

## Article

# Effect of Agricultural Employment and Export Diversification Index on Environmental Pollution: Building the Agenda towards Sustainability

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**Abstract:** Agricultural activities have a significant impact on environmental quality, because they generate waste that pollutes water and soil. In parallel, the supply of products has diversified in recent years to meet growing demand, exerting strong pressure on nature's capacity for regeneration and absorption of waste. This research aims to examine the impact of agricultural employment and the export diversification index on ecological footprints, using advanced techniques of panel data econometrics. This relationship is moderated by population density and real per capita product. Cross-section dependence and slope homogeneity were included in the econometric models. The cointegration and causality analysis was reinforced by estimating the short- and long-term elasticities, using the AMG, CCE-MG, FMOLS, and DOLS models. Using annual data for 96 countries, we found a heterogeneous impact of agricultural employment and the export diversification index on ecological footprint, between the short and long term. The findings reveal that the increase of the product increases the pressure on the ecological footprint. The achievement of SDGs must include joint efforts between countries, and not in isolation. Those responsible for environmental policy should promote the idea that production must be friendly to the environment and promote the green growth of countries. The adoption of new technology, higher productivity agricultural employment, and the regulation of exports of sustainable products can contribute to achieving environmental sustainability.

**Keywords:** agricultural employment; export diversification index; ecological footprint; FMOLS; AMG; CCE-MG

## 1. Introduction

The environmental challenges derived from climate change constitute a source of concern for achieving sustainable economic development. Consequently, the recent literature on the causes of environmental degradation has grown rapidly, particularly the evidence on the nexus between economic activity and greenhouse gas emissions. However, environmental sustainability requires a more thorough and meticulous analysis of all dimensions of environmental degradation. Various empirical studies have noted the importance of using a more holistic and comprehensive indicator of the deterioration of nature and suggest using

the ecological footprint (EF) as a measure of the destruction of nature [1–3]. According to data from the Global Footprint Network (2021), until 2008, the EF increased in most groups of countries. As of that year, the EF experienced a slight reduction in aggregate form. However, there are specific cases of countries where the behavior of EF is more dynamic, both in its growth and in its decrease [4]. In practice, EF is a more comprehensive indicator of the state of environmental deterioration, concerning polluting gas emissions [5,6]. Therefore, it is necessary to identify the factors that determine the behavior of EF in the short and long term, in light of the new econometric techniques available. This action will help those responsible for environmental policy-making decisions to achieve the environmental and economic sustainability of society.

There are several economic, social, and institutional aspects that can influence the temporal dynamics of EF [7–9]. However, in this research, we focus on two components that have not received sufficient attention in the previous literature and deserve special attention in the academic and political debate on environmental pollution: agricultural employment, and the export diversification index. In order to obtain consistent conclusions, the impact of the two variables on EF is moderated by the real per capita product and the population density. Development levels determine the strength of the relationship between economic and environmental variables [10]. It is well known that the level of development of countries is associated with the institutional framework, the effectiveness of the government, human capital, and environmental awareness, among other aspects that affect the quality of environmental policies. Therefore, the total sample of 96 countries was classified into four subgroups, using the gross national income to group them. The total sample of countries was classified into high-income countries (HIC), upper-middle-income countries (UMIC), lower-middle-income countries (LMIC), and low-income countries (LIC). Econometric estimates were made for the global panel of 96 countries and the panels of the four groups of countries.

First, we employed the cross-sectional dependence test formalized by Bailey et al. [11]. The findings of this stage indicated that there is cross-sectional dependence in the five series in all panels. This result is informative because it conditions the use of the unit root and second-generation cointegration tests. Both tests were systematically estimated as the starting point for subsequent econometric models [5,12–14]. In practice, the results indicate that on average, the changes in the values of the series in a country are associated with the changes in the values of the series in the rest of the countries. Usman et al. [7] and Nathaniel and Khan [15] used the CD test to examine the nexus between EF and the factors that determine it. Second, we evaluated the homogeneity in the slope between the panels using the Pesaran and Yamagata [16] test. We found enough evidence to reject the hypothesis of homogeneity of the slope between the panels. The later econometric models consider the cross-sectional dependence and the heterogeneity in the slope, to estimate the models and obtain consistent and unbiased parameters. Third, we estimated the stationarity of the series using the second-generation unit root test proposed by Herwartz and Siedenburg [17]. The results confirmed the hypothesis that the series has an integration order of one. The Herwartz and Siedenburg [17] test has been recently used in the environmental economics literature, particularly in research examining the link between environmental quality and human activity [18,19].

Fourth, we used a second-generation cointegration test to estimate the long-term relationship between the EF and the four covariates. Specifically, we performed Westerglund's [20] second-generation cointegration test. The findings show a cointegration relationship between EF, agricultural employment, export diversification index, population density, and real per capita product. In practice, this result implies that changes in regressors cause a significant change in EF, which is evident in the long term. Westerglund's [20] test has been used in recent literature that examined the factors that influence levels of contamination [21,22]. Fifth, in order to broaden the debate on the policy implications that the countries analyzed should adopt, we estimated the short- and long-term elasticities between the covariates and the FE. Specifically, we used the AMG and CCE-MG models.

Finally, the short and long-term analysis of the previous models were reinforced by estimating the FMOLS and DOLS models. The AMG and CCE-MG models show that the real product per capita increases the ecological footprint in all groups of countries, except in the LICs. This result offers an important lesson in environmental policy, because it indicates that economic growth is integrally destroying nature. This fact raises the need for a thorough review of the current development model, which is incompatible with environmental sustainability. In the short term, agricultural employment, the export diversification index, and population density do not significantly impact EF, although the impact differs with long-term elasticities.

The results of the long-run models differ from the short-term coefficients in the size of the elasticities. In general, long-term elasticities are more significant than short-term elasticities. At all levels of development, the product and export diversification index increase the EF. While agricultural employment decreases EF in HICs and UHICs, in LICs and LMICs, agricultural employment reduces EF. A possible explanation for this result is that environmental degradation is more visible and quantifiable in the long term. On the other hand, population density reduces EF in all countries, except the LICs. This result suggests that population concentration generates economies of scale concerning environmental pollution. Namely, pollution increases with population concentration, but at a decreasing rate. In the recent environmental literature, various empirical works have used this instrumental framework to verify the impact of economic and social variables on environmental quality [14,23,24].

These results highlight the importance of those responsible for environmental policy, including temporal dynamics, in applying climate change mitigation and adaptation strategies. Likewise, we found sufficient evidence to reject the hypothesis that EF does not cause the product in the global panel and the HICs. The underlying logic behind this result is that economic growth is occurring at the expense of environmental degradation. Furthermore, we found that the export diversification index causes EF in the Granger sense in the global panel, UMICs, and LMICs. Finally, we found a causal relationship that connects agricultural employment to EF in the HIC, ULIC, and LIC. Economic agents face the enormous challenge of applying mechanisms to mitigate environmental deterioration in blocks of countries, and not in isolation. Economic, social, and political integration between countries can be a tool to coordinate more effective pro-environmental policies that guarantee environmental sustainability for future generations. The joint application of environmental policies will increase their quality and guide the search for a more environmentally friendly development model. In general, this research contributes to highlighting the combined effect of agricultural employment and the export diversification index on EF and the combination of short- and long-term methods.

The remainder of the article is organized as follows: In the second section, we include a review of the previous literature on environmental degradation, focusing on the works that use EF to measure the deterioration of nature. In the third section, we describe the characteristics of the data. In the fourth part, we present the stages of the methodological strategy. In the fifth section, we report the results and discuss them with the recent literature. In the last section, we systematize the research findings into conclusions and propose pro-environmental policy implications to mitigate the adverse effects of natural pollution.

## 2. Literature Review

The theoretical framework of the environmental Kuznets curve (EKC) has been used in recent decades to examine the relationship between economic activities and the environment [25]. The literature that studies this relationship frequently uses carbon dioxide emissions as an indicator of the degradation of nature [26–28]. However, polluting gas emissions do not reflect the totality, complexity, and depth of the environmental problems caused by human activity [4,6]. In this sense, several empirical investigations suggest using comprehensive indicators of environmental quality to improve the quality and efficiency of pro-environmental policies. The EF allows evaluating the impacts of human activity on

nature using a criterion of sustainability of economic and social development [23,29–31]. High values of EF are associated with high consumption of natural resources, which implies a negative impact on the environment [32]. Some previous research concluded that economic growth increases EF, but certain factors can attenuate the positive relationship between output and HE. For example, activities such as agriculture, fishing, livestock, and infrastructure construction generate a high ecological impact [15,22,33–36]. However, the dynamics of the relationship between the consumption of natural resources and environmental sustainability varies from one country to another, depending on the countries' industrial structure and institutional framework [37]. Countries that base their economies mainly on agriculture and natural resource extraction have a high EF. This fact results from the excessive use of energy from polluting sources and the high levels of consumption in cities [21,38].

The analysis of the factors that determine the behavior of EF has focused on economic aspects and has been extended to institutional, political, and social components [29,39]. Although the evidence for the sources of contamination has increased in recent years, there is no consensus on the findings or the suggested policy implications. A combination of economic and institutional aspects, as determinants of environmental deterioration, can improve the inferences obtained from the econometric estimates. The development of new quantitative techniques facilitates the correction of possible biases of the estimators, generating a broader and more robust analytical framework. For example, Ahmed et al. [32] used the CUP-FM and CUP-BC methods and found that exports reduce environmental degradation in G7 countries. In contrast, Dogan et al. [40] revealed that exports are the most common cause of anthropogenic pressure on the environment in the long term. Several recent investigations have included the role of the underground economy as a factor that explains the pollution of nature [4]. Table 1 summarizes the main results of the factors that influence cross-sectional heterogeneity and the temporal dynamics of EF.

**Table 1.** Summary of the literature review.

Author [s]	Study Area	Time	Variable(s)	Methodology	Findings
Ahmed et al. [29]	Japan	1971–2016	EF, GDP, ENG, GLOB, FD, PD, R&D	The asymmetric and symmetric ARDL	Symmetric ARDL: GLOB and FD increase EF; Asymmetric ARDL: Positive and negative changes in GLOB reduce EF. FD stimulate EF. ENG increases EF. PD reduce EF. Support for the EKC hypothesis. Causality from GDP to EF
Sarkodie [30]	Australia, Brazil, China, Germany, India, Japan, Russia, and US	1961–2016	ECF, BIO, EF, ES, GDP, GDPC, PD, TRD	CIPS, CADF	Disparity in ECF and EF between income groups converge in the long-run
Sharif et al. [41]	Top ten solar energy-consuming countries	1990–2017	SE, EF	QQ regression	SE mitigates EF at various quantiles, except India and the United Kingdom. Bidirectional causality between EF and SE
Sharma et al. [23]	Eight developing countries of South and Southeast Asia	1990–2015	EF, GDP, GDP <sup>2</sup> , GDP <sup>3</sup> , RE, LEXP, PD	CS-ARDL	The N-shaped EKC is valid. RE reduces EF. PD increases EF. LEXP is not significant
Yao et al. [31]	BRICS and the Next-11 economies	1995–2014	ENE, EF, FD, NR, INV, IND, CORR, TRD	DEA method, GMM model	EF can be decreased by FD. EF can be decreased by CORR. INV is a determinant of ENE. Bi-directional causal relationships between ENE, EF, FD, CORR, NR, INV, IND, TRD
Ahmed et al. [38]	China	1970–2016	EF, GDP, NR, URB, HC, INT, ECF	The Bayer-Hanck cointegration, Bootstrap causality	NR, and URB increase EF. HC and INT reduce EF. Unidirectional causality from NR and URB to EF
Ahmed et al. [38]	G7 2ountries	1971–2014	EF, CO <sub>2</sub> , GDP, ENG, URB, HC, IMP, EXP, FDI	CUP-FM, CUP-BC	URB increases EF. HC reduces EF. GDP, IMP, and ENG increase EF. EXP, FDI, and reduce EF. Unidirectional causality from HC and URB to EF. Bidirectional causality between URB, GDP, and HC
Alvarado et al. [5]	77 countries	1996–2016	EF, AQ, R&D, AGR, TRD	Second-generation unit root test, FMOLS, D–H	Heterogeneous impact of R&D on environmental degradation. Bidirectional causality between AQ and R&D and between EF and R&D
Baz et al. [42]	Pakistan	1971–2014	EF, GDP, ENG, CAP	NARDL co-integration approach, Asymmetric causality test	Asymmetric feedback causality between ENG and EF. Symmetric: EF causes ENG

Table 1. Cont.

Author [s]	Study Area	Time	Variable(s)	Methodology	Findings
Destek and Sinha [33]	24 OECD countries	1980–2014	EF, GDP, RE, NRE, TRD, GDP <sup>2</sup>	FMOLS, DOLS, CCEMG	EKC hypothesis does not hold. U-shaped relationship between GDP and EF. RE reduces EF. NRE increases EF
Langnel and Amegavi [34]	Ghana	1971–2016	EF, GLOB, Economic globalization, Social globalization, Political globalization, ELEC, GDP, URB, ENG, URB, TRD, GDP, RE, EF	ARDL	EGLOB and SGLOB increase EF. PGLOB decreases EF. ELEC increase EF. GDP and URB increase EF. Bidirectional causality between EF and ELEC. GLOB causes EF
Nathaniel and Khann [15]	ASEAN countries	1990–2016	EF, GDP, URB, RE, HC, NR	Cointegration, AMG	GDP, TRD, and ENG increase FE. RE reduces EF
Nathaniel et al. [43]	BRICS	1992–2016	EF, GDP, URB, RE, HC, NR	AMG, CCEMG, PMG, FMOLS, DOLS, D-H, Granger Causality	GDP and NR increase the EF. RE decreases EF. HC is not significant. Bidirectional causality between HC, URB, and EF
Nathaniel et al. [35]	Coastal Mediterranean Countries	1980–2016	EF, FDI, NRE, URB, GDP	Quantile regression	FDI and URB reduce EF
Pata et al. [44]	Top ten countries with the largest ecological footprint	1992–2016	EF, GLOB, HDI, RE, NR	AMG	EKC is invalid. HDI and RE reduce EF. NR increases EF. GLOB is not significant
Sharif et al. [45]	Turkey	1965–2017	EF, GDP, RE, NRE	QARDL	RE decreases EF. The EKC is confirmed. Bi-directional causal relationship between RE, NRE, and GDP with EF
Udemba [36]	Nigeria	1981–2018	EF, GDP, ENG, FDI, AGR, POB	ARDL, Granger Causality	Positive relationship between GDP, EF, ENG, FDI, and AGR. Unidirectional causality from GDP to EF; from ENG to EF; from POB to EF; from GDP to ENG; and from POB to GDP
Alola et al. [46]	European Union [EU]	1997–2014	GDP, NRE, RE, Trade Policy, FR, EF	PMG-ARDL	GDP increases FE. RE reduces EF. NRE increases EF
Danish and Wang [47]	Next-11 countries	1971–2014	EF, GDP, ENG, URB	CCEMG	URB and GDP increase EF. ENG has a positive and significant impact on EF
Destek and Sarkodie [48]	11 newly industrialized countries	1977–2013	EF, GDP, ENG, FD	AMG	EKC is valid. Bidirectional causality between GDP and EF. Unidirectional causality from GDP to ENG
Dogan et al. [40]	MINT	1971–2013	EF, FR, EXP, URB, IMP, FD, ENG	Panel ARDL	EKC is valid. ENG, EXP, URB, and FD increase EF
Hassan et al. [49]	Pakistan	1971–2014	EF, HC, GDP, BIO	ARDL	BIO and GDP add to EF. HC reduces EF
Wang and Dong [50]	14 SSA	1990–2014	EF, RE, URB, GDP, NRE	AMG	RE adds to environmental quality. GDP, NRE, and URB increase EFP
Zafar et al. [51]	United States	1970–2015	EF, GDP, ENG, NR, FDI, HC	ARDL	HC, NR, and FDI reduce EF. GDP and ENG increase EF. Bidirectional causality between ENG and EF; and between GDP and EF. Unidirectional causality runs from NR to EF and from HC to NR.

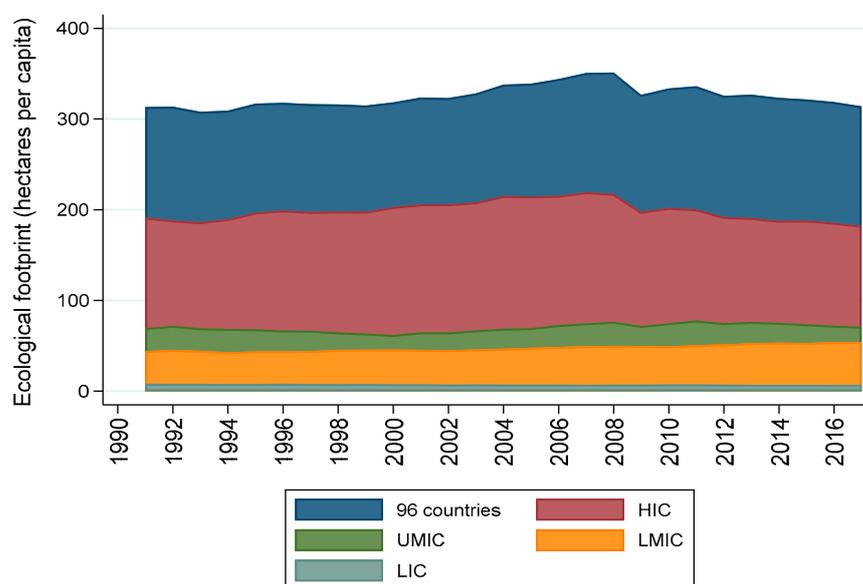
Note: EF: Ecological Footprint; URB: Urbanization; GDP: Gross Domestic Product; GDP<sup>2</sup>: Gros Domestic Product square; GDP<sup>3</sup>: Gros Domestic Product cubic; ENG: Energy Consumption; RE: renewable energy; NRE: Nonrenewable Energy; HC: Human Capital; NR: Natural Resources Rent; ECF: Ecological carbon footprint; SE: Solar energy consumption; QQ: Quantile on Quantile regression; AMG: Augmented Mean Group; CCEMG: Common Correlated Effects Mean Group; PMG: Pool Mean Group; D-H: Dumitrescu and Hurlin; IMP: Import; EXP: Export; FDI: Foreign Direct Investment; CUP-FM: continuously-updated fully modified estimators; CUP-BC: continuously-updated bias corrected estimators; GLOB: Globalization index; HDI: Human development index; CIPS: cross-sectional augmented IPS panel unit root test; INT: Interaction term (Urbanization × Human capital); TRD: Trade; AGR: Agricultural Sector; POB: Urban Population; PD: Population Density; FD: Financial Development; Consumption; CADF: cross-sectional ADF unit root test; FMOLS-MG: Fully Modified Ordinary Least Squares; DOLS-MG: Dynamic Ordinary Least Squares; CAP: Real Gross Fixed Capital Formation; ARDL: Autoregressive distributive lag model; FR: Fertility rate; ELEC: Electricity consumption; QARDL: Quantile Autoregressive Distributed Lag; DEA: Data Envelopment Analysis; ENE: Energy Efficiency; INV: Technology Innovation; IND: Industrial Structure; CORR: Corruption; GMM: Generalized Method of Moment; LEXP: life expectancy; BIO: Bio-capacity; ES: Ecological Status; GDPC: Income Level; AQ: Air Quality.

On the other hand, population trends play a significant role in determining the environmental quality of countries [3]. The conclusions on the association between the demographic indicators and EF indicate that population density can optimize of consumption of natural resources in a region or locality through economies of scale, technological innovation, and energy efficiency [52,53]. Likewise, in the long term, concentration of the population can exert pressure on PE, as a result of the increase in traffic congestion, the use of polluting energy, and the construction of new infrastructure to satisfy the demands of the urban population. In this context, the findings of Sharma et al. [23] point out the existence of a positive relationship between population density and EF in eight developing countries in South and Southeast Asia. Udemba [36] found a unidirectional causal relationship that

goes from population size to EF using a data panel. On the contrary, Ahmed et al. [29] and Ahmed et al. [52] concluded that population density decreases EF in Japan and Malaysia, respectively. Using a large sample of countries can provide more robust evidence of the link between population dynamics and PE. Several studies included other variables to explain the behavior of PE, such as urban concentration, globalization, consumption of renewable and non-renewable energy, and others [31,34,41,44]. The previous literature results are heterogeneous among themselves for various reasons: differences in levels of development, sample size, degree of institutionality, and methodological aspects, among others. Table 1 systematizes the review of the previous empirical literature that uses EF as a variable of the degradation of nature.

### 3. The Data and Statistical Sources

EF measures the amount of land and water that a human population needs to produce the resources it consumes and absorb waste using available technology [54]. This indicator is a tool to evaluate the holistic impact of environmental deterioration and inform about the policies required to mitigate the pollution. Data from the Global Footprint Network [55] show that EF has steadily increased, at an average of 2.1 percent per year since 1961: it went from 7.0 billion hectares per capita (hpc) in 1961, to 20.6 billion hpc in 2014 [56]. These results indicate that the earth's ecological overshoot began in the 1970s. Furthermore, the ecological overshoot continues to grow at an average rate of 2.0% per year [55]. In the last decade, the trend of EF has been partially reversed. The systematic decline in EF occurs not only globally, but also in some groups of countries. Figure 1 shows the evolution of the EF of the 96 countries classified according to gross national income. The EF of the 96 countries has decreased since 2008, with a slight increase in 2011. However, the EF is above 300 gha. In the HICs, the evolution of EF follows a similar trend to the group of countries analyzed. In the LICs, the levels of EF are the lowest compared to the other groups of countries and show a constant behavior during the period studied.



**Figure 1.** Temporal evolution of ecological footprint.

This research uses annual data from 1991 to 2018. Table 1 reports the countries included in the research, grouped according to the Atlas method. Table 2 reports the description of the variables used in the econometric estimates. The selection and inclusion of the four independent variables used the following arguments. First, in the previous literature on environmental economics, the impact of agricultural employment on EF has not received enough attention, even though agricultural activities cause a significant effect on the

regeneration and absorption capacity of polluting wastes from agriculture. Second, the growing demand for diversified products generates emissions, waste, and other pollutants that directly pressure the integral quality of nature. The consumerism patterns of modern economies are associated with the variety of products that are manufactured and exported to the international market. Consequently, the export diversification index captures this trend in modern economies. Third, population density is associated with economies of scale and agglomeration, which can be an instrument of policies to mitigate and adapt to environmental deterioration. Finally, the real per capita gross domestic product makes it possible to assess the impact of economic development on the integral degradation of nature.

**Table 2.** Description of variables and data sources.

Variable	Symbol	Definition	Measure	Source
Ecological footprint	$EF_{it}$	EF measures the amount of biologically productive land and water that the population requires to produce the resources it consumes and absorb the waste it generates using current technology	Hectares per capita	Global Footprint Network
Export diversification index	$XDI_{it}$	Export diversification can occur across either products or trading partners. Product diversification occurs through introducing new product lines (the extensive margin) or through exporting a more balanced mix of existing products (the intensive margin)	Index	International Monetary Fund
Employment in agriculture	$EA_{it}$	Employment is defined as persons of working age who were engaged in any activity to produce goods or provide services for pay or profit, whether at work during the reference period or not at work due to temporary absence from a job, or to working-time arrangement. The agriculture sector consists of activities in agriculture, hunting, forestry, and fishing	% of total employment	World Bank
Population density	$PD_{it}$	Population density is defined as the mid-year population divided by land area in square kilometers	People per sq. km of land area	World Bank
Economic growth	$Y_{it}$	Real per capita output is gross domestic product divided by midyear population	USD constant price of 2010	World Bank

Figure 2 illustrates the geographic coverage of the countries included in the research, where the four groups of countries classified according to the Atlas method are included.

Table 3 reports the descriptive statistics and the partial correlation matrix between the variables. The analysis period has a temporal coverage from 1991 to 2018, corresponding to a fully balanced data panel. The temporal dimension and the sample of countries used represent a total of 2688 observations. Most of the variables do not show a high dispersion of data, except for the density of the population. Using the Kolmogorov–Smirnov test, the statistics show that all the variables satisfy the null hypothesis of a normal distribution, with a significance level of 1%. The partial correlation coefficients are reported in the lower part of Table 3.

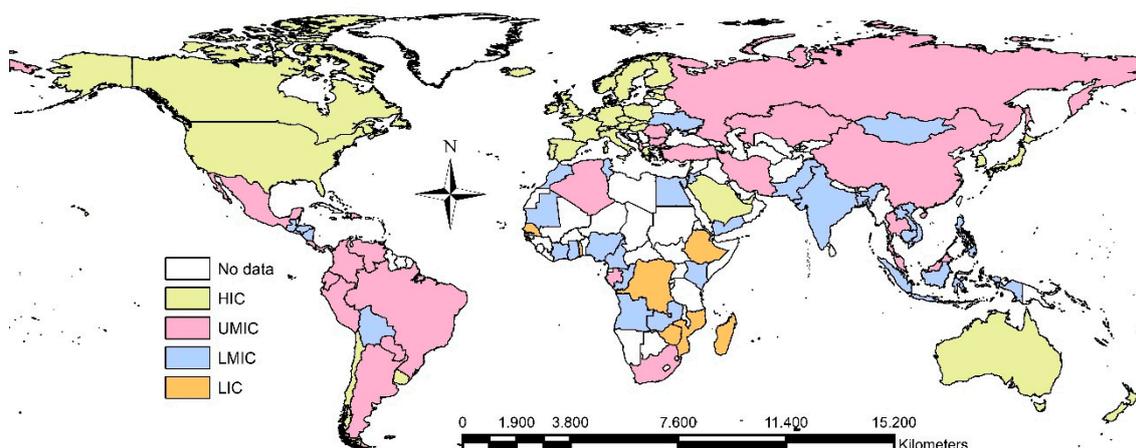


Figure 2. Geographical distribution of the countries.

Table 3. Descriptive statistics and correlation matrix of variables.

	$EF_{it}$	$Y_{it}$	$XDI_{it}$	$EA_{it}$	$PD_{it}$
Mean	0.97	8.64	3.07	26.22	4.06
Std. Dev. (Overall)	0.73	1.46	1.17	22.04	1.34
Std. Dev. (Between)	0.71	1.45	1.14	21.68	1.34
Std. Dev. (Within)	0.15	0.23	0.31	4.52	0.14
Min.	−0.78	5.10	1.12	−3.48	0.36
Max.	2.63	11.42	6.34	3.77	8.98
Kolmogorov–Smirnov test	0.08 ***	0.07 ***	0.99 ***	0.88 ***	0.99 ***
Observations	2688	2688	2688	2688	2688
Countries (N)	96	96	96	96	96
Time (T)	28	28	28	28	28
Ecological footprint	1.00				
Output	0.89 **	1.00			
Export diversification index	−0.52 **	0.48 **	1.00		
Employment in agriculture	−0.80 **	−0.88 **	0.47 **	1.00	
Population density	−0.07 **	0.06 **	−0.32 **	−0.12 **	1.00

Note: \*\* and \*\*\* indicate 0.1 and 1% of significance, respectively.

In order to verify that the covariates do not present the collinearity problem, we used the variance inflation factor (VIF) method. The VIF is the ratio of the variance in the presence of multicollinearity between covariates, and the variance in the absence of multicollinearity. The partial correlation between real per capita output and employment in agriculture is greater than 0.8. However, the two variables are different concepts and are treated as such in this research. The VIF is the inverse of the partial correlation coefficients. Therefore, when the VIF is greater than one and less than five, the problem of multicollinearity between the covariates is not significant [6]. From the test results shown in Table 4, all VIF values are less than five, which shows that the model does not have collinearity problems.

Table 4. Multicollinearity statistics.

Variable	VIF	SQRT VIF	Tolerance	Squared
Employment in agriculture	4.61	2.15	0.22	0.78
Export diversification index	1.46	1.21	0.69	0.31
Population density	1.14	1.07	0.88	0.12
Output	4.68	2.16	0.21	0.79
Mean VIF	2.97			

The analysis of the initial characteristics of the data facilitates the approach of the econometric strategy following the research objectives and the gap in the literature review.

#### 4. Econometric Strategy

The formulation of the econometric strategy combines several advanced methods of panel data econometrics. The dependent variable is  $EF_{it}$ , and the covariates are agricultural employment  $EA_{it}$ , export diversification index  $XDI_{it}$ , population density  $PD_{it}$ , and real per capita output  $Y_{it}$ .

##### 4.1. Cross-Section Test

First, we examine the effects of common shock using the Bailey et al. [11]. Aydin [57] points out that economic cooperation between countries and globalization have allowed global economies to share common economic, social, and commercial interests. The economic interaction between countries is mainly reflected in trade and capital flows [5]. This fact supports the existence of dependency between cross-sections (CD), the omission of which would cause the findings to be biased and the conclusions unreliable. Equation (1) poses the CD test using the following notation:

$$CD = \sqrt{\frac{2T}{N[N-1]}} \left( \sum_{i=1}^{N-1} \sum_{j=i+1}^N \sqrt{T_{ij} \hat{\rho}_{ij}} \right) \quad CD \sim N(0,1) \quad (1)$$

where  $N$  is the sample size,  $T$  measures the temporal coverage, and  $\hat{\rho}_{ij}$  is the error of the correlations for the individual cross-sections. One of the advantages of Bailey et al. [11] is that it eliminates the values of the means during the estimation of the correlation components. Therefore, the CD test has the null hypothesis that there is no cross-sectional dependence in the data. The statistical significance is determined from the  $p$ -value associated with the statistic and, consequently, the acceptance or rejection of the null hypothesis.

##### 4.2. Homogeneity Slope Test

In the second stage, we determined the homogeneity in the slope between the panels included in the sample of countries using the Pesaran and Yamagata [16] test. The main argument for assuming that there is no homogeneity between the slopes of the panels is that the sample contains highly heterogeneous countries in the institutional quality associated with the countries' level of economic and social development. It is logical to expect that institutional quality will have a heterogeneous effect on the effectiveness of pro-environmental policies. Furthermore, in the theoretical framework of the EKC, the perception of the importance of environmental care differs between developing and developed countries. Therefore, the intensity of the relationship between the variables must be different between the panels. Equations (2a) and (2b) formalize the slope homogeneity of the test. The term  $\check{\Delta}_{SH}$  is the homogeneity test, and  $\check{\Delta}_{Adjusted-SH}$  is the homogeneity-adjusted test, while  $k$  is the lags, and  $\check{\xi}$  is a factor common.

$$\check{\Delta}_{SH} = [N]^{\frac{1}{2}} [2k]^{-\frac{1}{2}} \left( \frac{1}{N} \check{\xi} - k \right) \quad (2a)$$

$$\check{\Delta}_{Adjusted-SH} = [N]^{\frac{1}{2}} \left( \frac{2k[T-k-1]}{T+1} \right)^{-\frac{1}{2}} \left( \frac{1}{N} \check{\xi} - 2k \right) \quad (2b)$$

##### 4.3. Unit Root Test

Third, the existence of cross-section dependence implies the need to use second-generation unit root tests. In this research, we used the unit root test formalized by Herwartz and Siedenburg (2008). This test generates reliable results when there is cross-

section dependence and a heterogeneous slope. Equation (3) formalizes the Herwartz and Siedenburg [17] test.

$$t_{HS} = \frac{\sum_{t=1}^T y'_{t-1} \Delta y_t}{\sqrt{\sum_{t=1}^T y'_{t-1} \bar{e}_t \bar{e}'_t y_{t-1}}} \rightarrow_d N(0, 1) \quad \bar{e}_t = \Delta y_t = e_t \quad (3)$$

The term  $\bar{y}_t$  represents the transversal mean of the time, and  $e_t$  is the error term. The optimal length of the lag is determined using the information criterion of Akaike [58]. Finally,  $\varepsilon_{it}$  is the error term. The null hypothesis of this test is that there is homogeneity in the slope of the panels.

#### 4.4. Cointegration Test

In the fourth stage, we used the Westerlund [20] cointegration test to determine the existence of a long-term equilibrium relationship between the five series. Some cointegration tests, such as those of Kao [59] and Pedroni [60] do not explicitly incorporate cross-sectional dependence and heterogeneity in the slope in calculating the cointegration vector. One of the advantages of the Westerlund [20] test is that it allows some flexibility in estimating cointegration in some of the panels and the entire panel. There may be cointegration in a large sample of cross-sectional units in a part of the sample and not necessarily in the whole panel. In addition, the test is flexible, to compare the results between a trending or non-trending cointegration model. Equation (4) formalizes the test:

$$\alpha_i(L) \Delta y_{it} = \delta_{1i} + \delta_{2i} t + \alpha_i (y_{it-1} - \beta'_i X_{it-1} + \lambda_i [L]' v_{it}) + \varepsilon_{it} \quad (4)$$

The term  $\alpha_i$  is the cointegration vector between the five series,  $\beta_i$  is the error correction coefficient that captures the temporal dynamics of the regressors, and  $\delta$  in the intercept. The term  $\Delta y_{it}$  is the dependent variable (EF), and  $X_{it}$  is a covariants matrix. Therefore, the null hypothesis is that there is no cointegration between the series.

#### 4.5. Short- and Long-Run Elasticities

In the fifth stage, we examined the short- and long-term relationships between the regressors with the EF. To obtain the short-term elasticities, we implemented the 'augmented mean group' (AMG) approach proposed by Eberhardt and Teal [61] and the common correlated effects mean group (CCE-MG) method developed by Pesaran [62]. The objective of estimating the short- and long-term elasticities between the series has two dimensions. On the one hand, the short- and long-term elasticities allow us to broaden the time horizon of analysis obtained in the previously formalized models. On the other hand, the AMG and CCE-MG estimators have been shown to be useful to infer pro-environmental policy lessons, through normative instruments that consider temporal dynamics. In parallel, the analysis of the previous models is reinforced by estimating fully modified least squares (FMOLS) and dynamic ordinary least squares (DOLS) models. One of the advantages of the FMOLS and DOLS models is that they generate estimators free of endogeneity problems, sample size bias, and serial correlation [63]. The inclusion of the time horizon is important because efforts to mitigate environmental degradation have an immediate effect and a temporarily lagged effect. These tests are formalized in stages in Equations (5a) and (5b).

$$\text{Stage 1: } \Delta EF_{it} = b' \Delta x_{it} + \sum_{t=2}^T c_t \Delta D_t + e_{it} \implies \hat{c}_t \equiv \hat{\mu}_t \quad (5a)$$

$$\text{Stage 2: } \Delta EF_{it} = a_i + b'_i x_{it} + c_i t + d_i \hat{\mu}_t + e_{it} \implies \hat{b}_{AMG} = N^{-1} \sum_i \hat{b}_i \quad (5b)$$

In this case, the first stage includes the first least-squares difference and the second stage contains cross-sections dependence. In Equations (5a) and (5b),  $b$  is the estimators,  $c$

is a factor common,  $d$  is a deterministic component,  $\hat{\mu}$  is the error correction factor, and  $e$  is the idiosyncratic error of the model.

## 5. Results and Discussion

The results of the estimation of the stages of the econometric strategy are reported in this section. Table 5 reports the estimators and their respective  $p$ -value obtained through the test of Bailey et al. [11], used to verify the dependency in the cross-sections. The results show sufficient evidence to reject the null hypothesis of independence between the cross-sections in the five series. The cross-sectional dependence in the sample is a sign that there is the possibility of a common shock in all the countries covered by the research. This result implies that shocks to the ecological footprint, agricultural employment, the export diversification index, population density, or real per capita product generate a significant impact on the series for the rest of the countries. The ecological environment faces enormous challenges due to the effects generated by economic activities, particularly those that directly influence EF, such as agriculture. Several factors explain the existence of the cross-sections dependence, such as trade agreements, the relocation of industry, the division of production processes in several countries, and flows of capital and people can explain the cross-sectional dependency between the series. Some recent research has used this cross-sectional dependency test to analyze the determinants of environmental pollution [6,64].

**Table 5.** Results of cross-section dependence [11].

Series	Statistics	$p$ -Value
Ecological footprint	220.25 <sup>a</sup>	0.00
Output	350.74 <sup>a</sup>	0.00
Export diversification index	347.50 <sup>a</sup>	0.00
Employment in agriculture	342.92 <sup>a</sup>	0.00
Population density	350.35 <sup>a</sup>	0.00

Note: <sup>a</sup> is significant at 0.1% level.

Table 6 reports the test results of the homogeneity of the coefficients between the panels using the Pesaran and Yamagata [16] test. The results are consistent with both the delta, and delta-adjusted estimators, at a significance level of 0.1%. This finding means that the slope coefficients are not homogeneous. Various economic and environmental reasons support the existence of heterogeneity in the slope of the panels. On the one hand, the intensity of the nexus between regressors and EF may differ according to the level of institutionality achieved by each country [3,65]. Likewise, the heterogeneity in the slope between the panels may be associated with the effectiveness of pro-environmental policies and the industrial structure of each country.

**Table 6.** Results from the Pesaran and Yamagata homogeneity test.

Tests	Delta	$p$ -Values
$-\Delta$	42.46 <sup>a</sup>	0.000
$-\Delta_{adj}$	48.14 <sup>a</sup>	0.000

Note: <sup>a</sup> is significant at 0.1% level.

To determine the unit root properties of the series, we used the second-generation unit root test of Herwartz and Siedenburg [17]. The results of this test are reported in Table 7. The null hypothesis of unit root cannot be rejected when the variables are in levels, as demonstrated by the large  $p$ -value ( $p$ -value > 0.05). On the contrary, when the series is in first differences, there is enough evidence to reject the null hypothesis of the non-existence of a unit root. The EF, agricultural employment, the export diversification index, population density, and the real product per capita do not have unit roots in differences. Therefore,

the null hypothesis is rejected for the five covariates in all groups of countries. This fact implies that the series are stationary in first differences and, therefore, are integrated in order one, I [1]. Several recent investigations in the environmental economics literature have employed this unit root test [18,19,66–68].

**Table 7.** Results of second-generation unit root tests [17].

	Levels	First Differences
<i>96 countries</i>		
Ecological footprint	−1.15	−3.83 <sup>a</sup>
Output	1.74	−2.65 <sup>b</sup>
Export diversification index	0.06	−3.27 <sup>a</sup>
Employment in agriculture	3.09	−3.51 <sup>a</sup>
Population density	1.33	−2.67 <sup>b</sup>
<i>High income countries</i>		
Ecological footprint	−0.84	−3.72 <sup>a</sup>
Output	2.13	−1.86 <sup>c</sup>
Export diversification index	0.08	−2.63 <sup>a</sup>
Employment in agriculture	2.72	−3.05 <sup>a</sup>
Population density	−0.63	−2.58 <sup>b</sup>
<i>Middle-high income countries</i>		
Ecological footprint	−1.89	−3.12 <sup>a</sup>
Output	1.53	−3.04 <sup>b</sup>
Export diversification index	0.11	−2.83 <sup>b</sup>
Employment in agriculture	3.47	−2.73 <sup>b</sup>
Population density	1.87	−0.97 <sup>c</sup>
<i>Middle-low income countries</i>		
Ecological footprint	1.07	−3.31 <sup>a</sup>
Output	2.51	−2.71 <sup>b</sup>
Export diversification index	−1.14	−2.91 <sup>b</sup>
Employment in agriculture	1.34	−3.24 <sup>a</sup>
Population density	0.99	−0.65 <sup>c</sup>
<i>Low income countries</i>		
Ecological footprint	−1.24	−3.34 <sup>a</sup>
Output	−0.21	−1.59 <sup>c</sup>
Export diversification index	−0.24	−2.80 <sup>b</sup>
Employment in agriculture	0.39	−3.16 <sup>a</sup>
Population density	−1.07	−3.52 <sup>c</sup>

Note: <sup>a</sup>, <sup>b</sup> and <sup>c</sup> are significant at 0.1%, 1%, and 5% level, respectively.

The cointegration results allow evaluating the dynamics of the relationship between the series analyzed in a long-term horizon, facilitating the design of mechanisms to mitigate environmental deterioration. It is well known that the most effective environmental policies are planned in the long term, by influencing the population's behavior. Table 8 reports the results of the cointegration test formalized in Equation (5). One of the advantages of the Westerlund [20] cointegration test is that it allows comparing the findings obtained with/without the cross-sectional averages and with/without the time trend. Furthermore, the estimators allow differentiating the cointegration in some of the panels or all the panels. The evidence found in this test indicates that there is sufficient evidence to reject the null hypothesis of non-cointegration between EF, agricultural employment, the export diversification index, population density, and real per capita output.

**Table 8.** Results of the Westerlund [20] cointegration test.

Variance Ratio	Without Cross-Sectional Averages				With Cross-Sectional Averages			
	Without Time Trend		With Time Trend		Without Time Trend		With Time Trend	
	Statistic	<i>p</i> -Value	Statistic	<i>p</i> -Value	Statistic	<i>p</i> -Value	Statistic	<i>p</i> -Value
<i>96 countries</i>								
Test some panels	−9.20 <sup>a</sup>	0.00	−11.40 <sup>a</sup>	0.00	−8.71 <sup>a</sup>	0.00	−6.42 <sup>a</sup>	0.00
Test all panels	−5.07 <sup>a</sup>	0.00	−8.61 <sup>a</sup>	0.00	−4.92 <sup>a</sup>	0.00	−5.29 <sup>a</sup>	0.00
<i>High income countries</i>								
Test some panels	−4.15 <sup>a</sup>	0.00	−3.40 <sup>a</sup>	0.00	−4.50 <sup>a</sup>	0.00	−9.54 <sup>a</sup>	0.00
Test all panels	−3.12 <sup>b</sup>	0.00	−1.22 <sup>b</sup>	0.00	−3.07 <sup>a</sup>	0.00	−7.29 <sup>c</sup>	0.00
<i>Upper medium income countries</i>								
Test some panels	−5.36 <sup>a</sup>	0.00	−3.56 <sup>a</sup>	0.00	−1.84 <sup>a</sup>	0.00	−6.97 <sup>a</sup>	0.00
Test all panels	−4.28 <sup>a</sup>	0.00	−1.96 <sup>b</sup>	0.00	−5.74 <sup>a</sup>	0.00	−5.38 <sup>a</sup>	0.00
<i>Lower-medium income countries</i>								
Test some panels	−4.89 <sup>a</sup>	0.00	−6.68 <sup>a</sup>	0.00	−2.52 <sup>a</sup>	0.00	−6.27 <sup>a</sup>	0.00
Test all panels	−3.21 <sup>a</sup>	0.00	−7.40 <sup>a</sup>	0.00	−3.17 <sup>b</sup>	0.00	−5.60 <sup>b</sup>	0.00
<i>Low income countries</i>								
Test some panels	−5.67 <sup>a</sup>	0.00	−8.37 <sup>a</sup>	0.00	−6.92 <sup>a</sup>	0.00	−5.19 <sup>a</sup>	0.00
Test all panels	−5.14 <sup>a</sup>	0.00	−7.04 <sup>b</sup>	0.00	−5.23 <sup>c</sup>	0.00	−4.48 <sup>a</sup>	0.00

Note: <sup>a</sup>, <sup>b</sup>, and <sup>c</sup> are significant at 0.1%, 1%, and 5% level, respectively.

Furthermore, all parameters are statistically significant, at least at 5% significance. Therefore, it is concluded that there is cointegration in all the panels between the series. The findings of the tests applied for the HIC, UMIC, LMIC, and HIC are consistent with the results of the overall panel. Several reasons support the equilibrium of relationship between the variables of this research. First, agricultural employment directly impacts environmental quality, due to the expansion of the agricultural frontier and the generation of waste and residues that pollute the soil and the seas. Consequently, agricultural employment is a factor that affects the overall quality of the environment. Second, the export diversification index is associated with EF in the long term, because the productive activity that requires the manufacture and export of goods and services with a greater variety causes environmental pollution. Third, population density has a long-term relationship with EF, because the way the population is distributed in the territory determines the level of demand for consumer goods. Thus, areas with a higher density have higher consumption levels, which puts pressure on nature's regeneration and adaptation capacity. Recently, several applied investigations on environmental deterioration used this methodology to examine the long-term equilibrium relationship between economic and environmental variables [69–71].

Table 9 reports the short-term ecological footprint elasticity results obtained through the augmented means group estimator (AMG) and the common correlated effects (CCEMG). The unobservable common factors in the AMG method are treated as a common dynamic process. The CCE-MG method includes unobservable common factors in the stochastic error term. The CCEMG estimator and the AMG estimator generate robust estimators of the heterogeneity of the parameters and the cross-sectional dependence. The main difference between the CCE-MG and AMG estimators is the approximation of the unobserved common factors. The AMG estimator uses a two-step method to estimate the unobserved common dynamic effect and allows for cross-sectional dependence, by including the common dynamic effect parameter.

The findings are quantitatively similar for both short-term elasticities. With the AMG estimates, the product has a positive and significant effect on EF in the 96 countries, UMICs, and LMICs. With the CCE-MG estimator, the impact of the real per capita product is also positive. However, it is significant for almost all groups, except the LICs. For the rest of the variables, the coefficients have the same sign with both estimators. The first conclusion of the short-term elasticities is that they are extremely small. However, the explanation for the result obtained is based on the fact that, in the short term, the impacts of environmental degradation are not always visible. It takes several years to make visible the magnitude of the adverse effect of human activity on nature. Destek and Sarkodie [48] and Pata et al. [44] used the AMG and CCE-MG models in similar environmental investigations.

Table 9. Short-run elasticity.

	Panel AMG					Panel CCE-MG				
	96 Countries	HIC	UMIC	LMIC	LIC	96 Countries	HIC	UMIC	LMIC	LIC
Output	0.81 <sup>a</sup> (5.40)	0.58 (1.59)	0.60 <sup>c</sup> (2.50)	0.70 <sup>a</sup> (4.27)	0.65 (1.48)	0.95 <sup>a</sup> (7.80)	1.07 <sup>a</sup> (4.11)	1.02 <sup>a</sup> (6.33)	0.71 <sup>a</sup> (4.09)	0.63 (1.44)
Export diversification index	0.06 (1.40)	0.14 (1.74)	0.06 (0.76)	0.04 (0.79)	0.03 (0.96)	0.04 (1.55)	0.07 (1.34)	0.06 (1.03)	0.02 (0.37)	0.04 (1.30)
Employment in agriculture	0.0004 (0.03)	0.0002 (0.01)	−0.01 (−0.48)	0.03 (1.11)	0.02 (1.55)	0.005 (0.39)	−0.01 (−0.69)	−0.01 (−1.05)	0.02 (0.79)	0.02 (1.74)
Population density	2.97 (0.69)	−0.75 (−0.20)	13.59 (1.21)	1.50 (0.17)	−14.86 (−0.93)	0.35 (0.09)	−1.46 (−0.57)	10.26 (1.15)	−3.31 (−0.43)	2.37 (0.63)
c_d_p						1.08 <sup>a</sup> (3.87)	0.86 <sup>a</sup> (3.67)	1.11 <sup>a</sup> (3.30)	1.06 <sup>b</sup> (3.08)	0.96 <sup>a</sup> (4.28)
Trend	0.0001 (0.28)	−0.0001 (−0.72)	−0.0003 (−0.96)	0.0004 (1.41)	−0.0003 (−0.62)	0.0001 (0.47)	−0.005 (−0.28)	−0.0003 (−1.20)	0.0005 (1.23)	−0.0003 (−0.93)
Ecological footprint _avg	1.18 <sup>a</sup> (3.78)	0.81 <sup>a</sup> (3.45)	1.43 <sup>b</sup> (3.05)	1.21 <sup>b</sup> (3.01)	1.01 <sup>a</sup> (4.12)					
Output _avg	−0.73 <sup>c</sup> (−1.97)	−0.16 (−0.31)	−0.62 (−1.12)	−0.47 (−1.14)	−0.63 <sup>b</sup> (−2.82)					
Exports _avg	−0.10 (−0.91)	−0.11 (−0.66)	−0.11 (−0.92)	−0.04 (−0.40)	−0.003 (−0.05)					
EA_avg	0.03 (0.96)	−0.01 (−0.20)	0.02 (0.53)	−0.02 (−1.18)	−0.02 (−0.69)					
DP_avg	3.38 (0.75)	−2.64 (−0.76)	0.58 (0.07)	2.03 (0.26)	26.02 (1.19)					
Constant	−0.001 (−0.29)	0.02 (0.58)	0.01 (0.92)	−0.01 (−0.88)	0.01 (0.70)	−0.01 <sup>a</sup> (−3.57)	−0.004 (−1.28)	−0.07 <sup>b</sup> (−3.15)	−0.05 <sup>a</sup> (−3.58)	0.03 <sup>b</sup> (3.17)
Observations	2688	952	700	840	196	2688	952	700	840	196
Countries [N]	96	34	25	30	7	96	34	25	30	7
Chi-squared	30.87	9.592	14.72	21.33	4.24	62.09	18.98	56.23	18.27	4.77

Note: <sup>a</sup>, <sup>b</sup>, and <sup>c</sup> are significant at 0.1%, 1%, and 5% level, respectively.

Table 10 reports the elasticities of the EF, concerning the long-term covariates obtained using the FMOLS and DOLS models. Both models consider the serial correlation and endogeneity that may exist in the model. The two models generate similar results for each variable, in terms of sign and statistical significance, although they vary slightly in terms of magnitude. The DOLS results show that the real product per capita significantly impacts the EF in the global panel, UMICs, and the LICs. In HICs, in addition to the real per capita product, the population density is also significant at 1%. The export diversification index in this group reduces the EF. Agricultural employment only has a negative impact on EF in LMICs.

This result is consistent with the countries' economic structure, since their productive matrix is not sufficiently diversified, and production is based on primary activities. On the other hand, in the results of the FMOLS model, almost all the variables are significant in all groups of countries. The real per capita product and the export diversification index positively impact the EF in almost all groups, with a significance level of 1%. Employment in agriculture and population density reduces EF, although the magnitude of the impact is small and is not significant in LMICs and LICs. Findings on the long-term elasticities of EF suggest that the export diversification index, agricultural employment, and population density play an important role in determining the EF in the countries included in the research. Unlike the short-term elasticities, the long-term ones allow a clear visualization of the impact of the covariates on the EF. These results highlight the importance of broadening the time horizon in understanding the factors that influence environmental pollution.

A rigorous analysis of the causality between the variables is necessary for the construction of solid pro-environmental policy. We used the approach proposed by Dumitrescu and Hurlin [72], which considers the heterogeneity between the series. Table 11 presents the results of the test panel average and the probability values associated with each variable. The null hypothesis of non-causality is rejected for the 96 countries. In this group, there is bidirectional causality between the EF and the export diversification index; and between EF and employment in agriculture.

**Table 10.** Long-run elasticity.

	Panel-FMOLS		Panel-DOLS	
	Coefficient	t-Statistic	Coefficient	t-Statistic
<i>96 countries</i>				
Output	1.06 <sup>a</sup>	80.07	0.43 <sup>b</sup>	10.48
Export diversification index	0.10 <sup>a</sup>	21.86	−0.14	−1.48
Employment in agriculture	−0.01 <sup>a</sup>	−17.44	−0.04	−1.67
Population density	−2.85 <sup>c</sup>	−3.39	1.16	0.09
<i>High income countries</i>				
Output	1.38 <sup>a</sup>	54.23	0.23 <sup>c</sup>	4.77
Export diversification index	0.15 <sup>a</sup>	2.33	−0.16 <sup>c</sup>	−2.20
Employment in agriculture	−0.02 <sup>b</sup>	−11.85	−0.06	−0.95
Population density	−9.06 <sup>c</sup>	−2.41	8.34 <sup>c</sup>	2.32
<i>Upper-medium income countries</i>				
Output	1.11 <sup>a</sup>	55.38	0.75 <sup>c</sup>	6.56
Export diversification index	0.12 <sup>b</sup>	16.00	−0.18	−1.13
Employment in agriculture	−0.02 <sup>b</sup>	−9.18	−0.06	−0.24
Population density	−1.47 <sup>c</sup>	−3.82	−1.07	−1.73
<i>Lower-medium income countries</i>				
Output	0.75 <sup>a</sup>	28.42	0.33 <sup>c</sup>	3.89
Export diversification index	0.02	−1.70	−0.10	0.51
Employment in agriculture	0.00 <sup>b</sup>	−8.95	−0.01 <sup>c</sup>	−2.10
Population density	−2.03	−0.16	−5.32	−0.80
<i>Low income countries</i>				
Output	0.75 <sup>b</sup>	13.50	0.68 <sup>c</sup>	7.84
Export diversification index	0.06 <sup>b</sup>	7.24	0.02	0.45
Employment in agriculture	−0.00 <sup>c</sup>	−2.59	−0.02	0.71
Population density	1.49	0.31	2.05	0.14

Note: <sup>a</sup>, <sup>b</sup>, and <sup>c</sup> are significant at 0.1%, 1%, and 5% level, respectively.

**Table 11.** Results of Dumitrescu and Hurlin [72] panel causality test.

Relation	Statitis	96 Countries	HIC	MHIC	MLIC	LIC
Ecological footprint → Output	Z-bar	4.31 <sup>c</sup>	3.30 <sup>c</sup>	0.91	2.33	2.14
	p-value	0.02	0.05	0.51	0.08	0.12
Output → Ecological footprint	Z-bar	1.16	0.19	−1.06	0.76	4.31 <sup>c</sup>
	p-value	0.43	0.85	0.36	0.48	0.02
Ecological footprint → Export diversification index	Z-bar	4.00 <sup>c</sup>	2.01	2.28	2.99 <sup>b</sup>	−0.13
	p-value	0.05	0.15	0.18	0.01	0.93
Export diversification index → Ecological footprint	Z-bar	7.64 <sup>a</sup>	2.50	5.13 <sup>a</sup>	6.12 <sup>b</sup>	0.43
	p-value	0.00	0.11	0.00	0.01	0.72
Ecological footprint → Employment in agriculture	Z-bar	3.92 <sup>c</sup>	4.12 <sup>a</sup>	0.41	0.82	2.94 <sup>c</sup>
	p-value	0.02	0.00	0.68	0.51	0.03
Employment in agriculture → Ecological footprint	Z-bar	4.81 <sup>a</sup>	2.94 <sup>c</sup>	1.69	2.96 <sup>c</sup>	2.02 <sup>c</sup>
	p-value	0.00	0.03	0.12	0.03	0.03
Ecological footprint → Population density	Z-bar	−0.88	2.11	−0.75	−2.32	−1.69
	p-value	0.50	0.13	0.49	0.08	0.06
Population density → Ecological footprint	Z-bar	0.22	2.31	1.66	−2.95 <sup>a</sup>	−1.32
	p-value	0.87	0.06	0.17	0.00	0.08

Note: <sup>a</sup>, <sup>b</sup>, and <sup>c</sup> are significant at 0.1%, 1%, and 5% level, respectively.

Furthermore, we found a unidirectional causal relationship that goes from the EF to the real per capita product in the global panel. In the HICs, we found a unidirectional causal relationship from the EF to the real per capita product, and a two-way causal relationship between EF and employment in agriculture. In the LICs, the findings show unidirectional causality from the real per capita product towards EF and bidirectional causality between

EF and employment in agriculture. In the MLICs, we found a two-way causal relationship between the EF and the export diversification index; and a one-way causal relationship from population density to EF. Finally, in the MHICs, we found unidirectional causality from the index of diversification of exports to the EF.

## 6. Conclusions and Policy Implications

Globally, about 44% of the population still lives in rural areas, who are mainly employed in agricultural activities. Agricultural employment has a significant impact on environmental quality, because it generates waste that is dumped directly into the soil or water. In addition, agricultural employment activities are related to the occupation of arable land and the expansion of the agricultural frontier, which reduces plant cover. Consequently, agricultural activities are a significant source of environmental deterioration and pressure on the regeneration capacity and absorption of waste by nature. In parallel, agricultural and industrial production has diversified in recent years, in response to increasing consumption levels. In this sense, agricultural employment and the diversification of exports play an essential role in providing food and other consumer goods for the urban population, reducing the barriers imposed by geographical distance. These aspects motivate an exhaustive analysis of the impact of agricultural employment and the export diversification index on the integral quality of nature, as measured by EF. EF reflects the degree of environmental deterioration in a more comprehensive way than other indicators of environmental degradation. In order to achieve the objective of this research, we employed a set of second-generation panel data econometrics techniques to examine the behavior of the EF.

The sustainability of economic development requires environmental sustainability as part of a dynamic process. In order to achieve the objective of this research, we employed a set of second-generation panel data econometrics techniques to examine the behavior of the EF. We included four regressive variables in the quantitative models: agricultural employment, the export diversification index, population density, and real per capita output. In addition, the estimated models include the dependency on cross-sections and the heterogeneity of slope. This fact allows us to obtain estimators consistent with the recent environmental literature and consistent with the characteristics of the data.

The conclusions of the research are synthesized in the following items: First, we found a long-term relationship between EF and the four covariates, both at the level of the global panel and of the four groups of countries. Second, these results support several policy implications. On the one hand, those responsible for environmental policy must consider that, in the long term, activities associated with agricultural employment can cause permanent changes in EF, which poses a risk to the environmental sustainability of economic development. On the other hand, business and political efforts to diversify the portfolio of export products directly impact environmental quality as measured by the EF. High-income and upper-middle-income countries should lead efforts to achieve environmental sustainability. Specifically, this group of countries could focus on stricter regulation of companies exporting manufactured products to developing countries. The trade-in of environmentally friendly products benefits society by improving the quality of life, which produces a healthier environment. Likewise, the countries of both groups of countries could make information on the capital flows associated with investment firms in developing countries transparent, to improve environmental regulation. In addition, lower-middle and lower-income countries should apply stricter environmental regulations to companies engaged in agriculture oriented towards international trade. Developing countries need to adopt good environmental practices in activities associated with foreign investment. Sustainable development objectives must take precedence over the maximization of non-inclusive growth. In the long term, traditional practices of maximizing production will leave developing countries without natural resources and without a green and inclusive development.

Second, regulations aimed at protecting the environment should consider that environmental impacts are more visible in the long term than in the short term. Therefore, environmental policy decisions cannot be based only on short-term evidence, and the focus of economic sustainability should be associated with the medium and long term. Third, the results offer partial evidence in favor of the EKC, particularly concerning export diversification. Third, using the causality models, we conclude that there is enough evidence to give concern about the sustainability of economic and social development. We show that agricultural employment and the export diversification index have a causal relationship with EF. These results should constitute a call for collective actions by the countries regarding the current situation of the environment and the future sustainability of the economic development model. The main limitations of our research are the lack of more recent data from the series and the lack of data for all countries. Future research should deepen the analysis of the factors that influence the behavior of EF and the search for environmental mitigation mechanisms that guarantee the quality of life of future generations.

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