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Environmental pressure measurement: A composite and discriminant approach

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ABSTRACT

This paper presents a planning-focused statistical approach to the measurement and interpretation of environmental pressure in diverse economic systems. The paper concentrates on OECD and BRICS nations during the period 2000-2023, using a distance-based composite indicator and multivariate classification methods to inform evidence-based environmental and industrial planning. Environmental pressure is assessed by a non-compensatory composite index based on carbon dioxide, methane, and nitrate emissions, reflecting structural stress generated by energy consumption, industry, and agriculture. The composite index facilitates longitudinal analysis and cross-national comparison, offering a composite yet policy-useful measure of aggregate environmental pressure. To provide a dynamic perspective, Linear Discriminant Analysis is used to assess whether emission structures distinguish statistically advanced and emerging economies and to specify transition or hybrid patterns. The findings indicate the persistent diversity of institutional categories and the increasingly blurred line between OECD and BRICS nations. Misclassifications are interpreted not as model errors, but as statistically meaningful signals of structural transition and partial convergence in emission profiles. This evidence challenges rigid development-based classifications and supports a continuum-based interpretation of environmental pressure. From a socio-economic planning perspective, the proposed framework enhances statistical measurement for sustainability by linking composite indicators with structural diagnostics. It provides a decision-support tool for identifying transition cases, monitoring convergence processes, and designing differentiated environmental policies aligned with country-specific emission structures rather than institutional labels alone.

1. Introduction

In recent decades, growing environmental pressure associated with economic development and industrial transformation has become a central challenge for socio-economic planning. It has become essential for policymakers to observe environmental stress not merely in aggregation, but also in terms of structural differences. When environmental constraints become intertwined with economic growth, structure, and size, the assessment process becomes an essential input for planning [1].

The OECD countries and the BRICS countries can be differentiated and are often used in literature as a useful shortcut proxy for stages of development [2]. Yet, the OECD and BRICS categorization could be overly dogmatic and lacking in substance if not empirically assessed against real-world environmental scenarios [3]. This is particularly the case where the evolution of production structures, energy diversification, and the application of different environmental strategies could present patterns of convergence or divergence that might not necessarily fit the institutional categorizations [4].

From the socio-economic planning perspective, the OECD–BRICS classification is often used as a heuristic device to guide environmental and industrial policy design. Yet, policies based on rigid institutional grouping risk neglecting substantial internal heterogeneity and transitional dynamics. Countries that belong to the same group may well display starkly different environmental pressure profiles. These differences imply that standardized policy interventions can be inefficient or misaligned with actual structural conditions.

Against this background, the objective of this study is not only to compare environmental pressure across OECD and BRICS countries, but also to develop a planning-oriented analytical framework capable of identifying structural similarities, transition cases, and policy-relevant convergence dynamics. By integrating multidimensional synthetic indicators with multivariate classification techniques, the paper aims to

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support differentiated and adaptive environmental planning strategies based on actual emission configurations rather than institutional labels.

In the first phase, a distance-based synthetic indicator (EPCI) is calculated to measure the level of environmental pressure and its evolution during the time framework from 2000 to 2023.

The selection of carbon dioxide, methane, and nitrate emissions as the core variables of environmental pressure arises from their complementary representation of the three main anthropogenic sources of ecological stress: energy production, industrial processes, and agricultural activities. Carbon dioxide (CO_2) remains the principal driver of anthropogenic climate change, directly linked to fossil fuel combustion and industrial output [5]. Methane (CH_4), even though it is emitted in lower amounts, has a global warming potential about 28 times higher than CO_2 over a 100-year timeframe. Most of the emissions are related to livestock production, waste management, and fossil extraction [6]. Nitrate emissions, in turn, act as an important proxy for agricultural and soil degradation processes, representing nutrient runoff contributing to eutrophication and long-term deterioration of water quality [7], [8]. These three pollutants collectively embody the multidimensional character of environmental stress across sectors and are widely used in composite indicators of sustainability and environmental performance [9], [10], [11]. By integrating them into a single analytical framework, it becomes possible to capture both the cross-sectoral heterogeneity of environmental impacts and their temporal evolution [12]. This framework thus provides a more holistic assessment of structural convergence or divergence across OECD and BRICS countries.

Analytical and integrated perspectives are particularly relevant for socio-economic planning. This perspective allows policymakers to identify structures and dynamics of environmental pressure [13]. By combining synthetic monitoring with structural classification, the framework facilitates identifying countries to be kept under observation. These Countries could require differentiated policy responses, including transition economies that fall outside the usual structural development classification.

The application of the DP2 indicator allows the realization of rankings understandable both across and between countries [14]. This method acquires a long-term vision about the evolution of the environmental issue [15]. This phase addresses the typical needs of socio-economic planning by providing synthetic indicators to monitor the evolution of environmental pressures [16], [17].

In the second stage of analysis, structural differences in OECD and BRICS member states are analyzed. It is done with the help of Linear Discriminant Analysis (LDA) over three years: 2000, 2013, and 2023. On choosing these years, they denote an early stage in the study period, an intermediary part after the world financial and economic crisis [18] and currently denote an emerging phase with much emphasis on climate policies and transition [19]. Linear Discriminant Analysis gives an opportunity to establish how far and in what manner, considering chosen variables on the environment side, distinction is possible between groups [20].

The combination of DP2-based temporal analysis and the classificatory approach of discriminant analysis is one of the original elements of this research. In fact, DP2 conveys both a synthetic indicator of environmental pressure and its long-term evolution. At the same time, discriminant analysis facilitates an analysis of the multivariate configuration of the emissions and the interpretation of results in terms of convergence and problematic aspects.

The contribution of this study thus consists of two aspects. Firstly, it provides an empirical comparative study of pollution processes for both OECD and BRICS countries over an extended period. Secondly, this study advances an integrated methodological framework for the use of synthetic indicators and multivariate analysis from the perspective of planning environmental policies.

This study contributes to the socio-economic planning literature in that it introduces a quantitative approach based on the utilization of composite indicators and classification techniques that can serve as an evidence-based foundation for conducting policy analysis. In particular, the suggested methodology enables policymakers to reveal structural disparities and transition dynamics in the sphere of environmental pressure across countries.

About decision-making, statistical techniques such as composite indices and discriminant analysis play an irreplaceable role in simplifying complicated information on environment into easily understandable indices. Hence, through a combination of these two techniques, there will be increased chances of detecting converging and diverging patterns of development among various countries. The study makes several contributions to the extant literature in three key areas. First, the paper provides an integrated approach to the use of a non-compensatory composite indicator (DP2) along with discriminant analysis to evaluate both the level and structure of environmental pressure at once. Second, the study gives an alternative interpretation of the findings related to misclassification errors in discriminant analysis. Rather than being taken for modeling errors, they can be regarded as signals of change in structures and partially achieved convergence between different modes of development. Third, the study gives valuable implications for policy makers by proving that environmental pressure is best viewed as a continuum instead of a dichotomous variable.

With regard to the above-stated aims of the study, the following question arises:

> RQ: *How relevant is the traditional OECD/BRICS classification today from the standpoint of analyzing dynamics of environmental pressure in countries?*

Even though the division into OECD and BRICS countries has become quite popular for comparisons [21]. This research critically evaluates the empirical grounds for such an approach by investigating whether the environmental pressures still correspond to this division [22].

Finally, the rationale for choosing the period under consideration (from 2000 until 2023) is due to the necessity to observe the processes of transformation in the environmental sector to ensure data comparability and consistency [23].

The remainder of the paper is organized as follows. Section 2 provides a comprehensive review of the extant literature on environmental pressure, with reference to cross-country comparative analyses. Section 3 provides a comprehensive overview of the data, variables, and methodological framework employed in this study. This section includes the construction of a synthetic environmental pressure index and the application of discriminant analysis, which is a key element of the study. The fourth section of this study presents and discusses empirical results, with particular attention being paid to temporal dynamics and group differentiation. Finally, Section 5 concludes with a summary of the main findings, an outline of policy implications, and a discussion of the limitations of the research and directions for future research.

In doing so, the paper bridges quantitative measurement and socio-economic planning, supporting the development of adaptive and evidence-based environmental policies. More importantly, it moves beyond static institutional classifications, providing a dynamic and empirically grounded framework for understanding environmental pressure.

2. Literature review

The comparative assessment of environmental pressure between advanced and emerging economies has long been central to sustainability research [24]. This happens particularly in relation to policy design and long-term planning [25]. Early approaches often relied on simplified frameworks, such as the Environmental Kuznets Curve (EKC), about relationships between economic growth and pollution [26], [27]. However, a growing body of empirical evidence highlights that environmental trajectories are increasingly shaped by structural, technological, and institutional factors [28]. Analytical tools are becoming necessary to support adaptive planning strategies [29], [30].

From a planning perspective, the EKC framework provides limited operational guidance [31]. EKC does not adequately account for structural heterogeneity, sectoral composition, or policy-driven transition processes across countries [32].

In response to this complexity, scholars have progressively adopted composite and distance-based indices to evaluate sustainability and environmental pressure in a comparable way across heterogeneous economies. The development of non-compensatory synthetic indicators, such as DP2 and its extensions has been particularly relevant because they account for the correlation structure among variables and the asymmetric influence of extreme environmental stressors [33], [34]. Studies applying similar frameworks across the EU-27 or OECD samples show that while certain forms of convergence in pollution efficiency exist, structural divergence often persists, especially in energy-intensive sectors [35].

From a socio-economic planning perspective, synthetic indicators condense complex information into clear signals for decision-making [17]. Non-compensatory indices being especially suited to environmental monitoring [36].

Lyulyov and Pimonenko [37] further demonstrated that discriminant and clustering methods can successfully classify national environmental models by integrating economic, social, and environmental variables, revealing meaningful differentiation between high-income and emerging economies [38].

From a methodological perspective, LDA has shown to be a robust method in cross-country classification, especially when investigating environmental and socioeconomic heterogeneity [39], [40]. It conveys maximal group separation with the preservation of interpretability, thus being suitable for such studies comparing institutional or regional categories like OECD and BRICS. In the context of sustainability research, discriminant methods have been applied not only to assess emission profiles but also to investigate broader constructs like energy transition readiness [41] or human well-being under technological transformation [42].These techniques complement the use of synthetic indicators by identifying structural clusters, transition cases, and misclassification patterns that can be interpreted as signals of partial convergence between different development models.

Discriminant analysis is particularly valuable because it helps to identification boundary cases and transitional profiles that do not conform to predefined institutional groupings [20].

Empirical findings consistently highlight the growing environmental divergence between large-scale emerging economies, particularly China and India, and most OECD members [43]. Nonetheless, evidence of partial convergence is emerging, especially in middle-income BRICS economies pursuing energy diversification and environmental governance reforms [44], [45].

Comparative studies applying entropy measurements or composite indices [46], [47]. have found evidence to affirm that the convergence of certain dimensions of pollution, for example, methane abatement, may co-exist with the existence of divergence in other dimensions, namely carbon intensity and/or nitrate emissions. This condition underscores the idea that convergence and divergence do not have to exist as mutually exclusive outcomes but rather as co-existent phenomena.

These findings suggest that environmental convergence in the environment needs to be recognized as dynamic and sensitive to policies. The frameworks that use static group definitions in planning can overlook dynamic transition and allocate inadequate resources in policies.

Current literature tends increasingly towards integrating metrics of environment pressure with metrics of innovation, human capital, and institutional factors; acknowledging that technological and policy factors mediate the association between economic development and emissions [48], [20]. While in developed countries factors such as eco-innovation and digitalization have resulted in improvements in the emission efficiency of the economy in high-income countries; in the BRICS countries, similar improvements are limited by industrial structure and energy composition inertia in the BRICS countries [49].

The OECD/BRICS gap is better captured as a dynamic continuum rather than a fixed categorization based on the changing parameters of public policies and structures of production [50]. The Country's specific trends regarding carbon emissions and environmental performance are not merely based on the overall economic characterization but on the adoption of technology in different sectors [51], [52]. Using composite indices for an empirical assessment indicates varied trends for environmental transitions among different BRICS nations, some conforming to the emission patterns of developed nations but many others moving apart soon [53].

Overall, the literature converges around a few key messages. Firstly, environmental pressure needs to be analyzed using integrated frameworks that take both time and structure into consideration. Secondly, convergence between OECD and BRICS countries remains incomplete and asymmetric, reflecting their heterogeneous capacities in terms of technological innovation, as well as disparate implementation capabilities regarding environmental policy. Thirdly, the combination of synthetic indices (such as the Environmental Pressure Composite Index) with techniques of discriminant analysis enables the recognition of threshold cases and patterns of heterogeneity that would have otherwise remained hidden in aggregated statistics. Synthetic indicators condense complex information into clear signals for policymaking, with non-compensatory approaches being particularly appropriate for environmental assessment [54].

However, there is still a need to link composite indicators together with clustering and classification approaches that can reveal structural shifts in countries' development over time. Specifically, although many past studies have concentrated either on developing composite indices or clustering/classification analysis [55], [56] very few have considered using both approaches in an integrated manner [57],

At the same time, recent research on environmental data governance and indicators underscores the growing significance of valid, comparable and useful decision-making indicators in informed decisions. Yet, the problem of understanding whether and how these indicators can be interpreted in terms of structural convergence, divergence or shifts persists.

Firstly, there is a lack of integration among the two major analytical techniques that have been used in previous literature. Secondly, the issue of interpretability of the concept of structural convergence and divergence lacks development. Lastly, the approach taken in the past literature is static and not transitional, thus ignoring the dynamics of the pressure patterns. This paper bridges all these gaps with a dynamic framework of analysis.

3. Materials and methodology

3.1. Data and variables

The empirical analysis is based on a balanced panel dataset covering OECD and BRICS countries over the period 2000–2023. Data were retrieved from the World Bank database and refer to three key dimensions of environmental pressure: carbon emissions, methane emissions, and nitrate-related pollution. These variables were selected as they jointly capture different and complementary sources of environmental stress associated with energy use, industrial activity, agriculture, and structural economic change. The group categorization of the nations has been done based on their membership to the respective organization, with the BRICS categorization used extensively for the purposes of comparison in economic and environmental studies.

The choice of focusing on environmental emission variables is consistent with the objective of the paper, which is not to measure sustainability in a broad normative sense, but rather to assess the level, structure, and evolution of environmental pressure across countries characterized by different stages of economic development.

In the focus of emission-based indicators within a socio-economic planning perspective, one would be able to monitor directly the environmentally relevant stress concerning production structures, energy use, and agricultural practices. These variables are of relevance for policy design since they will be closely linked with regulatory instruments, sectoral interventions, and long-term environmental targets.

3.2. Analytical framework

Given the inherently multidimensional nature of environmental pressure, its assessment requires methodological approaches capable of synthesizing heterogeneous indicators into a coherent and interpretable measure, while preserving cross-country comparability and temporal consistency.

Methodological requirements are particularly binding in the planning context as decision-makers demand the use of tools that can guide them in monitoring processes over time. The issue has implications for the design and adjustment of environmentally and industry-related policies on different scales. Under such a framework, a relevant example of a suitable tool for the DP2 approach would be that provided by the DP2 method itself [58], as it enables a synthetic indicator to be created using distance functions, taking into consideration the contribution of each variable as well as their intercorrelations [59].

Compared with alternative aggregation techniques, such as principal component analysis, the DP2 approach presents several advantages. First, it avoids the loss of information typically associated with dimensionality-reduction methods, while effectively controlling for multicollinearity among indicators. Second, the weighting scheme is endogenous, as each variable contributes to the composite index according to its specific discriminatory power [30], [31]. Moreover, DP2 is a non-compensatory method: high levels of environmental pressure in one dimension cannot be fully offset by lower values in other dimensions, making the index particularly appropriate for capturing cumulative environmental stress [60], [61].

The non-compensatory structure of the DP2 index reinforces its ability to identify critical concentrations of environmental pressure that call for policy intervention. Disallowing offsetting effects across dimensions means that the index provides a conservative and policy-relevant signal of cumulative environmental stress and supports priority interventions and resource allocation in environmental policy frameworks. Another advantage of the DP2 method is its ability to analyse longitudinally. Through its consistent application over time, it is possible to track cross-sectional and dynamic patterns of environment pressure. In this analysis, DP2 is calculated for each country and each year. This enables the assessment of trends, convergence or divergence, and relative ranking over time of OECD and BRICS member-countries within the 2000-2023 timeframe. This temporal dimension substantially enhances the relevance of the index from a policy and planning perspective, as it supports the evaluation of structural changes in environmental pressure over time [62].

The framework ensures that that the issue of temporal consistency is considered, which helps in determining the trends that can emerge in the long term. The information obtained is critical in determining the efficacy of the adopted policy and how its alignment in the future can help in meeting long-term goals related to the environment.

3.3. Construction of the EPC index

Construction of the composite index involves the inclusion of carbon dioxide emissions, methane emissions, and nitrate emissions since each represents an environmental pressure from a different angle. Carbon dioxide emissions are an indication of pressure from energy generation and manufacturing industries on the environment, methane emissions are associated with agricultural activities and waste management processes, while nitrate levels indicate pressure from agriculture and water pollution.

However, despite the broad nature provided by the index proposal, it is important to highlight that some issues have not been considered within its calculation. These include issues like biodiversity and land use changes. In any case, it is important to emphasize that the purpose of the index does not include obtaining an all-encompassing indicator of environmental sustainability; it only captures sector-specific environmental pressure regarding emissions.

The process for building the EPCI is done step-by-step. To begin with, a data matrix is established, where each statistical unit (country) is described using the chosen environmental variables. For each variable, there is a reference value, generally representing the lowest observed value, which is used as the benchmark for the greatest environmental pressure.

The definition of common reference benchmark has great importance in relation to plans, as through this, decision-makers can measure levels of relative pressure on the environment within an understandable frame of reference. It enables countrywide comparisons and helps identify areas in which intervention in policies is needed.

The EPCI for each country is then calculated as a weighted sum of standardized distances from the reference values, according to the following general formulation:

$$DP2_{j,k} = \sum_{i=1}^{n} \left[\left(\frac{d_{i,j,k}}{\sigma_i} \right) \left(1 - R^2_{i,i-1,\ldots,1} \right) \right]; \; i = 1, 2, \ldots, n \quad k = 1, 2, \ldots, K$$

Where:

- i = 1, …, n; (variables) and j = 1, 2, …, m (areas),
- dij = $\left| x_{ij} - x^*_{ij} \right|$ is the difference between the value taken by the i-th variable in area j and the minimum of the variable in the least desirable theoretical scenario, namely the reference value of matrix X, and,
- σi is the standard deviation of variable i.
- $R^2_{i,i-1,i-2,\ldots,1}$ is the coefficient of multiple linear correlation squared in the linear regression of Xi over Xi-1, Xi-2, …, X1, and it indicates the part of the variance of Xi explained linearly by variables Xi-1, Xi-2, …, X1.

$k = 1, 2, \ldots, K$ *years*

EPC index should be regarded as a comparative indicator of environmental pressure. The larger the value of EPC index, the farther a country's environmental pressure from the reference point, implying high environmental pressure on the environment. The converse is true for a small value of the index, implying good environmental performance. It is imperative to stress the point that the index reflects the relative difference in environmental pressure among countries. This implies that changes in the level of the EPC index reflect differences in environmental pressures among countries.

3.4. Discriminant analysis

Although the DP2 index makes possible the tracking of the total amount of environmental pressure and dynamics of its change, it is unrelated to the evaluation of possible differences in the structure of emission profiles of various groups of countries.

For this purpose, Linear Discriminant Analysis (LDA) is used.

LDA is employed to evaluate whether carbon, methane, and nitrate emissions can statistically discriminate between OECD and BRICS countries, treated as two predefined groups. This task of classification is not meant for reproducing fixed group differences, but rather for testing whether structures of emissions correspond with institutional categories. These errors of classification offer meaningful indicators for the detection of transitional profiles and diverse demands of policy [20].

The analysis is done in three benchmark years, namely 2000, 2013, and 2023. These years have been chosen to represent an early point in the sample period, the post-global financial crisis era, and the current era of high climate policies and transitions.

It can be defined as a linear combination of the environmental variables in a way that the ratio of between-group variance to within-group variance is maximized [62]. In the case of binary classification, there will be only one estimated discriminant function for each benchmark year. Resulting scores enable countries to be positioned along a discriminant axis, which can easily show the degree of separation and overlap between groups.

Model performance is assessed by several complementary criteria: the percentage of correctly classified observations, Wilks' Lambda and other multivariate significance tests, such as Pillai's Trace, Hotelling-Lawley Trace, and Roy's Largest Root, and posterior probabilities of group membership. Besides, canonical discriminant plots will be used as a means of giving a graphical representation of the relative positions of OECD and BRICS countries in the discriminant space.

Prior to estimation, standard diagnostic checks regarding multivariate normality and homogeneity of covariance matrices were conducted. Although minor deviations of these assumptions were identified, LDA still has an appropriate application here given the exploratory nature of the analysis and its interpretative rather than strictly predictive focus. In addition, empirical studies in the past have also utilized these multivariate techniques for cross-country environmental analyses and show that LDA is robust enough against moderate violations of these assumptions.

3.5. Integrated methodological perspective

The approach that associates the synthetic indicators based on DP2 and discriminant analysis can be noted as an important methodological achievement of this paper. The reason is that while DP2 measures the whole extent of pressure and its dynamic development in the whole process, LDA enables consideration of the structure of emissions and the extent of separation of the OECD and BRICS countries in the statistics.

However, classification mistakes are seen not only as inaccuracies in the model but as significant signals pointing towards internal heterogeneity and transitional dynamics. Regions falling around or near the line of discrimination could reveal intermediate environmental characteristics, which define processes of both convergence and divergence that are not explicitly distinguished by classification arrangements.

Overall, this integrated framework supports a nuanced interpretation of environmental pressure trends and provides a helpful framework for analysis in the context of socio-economic planning and the formulation of nation-specific environmental policies independent of grouping patterns.

4. Results

It is worth mentioning that the empirical findings will be explored at two different steps. Firstly, there will be an examination of the evolution of EPCI, which has been calculated based on DP2. This will give insight into long-term evolution and cross-country variations related to total environmental pressure. Finally, findings related to discrimination analysis will be mentioned, which will inform readers on how structures of emissions affect OECD and BRICS nations.

In Fig. 1, it can be seen how, unlike the Chinese case, which shows a strong and continuous growth pattern regarding the values related to EPCI, in the case of the USA, a process of gradual reduction can be identified, particularly since mid-2005, according to stabilization and efficiency mechanisms.

Fig. 2 illustrates the trend in environmental pressure in OECD countries. Most OECD countries are found to have a trend in EPCI that is decreasing or stable over the period studied, especially from the late 2000s. This trend is indicative of a degree of decoupling between economic activities and environmental pressures.

In Fig. 3, it is evident how the EPCI of different countries shows differing paths of development for BRICS. Although there are countries within BRICS with moderate or stable EPCI, China and India are leaders with increased EPCI trends, symbolizing steady industrialization and increasing activity with higher emissions. These differences among various countries within BRICS show internal diversity, thereby calling for discriminant analysis.

To better grasp these issues, the empirical part is divided into two complementary phases. First, by building on the EPCI, the synthesis of the whole extent of the environmental pressure and the construction of the ranking allowing for a cross-country comparison throughout the whole period of 2000-2023 is done. Secondly, LDA is used for three key

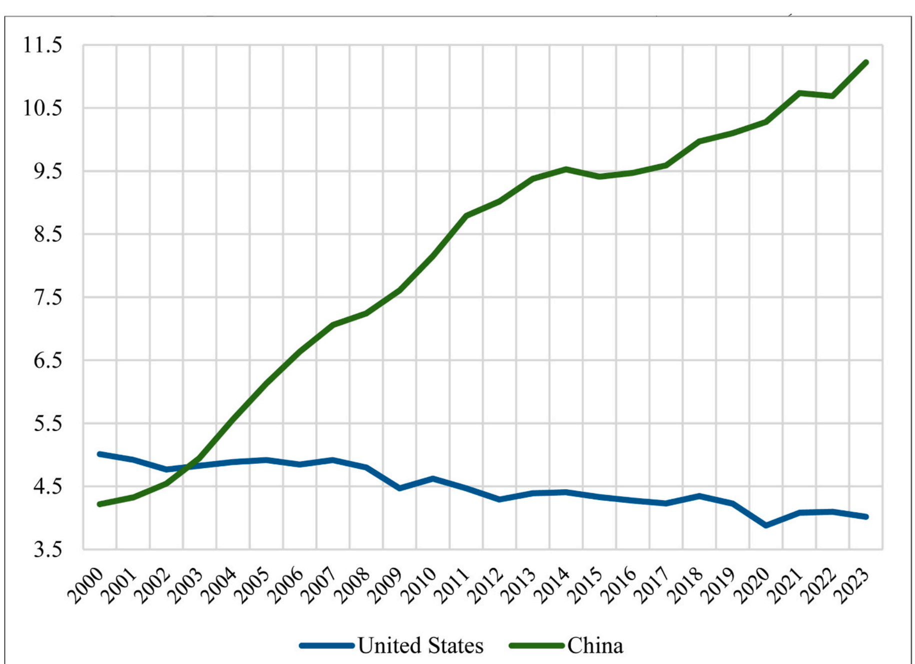

Fig. 1. Temporal evolution of EPCI, USA and China (2000 – 2023).
Source: Author's elaboration

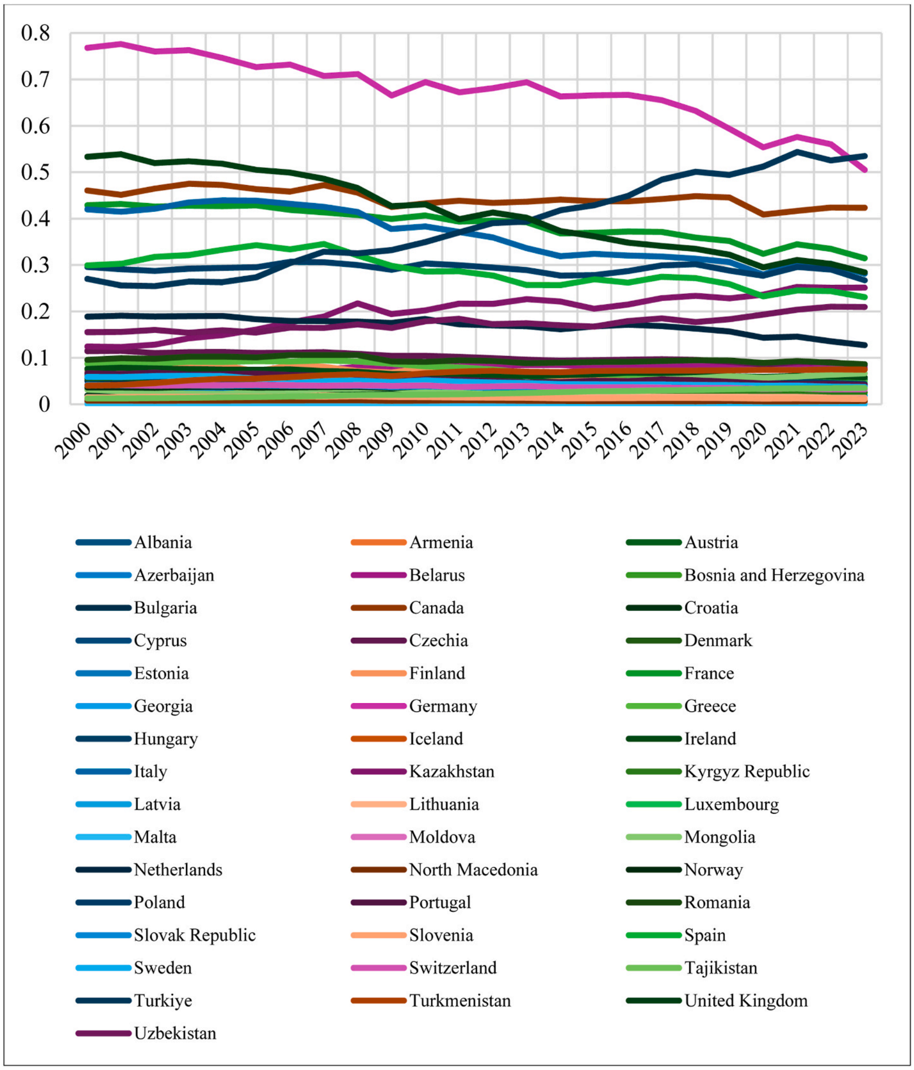

Fig. 2. Temporal evolution of EPCI, OECD countries (2000 – 2023).
Source: Author's elaboration

dates (2000, 2013, and 2023) to determine if the vector of indicators of pollution can differentiate in a statistically significant way between OECD countries and BRICS countries.

Concerning the EPCI, the rank reveals a high level of diversity among states, as well as a great diversity of evolutionary profiles. For instance, in 2023, high ranks are recorded for large states characterized by high production and demographic capacities, where China again dominates by a wide margin (EPCI = 11.2243), followed by the United States (EPCI = 4.0164), then India (EPCI = 3.8231); then come the remaining BRICS, where Russia ranks high (EPCI = 1.9663), then Brazil (EPCI = 1.4712), then South Africa, which shows moderate ranks (EPCI = 0.3780). Countries showing the lowest ranks are small countries characterized by minimal overall environment pressure. For example, the ranks are minimal for Malta (EPCI = 0.0003738), then Iceland (EPCI = 0.0022006).

Concerning the evolutionary pattern, there are divergent profiles, where some states register high evolutionary increases over time, especially China and India. Another pattern concerns several developed countries, specifically OECD members, where there are reductions or stabilizations over the years. This concerns, for example, the United States, where it declined from 5.0114 in the year 2000 to register a EPCI rank of 4.0164 by the year 2023. The United Kingdom declined from EPCI rank 0.5332 to register rank EPCI = 0.2845, where it stabilized. The Italian country also showed similar reductions, where it decreased from rank EPCI = 0.4202 to register rank EPCI = 0.2815.

Considering these heterogeneous temporal dynamics, the analysis next examines whether the joint configuration of carbon, methane, and nitrate emissions can statistically differentiate OECD and BRICS countries through a discriminant approach.

Fig. 4 portrays the canonical discriminant function used to discern the degree of separation in carbon, methane, and nitrate emissions between OECD and BRICS nations in the benchmark year 2000. The canonical discriminant function in Fig. 4 reveals that there is a distinct separation between the two groups using the canonical dimension, but there is also quite a small degree of overlap that is primarily driven by several nations in the BRICS cluster that lie closer to the OECD cluster's centroid. The implications of this situation are that there is currently not a complete structure alignment in the pressure and institutions in the early start of the time span and that there might be transitional structures in the BRICS group and not in the OECD cluster.

These findings from the discriminant analysis may be elaborated upon with respect to the structural features that underlie them. For instance, countries that fall into the OECD category typically demonstrate less environmental pressure, which may be attributed to their superior technological capability, stringent environmental policies, and the progressive shift towards the utilization of environmentally friendly

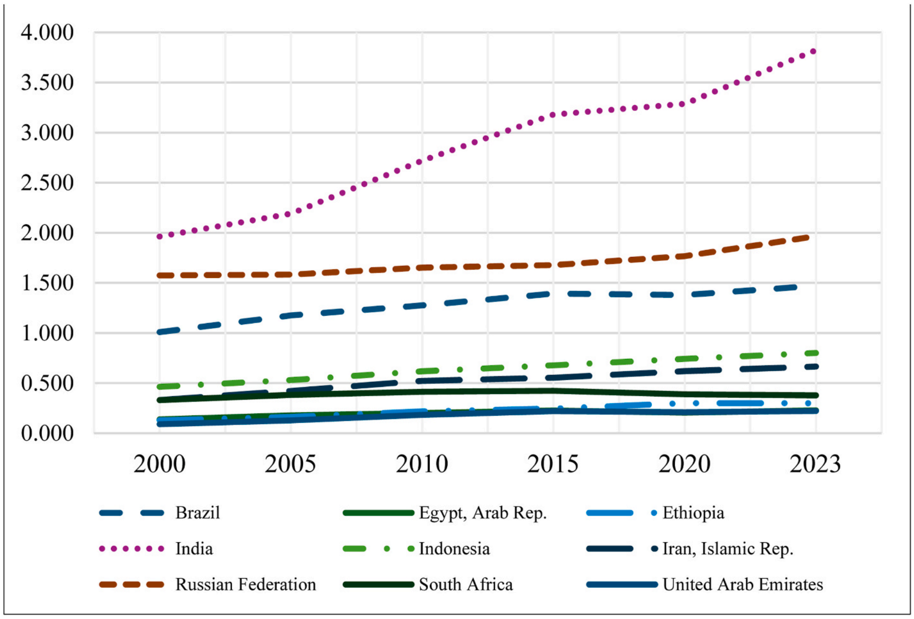

Fig. 3. Temporal evolution of EPCI, BRICS countries (2000 – 2023).
Source: Author's elaboration

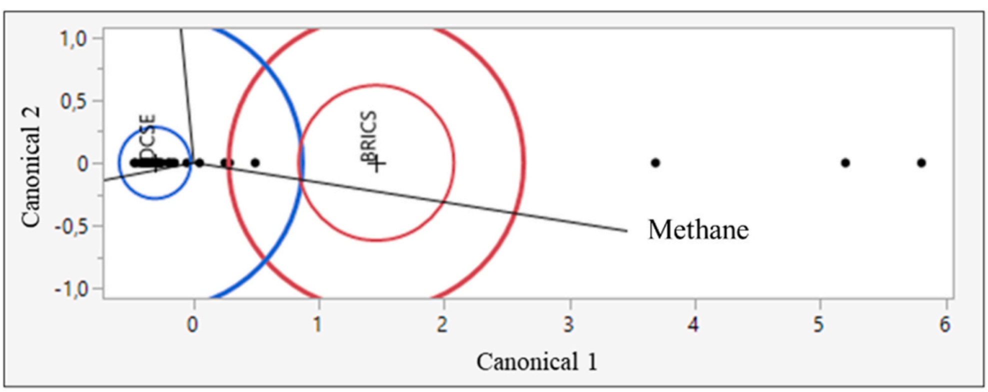

Fig. 4. Canonical Discriminant Function Plot – OECD vs BRICS (Benchmark Year 2000).
Source: Author's elaboration

energy sources. In contrast, countries belonging to the BRICS category demonstrate greater environmental pressure due to their more industrialized structure and dependence on fossil fuels. Nonetheless, the existence of instances where classification errors have occurred implies that these structural differences are changing over time, possibly pointing towards convergence.

Results for the benchmark year 2000 point to a statistically significant separation between the two country groups, namely OECD and BRICS countries. The value of canonical correlation suggests moderate but meaningful discriminating power, which in turn suggests that the environmental variables selected do capture relevant structural differences between the two groups while allowing for partial overlap (Table 1).

Multivariate tests of discriminant significance prove the statistically significant distinction between OECD and BRICS nations in 2000 (Table 2), and this holds true for 2013 and 2023 as well (Tables 4A and

Table 2
Multivariate tests of discriminant significance (OECD vs BRICS) 2000.

Test	Value	Exact F	Num DF	Den DF	Prob > F
Wilks' Lambda	0,6813259	8,2632	3	53	0,0001*
Pillai's Trace	0,3186741	8,2632	3	53	0,0001*
Hotelling–Lawley Trace	0,4 264	8,2632	3	53	0,0001*
Roy's Largest Root	0,4677264	8,2632	3	53	0,0001*

Source: Author's elaboration

Table 1
Summary of discriminant analysis statistics, 2000.

Eigenvalue	Percentage	Cumulative Percentage	Canonical Correlation	Likelihood Ratio	Approx. F	Num DF	Den DF	Prob > F
0,46772639	100,0000	100,0000	0,56451227	0,6813259	8,2632	3	53	0,0001*

Source: Author's elaboration