portugal, Romania, Russia, Rwanda, Saudi Arabia, Senegal, Serbia, Sierra Leone, Slovakia, South Africa, South Korea, Spain, Sri Lanka, Sudan, Sweden, Switzerland, Tajikistan, Tanzania, Togo, Tunisia, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States and Uruguay.

Table 1 shows the variables and notation used in this investigation, as well as their averages, standard deviations, and maximum and minimum levels. For the sample of the 86 economies, the average FSI is 61.56318, the standard deviation is 12.62436, the minimum is 32.8 corresponding to Burkina Faso in 2018, and the maximum is 84.3 corresponding to Finland in 2020. The average ANNI of the sample is 6.36E+11 USD, with a standard deviation of 2.00E+12 USD, with a minimum of 1.74E+09 USD corresponding to Burkina Faso in 2012 and a maximum of 1.71E+13 USD corresponding to the USA in 2019. The average CO_2 emissions are 746341.3 kt, with a standard deviation of 2454226 kt, the lowest emission is 6.6 kt which corresponding to Togo in 2012, while the highest CO_2 emission is 1.65E+07 kt corresponding to China in 2020.

Also note, from Table 1, that the average CH_4 emissions are 65275.73 kt of CO_2 equivalent with standard deviation 161738.6 kt, the lowest emission is 1009.982 kt corresponding to Burundi in 2012, while the maximum CH_4 emissions are 1186285 kt corresponding to China in 2020. The average N_2O emissions are 24718.78 kt with standard deviation 65833.55 kt, the lowest emission is 124.8322 kt corresponding to Bahrain in 2012, while the maximum N_2O emission is 551682.8 kt corresponding to China in 2016. The average temperature in all 86 countries is 18.35156°C with standard deviation 7.690974°C, the minimum is −0.085°C corresponding to Canada in 2014, and the maximum is 29.13°C corresponding to Mali in 2016. The percentage of arable land has an average of 18.32445% with standard deviation 14.81341%, the minimum is 0.1088853% corresponding to Oman in 2012, and the maximum is 60.8% corresponding to Serbia in 2015.

Below are the results of a sequence of graphical analyses that relate the dependent variable, FSI, with CO_2, N_2O, CH_4 emissions, as well as temperatures, arable land and ANNI in the 86 economies. Figure 1 shows the dynamics between the logarithm of ANNI and the logarithm of FSI. For all the economies analyzed, a positive relationship is observed between these variables. In this sense, an increase in ANNI is associated with an increase in FSI, as shown in Figure 1.

On the other hand, Figure 2 shows the relationship between the logarithm of CO_2 and the logarithm of FSI in all the economies. The results are mixed since there is a group of countries (49%) that shows a positive relationship between the logarithms of these variables. That is an increase in CO_2 emissions is associated with an increase in the FSI However, the rest of the countries present a negative relationship, i.e., a reduction in CO_2 emissions is related to an increase in FSI. This is due to structural differences among countries and the unique characteristics of each one. To better understand this behavior later, in Section 6, a clustering analysis will be performed to determine groups of countries that share

Table 1: Variables, notation and descriptive statistics

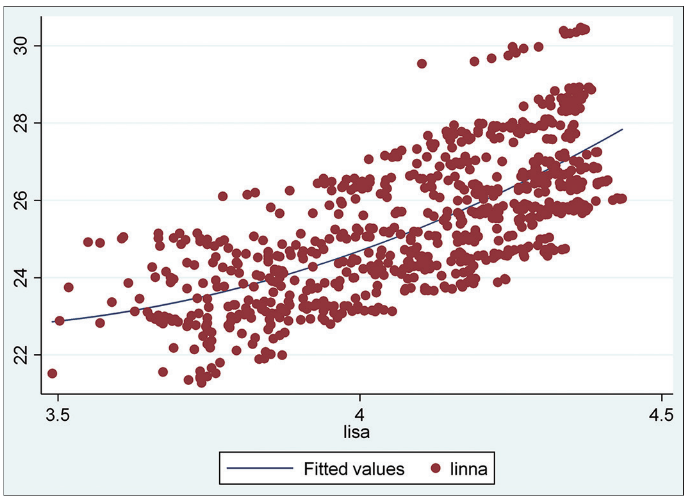
Variable	Notation	Average	Deviation	Minimum	Maximum
Food security index	*Isa*	61.56318	12.62436	32.8	84.3
Adjusted Net National Income	*Inna*	6.36E+11	2.00E+12	1.74E+09	1.71E+13
CO_2	*Carbono*	746341.3	2454226	6.6	1.65E+07
Methane	*Metano*	65257.73	161738.6	1009.982	1186285
N_2O	*Nitroso*	24718.78	65833.55	124.8322	551682.8
Temperatura	*Temperatura*	18.35156	7.690974	−0.085	29.13
Arable land	*Cultivables*	18.32445	14.81341	0.1088853	60.8

Source: Authors' own elaboration with data from Economist Impact (2022) and World Bank (2024) similar characteristics in the dynamics of the variables under study. Figure 2 shows a first phase, in which an increase in CO_2 emissions is associated with an increase in the FSI in the countries studied. A second phase is appears, in which carbon dioxide emissions decrease with an increase in the food security index. This last behavior may be related to public policies that promote environmental protection, which seek to reduce carbon dioxide emissions, greater citizen awareness, or companies' willingness to protect the environment by reducing their GHG emissions.

Likewise, Figure 3 shows the dynamics between the logarithm of CH_4 emissions and the logarithm of the FSI, for the economies explored in this research, a positive relationship between the variables is first observed, which indicates an increase in the logarithm of CH_4 emissions associated with an increase in the logarithm of the FSI, then a negative relationship indicating a logarithmic decrease in CH_4 emissions associated with a logarithmic increase in the FSI. Thus, Figure 3 shows the relationship between climate change (proxy for methane emissions) and food security. This figure illustrates, on the one hand, an increase in CH_4 emissions associated with an increased FSI. This may be related to the increase in meat production, which has a positive impact on food security but causes higher CH_4 emissions. Second, a negative slope is observed, showing a decrease in CH_4 emissions and an increased in FSI, suggesting that environmental policies and the primary sector's efforts to reduce CH_4 emissions are being successful.

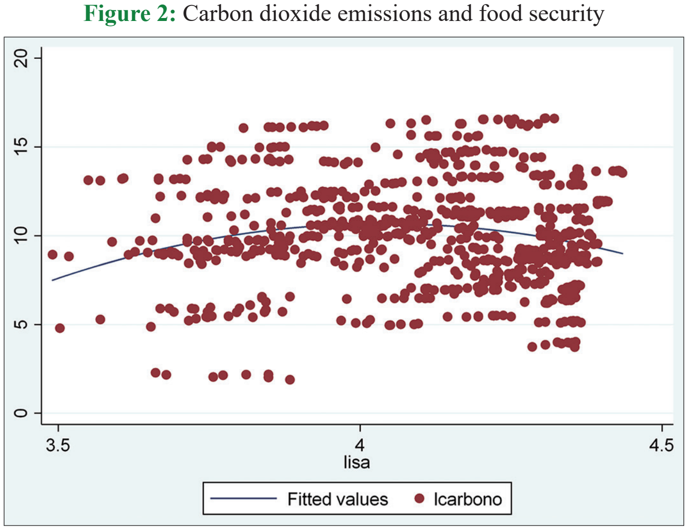
On the other hand, Figure 4 reveals the relationship between the logarithm of N_2O emissions and the logarithm of the FSI for the economies analyzed. Initially, a negative relationship is observed between the logarithms of these variables and later a positive trend appears. An increase in N_2O emissions is associated with a reduction in the FSI, then an increase in N_2O emissions is related to an increase in the FSI. Figure 4 shows that N_2O emissions have not been controlled over time. It is a GHG, more potent than CO_2 and CH_4, and is mainly associated with the agricultural sector. N_2O emissions have increased by 40% between 1980 and

Figure 1: Adjusted net national income and food security



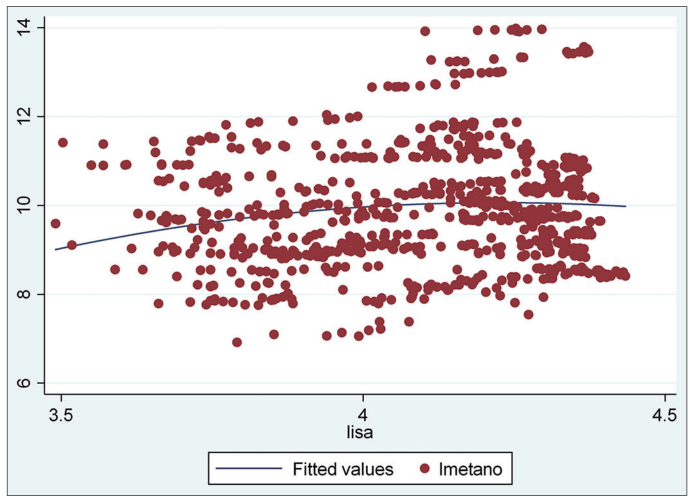
Source: Authors' own elaboration with data from Economist Impact (2022) and World Bank (2024)

Figure 2: Carbon dioxide emissions and food security



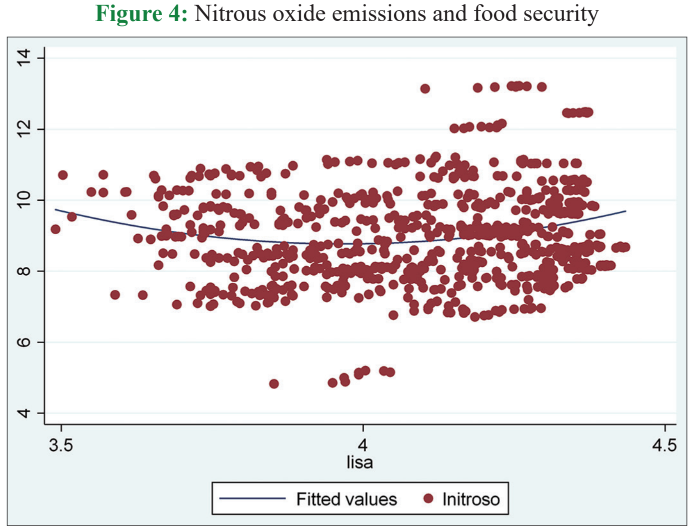
Source: Authors' own elaboration with data from Economist Impact (2022) and World Bank (2024)

Figure 3: Methane emissions and food security



Source: Authors' own elaboration with data from Economist Impact (2022) and World Bank (2024)

Figure 4: Nitrous oxide emissions and food security



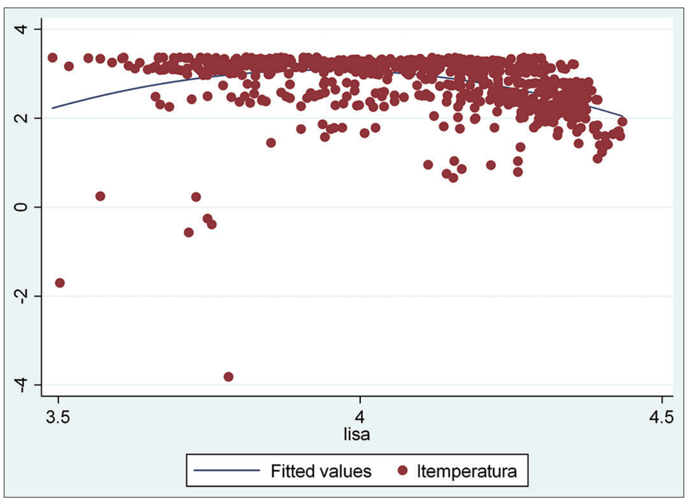
Source: Authors' own elaboration with data from Economist Impact (2022) and World Bank (2024)

2020, significantly accelerating climate change. Finally note that agricultural production also contributes to increased food security.

Below, Figure 5 shows the relationship between the logarithm of temperatures and the logarithm of the FSI for the economies in the sample. At first, a positive relationship is observed between the logarithms of these variables and later a negative one. An increase in temperature is associated with an increase in the FSI, then a reduction in temperature is related to an increase in the FSI. Figure 5 suggests that public policies in the different countries, citizen actions, and corporate commitment have slowed global warming, which has contributed to increased food security in the various countries analyzed.

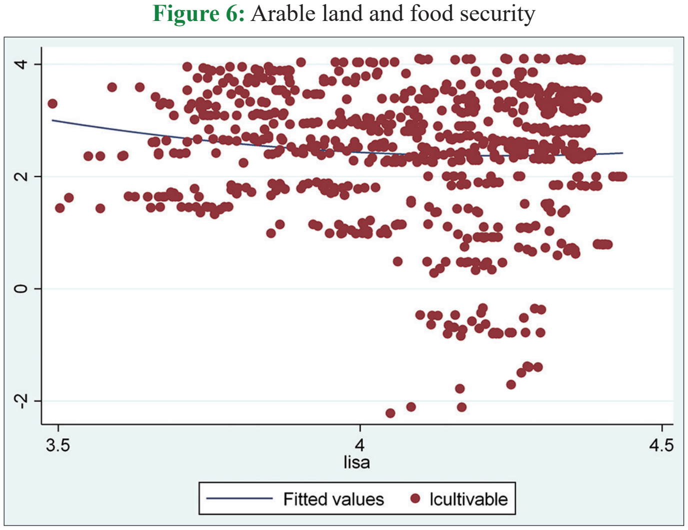
Finally, Figure 6 shows the relationship between the logarithm of the percentage of arable land as a proportion of total land and the logarithms of the FSI for the economies under study. A negative relationship is observed between the variables indicating that countries with higher proportions of arable land are associated with lower FSI, which may be related to the fact that countries specialized in agriculture are poorer than countries that specialize in industry and services, which enjoy higher incomes and food purchasing power.

Figure 5: Temperature and food security



Source: Authors' own elaboration with data from Economist Impact (2022) and World Bank (2024)

Figure 6: Arable land and food security



Source: Authors' own elaboration with data from Economist Impact (2022) and World Bank (2024)

In summary, Figure 1 shows a positive relationship between ANNI and FSI. Also, Figures 2, 3 and 5 show that the behavior between CO_2, CH_4, and temperatures with FSI is represented by concave curves downwards. On the other hand, Figure 4 shows the relationship between N_2O emissions with FSI with a tendency of a convex curve upwards. Finally, Figure 6 shows a negative relationship between arable land and FSI. To better understand this behavior of concave and convex trends, a clustering analysis will be performed in section 6 to delimit groups of countries that share common characteristics in the dynamics of the variables under study.

4. COINTEGRATION, GRANGER CAUSALITY AND PANEL DATA

This section is divided into two parts. The first part is devoted to the statistical analysis of the study variables, estimating stationarity, cointegration and Granger causality to avoid problems related to spurious regressions. The second part presents the main results of panel data estimations, both static and dynamic. The purpose is to examine the interaction among the FSI, ANNI, CO_2, N_2O, and CH_4 emissions, temperatures and arable land for the sample of 86 countries. The variables are expressed in logarithms: *lisa* is the logarithm of the FSI, *linna* is the logarithm of the ANNI, *lcarbono* is the logarithm of CO_2 emissions, *lmethane* is the logarithm of CH_4 emissions, *lnitroso* is the logarithm of N_2O emissions, *ltemperatura* is the logarithm of temperatures, and *lcultivable* is the logarithm of arable land. The period analyzed is 2012-2020, which allows having 86 countries and 9 years. A balanced panel is estimated with the Stata package. The main results are expressed in the next section.

4.1. Stationarity

Table 2 shows in row 1 the stationarity of the FSI series, the null hypothesis of the existence of a unit root is rejected in levels. Row 2 indicates stationarity in second differences of ANNI, while rows 3, 4 and 5 show the stationarity in first differences of CO_2, CH_4 and N_2O. Subsequently, row 6 shows that temperatures are stationary in levels. Finally, row 7 shows that arable land is stationary in levels.

4.2. Cointegration

Cointegration means that even though the series are not stationary at an individual level, a linear combination of two or more time series can be stationary, this phenomenon can be conceived as the stationary difference between a pair of series. The vector of coefficients that create this stationary series is the cointegrating vector. Table 3 shows the results of cointegration tests between the dependent variable FSI and the explanatory variables. Row 1 shows that the null hypothesis of no cointegration is rejected, therefore the FSI and ANNI series are cointegrated. Row 2 shows the results of cointegration between the FSI and CO_2 emissions. Subsequently, row 3 shows cointegration between the FSI and CH_4 emissions. On the other hand, row 4 shows cointegration

Table 2: Unit root tests

Variable	Series	P-value	Observations
1	*Isa*	0.0077	H_0 is rejected
2	*D2.inna*	0.0000	H_0 is rejected
3	*D.carbono*	0.0000	H_0 is rejected
4	*D.metano*	0.0000	H_0 is rejected
5	*D.nitroso*	0.0000	H_0 is rejected
6	*Temperatura*	0.0000	H_0 is rejected
7	*Cultivable*	0.0000	H_0 is rejected

H_0: Panels contain unit roots. Source: Authors' own elaboration with data from Economist Impact (2022) and World Bank (2024), Stata

Table 3: Cointegration estimates

Estimates	Series	P-value	Test
1	*Linna and lisa*	0.0020	H_0 is rejected
2	*Lcarbono and lisa*	0.0007	H_0 is rejected
3	*Lmetano and lisa*	0.0093	H_0 is rejected
4	*Lnitroso and lisa*	0.0126	H_0 is rejected
5	*Ltemperatura and lisa*	0.0007	H_0 is rejected
6	*Lcultivable and lisa*	0.0050	H_0 is rejected

H_0: No Cointegration. Source: Authors' own elaboration with data from Economist Impact (2022) and World Bank (2024), Stata

between the FSI and N_2O emissions. Likewise, row 5 presents the cointegration estimates between the FSI and temperatures. Finally, row 6 shows cointegration between the FSI and arable land where the null hypothesis of no cointegration is rejected and, therefore, the series are stationary.

The results of the cointegration estimates indicate that the variables are cointegrated, the idea suggests the possible presence of causality between the independent variables with the explained variable, that is, causality between sustainable development, climate change and food security.

4.3. Granger Causality

Granger causality is a fundamental analysis to detect relationships between variables. Dumitrescu and Hurlin (2012) propose the methodology to estimate Granger's (1969) causality test for panel data. The authors use individual Wald statistics of Granger non-causality averaged across cross-section units. The test consists of establishing the null hypothesis of non-existence of causality between two variables, the rejection criterion is based on detecting significance levels ≤0.05. Next, causality tests are performed for the different variables of interest for this research. Table 4 shows the causality tests between all the variables of interest with 1-year lag, there are important findings, the ANNI, CO_2, CH_4, N_2O, temperatures and arable land Granger-cause the FSI.

The previous results reinforce the research hypothesis that sustainable development and climate change are relevant to global food security. In summary, derived from this section, the cointegration shows a stable relationship among sustainable development, climate change and food security, and the Granger causality analysis indicates that sustainable development and climate change Granger-cause food security.

4.4. Static and Dynamic Panel Data Models

The use of panel data is very useful for applied research and therefore its use is increasingly frequent. Panel data is a sample

Table 4: Dumitrescu and Hurlin (2012) Granger non-causality test

Lag	Hipothesis	P-value	Observations
Lag order: 1	*Linna* does not Granger-cause *lisa*	0.0000	H_0 is rejected
	Lcarbono does not Granger-cause *lisa*	0.0000	H_0 is rejected
	Lmetano does not Granger-cause *lisa*	0.0083	H_0 is rejected
	Lnitroso does not Granger-cause *lisa*	0.0000	H_0 is rejected
	Temperatura does not Granger-cause *isa*	0.0000	H_0 is rejected
	Lcultivable does not Granger-cause *lisa*	0.0017	H_0 is rejected

Source: Authors' own elaboration with data from Economist Impact (2022) and World Bank (2024), Stata

of characteristics that countries have over time, that is, it is a simultaneous combination of time series and cross-sectional data. The model to be estimated is as follows:

$$y_{it} = \alpha + \beta X_{it} + u_{it} \tag{1}$$

where y_{it} is the dependent variable, in this case FSI, that changes depending on i = 1,…,n (n = 86 the number of countries) and t = 1,…,T (T = 9 the number of years), X_{it} are exogenous variables: ANNI, CO_2, N_2O, CH_4, temperatures and arable land, as usual u_{it} are random disturbances. Ordinary Least Squares (OLS) estimates will be biased as stated by Nickell (1981) and Arellano and Bover (1990), even for samples with large values of n and when T is small, in this case n = 86 y T = 9. To avoid biases, alternative estimates are proposed, such as estimates with dynamic panel data models, thus obtaining unbiased, optimal, efficient and consistent estimators. The use of panel data has several advantages because it examines a greater number of observations with more and better information, allowing for a greater number of variables and less multicollinearity between data of the explanatory variables, as well as greater efficiency in the estimation. It also solves the problem of omitted variables, since variables that do not change over time can be eliminated by taking differences. The dynamic model to be estimated is as follows:

$$y_{it} = \alpha y_{it-1} + \beta X_{it} + u_{it} \tag{2}$$

Where y_{it-1} is the lagged dependent variable. For the estimation of dynamic panel data, the Generalized Method of Moments (GMM) of Arellano and Bover (1995) is used. The GMM system estimator uses difference equations that are instrumentalized with the lags of the level equations, and also links instrumentalized level equations with the lags of the difference equations (Bond, 2002). The system GMM estimator establishes relaxed conditions to guarantee consistent estimators of the parameters even in the presence of endogeneity and with unobserved individual-country effects. This approach was developed by Arellano and Bover (1995), and later includes improvements that were made by Blundell and Bond (1998). The estimator thus obtained has advantages over estimators such as Fixed Effects and others, since it estimates unbiased parameters in small samples or in the presence of endogeneity. The optimal GMM estimator consists of a system consisting of a regression that jointly contains information in levels and in differences in terms of moment conditions (Arellano and Bover, 1995).

Next, results of both static and dynamic panel data estimations are shown. Table 5 presents the estimates of static panel data models: Ordinary least squares (OLS), cross section (BS), fixed effects (FE) and random effects (RE). The first column of the table shows that the dependent variable is the logarithm of the FSI, and all the independent variables are in logarithms, the constant, the coefficient of determination R^2, the Lagrange Multiplier test, the Hausman test, and the number of countries and observations. The second column of the Table 5 shows the OLS estimation which indicates that the coefficients of *linna*, *lcarbono*, *lmetan*o, *lcultivable* and the constant are significant, while the coefficients of *lnitroso* and *ltemperatura* are not significant, finally the coefficient of determination R^2 is 0.5519. The third column shows the cross-sectional BE estimates, the coefficients of *linna* and *ltemperatura* are significant, while the coefficients of the rest of the variables are not statistically significant; here the coefficient of determination R^2 is 0.6310. The fourth column presents the estimates by FE, the coefficients of *linna, lcarbono, lnitroso, lcultivable* and the constant are significant, while the coefficients of *methane* and *ltemperatura* are not significant, the coefficient of determination R^2 is 0.3567. The fifth column shows the estimation by RE, the coefficients of *linna, lmetano, lcultivables* and the constant are significant, while the coefficients of *lnitroso and ltemperatura* are not significant, the coefficient of determination R^2 is 0.5519.

The Lagrange Multiplier test is also presented, which yields a prob > chi2 = 0.0000, If the test is not rejected, there is no difference between OLS and RE, and it is preferable to use the OLS method. In this case, the null hypothesis is rejected indicating that the RE estimate is preferable to the OLS estimate. The Hausman test is then presented with prob > chi2 = 0.0000, the null hypothesis is rejected, indicating that the FE and RE estimators differ systematically and, therefore, the FE model is preferable. The null hypothesis of Hausman's test is that the RE and FE estimators do not differ substantially, if the null hypothesis is rejected, as in this case, FE is appropriate. In order to mitigate autocorrelation problems, dynamic panel data models are estimated; the main results are shown in Table 6. The estimates of dynamic panel data models are presented: Generalized Method of Moments (GMM) in differences in one stage and in two stages, GMM system in one stage and in two stages. The first column presents the dependent variable, the independent variables, the first and second order serial autocorrelation tests, and the Sargan test. The second column shows the estimation by GMM in differences in one stage, where only the *lisa*L1 coefficient is significant at 5%. The third column shows the estimation by GMM in two-stage differences, where the coefficients of *lisa*L1, *lmetano*, *ltemperatura* and the constant are significant, the first-order serial autocorrelation is admitted and the second-order serial autocorrelation is rejected, the Sargan test

Table 5: Static panel data estimates

Dependent variable: Lisa	OLS	BE	FE	RE
Linna	0.1326165 (0.000)	0.1037076 (0.000)	0.1863675 (0.000)	0.1326165 (0.000)
Lcarbono	0.0116904 (0.000)	1.74e-06 (0.899)	0.0198728 (0.000)	0.0116904 (0.000)
Lmetano	−0.0216765 (0.092)	−0.0280671 (0.199)	−0.0038592 (0.799)	−0.0216765 (0.092)
Lnitroso	−0.0180011 (0.230)	−0.0348851 (0.113)	0.0895547 (0.000)	−0.0180011 (0.230)
Ltemperatura	0.0032746 (0.765)	−0.0503539 (0.033)	0.0084504 (0.466)	0.0032746 (0.765)
Lcultivable	0.0358637 (0.004)	0.0019201 (0.895)	0.0643236 (0.019)	0.0358637 (0.004)
Constant	0.8845546 (0.000)	2.186384 (0.000)	−1.800254 (0.000)	0.8845546 (0.000)
R^2	0.5519	0.6310	0.3567	0.5519
ML BP				Prob>Chi2=0.000
Hausman test				Prob>Chi2=0.000
Number of countries	86	86	86	86
Number of observations	772	772	772	772

Source: Authors' own elaboration with data from Economist Impact (2022) and World Bank (2024), Stata

Table 6: Dynamic panel data estimates with GMM

Dependent variable: *Lisa*	GMM differences (one stage)	GMM differences (two stages)	GMM system (one stage)	GMM system (two stages)
*LisaL*1	0.7160727 (0.000)	0.7326047 (0.000)	0.6522521 (0.000)	0.7211535 (0.000)
Linna	0.0265567 (0.333)	0.0321352 (0.079)	0.0439288 (0.000)	0.036371 (0.000)
Lcarbono	0.0054623 (0.781)	−0.008681 (0.508)	0.0043475 (0.363)	−0.0034999 (0.444)
Lmetano	−0.0786552 (0.138)	−0.1056516 (0.000)	−0.0299939 (0.374)	−0.0504645 (0.012)
Lnitroso	0.0249854 (0.534)	0.0231674 (0.251)	0.0306109 (0.249)	0.027595 (0.097)
Ltemperatura	−0.0123598 (0.335)	−0.0178474 (0.000)	−0.0104794 (0.388)	−0.0175947 (0.000)
Lcultivable	−0.0210777 (0.626)	−0.010355 (0.699)	0.0067133 (0.758)	−0.0327921 (0.021)
Constant	1.084793 (0.063)	1.300772 (0.001)	0.3070238 (0.073)	0.6539753 (0.000)
First-order serial correlation	---	Prob>Z = 0.0002	---	Prob>Z = 0.0001
Second-order serial correlation	----	Prob>Z = 0.5381	----	Prob>Z = 0.5102
Sargan test	Prob>Chi2=0.0834	Prob>Chi2=0.4131	Prob>Chi2=0.0650	Prob>Chi2=0.2464
Number of countries	86	86	86	86
Number of observations	598	598	686	686

Source: Authors' own elaboration with data from Economist Impact (2022) and World Bank (2024), Stata admits the validity of the instruments and the correct specification of the model.

Likewise, the fourth column presents the one-stage system by GMM, where the coefficients of *lisa*L1 and linna are significant, while the coefficients of the rest of the explanatory variables are not significant. The fifth column shows the two-stage system by Generalized Method of Moments, where the coefficients of *lisa*L1, *linna, lmethane, ltemperatura, lcultivable* and the constant are significant, the first-order serial autocorrelation is not rejected and the second-order serial autocorrelation is rejected, the Sargan test admits the validity of the instruments and the correct specification of the model. Table 7 is presented below, the best-fitting model, with all the significant coefficients and with the expected signs, the first-order serial autocorrelation is admitted, the second-order is rejected, the correct specification of the model is admitted.

4.5. Discussion of Panel Data Results

The estimates indicate that the logarithm of the FSI shows a positive relationship with the lagged logarithm of the food security index and with the logarithm of ANNI, on the other hand, the logarithm of the FSI shows a negative relationship with the logarithm of temperatures. The model estimated in two-stage GMM system indicates that a 1% increase in ANNI will have an impact of 3.85719% on the FSI, while a 1% increase in temperatures causes a decrease of 1.68229% in the FSI in the whole sample. In summary, empirical evidence shows that ANNI has a positive impact on the FSI, that is, sustainable development has a positive impact on food security. Moreover, increasing temperature has negative effects on the FSI, that is, climate change has negative effects on food security. This supports the interaction of sustainable development, climate change, and food security. The two-stage system GMM estimation is the model that best explains the relationship between ANNI, temperatures and the FSI.

5. CLUSTER ANALYSIS

Cluster analysis will be used as an alternative research framework to investigate the interactions among sustainable development, climate change, and food security for the 86 countries. Cluster analysis is used as a fitting multivariate statistic because of its ability to identify inherent groupings among countries based on various simultaneous similarities (Mooi et al., 2018). Mainly, the use of the k-means clustering algorithm has been based on its efficacy in sustainability research regarding pattern identification among countries in terms of environmental and economic indicators (Xu and Wunsch, 2010). The k-means algorithm works by dividing observations into k groups minimizing the within-cluster sum of squares (*WCSS*) that is represented as:

$$WCSS = \sum_{i=1}^{k} \sum_{x \in C_i} x - \mu_i^{\,2} \tag{3}$$

Where C_i is the i^{th} cluster, x is an observation (country) in that particular cluster, and μ_i is the centroid of cluster C_i (Lloyd, 1982). To minimize this function, the algorithm creates clusters where each group of countries has maximum internal similarity and a maximum difference with other nations located in other clusters. The data preprocessing that preceded running the k-means algorithm involved a normalization process to optimize results. Since the seven variables under study had very diverse scales that ranged from percentages for arable land to trillions of USD for ANNI and millions of kilotons for emissions, normalization had to be used to prevent large-magnitude variables from affecting the process of clustering (Kassambara, 2017). Z-score normalization is carried out by applying $z = (x-\mu)/\sigma$, where x represents the original value of a variable for a given country, μ is the mean of that variable across all countries, and σ is the standard deviation for all countries. After normalization, the optimal cluster size is determined using two more approaches: the elbow method and silhouette analysis (Kodinariya and Makwana, 2013). The elbow method evaluates the relationship between the within-cluster sum of squares and cluster size and picks out at what point adding more clusters provides decreasing returns. On the other hand, silhouette analysis measures how well every country is assigned to its cluster to other clusters, hence giving a measurement of cluster cohesion and separation. The silhouette value for a particular country *i*:

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), a(i)\}} \tag{4}$$

Where $a(i)$ refers to the average distance between country i and other countries in the same cluster, and $b(i)$ refers to the average distance between country i and its closest neighboring cluster (Rousseeuw, 1987). The average silhouette width for all countries is used to measure cluster effectiveness and ranges from −1 to 1; higher values indicate better separation between clusters. The findings of the optimization analysis are presented in Figure 7. The left panel of Figure 7 shows the *WCSS* as a function of cluster numbers, representing the elbow technique. The right panel displays silhouette values for different cluster numbers. The graph of *WCSS* displays a clear elbow at k = 2 where the value of *WCSS* goes down from 403.16 at k = 2 to 302.34 at k = 3, representing a decrease of 25%. After this point, the decreased slope is increasingly smaller.

The silhouette analysis in the right panel of Figure 7 confirms a peak silhouette value of 0.73 at k = 2. This result reflects high cohesion within the clusters and good separation between them. Considering configurations with more than a significant cluster number (k = 4 and k = 5), the resulting silhouette values are moderately reduced at 0.32 and 0.31, respectively, much less than that found at k = 2. Combining the results of both approaches as

Table 7: Best model

Dependent variable: Lisa	GMM system (two stages)
LisaL1	0.7026126 (0.000)
Linna	0.0385719 (0.000)
Ltemperatura	−0.0168229 (0.000)
Constant	0.299228 (0.001)
First-order serial correlation	Prob>Z = 0.0001
Second-order serial correlation	Prob>Z = 0.4910
Sargan test	Prob>Chi2=0.4193
Number of countries	86
Number of observations	686

In parentheses the corresponding standard error. Source: Authors' own elaboration with data from Economist Impact (2022) and World Bank (2024), Stata presented in Table 8, k = 2 is most appropriate for cluster numbers for the given data, with an optimal balance between model parsimony and explanatory sufficiency. This agrees with current advice in cluster research practice (Madhulatha, 2011; Kodinariya and Makwana, 2013). The k-means algorithm successfully partitioned the sample of 86 nations into two well-differentiated clusters with very different features. The mean values for every variable by cluster are presented in Table 8. Appendix 1 contains the countries belonging to each cluster.

Cluster 1 contains 84 countries (97.7% of the sample) and is characterized by relatively lower food security (mean FSI = 61.28), substantially lower ANNI (358 billion USD), higher CO_2 emissions (763 million tons), lower methane and N_2O emissions, higher average temperatures (18.49°C), and a slightly higher percentage of arable land (18.41%).

Contrasting sharply with this trend is Cluster 2, which contains only two members: China and the United States, making it a notable outlier in the analysis. This cluster has very high levels of food security (mean FSI = 73.56), a very high ANNI (12.3 trillion USD), low CO_2 emissions (45.4 million tons), as well as very high emissions of CH_4 (926 million tons) and N_2O (399 million tons), reduced average temperatures (12.59°C), and relatively lower arable land.

5.1. Visual Analysis of Cluster Distributions

Figure 8 displays a radar plot that presents the two groups' standardized profiles, thus capturing a multivariate overview of the distinctive profiles that make the groups unique. Figure 8 successfully communicates a graphical representation of the intricate patterns revealed by the cluster analysis, thus facilitating easy comparison of the concurrent fluctuations of the seven variables across the groups.

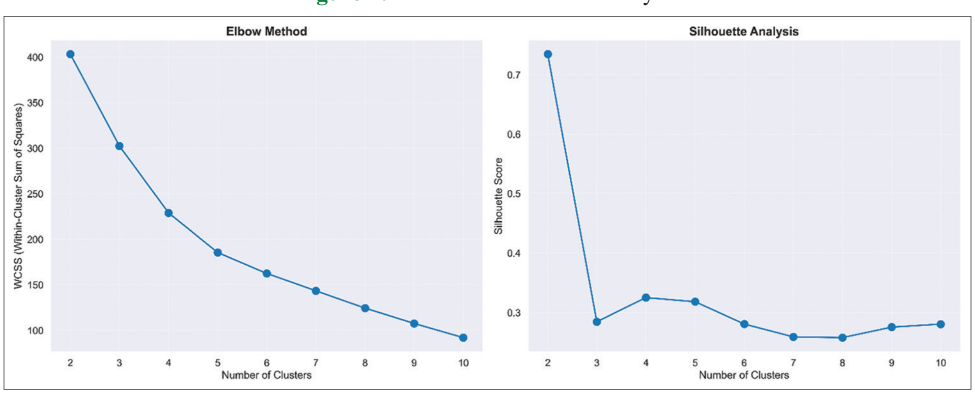
The radar plot displays the important differences in the attributes of Cluster 1 (in purple) and Cluster 2 (in yellow). Cluster 2, including the United States and China, displays a distinctive pentagonal shape with significant extensions along the three dimensions of ANNI, CH_4 and N_2O emissions. Standardized values for the two nations along these three dimensions are significantly higher than those of Cluster 1. Most strikingly, the enormous difference in income, with Cluster 2 nearing the maximum normalized value, underscores the incredible economic power of the two nations.

The Food Security dimension has high values for Cluster 2, yet the level of disparity is not comparable to that found regarding economic resources. This result is supported by econometric tests showing a positive correlation between ANNI and FSI. It is concluded that the high economic progress achieved by China and the United States is a factor of greater food security. Notably, while nations in Cluster 2 present high methane and N_2O emissions, their normalized CO_2 emissions are lower than those in Cluster 1. This paradoxical result, backed by scatter plot analyses, can be explained by differences between the two clusters in terms of their economies' structure and energy use efficiency. While being significant emitters in absolute terms, the United States and China may show a more efficient use of carbon compared to the economic performance of some countries in Cluster 1 that have followed carbon-intensive development paths (Friedlingstein et al., 2024).

The temperature dimension shows that Cluster 2 has lower temperatures than Cluster 1, which is consistent with the geographical locations of China and the United States in temperate climatic regions. Conversely, many countries in Cluster 1 are in tropical and desert regions with high average temperatures. This difference may partially explain the higher levels of food security in Cluster 2, as extreme temperatures are known to harm agricultural productivity (Ortiz-Bobea et al., 2021).

The characteristic of arable land suggests that the two groups have comparatively similar standardized scores, meaning that the ratio of land used for farming cannot be a differentiating factor. As a result, it suggests that the quality and effectiveness of land use, as opposed

Figure 7: Elbow and silhouette analysis



Source: Authors' elaboration

Table 8: Clustering and centroid results

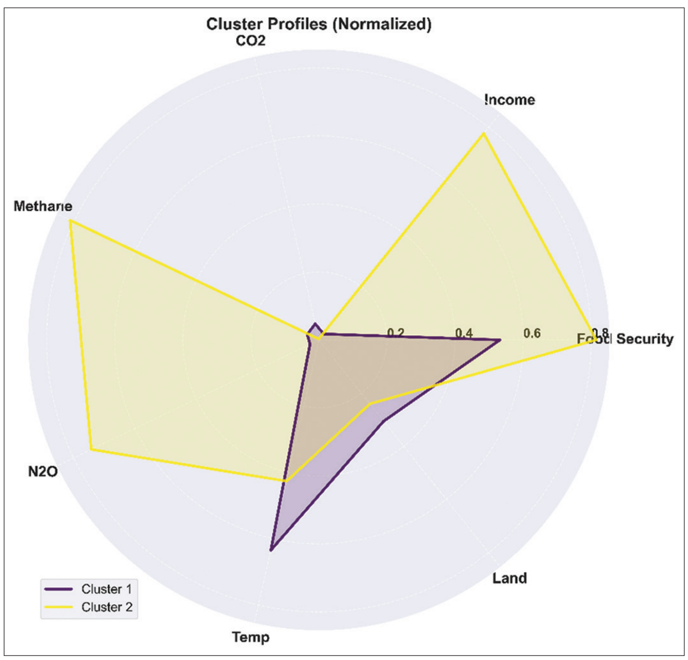
Cluster	Food security index	Adjusted net national income	CO_2	Methane	N_2O	Temperature	Arable land
Cluster 1	61.28	357579495315.89	763029.90	44759.89	15807.71	18.49	18.41
Cluster 2	73.56	12333024062682.40	45420.07	926166.98	398983.49	12.59	14.54

Source: Authors' elaboration

to the mere area of land available, could have a more important function in explaining differences in the level of food security.

The radar plot, in Figure 8, is a key tool for presenting the intricate, multi-dimensional relationships between sustainable development, indicators of climate change, and food security. The different configurations of the two groups emphasize the varying modes of interaction about economic resources, greenhouse gas emissions, and climatic conditions among the two groups of nations, thus demonstrating trends that could remain hidden with univariate or bivariate analyses. The vast discrepancies among the geometries of the two groups also support the contention that China and the United States operate under significantly different conditions regarding the dynamics of sustainable development, climate change, and food security compared to the global scale. The extensive economic resources owned by these nations offer a protective shield against the potentially harmful effects of high methane and nitrous oxide emissions on the security of foods. This trend is absent in most other nations (Fan et al., 2021).

Figure 8: Radar plot for clustering



Source: Authors' elaboration

5.2. Cluster Analysis Removing China and USA

After identifying the unique roles of China and the United States, another cluster analysis is carried out on the remaining group of 84 countries to examine more complex patterns. Figure 9 presents the optimization results relevant to the overall analysis. The elbow method (left plot) discloses a more subtle trend than the first analysis, with a sharp decline from 2 to 4 groups and a muted decline thereafter. The silhouette analysis (right plot) shows best values at k = 5 (0.293) and k = 8 (0.304), suggesting significant groupings at the indicated levels.

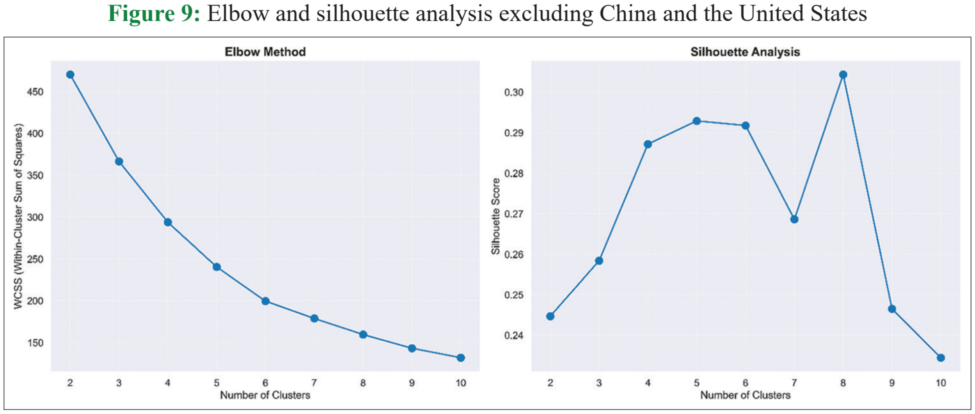
Considering the methods utilized and the nature of the results achieved, the eight-cluster solution was chosen for the next step of the analysis. It produces a more precise typology of country profiles with the added advantage of having good silhouette scores. The eight-cluster solution identifies discrete groupings of nations with different profiles across the seven variables of concern presented in Table 9. Countries included in each group are presented in Appendix 2.

Cluster 1 has 23 countries with high food security (73.02), medium income (422 billion USD), medium CO_2, and low methane and N_2O emissions, combined with cooler climates (11.72°C) and medium shares of arable land (15.37%). Developed European countries and industrialized economies like Austria, Finland, Italy, the Netherlands, New Zealand, Norway, South Korea, and Switzerland comprise this category.

Cluster 2 (31 countries): Low food security (53.12), low income (113 billion USD), moderate CO_2 emissions, low-to-moderate methane and N_2O emissions, high temperatures (24.74°C), and low arable land (11.30%). This cluster comprises mainly developing countries in Africa, the Middle East, and Southeast Asia, including Algeria, Angola, Ethiopia, Kenya, Kuwait, Madagascar, and Saudi Arabia.

Cluster 3 (Brazil): Moderate food security (66.68), low income (44.2 billion USD), very low CO_2 emissions, very high methane (438,255 kt) and N_2O emissions (175,325 kt), high temperatures (24.82°C), and low arable land (6.55%). Brazil stands alone due to its unique combination of moderate food security despite high emissions from agriculture and deforestation.

Figure 9: Elbow and silhouette analysis excluding China and the United States



Source: Authors' elaboration

Table 9: Clustering and centroids results excluding China and the United States

Cluster	Food security index	Adjusted Net national income	CO_2	Methane	N_2O	Temperature	Arable land
Cluster 1	73.0	422076707297.9	162197.2	17558.7	7832.1	11.7	15.4
Cluster 2	53.1	113173196675.4	257862.5	32747.2	10943.8	24.7	11.3
Cluster 3	66.7	44190231919.9	19956.5	438255.1	175325.5	24.8	6.5
Cluster 4	62.1	55610355590.2	10983355.1	19028.4	4380.5	23.4	7.2
Cluster 5	77.2	2733192851666.8	81863.5	48505.9	30783.5	11.7	26.0
Cluster 6	55.6	57602925111.8	339606.3	13395.9	7498.2	17.6	43.1
Cluster 7	58.7	615884260119.4	543553.4	142877.8	54039.2	17.2	15.4
Cluster 8	66.3	1119394668514.8	73597.6	587615.2	63261.1	2.6	7.4

Source: Authors' elaboration

Cluster 4, which has four countries, exhibits a moderate food security level (62.10), a low-income level (55.6 billion USD), very high CO_2 emissions (10,983,355 kt), low emissions of methane and N_2O, high-temperature averages (23.39°C), and low arable land (7.24%). This small cluster includes Côte d'Ivoire, Ecuador, Oman, and Uruguay and is characterized by extremely high carbon emissions compared to economic productivity.

Cluster 5 (4 countries): Very high food security (77.24), very high income (2.73 trillion USD), moderate CO_2 emissions, moderate methane and N_2O emissions, cool temperatures (11.68°C), and high arable land (25.99%). This cluster comprises major European economies and Japan: France, Germany, Japan, and the United Kingdom.

Cluster 6, which has 14 countries, is defined by low food security (55.64), low-income level (57.6 billion USD), medium carbon dioxide emission, very low methane and nitrous oxide emissions, mean temperatures (17.55°C), and high percentage of arable land (43.13%). This cluster includes countries with agricultural potential but with food security constraints, such as Bangladesh, Belgium, Bulgaria, Denmark, Hungary, Romania, and Ukraine.

Cluster 7 (6 countries): Moderate food security (58.66), high income (616 billion USD), high CO_2 emissions, high methane and N_2O emissions, moderate temperatures (17.22°C), and moderate arable land (15.39%). This cluster includes large economies with significant agricultural and industrial sectors: Argentina, Cameroon, Canada, Indonesia, Mexico, and Pakistan.

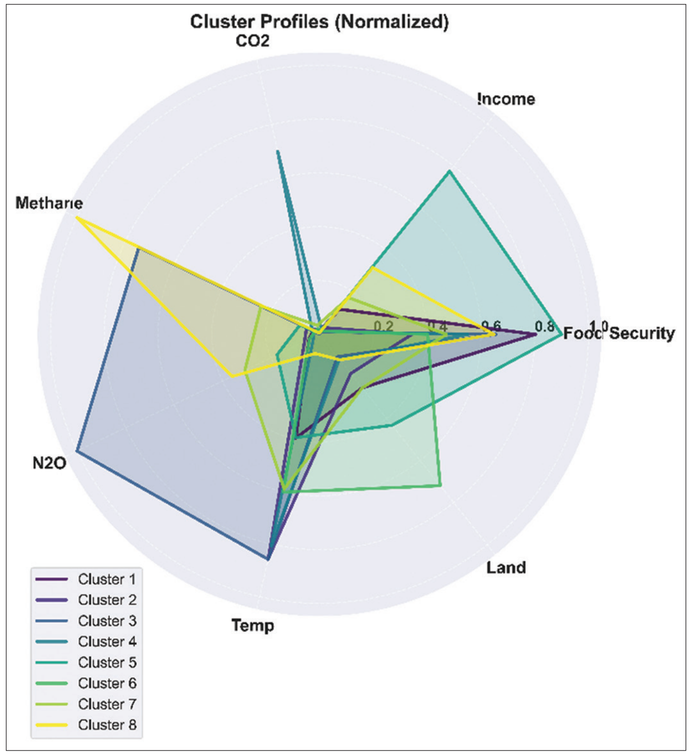
Cluster 8 (Russia): Moderate food security (66.33), high income (1.12 trillion USD), moderate CO_2 emissions, very high methane emissions (587,615 kt), moderate N_2O emissions, very low temperatures (2.59°C), and low arable land (7.43%). Russia forms its cluster due to its unique combination of extreme cold, high methane emissions, and moderate food security despite challenging climatic conditions.

5.3. Visual Analysis of Cluster Distributions Excluding China and the United States

The radar plot in Figure 10 displays the specific features of each of the eight clusters in comparison to the seven normalized variables under study.

The radar plot for the clustering analysis in Figure 10, excluding China and the United States, provides the following results:

Figure 10: Radar plot for clustering excluding China and the United States



Source: Authors' elaboration

a) Economic-food security relationship: Clusters with higher normalized income values (Clusters 5 and 7) also tend to show higher food security, reinforcing the positive relationship in the econometric analysis.
b) Different groups have different emission patterns. Cluster 3, Brazil, and Cluster 8, Russia, have high methane emissions, and Cluster 4 shows relatively high CO_2 emissions. These show that policies to address climate change mitigation need to be tailored to suit the unique characteristics of a particular country.
c) Temperature-food security relationship: Clusters with the highest food security (Clusters 1 and 5) have lower temperatures, while clusters with the lowest food security (Clusters 2 and 6) tend to have higher temperatures, supporting the negative temperature-food security relationship found in the econometric analysis.
d) Cluster 6 has a very high measure for arable land but, at the same time, shows relatively low food security levels. The finding suggests that access to land alone does not guarantee

food security if economic resources and efficient agricultural methods are lacking.

Complete cluster analysis yields more complex patterns than the initial two-cluster solution. While the China-US cluster remains prominent with its great economic size, the more sophisticated examination finds excellent differences in how different groups of nations prioritize economic development, environmental issues, and food security. These findings emphasize the need for policy intervention attuned to the unique needs and opportunities faced by different groups of nations.

5.4. Discussion of Cluster Results

Cluster analysis identifies a broad hierarchical distinction across the international landscape of sustainable development, climate change, and food security. At the top level, a striking disparity exists between China and the USA (labeled as Cluster 2 in the initial analysis) and the rest of the world (Cluster 1), highlighting the outstanding economic hegemony as well as the greenhouse gas emitting patterns of these two nations (Crippa et al., 2023). The radar plots (Figures 8 and 10) indicate this overarching division, with Figure 8 highlighting the sharply divergent profiles of these two economic giants compared to the rest of the world.

The significant economic power displayed by the United States and China, as measured using the Agricultural Nutritional Index (ANI), appears to augment their respective food security indicators, even under high CH_4 and N_2O emissions. The findings also show that economic assets can counter climate change's impacts on food stability, in addition to supporting the findings of Fan et al. (2021) and Tubiello et al. (2022). The uneven distribution of economic resources, as presented in Figure 8, highlights that wealth is distributed in two nations only, affecting the development of world policies to achieve the goal of food stability.

The exclusion of China and the United States allows a more in-depth examination that identifies eight distinct clusters (Figure 10), with the first Cluster 1 showing particular diversity. The cluster solution with more points allows for the identification of several subcategories with distinct features: advanced economies with high food security and moderate emissions (Clusters 1 and 5), developing economies with low food security and varying patterns of emissions (Clusters 2, 4, and 6), and exceptional case examples such as Brazil (Cluster 3) and Russia (Cluster 8), which are represented as singleton clusters with a unique set of variables.

Advanced cluster analysis confirms the correlation of economic resources with food security as evidenced by Cluster 5, which consists of France, Germany, Japan, and the United Kingdom, with the highest food security indexes (77.24) along with high ANNI values of 2.73×10^{12} USD. However, the research identifies that the correlation is not simple. For instance, the nations that belong to Cluster 6 have a high percentage of cultivable land (43.13%) but have relatively low food security of 55.64, which suggests that land is not a guarantee of food security if economic resources and proper farm systems are lacking.

Temperature patterns across different cluster groups provide improved insights into the temperature-food security relationship. Clusters with the best conditions supporting food security (Clusters 1 and 5) have the lowest average temperatures documented (11.72°C and 11.68°C, respectively), while those with compromised food security, such as Cluster 2, have the highest average temperature of 24.74°C. The above finding is corroborated by findings of econometric studies that have revealed a negative relationship between temperature and the level of food security, thus supporting past studies that posit an adverse effect of rising temperatures on farm productivity in areas that already enjoy high-temperature conditions (Ortiz-Bobea et al., 2021; Tigchelaar et al., 2023).

The heterogeneous relationship between greenhouse gas emissions and food security across different groupings, as demonstrated through radar plots and univariate analyses, indicates that one-size-fits-all policy-making to address the climate emergency could be ineffective or even counterproductive if it ignores these underlying structural differences (Barrett et al., 2022). For example, the economies grouped in Cluster 4 have notably high CO_2 emissions in their economic output compared to other groupings, pointing to specific challenges in the transition to low-carbon development pathways, while Clusters 3 and 8 face specific challenges with methane emissions.

Many countries in Clusters 2 and 6 also face reduced food security and shrinking economic means, thus pointing to increased vulnerability to the impacts of climate change. Such an observation aligns with research findings showing that economically vulnerable countries face disproportionately high barriers to adequately re-structuring their food systems to respond to climate change's impacts (Niles et al., 2021; Kummu et al., 2021). The radar charts in Figures 8 and 10 are handy in depicting these multifaceted vulnerabilities, showing how different clusters face distinct combinations of challenges across the seven variables considered.

6. CONCLUSION

The empirical evidence presented in this research reveal that GHG emissions such as CO_2, CH_4, and N_2O, which cause an increase in temperature and are used in this work as proxies for climate change, have negative effects on the Food Security Index, while ANNIE, a proxy for sustainable growth, has a positive impact on the Food Security Index. Greater efforts to increase ANNIE for environmental degradation, as well as a decrease in GHG emissions and temperature would contribute to promoting food security in the 86 economies analyzed in this research, which will result in the well-being of the world population.

The impact climate change on food security and sustainable development is assessed in 86 economies, whose information is available in the period 2012-2020. The empirical evidence from the best model, two-step system GMM dynamic panel data, supports the hypotheses of this work: There is a positive impact of sustainable development on food security and a negative effect of climate change on food security, in the countries that were the object of this investigation. Derived from this research, it is suggested that decision makers create and implement strategies to promote sustainable development, as well as mitigate climate change, reduce CO_2, CH_4, and N_2O emissions, and stabilize temperatures, to boost food security, as well as contribute to the well-being of the world population.

The results obtained from cluster analysis complement the econometric analysis by clarifying structural differences between countries that panel data models might overlook. Initially, two clusters are identified: One with only two members, China and the United States, and the other with the remaining countries. Subsequently, a cluster analysis is performed that eliminates China and the United States to identify more complex patterns. In this case, eight clusters are identified that share similar characteristics in the dynamics of all the variables under study, allowing for a more in-depth examination. There are now two clusters with only one member, Brazil and Russia. Other cluster is determined by France, Germany, Japan, and the United Kingdom, all of them from G7. The largest cluster includes 31 countries. Radar charts allow the specific characteristics of each of the eight clusters to be visualized in relation to all the variables under study.

It worth noting that the empirical findings obtained from cluster analysis in eight groups are more complex than often assumed and vary significantly according to countries' development stages and structural characteristics. These results have important implications for environmental policy design, suggesting the need for cluster-specific approaches rather than the one-size-fits-all solutions typically proposed in econometric approaches.

Finally, more research is needed to include more countries and more years when data are available. In addition, future research will use alternative causality tests that include machine learning and neural networks.

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APPENDIX

Appendix 1: Clustering including all countries

Cluster	Number of countries	Countries
Cluster 1	84	Algeria, Angola, Argentina, Austria, Azerbaijan, Bahrain, Bangladesh, Belarus, Belgium, Benin, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Canada, Colombia, Congo (Dem. Rep.), Costa Rica, Czech Republic, Cote d'Ivoire, Denmark, Dominican Rep., Ecuador, Egypt, El Salvador, Ethiopia, Finland, France, Germany, Ghana, Greece, Haiti, Hungary, Indonesia, Israel, Italy, Japan, Kazakhstan, Kenya, Kuwait, Laos, Madagascar, Malaysia, Mali, Mexico, Nepal, Netherlands, New Zealand, Nicaragua, Norway, Oman, Pakistan, Paraguay, Peru, Philippines, Poland, Portugal, Romania, Russia, Rwanda, Saudi Arabia, Senegal, Serbia, Sierra Leone, Slovakia, South Africa, South Korea, Spain, Sri Lanka, Sudan, Sweden, Switzerland, Tajikistan, Tanzania, Togo, Tunisia, Uganda, Ukraine, United Arab Emirates, United Kingdom, Uruguay
Cluster 2	2	China, United States

Appendix 2: Clustering excluding China and the United States

Cluster	Number of countries	Countries
Cluster 1	23	Austria, Azerbaijan, Belarus, Botswana, Costa Rica, Czech Republic, Finland, Greece, Israel, Italy, Kazakhstan, Netherlands, New Zealand, Norway, Peru, Poland, Portugal, Slovakia, South Korea, Spain, Sweden, Switzerland, Tajikistan
Cluster 2	31	Algeria, Angola, Bahrain, Benin, Burkina Faso, Cambodia, Colombia, Congo (Dem. Rep.), Dominican Rep., Egypt, Ethiopia, Ghana, Kenya, Kuwait, Laos, Madagascar, Malaysia, Mali, Nepal, Nicaragua, Paraguay, Philippines, Saudi Arabia, Senegal, Sierra Leone, South Africa, Sri Lanka, Sudan, Tanzania, Tunisia, United Arab Emirates
Cluster 3	1	Brazil
Cluster 4	4	Cote d'Ivoire, Ecuador, Oman, Uruguay
Cluster 5	4	France, Germany, Japan, United Kingdom
Cluster 6	14	Bangladesh, Belgium, Bulgaria, Burundi, Denmark, El Salvador, Haiti, Hungary, Romania, Rwanda, Serbia, Togo, Uganda, Ukraine
Cluster 7	6	Argentina, Cameroon, Canada, Indonesia, Mexico, Pakistan
Cluster 8	1	Russia