Analysis of European environmental policies: improving decision making through eco-efficiency

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Abstract

There is extensive literature that defines eco-efficiency as the efficiency with which ecological resources are used to satisfy human needs. It ensures production while consuming fewer natural resources and thus reduces the environmental impact. The aim of this work is to fill the gap in the literature by defining eco-efficiency in terms of production and deaths due to pollution. Data Envelopment Analysis (DEA) and the Malmquist Index (MI) are used for this purpose. Both techniques are applied to 20 European countries during the period 2014-2018. In addition, the spatial dependence of eco-efficiency obtained in the DEA analysis is studied using geostatistical techniques. The results reveal the good performance of almost all European countries, which are conditioned neither by their wealth nor by their economic growth. Eastern European countries show the most room for improvement. Finally, the spatial dependence of eco-efficiency in Europe during the period 2014-2018 was confirmed by detecting a significant cluster of low eco-efficiency countries in Eastern Europe. Researchers and policymakers can benefit from the results to provide country-specific investment policies to achieve higher benefits towards eco-efficiency in Europe.

Keywords: Eco-efficiency; Data Envelopment Analysis; Spatial dependence

1. Introduction

For more than three decades, environmental degradation has become a focus of collective concern. Its consequences are becoming increasingly visible, requiring coordinated action by all territories to solve the serious environmental problems caused, almost entirely, by human activity [1, 2]. Numerous climate summits have highlighted the planet's global interest in establishing international agreements to curb global warming. A common commitment is needed to protect the biosphere, where the transition to sustainable development (SD) requires appropriate management of resources [3, 4, 5]. This commitment has been highly significant in recent studies on the management of collaborative decision-making processes in smart cities [6, 7, 8, 9].

The literature shows a bidirectional relationship between economic growth and environmental pollution [10, 11, 12]. While the former is necessary to ensure the development and well-being of the population, reducing poverty and improving the quality of life, a large critical mass considers it to be one of the main causes of atmospheric destruction [13, 14]. For some authors, the solution lies in a collaborative economy, which has the potential to stimulate sustainable economic development and energy efficiency [15, 16, 17]. However, the adoption of measures aimed at reducing CO_2 emissions could have a very negative impact on growth. According to Maksimović et al. [18], understanding the link between the two concepts will permit the adoption of appropriate transitional measures, aimed at promoting the use of sustainable resources without limiting the development of nations. All of this has led to the interest of the scientific community and has led to the emergence of countless studies focused on analysing this nexus [19, 20, 21, 22].

In this respect, energy and waste are two of the main sources of pollution, and their increasing volume is attributed to scenarios characterised by significant economic growth [23, 24, 25]. Energy is estimated to generate 60% of all greenhouse gas (GHG) emissions, while waste is responsible for more than 1.6 billion tonnes of CO_2 emissions. Humanity faces the great challenge of introducing new, more environmentally friendly practices while ensuring the health of the population. The World Health Organisation has confirmed that pollution causes 1 in 5 deaths worldwide.

The use of renewable energy (RE) and proper waste management would reduce GHG emissions and mitigate the effect that human actions have on climate change (CC). According to Saidi and Omri [11], energy policies should be designed "ad hoc" for each territory, taking into account its economic and environmental situation, as well as the origin of the energy sources used. As a result of their analysis, they propose establishing incentive mechanisms to favour universal access to these supplies, as well as promoting research to encourage the introduction of new forms of production to guarantee the reduction of emissions, without harming economic results.

This is the context for the concept of “eco-efficiency” originally proposed by Schaltegger and Sturm [26] and defined by the OECD [27] as the efficiency with which ecological resources are used to satisfy human needs. It is about ensuring production while consuming fewer natural resources and thus reducing the environmental impact. An increase in eco-efficiency would be linked to a situation in which it is possible to maintain or increase the economic value of production while reducing environmental impacts [28]. This has been calculated to analyse very diverse productive sectors, such as agriculture [29], industry [30], construction [31] and even tourism [32]. This research aims to fill the gap in the literature, looking not only at the economic value of production but also at the reduction in deaths due to pollution as a consequence of the use of sustainable resources and a greater involvement of countries in environmental protection. The analysis focuses on 20 European countries for the period 2014-2018, aiming to answer the following research questions:

Q1. To what extent is the introduction of sustainable practices having a positive impact on nations? Does the wealth of countries condition their level of eco-efficiency?

Eco-efficiency will be calculated using Data Envelopment Analysis (DEA) where the time span will be treated as an inter-temporal period in order to avoid specific events distorting the results. While for changes in productivity, sequential MI is proposed in order to avoid the destruction of technology that emerges in other versions of the MI and, in this way, reproduce the actions of countries in their involvement with CC. The results reveal that European countries are mostly succeeding in turning sustainable practices into higher levels of production while reducing deaths from pollution. Furthermore, the level of wealth and economic growth is not binding in its environmental implications.

Q2. Is there spatial dependence in European eco-efficiency in the period 2014-2018?

In many cases, the outcomes of the actions of agents such as individuals, political parties, groups etc. depend not only on the characteristics of the particular individual, but also on their geographical position. Interestingly, social scientists are interested in this spatial structure, as it is almost completely absent in most empirical analyses in the social sciences [33]. Therefore, in this paper we study the spatial dependence of Europe's eco-efficiency during the period 2014-2018. The results obtained will support policymakers and researchers in establishing country-specific investment policies taking into account their neighbouring countries, and considering common European policies for sets of countries with similar characteristics, with the aim of obtaining greater benefits. To this end, the geostatistical techniques Global and Local Moran Index were used in order to detect spatial dependence in the eco-efficiency obtained in the DEA. The analysis carried out confirms the existence of two clearly differentiated clusters according to their spatial location.

The empirical analysis of this research will advance the literature, addressing novel aspects that will expand the available information on the relevance of using sustainable resources. Specifically, the contributions to the literature are the following: (1) a variant of the traditional concept of eco-efficiency is proposed to determine the effects that environmental policies have on health and the economy; (2) evidence is obtained on the economic profile of the countries most involved in the mitigation of global warming; (3) the progress made by European countries in an attempt to improve the environmental situation is assessed; (4) the possible influence of neighbouring countries on climate engagement is determined; (5) the breadth of the period analysed will enable robust evidence to be obtained, which is directly applicable by decision-makers in order to guide the most appropriate policies for each country, taking into account relationships with neighbouring countries.

The paper is structured as follows. Section 2 reviews the literature on eco-efficiency as a way to ensure SD. Section 3 presents the methodologies and variables used. Section 4 analyses the results obtained in the research. Finally, the conclusions and contribution of the study are summarised in section 5.

2. Literature review

Energy consumption emits large amounts of CO_2, causing serious damage to ecosystems and biodiversity [34]. The consequences are increasingly visible: glacier retreat, extreme seasonal events, changes in agricultural productivity and even adverse health effects. These are so-called long-lived GHGs, with 50% persisting in the atmosphere for around 30 years, 30% for centuries and 20% for thousands of years. International agreements on CC have forced countries to limit their emissions in order to curb environmental problems and, as a consequence, there is an exodus to ERs. The aim is to seek and introduce new energy sources into production systems that guarantee environmental cleanliness without neglecting energy security, thus ensuring the SD of nations [35, 36]. All of this without forgetting that its use has very positive effects on health, thus reducing health costs derived from environmental pollution [37].

In addition, saving energy and combating CC can also be achieved by recycling waste (RW). This is a practice that reduces the demand for new raw materials, resulting in a lower consumption of energy resources and thus a reduction in GHG emissions [38]. Population growth coupled with rapid economic development and excessive urbanisation are the main causes of an increase in waste, threatening SD [39]. Humanity is faced with the need to modify its future strategies, where the use of SR and RW is gaining momentum.

The scientific community has taken up this issue, covering the different aspects of RE and RW with a growing research output. One stream of literature has focused on analysing the possible relationship between the use of ER and economic growth, and vice versa. Authors such as Apergis and Payne [40], Bhattacharya et al. [41], Koçak and Şarkgüneşi [42] and Shabaz et al. [43] have shown that RE has a stimulating impact on economic growth, hiding the need to modify not only productive systems, but also any daily activity that requires energy consumption. Membership of the European Union has been analysed to determine whether international trade contributes to efficiency in innovation, with the result that it is not significantly related to increased efficiency gains [44].

Although technological innovation has been shown to be a source of competitive advantage for firms [45], Khan et al [46] found that technological innovation, economic growth and direct foreign investment have negative consequences on RE. Government complicity is required to encourage and incentivise their use by ensuring the implementation of clean energy systems. In this sense, their ability to minimise the environmental effects of human actions has also been assessed [47, 48, 49].

With regard to RW, it has been shown that it requires a cultural change in the population where their involvement is supported by policies that favour this transition [50]. Industrialisation processes are usually associated with a progressive increase in waste generation, with negative environmental consequences [51]. The action of recycling should be conceived as a way of reducing waste production and mitigate its harmful effects [52]. According to Zhang et al. [53] it is an economically viable and biosphere-friendly activity. Cudjoe et al. [38] obtain evidence of the energy and environmental benefits of RW, its implementation would lead to significant electricity savings, in turn limiting GHG emissions.

At the same time, and as a result of the need to curb CC, the notion of eco-efficiency has arisen, and an extensive literature has developed around it. It is a multidimensional concept designed to analyse specific analytical contexts [54], which has led to its application using a wide variety of combinations of economic and environmental measures [55, 56]. Huppes and Ishikawa [57] consider that regardless of the variables used for its calculation, the objective should be to generate economic value while reducing environmental impact. Kuosmanen and Kortelainen [58] consider that eco-efficiency is a necessary condition for sustainability, but the promotion of eco-efficiency does not guarantee attaining it.

Eco-efficiency has been calculated in the literature in a wide variety of settings using a wide variety of methodologies. For example, Gössling et al. [59] calculate ratios to assess the environmental problems associated with tourism. Gumus et al. [60] propose an integrated input-output life cycle assessment and multi criteria decision making, assessing the eco-efficiency of the American manufacturing sector. Abdella et al. [56] construct an input-output model applied to the food sector. DEA is gaining popularity in this field due to the flexibility implemented in its variants: super efficiency and slacks-based measure [61], non-convex metafrontier DEA [62] and two-stage network DEA [63, 55], among others. This research proposes the use of DEA with an intertemporal dimension to determine which countries are able to obtain higher returns, measured in terms of GDP purchasing power standards (GDPpps) and reduction of deaths due to pollution, by introducing sustainable practices in their economies (RE, RW, national expenditure on environmental protection, employment and volume of employment in this sector).

3. Methods and Materials

The empirical analysis was carried out on a panel of European countries for the period 2014-2018. The limitation of statistical information about some variables prevented a complete study of all European territories, focusing the research on 20 nations, considered representative of the environmental policies adopted in this continent. DEA methodology, sequential MI, and spatial autocorrelation measures facilitated the resolution of the two research questions posed in Section 1.

3.1. Methods: DEA, MI and Spatial Autocorrelation Measures

DEA is a non-parametric linear programming method used to obtain a measure of the technical efficiency of each of the decision making units (DMUs) that make up the sample. These observations are characterised by a set of inputs and outputs, used to obtain the optimal combination to define a production frontier, formed only by efficient DMUs. The level of inefficiency will be determined by the distance between the score obtained and the efficient frontier, so that only efficient DMUs will form part of it. Depending on the characteristics of the problem to be analysed, the empirical analysis can be approached in such a way that the outputs are maximised with the available resources (output orientation) or vice versa, the inputs are minimised in order to obtain a set production level (input orientation). The original model proposed by Charnet et al. [64] is built under the constant returns to scale (CRS) perspective, i.e. assuming homogeneous behaviour of inputs and outputs. In order to relax this assumption, which is sometimes too restrictive and unrealistic, Banker et al. [65] introduce variable returns to scale (VRS), giving flexibility to the behaviour of the variables.

DEA has been widely accepted in the scientific community due to its great flexibility in defining the problem: it accepts different units of measurement for inputs and outputs; it does not require the establishment of a functional relationship between the variables; it admits the direct comparison of some DMUs with others, as well as with a combination of them [66]. It is a methodology whose application covers a wide area of interest, from the valuation of healthcare systems [67] to sectors such as energy [68], insurance [69], agriculture [70], tourism [71], education [72], water security [73], and even to estimate environmental performance [74].

Given the characteristics of the problem posed, the Banker et al. [75] output orientation model is proposed in this research. In addition, it was given an intertemporal dimension. The introduction of an undesirable output in the model was carried out following the proposal of Seiford and Zhu [76]. These authors propose the application of a linear monotone decreasing transformation, in order to preserve the convexity relationships. The efficiency level takes values equal to or greater than 1, where 1 represents the maximum level of efficiency and the excess over unity determines the proportion by which outputs should increase with the available resources. The score is bounded between 0 and 1, and is determined from the inverse of the efficiency level.

Productivity changes were calculated using the MI originally proposed by Caves et al [77]. It is a non-parametric methodology based on DEA, permitting the calculation of the progress in efficiency in accordance with technological changes during the period under analysis. Observations outside the frontier are situations where the use of resources was less efficient compared to the practices adopted in the best years. The specification introduced by Färe et al [78] permits decomposition of the MI into technical change (TC) and efficiency change (EC). The latter measures the overall change in relative efficiency from the distance between the observed output and the maximum level that could be obtained in two consecutive periods. It is associated with the change in the relative position of each DMU with respect to the technological frontier, resulting from the management of the production process itself and the capacity to introduce technological progress in its production function. Whereas the TC is calculated as a geometric mean of two ratios, determining the variation of production technologies. In this case, the existence of technical progress is considered by referring to innovations and techniques that shift the production frontier. Tulkens and Van Eeckaut [79] incorporate the accumulation of technology over time, sequential MI, thus avoiding the results yielding information which could be economically confusing, such as technological destruction. Values greater than 1 determine productivity increases caused by TC and/or EC.

Spatial autocorrelation, used in the second part of the research, measures the dependence of a variable on itself at different locations in space [80]. The Global and Local Moran Index are commonly used as an indicator of spatial dependence in a data set. The Global Moran Index (I) allows for the measurement of spatial autocorrelation between all observations of a variable [81, 82]. In our case, positive values of the index indicate a positive spatial autocorrelation in the eco-efficiency of the 20 European countries; when the eco-efficiency of a country increases or decreases, the eco-efficiency of its neighbours also increases or decreases, respectively. Conversely, negative values of the index indicate a negative spatial autocorrelation in European countries; when the eco-efficiency of countries increases or decreases, the eco-efficiency of their neighbours decreases or increases, respectively. There is no spatial autocorrelation between the 20 European countries when the value of the index is close to zero. The expression of the index is as follows:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \sum_{i}^{n}(x_i - \bar{x})^2} \qquad i \neq j$$

where I denotes Global Moran's Index, n the total number of European countries, x_i is the eco-efficiency of the ith country (i = 1,2,…,n), $\bar{x}$ represents the mean of x_i, w_{ij} refers to the elements in a spatial neighbourhood matrix which depends on the criteria used to define the concept of neighbour. We define neighbours as the spatial units that share a border [83]. For this, w_{ij} has the following form:

$$w_{ij} \begin{cases} 0, \text{ if j } \notin \text{V(i)}; \\ \frac{1}{n_{ij}}, \text{ if j} \in \text{V(i), with } n_i = \# V(i); \\ 0, \quad if\ i = j = 1, \ldots, n, \end{cases}$$

where i and j represent whichever two of the n countries and $V(i)$ the set of neighbours of i. In this way, no country is a neighbour of itself and the values in each row add up to unity because the weights w_{ij} are standardised. Taking into account proximity and socio-economic reasons, we have considered modifying the w_{ij} by considering Sweden as a neighbour of Denmark, France as a neighbour of the United Kingdom [84] and, finally, Germany as a neighbour of Italy (the latter because no information is available for Switzerland).

In short, the Global Moran Index compares how similar each country is to its neighbours, averaging all these comparisons to obtain a spatial pattern of eco-efficiency. Sometimes it is necessary to delve deeper into the analysis to determine exactly which countries are similar or different from their neighbours, using the Local Moran Index (I_i). It is a Local Indicator of Spatial Association (LISA), which was introduced by Anselin [83]. This ratio determines whether the spatial correlation scheme detected in all countries in the study is also maintained locally. The formula of the index is:

$$I_i = \frac{(x_i - \bar{x})}{\frac{\sum_{j}^{n}(x_j - \bar{x})^2}{n-1}} \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_j - \bar{x}) \qquad i \neq j$$

where I_i denotes Local Moran's Index.

In the notation which has become usual in this context, positive index values indicate a grouping of similar eco-efficiency levels, i.e. a cluster of countries with high values of eco-efficiency surrounded by neighbouring territories with similar levels (HH) or vice versa with low values (LL). Conversely, negative values show a different eco-efficiency association, countries with low eco-efficiency levels surrounded by neighbours with high eco-efficiency (LH) or high eco-efficiency levels surrounded by low eco-efficiencies (HL) [85].

3.2 Materials

The empirical analysis was carried out on a base of 20 European countries over a period of 5 years, using the latest published data (2014-2018). The calculation of eco-efficiency determines the capacity of production units, countries and companies to produce more products or offer more services while consuming fewer resources and limiting pollution [86]. The literature shows that the environmental variables used varied greatly, depending on the purpose of the study. Thus, studies have focused on reducing CO_2 emissions [87], unsorted waste [88], water footprint [89] and energy use [90], among others.

The DEA methodology is highly conditioned by the inputs and outputs used; hence the objectives set out in the research questions guided the choice. The constructed production function seeks to assess the extent to which environmental policies reduced deaths due to pollution (undesired output) and increased the country's added value (desired output). Table 1 presents the variables used, as well as the units of measurement and the sources from which they were extracted.

Table 1. Variables used in DEA and sequential MI

Variable	Role	Unit	Source
GDPpps	desirable output	billion purchasing power standards	Eurostat
Pollution mortality (PM)	undesirable output	1000000 inhab	OECD
Employment in environmental sector (Employment)	input	Full-time equivalent	Eurostat
National expenditure on environmental protection (Expenditure)	input	%GDP	OECD
Recycling waste (RW)	input	% total waste	OECD
Renewable energy (RE)	input	% total energy	Eurostat

Following the proposal of authors such as Li et al. [91] and Bresciani et al. [92] the inputs were delayed by one year, in order to reflect the time lag between the introduction of the measures and the attainment of economic results (GDPpps). In the case of deaths due to pollution, the time lag was extended by another year to take into account the maturation delay of illness. Table 2 presents the main statistics of the sample.

Table 2. Descriptive statistics of the variables (2014-2018)

	$GDPpps_t$	PM_{t+1}	$Employment_{t-1}$	$Expenditure_{t-1}$	RW_{t-1}	RE_{t-1}
Mean	698.69	294.72	0.02	0.02	27.41	21.16
SD	839.70	180.19	0.01	0.01	8.28	12.75
Max	3,158.34	732.82	0.06	0.06	53.30	54.16
Min	28.06	56.84	0.01	0.01	12.63	3.50

As Table 2 shows, the countries analysed have a wide dispersion in their positions with regard to CC, indicating that those most implicated in terms of expenditure, RW and RE do not always obtain the desired results. While Belgium and Austria allocate a significant part of their annual budget to environmental expenditure, it is Sweden, Slovenia and Germany that are making the greatest changes to their production systems in order to reduce pollution (RE, RW and RW respectively). However, the statistics reveal that this does not always result in a reduction in PM, Finland is the country with the lowest and Poland the highest, in line with the results of the study by Khomenko et al [93]. In terms of GDPpps, Germany ranks first, followed by the United Kingdom, France, Italy and Spain.

4. Results and discussion

Q1. To what extent is the introduction of sustainable practices having a positive impact on nations? Does the wealth of countries condition their level of eco-efficiency?

The DEA and sequential MI permitted the calculation of eco-efficiency levels and productivity changes, respectively. The columns in Table 3 show the eco-efficiency level (EFF level), the score (EFF score), the number of times the country obtained the maximum eco-efficiency (NºEFF=1), changes in productivity (MI), technological change (TC), eco-efficiency change (EC), the country's wealth measured in terms of GDP purchasing power parity per capita (GDPppp per capita) and the average growth in the period 2014-2018.

Table 3. Eco-efficiency levels and productivity changes.

	EFF level	EFF score	Nº EFF=1	MI	TC	EC	GDPppp per capita (€)	Growth GDP (%)
France	1	1	5	1.020	1.010	1.010	43,013	1.5
Ireland	1	1	5	1.153	1.019	1.131	71,092	10.8
Spain	1	1	5	1.019	1.009	1.010	37,193	2.7
United Kingdom	1	1	5	0.986	1.012	0.974	44,179	2.0
Sweden	1.002	0.998	1	1.008	1.044	0.966	50,444	2.8
Finland	1.004	0.996	2	0.993	1.013	0.980	45,303	1.4
Luxembourg	1.006	0.994	2	0.910	1.010	0.901	108,927	2.6
Portugal	1.016	0.984	3	1.047	1.007	1.039	31,598	2.2
Germany	1.021	0.980	2	0.982	1.060	0.926	50,622	1.9
Estonia	1.055	0.948	1	0.957	1.006	0.952	32,057	3.6
Netherlands	1.061	0,942	1	0.986	1.004	0.983	52,960	2.2
Belgium	1.090	0.917	1	0.982	1.062	0.925	48,567	1.7
Denmark	1.295	0.772		1.023	1.019	1.004	52,348	2.4
Italy	1.327	0.754		1.002	1.022	0.981	39,545	0.9
Austria	1.418	0.705		1.055	1	1.055	52,514	1.7
Slovenia	1.860	0.538		1.066	1.017	1.049	34,371	3.5
Poland	2.175	0.460	1	1.043	1.043	1	28,541	4.2
Lithuania	2.511	0.398		1.014	1.020	0.994	31,610	3.2
Czechia	3.904	0.256		0.971	1.000	0.970	36,492	3.7
Latvia	5.131	0.195		1.080	1.018	1.061	26,985	3.0
Mean	**1.594**	**0.792**		**1.015**	**1.020**	**0.996**	**45,918**	**2.9**

At a global level, the results show that Europe should increase its output by 59.4% with the available resources. Productivity during these five years barely increased by 1.5%; this growth was mainly due to the introduction of new technologies (2.0%), given that eco-efficiency underwent a slight variation (-0.4%). Furthermore, there is a large dispersion among the countries analysed. While 12 of them have inefficiency levels below 10%, others such as Poland, Lithuania, Czechia and Latvia require profound structural changes in order to reduce it (117%, 151%, 290% and 413%, respectively). However, it should be borne in mind that the DEA derives its results from a comparison with the observations in the sample. In this sense, the European level of environmental awareness is very high, being at the forefront in the introduction of sustainable practices, well ahead of the USA [94], thus explaining the results of these countries.

France, Ireland, Spain and the United Kingdom lead the way in their involvement in the European attempt to curb GHG emissions. All of them have demonstrated their ability to use their resources efficiently, reducing PM and increasing their production (EFF level =1) (*Q1*). However, the performance of Ireland stands out, where productivity has grown by more than 15%, due both to the introduction of innovative processes (TC=1.9%) and the ECs that took place during the period analysed. However, Latvia, which turned out to be the most inefficient country, has the next highest productivity increase (MI=8%) as a consequence of both TC (1.8%) and EC (6.1%). These results show that the level of eco-efficiency in no way underlies changes in productivity and that, despite differences, European nations are demonstrating a strong commitment to protecting the planet (*Q1*). Europe as a whole is highly involved in environmental issues, signing all international agreements on climate change and setting individual targets as a continent.

In December 2019, the European Green Deal was launched to give a boost to CC measures. It approved a very demanding package of measures with the aim of reducing GHG emissions by 55% by 2030, and achieving complete neutrality by 2050. In June 2021, EU environment ministers agreed on a CC adaptation strategy aimed at making society resilient to this biosphere-invasive scourge [95]. All this requires enhancing the use of RE, positioned as the fundamental tool to achieve environmental clean-up [96].

The last columns corroborate that environmental policies are in no case conditioned by a country's wealth or economic growth (*Q1*). For example, Spain, with below-average per capita income and economic growth, has shown a strong commitment to emission reduction measures; in contrast to other countries such as Czechia which, under similar economic conditions, has a margin for improvement of 290%. At the same time, in crisis situations such as the one experienced in the years after 2007, Burns et al. [97] showed that environmental policies are relegated to the background, leading to significant negative consequences for air quality.

Ultimately, the results show that there is a strong European awareness of taking measures to ensure environmental protection as a means to ensure the cleanliness of the biosphere, irrespective of the level of wealth and growth of countries. According to Zhang et al. [98] there should be a political dialogue in order to introduce civil perceptions on how to implement sustainable solutions in their regulations.

Q2. Is there spatial dependence in European eco-efficiency in the period 2014-2018?

In order to understand the spatial patterns in 2014-2018, eco-efficiency was mapped. Figure 1 shows the persistence of eco-efficiency levels over the period analysed. Countries with high eco-efficiency levels are grouped in the west of Europe (Portugal, Spain, France, Italy, the UK, Luxembourg, Ireland, Belgium, Denmark, Germany, Italy, the Netherlands, Austria, Sweden and Estonia), with the east having the worst performers (Latvia, Lithuania, Poland, the Czech Republic and Slovenia). Onat et al. [99] confirm these results in a regionalised assessment of the eco-efficiency of electric vehicles in Europe.

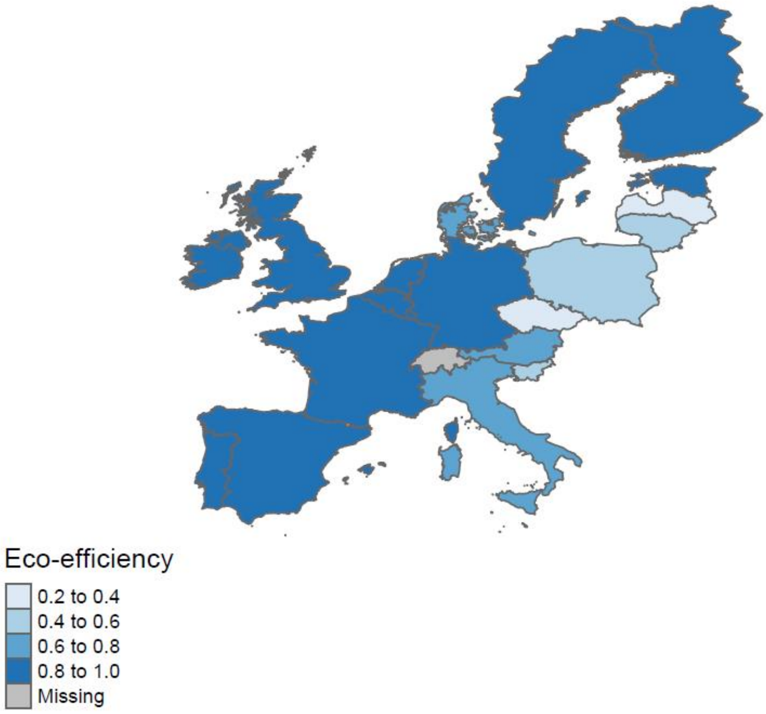

Figure 1. Spatial distributions of eco-efficiency from 2014 to 2018

Next, in order to test the significance of eco-efficiency dependence on space the Moran's test for spatial autocorrelation was calculated. The null hypothesis of no spatial correlation (Ho:I=0) was tested where the p-value was obtained using asymptotic distribution or by means of the Monte-Carlo test [100]. As seen in Table 4 there was a spatial dependence in the European eco-efficiency in the period 2014-2018 as the p-values obtained are significant (p-values <0.05) (*Q2*).

Table 4. Values of the Global Moran's Index and associated p-values to eco-efficiency

	Moran Global Index	Expectation	Variance	p-value M	p-value MC
[2014-2018]	0.441	-0.053	0.039	0.006	0.009

The Local Moran's Index detects 4 clusters (HH, HL, LL, LH), where mainly HH and LL predominate. Specifically, HH (blue) is formed by Portugal, Spain, France, the UK, Luxembourg, Ireland, Belgium, the Netherlands, Finland and Sweden, all of them characterised by high levels of eco-efficiency like their neighbours. Similarly, LL (red), consisting of Italy, Austria, Latvia, Lithuania, Poland, the Czech Republic and Slovenia, is the cluster of countries with low levels of eco-efficiency, close to territories with similar values. On the other hand, Germany and Estonia, classified in HL (orange), are characterised by a high eco-efficiency compared to neighbouring countries, the latter reaching lower values. Finally, Denmark, in LH (green), has low eco-efficiency levels, surrounded by territories with higher levels (Figure 2) (*Q2*).

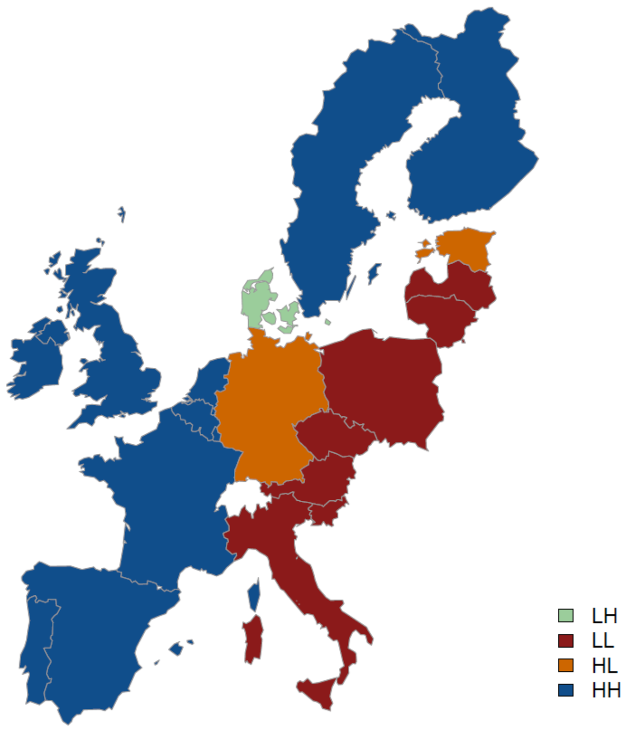

Figure 2. Local Moran's Index of eco-efficiency from 2014 to 2018

Significant Local Moran's Index are combinations of similar or dissimilar values more marked than what might have been observed based on random spatial distribution [101]. In this study only the cluster LL formed by Latvia, Lithuania, Poland and the Czech Republic is statistically significant. This group includes the countries with the worst eco-efficiency performance and require profound structural changes in order to reduce it (*Q2*).

5. Conclusions

Growing concern about CC has provoked a great commitment from the scientific community, with innumerable research projects being carried out on this paradigm. In this paper, we seek to make a novel contribution by proposing both an alternative version of the traditional eco-efficiency measure and the application of geostatistical techniques to measure spatial dependence in the period 2014-2018. Using intertemporal DEA and sequential MI, we quantified the adequacy of the measures adopted by European countries in their attempt to reduce the adverse effects of pollution without negatively influencing economic growth. A novel definition of eco-efficiency is proposed where the outputs determine the positive effect of sustainable practices introduced in the EU countries, considering a near and wide time horizon. The results reveal that almost all European countries are doing well, and this is not conditioned by either their wealth or their economic growth. The Eastern European countries have shown the greatest room for improvement, and the behaviour patterns of the more advanced countries such as Ireland, Spain, France and the United Kingdom need to be analysed.

Finally, the descriptive spatial study confirmed a significant spatial dependence in the eco-efficiency of the 20 European countries studied. Specifically, two predominate clusters were detected: a cluster of high eco-efficiency formed by West European countries and another cluster of low eco-efficiency composed of East European countries. Only the low eco-efficiency cluster was significant which is formed by Latvia, Lithuania, Poland and the Czech Republic. The results of this research can be used by decision-makers when implementing policies adapted to the needs of each country, taking into account the spatial structure of the European continent.

The LL cluster countries have very limited levels of eco-efficiency compared to the various remaining European countries. The implementation of renewable and environmentally friendly technologies requires proper financing. Thus, EU decision-makers should take this situation into account when allocating resources for CC mitigation in Europe.

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