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SPATIAL CLUSTERING AND MACHINE LEARNING TO OPTIMIZE CARBON TAX DESIGN ACROSS ECONOMIC-ENVIRONMENTAL JURISDICTIONS

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Abstract

This study focuses on designing a carbon tax policy based on spatial clustering and machine learning to identify optimal jurisdictions based on environmental-economic performance. The research aims to identify spatial patterns of environmental-economic performance across 38 countries, cluster countries based on similarity profiles using data-driven clustering methods, model the relationship between carbon prices/taxes, economic indicators, and environmental indicators, and recommend optimal carbon tax ranges for each jurisdictional cluster. Adopting a quantitative approach, this study utilizes secondary data from 38 countries, encompassing variables such as carbon prices/taxes, GDP, carbon emissions, energy consumption, industrial contribution to GDP, Environmental Performance Index (EPI), and climate change scores. The analysis employs Ward's hierarchical clustering method and evaluates silhouette coefficients to assess clustering validity. The results classify countries into five distinct clusters with varying environmental-economic characteristics. Developed nations with high environmental performance (e.g., Sweden, Norway, Denmark) are recommended to implement high carbon taxes (USD 100–150 per ton CO_2), while developing countries with high emission intensity (e.g., Indonesia, Kazakhstan) are advised to adopt low initial rates (<USD 15 per ton CO_2). Transitional economies are suggested to implement intermediate rates (USD 20–60 per ton CO_2). This study underscores the necessity of carbon tax policy differentiation based on economic capacity and environmental performance, as well as the importance of international cooperation in technology transfer and energy transition financing. The theoretical contribution lies in integrating Pigouvian Tax frameworks, spatial approaches, and machine learning to develop a more adaptive environmental fiscal policy design.
Keywords: carbon tax, spatial clustering, economic-environmental performance, machine learning, climate policy

Abstrak

Penelitian ini fokus pada perancangan kebijakan pajak karbon berbasis spatial clustering dan machine learning dengan tujuan mengidentifikasi yurisdiksi optimal berdasarkan kinerja ekonomi-lingkungan. Studi ini bertujuan untuk mengidentifikasi pola spasial kinerja ekonomi-lingkungan di 38 negara, mengelompokkan negara berdasarkan kesamaan profil menggunakan metode clustering berbasis data, memodelkan hubungan antara harga/pajak karbon, indikator ekonomi, dan indikator lingkungan, serta merekomendasikan rentang pajak karbon optimal bagi setiap kelompok yurisdiksi. Penelitian ini menggunakan pendekatan kuantitatif dengan menggunakan data sekunder dari 38 negara yang mencakup variabel harga/pajak karbon, PDB, emisi karbon, konsumsi energi, kontribusi industri terhadap PDB, Indeks Kinerja Lingkungan (EPI), dan skor perubahan iklim. Analisis dilakukan dengan metode hierarchical clustering Ward linkage serta evaluasi silhouette coefficient untuk mengukur validitas pengelompokan. Hasil analisis mengelompokkan negara ke dalam lima klaster dengan karakteristik ekonomi-lingkungan yang berbeda. Negara maju dengan kinerja lingkungan tinggi (misalnya Swedia, Norwegia, Denmark) direkomendasikan menerapkan pajak karbon tinggi 100–150 USD/ton CO_2, sementara negara berkembang dengan intensitas emisi tinggi (misalnya Indonesia, Kazakhstan) realistis memulai dengan tarif rendah <15 USD/ton CO_2. Negara transisi direkomendasikan berada pada rentang menengah 20–60 USD/ton CO_2. Penelitian ini menegaskan pentingnya diferensiasi kebijakan pajak karbon berdasarkan kapasitas ekonomi dan kinerja lingkungan, serta perlunya kerja sama internasional dalam transfer teknologi dan pendanaan transisi energi. Kontribusi teoritis studi ini adalah integrasi kerangka Pigouvian Tax, pendekatan spasial, dan machine learning untuk merumuskan desain kebijakan fiskal lingkungan yang lebih adaptif.
Kata kunci: pajak karbon, spatial clustering, kinerja ekonomi-lingkungan, machine learning, kebijakan iklim

INTRODUCTION

The global climate crisis compels countries to formulate effective fiscal policies to reduce carbon emissions, one of which is the implementation of carbon taxation (Adam et al., 2022; Ghazouani et al., 2020). However, the effectiveness of a carbon tax largely depends on policy design that accounts for the spatial heterogeneity of economic and environmental performance (Pan et al., 2024). Conventional "one-size-fits-all" approaches often overlook structural variations across countries, thereby rendering policies suboptimal or even counterproductive (Kim et al., 2024; Tu & Wang, 2022). In this context, the integration of spatial clustering and machine learning offers a novel perspective for identifying jurisdictions with similar economic–environmental profiles, thereby enabling more precise and evidence-based carbon pricing.

Although carbon tax policies have been implemented across numerous countries, several major challenges persist, particularly the stark cross-country disparities in carbon pricing levels, as evidenced by comprehensive carbon prices in 2019 ranging from as low as −128.35 USD per ton CO_2 to as high as +146.25 USD per ton CO_2 (Carhart et al., 2022), the methodological limitations in simultaneously clustering jurisdictions based on both economic and environmental performance, and the absence of an integrative framework that leverages spatial analytics and machine learning to formulate adaptive carbon pricing policies across different contexts.

Previous studies have predominantly focused on examining the impact of carbon taxation either on emission reduction or on economic growth in isolation (Noubissi et al., 2023; Li et al., 2025), with limited research integrating economic variables (e.g., GDP, industrial contribution, energy consumption) and environmental variables (e.g., carbon emissions, Environmental Performance Index, climate change risks) within a single spatial analysis model. Moreover, although machine learning has been widely applied to predict carbon prices or emissions (Yu et al., 2024; Nadirgil, 2023), its application to jurisdictional clustering in support of environmental fiscal policy design remains scarce.

This study proposes a hybrid approach that integrates spatial clustering to identify groups of countries with similar economic–environmental profiles and machine learning algorithms to model inter-variable relationships and recommend optimal carbon pricing ranges for each group. Such an approach is expected to reduce policy bias arising from structural heterogeneity across countries. The study provides an opportunity to examine whether data-driven spatial clustering can serve as a foundation for formulating carbon tax policies that are more efficient, equitable, and impactful. Against the backdrop of the growing urgency of climate change mitigation, the development of policy intelligence grounded in data-driven governance has become an imperative.

This study aims to develop an analytical framework that integrates spatial clustering and machine learning in the design of carbon tax policies tailored to jurisdictional characteristics. Specifically, it seeks to identify the spatial patterns of economic–environmental performance across 38 countries, cluster countries based on profile similarities using data-driven clustering methods, model the relationships between carbon prices, economic indicators, and environmental indicators, and recommend optimal carbon pricing ranges for each group of jurisdictions. The main contribution of this study lies in developing the theoretical insight that the effectiveness of carbon taxation can be enhanced through a policy differentiation approach grounded in spatial clustering and artificial intelligence.

LITERATURE REVIEW

Carbon Tax and Environmental Fiscal Policy

A carbon tax is an economic instrument designed to internalize the negative externalities of greenhouse gas emissions by assigning a price to each ton of CO_2 emitted (Timilsina, 2022; Nong et al., 2021). According to Pigouvian Tax theory (Pigou, 1920), the tax rate should equal the marginal social cost of emissions in order to promote efficient resource allocation and reduce pollution (Chan, 2020; Chen et al., 2024). Within a fiscal context, this policy serves not only as an environmental control mechanism but also as a source of government revenue that can be allocated to energy transition investments (Barrage, 2019; Y. T. Chan, 2020).

Spatial Approach in Environmental Policy Analysis

Spatial analysis in environmental economics builds upon the theory of Spatial Autocorrelation (Tobler, 1970), which posits that phenomena in one region are closely related to those in surrounding regions (Afanasyev & Kudrov, 2020; Bathelt & Storper, 2023). This principle provides a critical foundation for understanding that carbon emissions, energy consumption, and environmental fiscal policies do not operate in isolation but instead form spatial patterns that mutually influence one another (Xu & Li, 2022; Liu & Yang, 2021). The application of Spatial Econometric Models (Anselin, 1988) enables researchers to capture these geographic interdependencies, both in the form of spillover effects and feedback effects across countries. In the context of carbon taxation, spatial approaches offer a more precise analytical framework to map emission distributions and identify cross-jurisdictional disparities (Wang et al., 2022; N. Chan & Sayre, 2023). For instance, a carbon pricing policy implemented in one European country may affect the industrial competitiveness of neighboring countries with different emission intensities (Zhong & Pei, 2022). Thus, spatial analysis is not only relevant for estimating the feasibility of differentiated tax policies but also essential for assessing the effectiveness of environmental fiscal instruments at regional and global scales. This approach creates opportunities for designing policies that are more adaptive, collaborative, and grounded in interconnected geo-economic realities.

Machine Learning and Spatial Data Processing for Environmental-Economic Data

Machine learning provides a predictive and classificatory analytical framework capable of effectively handling non-linear and multivariate data (Q. Wang et al., 2020; Janiesch et al., 2021; Uddin et al., 2022). The integration of spatial clustering with ML enables the grouping of countries or regions based on similarities in their economic–environmental profiles, which subsequently serves as the basis for more targeted policy recommendations (Jemeļjanova et al., 2024; J. Wang & Zhuang, 2022).

Misiuk & Brown (2023) argue that spatially clustered data may induce bias in the training and validation of ML models. Their proposed covariance weighting approach improves model performance, particularly when dealing with highly clustered datasets. Jemeļjanova et al. (2024) further emphasize that no standardized systematic methodology currently exists for addressing spatial autocorrelation, implying that the selection of techniques must be tailored to the characteristics of the data.

Integration of Spatial Approaches, Macroeconomic Modeling, and Spatial-Temporal Modeling in Carbon Tax Design

C. Kim et al. (2024) developed a Gaussian mixture model to design CO_2-to-fuel supply chains by incorporating geographical and social dimensions, demonstrating the potential for cost savings through optimal facility placement. Similarly, Rahmati et al. (2023) applied k-means and self-organizing maps within a hub location model that integrates multiple carbon policies, finding that cap-and-trade outperforms other mechanisms in terms of economic efficiency for the transportation sector.

Barrage (2019) linked carbon taxation to capital taxation within a Dynamic General Equilibrium framework, showing that tax distortions reduce the optimal rate by 8–24% compared to the lump-sum tax assumption. Y. T. Chan, (2020), employing a two-country E-DSGE model, highlighted that economic conditions shape the responsiveness of optimal tax rates and that international cooperation does not necessarily lower emission stocks. X. Chen et al. (2020) underscored the importance of sector-specific tax differentiation and channel leadership in low-carbon supply chains.

Gong et al. (2024) introduced a Dynamic Spatial–Temporal Graph Convolutional Recurrent Network (DSTGCRN), which outperformed conventional emission prediction models by up to 40% in terms of MAE. J. Wang & Zhuang, (2022) combined k-means clustering with BiLSTM and BiGRU for carbon price forecasting in China, demonstrating superior performance compared to benchmark models.

Economic Growth Dynamics, Environmental Tax Instruments, and Economic-Environmental Performance Evaluation at Various Scales

W. Li et al. (2019) applied symbolic regression and the Apriori algorithm to cluster countries based on emission–economic growth relationships, identifying two main clusters differentiated by income levels and carbon intensity. Mardani et al. (2020) integrated self-organizing maps and Artificial Neural Networks (ANN) to predict emissions from energy consumption and economic growth in G20 countries, achieving high predictive accuracy.

Y. Li & Song (2021) compared the effectiveness of carbon and fuel taxes in China using a panel spatial econometric model, showing that both instruments have distinct advantages, though their effects depend on regional economic conditions. L. Li et al. (2021) evaluated the performance of energy communities under a carbon tax scheme using a Nash bargaining mechanism, finding that the distribution of emission responsibilities generates differentiated economic and environmental outcomes.

Cao et al. (2025) combined Bayesian-optimized XGBoost with nighttime light (NTL) imagery to estimate emissions in Shaanxi, China, identifying high–high clustering patterns in economically advanced areas. G. Wang et al. (2021) employed NSGA-II to optimize low-carbon land use planning in Eindhoven, revealing vegetation as the most influential geographic factor in emission reduction.

From the above review, it can be identified that prior studies have integrated machine learning, spatial analysis, and economic modeling across various environmental policy contexts. However, most of these studies have concentrated on a single domain, such as price or emission forecasting, supply chain design, or economic growth analysis, thereby lacking a comprehensive integration of economic and environmental variables for cross-country carbon tax design. This study addresses that gap by combining spatial clustering and machine learning to identify optimal jurisdictions for carbon taxation policies based on economic–environmental performance.

RESEARCH METHOD

This study employs a quantitative approach with an exploratory–comparative design. The primary objective is to identify the spatial patterns of countries' economic–environmental performance and to cluster them based on profile similarities using hierarchical clustering analysis. This methodology is chosen for its ability to uncover latent structures within multidimensional data encompassing both economic and environmental indicators (Gao, 2021; Korir, 2024; Kudal et al., 2023). The use of Ward's linkage in hierarchical clustering is justified by its superiority in minimizing intra-cluster variance, thereby producing more homogeneous groups compared to other linkage methods (Randriamihamison et al., 2020; Bu et al., 2020; Dogan & Birant, 2021).

The research sample consists of 38 countries with diverse levels of development, economic structures, and environmental performance. Data were sourced from the World Bank, IEA, and World Economic Forum (WEF). The variables used include Carbon Price, GDP, Carbon Emissions, Energy Consumption, Industry (% of GDP), the Environmental Performance Index (EPI), and the Climate Change Index. The stages of the hierarchical clustering analysis consist of six steps, as illustrated in Figure 1.

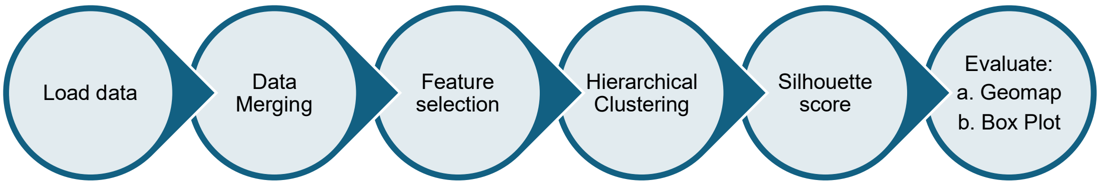

Figure 1 Stages in hierarchical clustering analysis
Source: Data compiled by researchers, 2025

The Hierarchical Agglomerative Clustering (HAC) method is employed to group countries based on similarities in their economic–environmental profiles. Ward's linkage is selected for its ability to minimize within-cluster variance, thereby producing more homogeneous groups. The Ward's linkage formula is expressed as follows:

$$d_{(A\cup B),C} = \sqrt{\frac{|C|+|A|}{T} {d^2}_{AC} + \frac{|C|+|B|}{T} {d^2}_{BC} - \frac{|C|}{T} {d^2}_{AB}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \; 1$$

Euclidean distance is employed to measure the proximity between objects. The formula for Euclidean distance is expressed as follows:

$$d(x,y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \; 2$$

The criteria for cluster separation are determined based on the silhouette coefficient and dendrogram analysis, with the formula expressed as follows:

$$s(i) = \frac{b(i) - a(i)}{max\ \{a(i), b(i)\}} \qquad \text{.........................} \ 3$$

The subsequent analysis includes the use of box plots to compare the distribution of variables across clusters. Geo-mapping is employed to visualize the spatial distribution patterns of clusters across countries, while inter-variable relationships are examined through a correlation matrix to model the associations among carbon pricing, GDP, emissions, and the Environmental Performance Index (EPI). Data processing was conducted using Orange Data Mining software version 3.39.0.

RESEARCH RESULTS

Data from 38 countries reveal significant heterogeneity in economic–environmental performance, as illustrated in Figure 2. High-income countries with strong environmental governance (e.g., Switzerland, Norway, Sweden, Denmark, and the Netherlands) tend to impose relatively high carbon prices (>90 USD per ton of CO_2) and consistently achieve Environmental Performance Index (EPI) scores at or near 100. This group also generally exhibits lower carbon emission intensity relative to economic output, indicating the effectiveness of market-based environmental policy instruments.

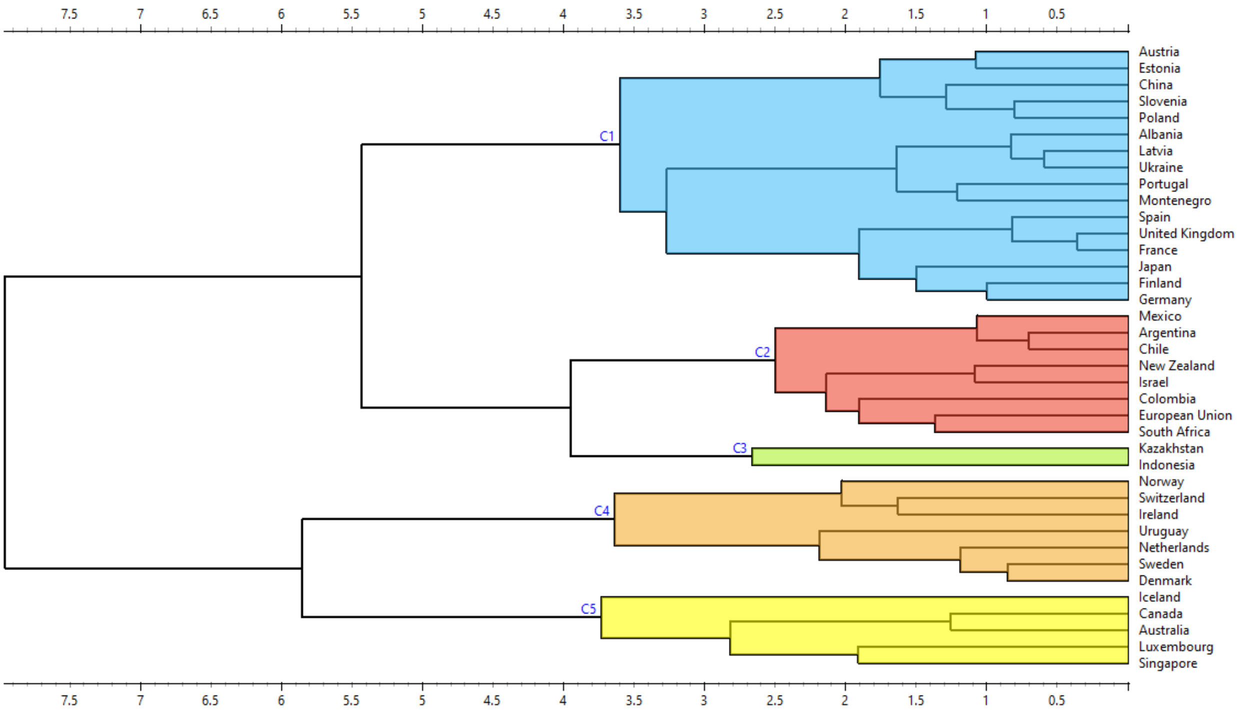

Figure 2 Hierarchical Clustering by R egion

Source: Orange Data Mining 3.39.0

In contrast, developing countries such as Indonesia, Kazakhstan, Ukraine, and Poland set extremely low carbon prices (<1 USD per ton of CO_2), despite the industrial sector contributing a substantial share to GDP (≥30%). This indicates limited fiscal and institutional capacity to internalize the negative externalities of carbon emissions. These countries also record low Environmental Performance Index (EPI) scores (≤65), reflecting weak overall environmental performance. The hierarchical clustering method categorizes the countries into five main clusters, as presented in Table 1.

Table 1 Cluster Division and Cluster Profiles

Cluster	Categories	Country	Profile
C1	Industrialized Countries with Low-Medium Carbon Prices	Albania, Austria, China, Estonia, Finland, France, Germany, Japan, Latvia, Montenegro, Poland, Portugal, Slovenia, Spain, Ukraine, United Kingdom	Medium-high GDP, strong industry, relatively high emissions, carbon price <50 USD/ton
C2	Emerging Economies with Moderate Carbon Policies	Argentina, Chile, Colombia, European Union, Israel, Mexico, New Zealand, South Africa	Carbon price 3–70 USD/ton, EPI moderate to high, but fiscal capacity still limited
C3	Middle-income countries with very low carbon prices	Indonesia, Kazakhstan	Carbon price <1 USD/ton, high emission intensity, low EPI, dominant industrial sector
C4	Developed Countries with High Carbon Prices and Excellent EPI	Denmark, Ireland, Netherlands, Norway, Sweden, Switzerland, Uruguay	Carbon price >90 USD/ton, EPI close to 100, per capita emissions relatively controlled
C5	Developed Countries with High Economies but Moderate Carbon Prices	Australia, Canada, Iceland, Luxembourg, Singapore	Very high GDP, massive energy consumption, carbon price of 18–66 USD/ton, but still maintaining environmental performance through non-fiscal regulations

Source: Data compiled by researchers, 2025

The model of relationships between carbon pricing, economic indicators, and environmental indicators presented in Table 2 suggests several key findings. First, carbon pricing is positively correlated with GDP per capita and the Environmental Performance Index (EPI). Wealthier countries with greater fiscal capacity are more capable of setting higher carbon prices without imposing substantial socio-economic burdens. Second, carbon pricing is negatively correlated with emission intensity and per capita energy consumption. Countries with higher carbon prices generally succeed in reducing emissions relative to economic output through renewable energy innovation, industrial efficiency, and green tax incentives. Finally, the share of industry in GDP demonstrates ambivalent effects. In countries with strong environmental governance (Cluster 4), even when the industrial sector is large (>20% of GDP), emission levels remain low due to energy efficiency measures and the transition toward low-carbon technologies. Conversely, in countries with weaker governance (Cluster 3), a large industrial sector contributes to high emission intensity as production remains heavily reliant on fossil fuel-based technologies.

Table 2 Pearson Correlation of Research Variables

	Carbon Price	GDP	Carbon emission	Energy cons	Industry % PDB	EPI	Climate Change
Carbon Price	1.000						
GDP	0.540	1.000					
Carbon emission	-0.102	0.371	1.000				
Energy cons	0.195	0.500	0.516	1.000			
Industry % PDB	-0.160	-0.167	0.116	-0.102	1.000		
EPI	0.331	0.404	0.208	0.279	-0.225	1.000	
Climate Change	0.296	0.398	0.082	0.361	-0.394	0.071	1.000

Source: Data compiled by researchers, 2025

The clustering results and relational model indicate that carbon tax design cannot be uniform across countries. Advanced economies in Europe (C4) may serve as benchmarks for progressive carbon pricing policies, whereas developing countries (C1 and C3) require a gradual approach that integrates energy transition subsidies, green investment incentives, and institutional strengthening. Accordingly, an effective carbon tax policy must be grounded in each country's specific economic–environmental profile rather than solely in global targets.

The quality of cluster separation, as illustrated by the silhouette plot in Figure 3, shows an overall average value of approximately 0.20, which can be categorized as moderate. This indicates that the separation between clusters is reasonably good, although not fully optimal. Cluster C1, with a value of 0.128, demonstrates a positive yet relatively small result, suggesting a degree of homogeneity but also some overlap with other clusters, particularly C2. In contrast, C2, with an average value of 0.540, exhibits very strong separation and high internal consistency, reflecting a uniform economic–environmental profile among the countries in this group. Similarly, Cluster C3, with a score of 0.524, also indicates strong clustering performance despite consisting of only two countries, namely Indonesia and Kazakhstan. This finding underscores that these two countries share highly similar economic–environmental characteristics that are significantly distinct from other clusters. Meanwhile, Cluster C4 records a value of 0.207, which falls within a moderate range, signaling heterogeneity among advanced economies with high carbon prices. While similarities exist within this cluster, variations in energy transition policies among its members contribute to its moderate separation. Finally, Cluster C5, with a score of 0.145, reveals relatively weak clustering strength. This suggests that although the countries in this group share common features as advanced economies with moderate carbon prices, their proximity to Cluster C4 results in less clearly defined boundaries.

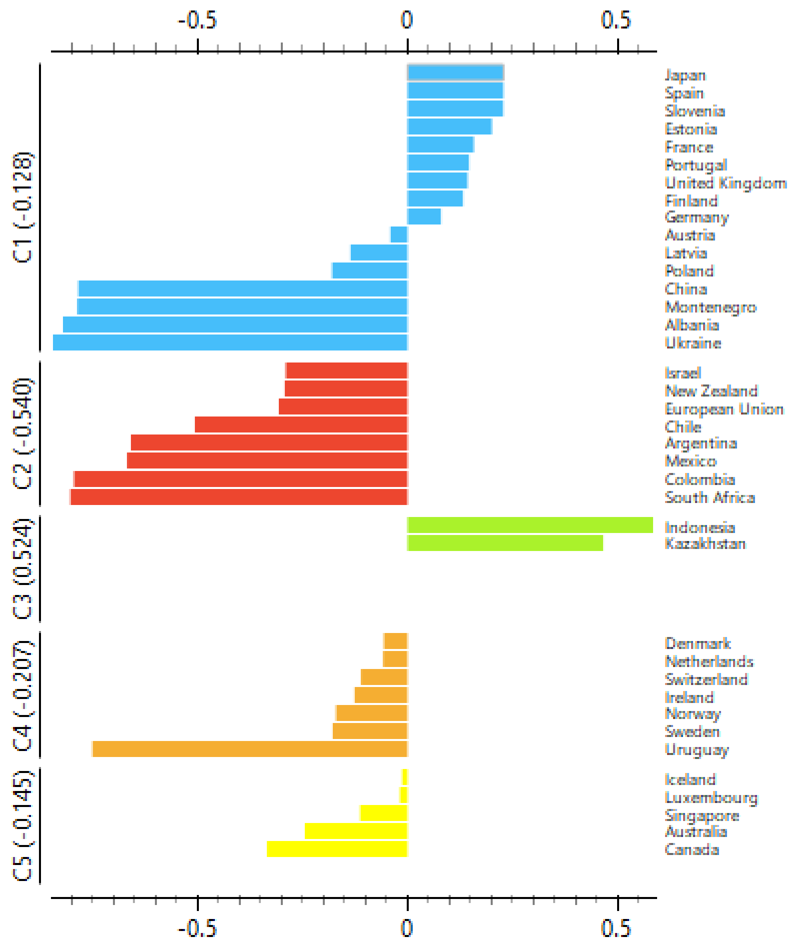

Figure 3 Silhouette Plot

Source: Orange Data Mining 3.39.0

The internal consistency of each cluster exhibits considerable variation. Cluster C1 shows low consistency due to its high degree of heterogeneity, as this group combines advanced European economies such as Germany and the United Kingdom with transition countries like Poland, Ukraine, and Albania. This condition explains why the silhouette score of this cluster is relatively low. In contrast, Cluster C2 demonstrates high consistency, where Latin American countries together with Israel, the European Union, and New Zealand share carbon policy patterns characterized by moderate pricing levels and relatively balanced fiscal capacities. Cluster C3 exhibits exceptionally high consistency, as it consists of only two countries—Indonesia and Kazakhstan—that are strongly aligned in their economic–environmental indicators, marked by low carbon prices, high emission intensity, and low EPI scores. Meanwhile, Cluster C4 reflects moderate consistency, with Northern European countries that consistently implement high carbon taxes and demonstrate superior environmental performance, although differences in energy policy implementation prevent their consistency score from reaching the levels observed in C2 or C3. Finally, Cluster C5 displays weak consistency, as it comprises non-European advanced economies such as Canada, Australia, and Singapore. Although these countries share high economic orientation with moderate carbon regulation, differences in energy structures—such as Australia's reliance on coal and Singapore's dependence on imported energy—reduce the level of homogeneity within this cluster.

The implications of this clustering for carbon tax design highlight the necessity of tailoring strategies to the specific characteristics of each country group. Cluster C1, which exhibits moderate heterogeneity, requires differentiated policy approaches given the diverse fiscal and institutional capacities within the group; Eastern European countries, for example, may require longer transition phases compared to their Western European counterparts. In contrast, Cluster C2, characterized by high internal consistency, represents an ideal candidate for regional policy harmonization, as the similarity of economic–environmental profiles facilitates more uniform carbon pricing and supports the adoption of a collective carbon tax framework. Cluster C3, despite its small size, displays very high consistency yet reflects countries lagging behind in climate policy. These countries necessitate international support in the form of energy transition financing and green technologies before they can significantly increase their carbon prices. Meanwhile, Cluster C4 demonstrates a combination of heterogeneity and strong policy orientation, enabling its member states to serve as global role models. With robust fiscal capacities and strong environmental commitments, this cluster has the potential to set global benchmarks for carbon pricing. Finally, Cluster C5, which exhibits weak consistency, demands country-specific approaches due to the diverse energy contexts of its members. Policy harmonization within this group is more difficult to achieve, making bilateral or small-scale multilateral cooperation a more pragmatic strategy.

The box plot analysis reveals variations in the distribution of carbon prices, GDP, carbon emissions, energy consumption, industrial structure, as well as environmental and climate performance across clusters. For the carbon price variable, Cluster C4 exhibits a high median above USD 100 with a narrow spread, indicating consistent policy implementation among advanced European economies. In contrast, Cluster C5 shows a medium median ranging between USD 20 and 60 with wide variation, reflecting divergent strategies, such as those between Singapore and Australia. Clusters C1 and C2 present low medians below USD 30 but with significant outliers, suggesting heterogeneity in carbon fiscal policies. Meanwhile, Cluster C3 consistently remains at a very low level, below USD 1, with a uniform distribution across countries.

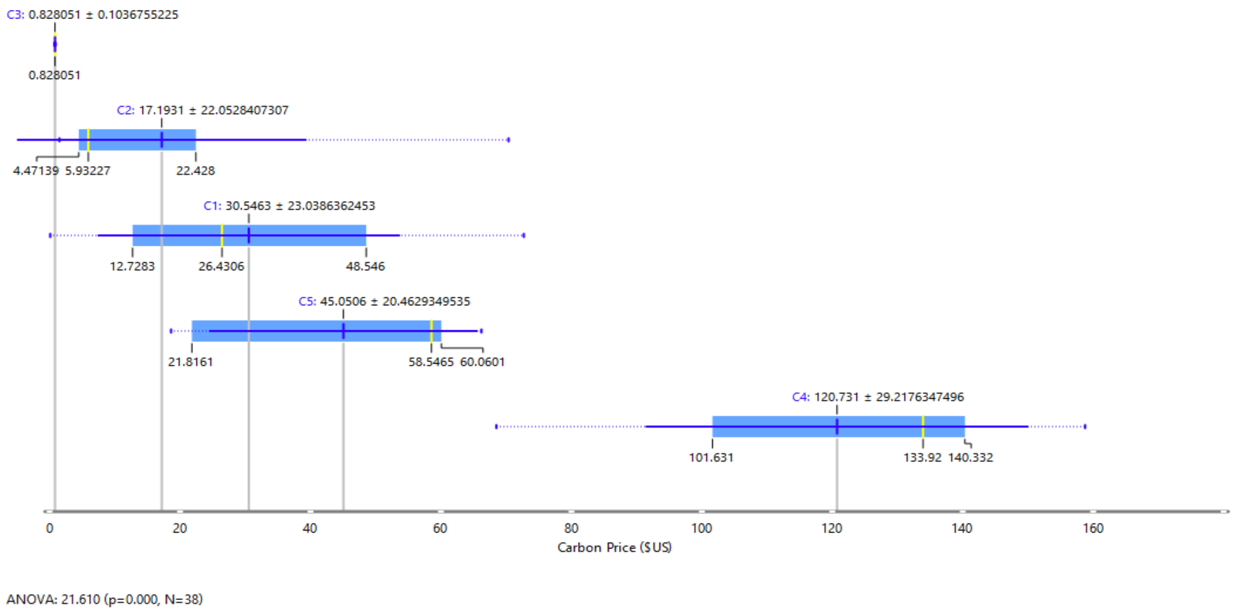

Figure 4 Box Plot per Carbon Price Variable

Source: Orange Data Mining 3.39.0

The distribution of GDP further underscores differences in fiscal capacity. Clusters C4 and C5 consist of high-income countries with considerable variation, where Luxembourg and Switzerland emerge as outliers. Clusters C1 and C2 fall within the middle range, driven primarily by contributions from Eastern European and Latin American countries, while Cluster C3 occupies the lower-middle category consistent with its fiscal capacity. In terms of carbon emissions, Cluster C5 exhibits high per capita emissions due to intensive energy consumption, whereas Cluster C4 shows relatively low emissions despite high GDP, indicating the effectiveness of carbon policy. Clusters C1, C2, and C3 demonstrate substantial variation, reflecting differences in energy and industrial structures.

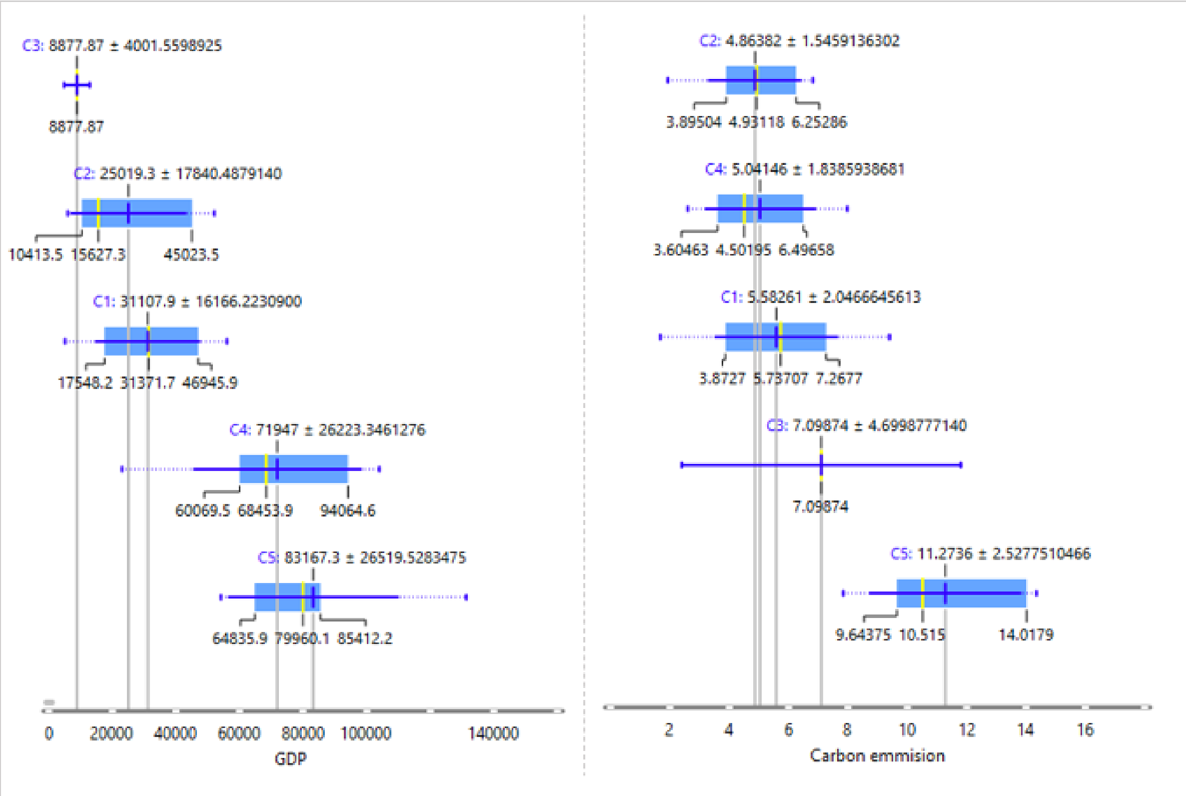

Figure 5 Box Plot per variable GDP and Carbon emission

Source: Orange Data Mining 3.39.0

Energy consumption is highest in Cluster C5, with a median exceeding 5,000 TOE per capita, reflecting high energy intensity. Cluster C4 is at a moderate level consistent with energy efficiency, whereas Cluster C3 records low consumption but remains fossil-fuel based, resulting in persistently high emission intensity. In terms of industrial structure, Cluster C3 dominates with contributions exceeding 35 percent of GDP, while Clusters C4 and C5 occupy intermediate levels supported by efficient technologies. Clusters C1 and C2, meanwhile, display greater variability due to their ongoing transition toward service-oriented and green sectors.

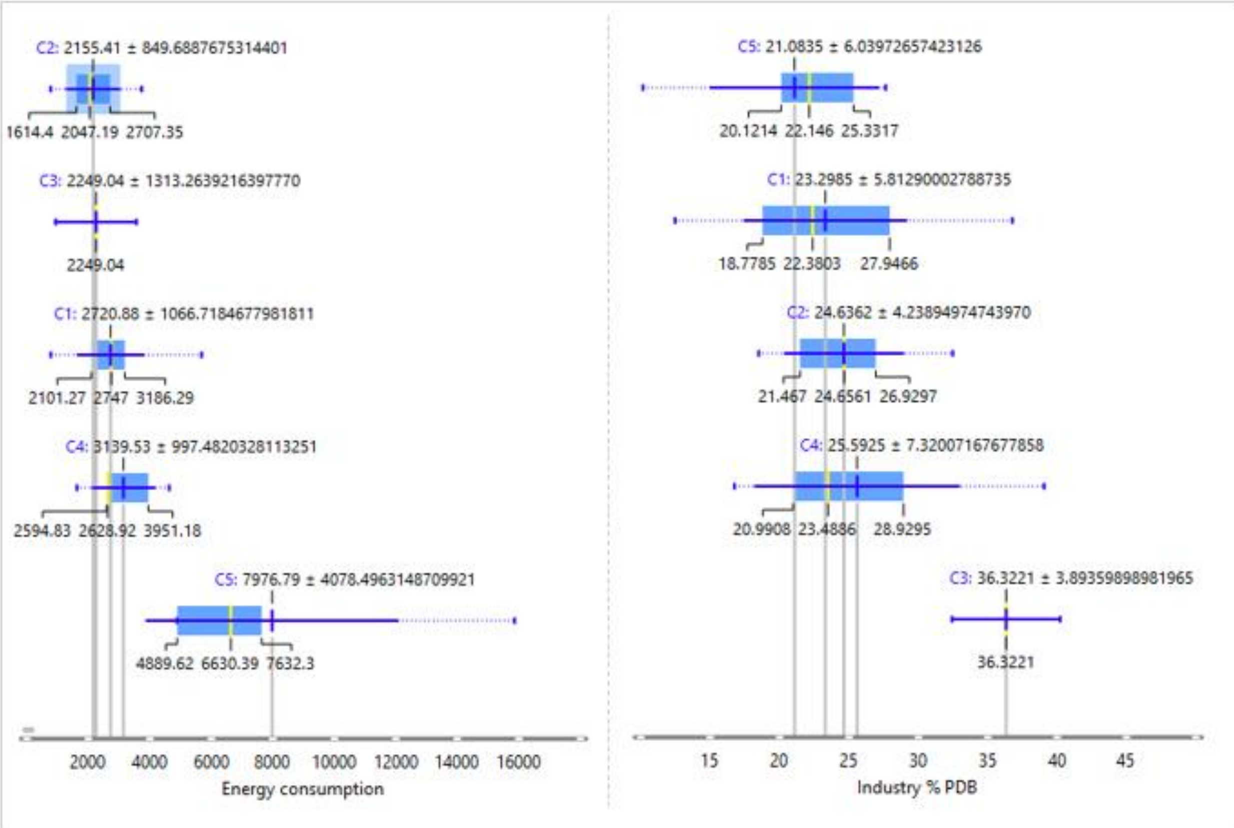

Figure 6 Box Plot per variable Energy consumption and Industry % GDP

Source: Orange Data Mining 3.39.0

For the EPI variable, Clusters C4 and C5 dominate with scores above 90, while Cluster C1 records relatively high but heterogeneous values. Cluster C2 falls within a moderate range of 60–80, and Cluster C3 ranks the lowest with scores below 60. Regarding the climate change index, Cluster C4 demonstrates relatively strong performance with scores above 80, whereas Cluster C5 exhibits greater variability. Clusters C1 and C2 are positioned at moderate levels, while Cluster C3 records the lowest performance due to high vulnerability and weak adaptive capacity.

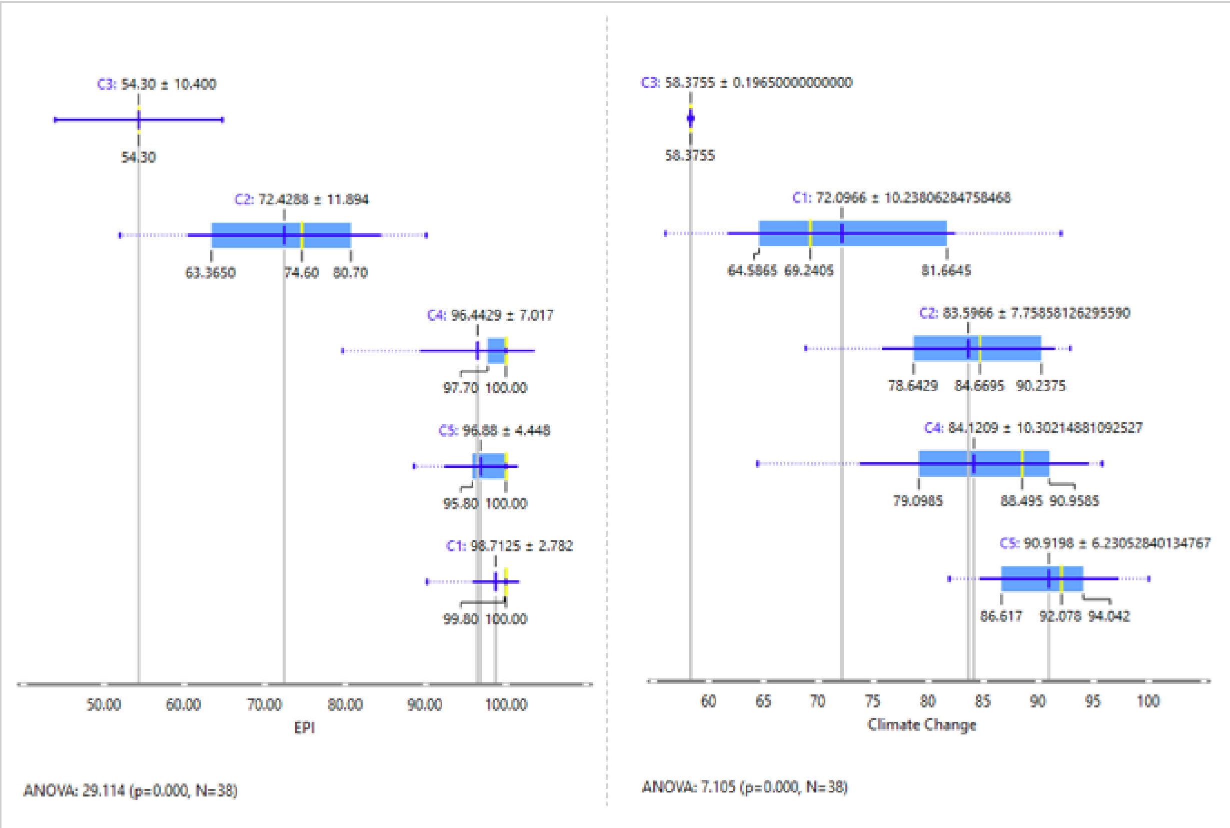

Figure 7 Box Plot per EPI and Climate Change Variable

Source: Orange Data Mining 3.39.0

Based on these distributional results, the recommended range of optimal carbon prices is formulated by considering the balance between economic capacity and environmental performance. Cluster C1, consisting of mid-industrial economies with high heterogeneity, is advised to adopt a transitional rate of USD 30–60 per ton of CO_2, complemented by green technology support. Cluster C2, comprising transition economies such as Latin America, Israel, and parts of the European Union, is recommended to fall within the range of USD 20–50 per ton of CO_2, with gradual increases in line with strengthening fiscal capacity. Cluster C3, which includes lower-middle-income countries with high emissions and institutional weaknesses, such as Indonesia and Kazakhstan, is suggested to start below USD 15 per ton of CO_2, supported by international assistance to avoid excessive economic burdens. Cluster C4, consisting of advanced economies with high EPI scores and already high carbon prices, is recommended to be within the range of USD 100–150 per ton of CO_2, consistent with net-zero targets and the Paris Agreement. Finally, Cluster C5, comprising advanced economies with high energy consumption, is recommended to adopt a range of USD 50–90 per ton of CO_2, with a focus on energy decarbonization and improving industrial efficiency.

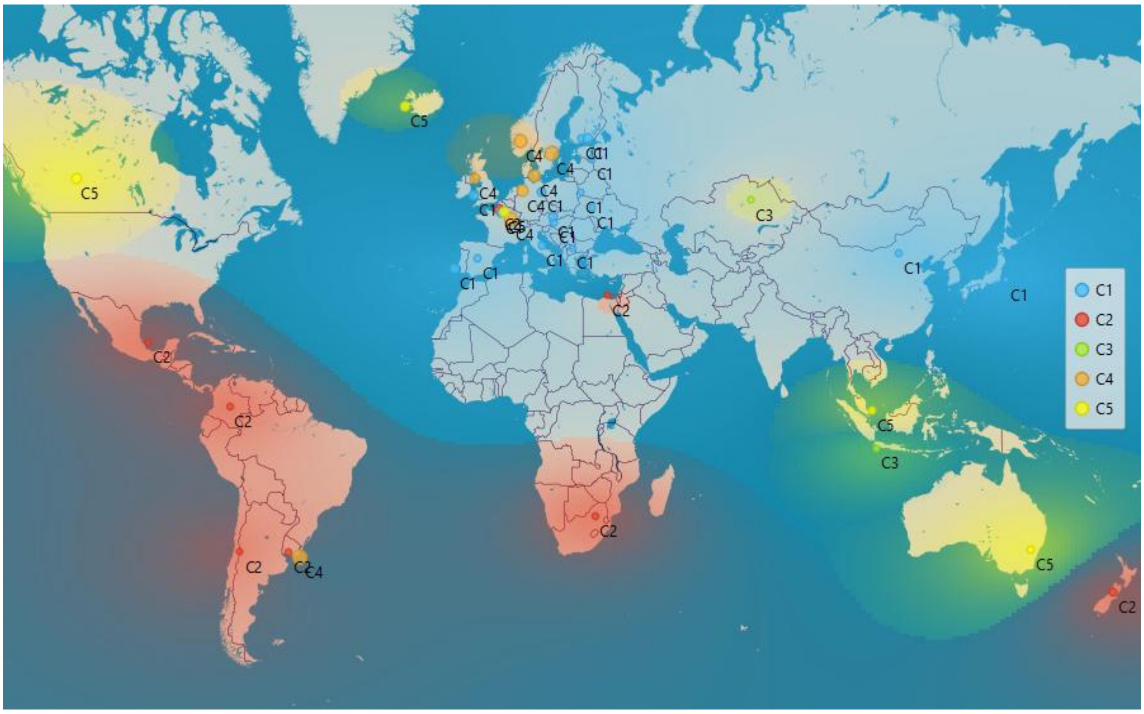

Figure 8 Geo Map Visualization

Source: Orange Data Mining 3.39.0

The geo-mapped cluster-based analysis of carbon taxes presented in Figure 8 reveals a clear spatial pattern in the distribution of economic–environmental performance across countries. Cluster 1, illustrated in blue, is widely distributed across Eastern Europe, parts of Western Europe, and East Asia. Countries within this cluster generally have medium to high GDP levels but continue to face relatively high emission intensity. Cluster 2, depicted in red, is concentrated in Latin America—including Argentina, Chile, Mexico, and Colombia—as well as Israel and South Africa. This pattern underscores the characteristics of transition economies with limited fiscal capacity, although they have begun to adopt carbon taxes at moderate rates. Meanwhile, Cluster 3, shown in green, consists solely of Indonesia and Kazakhstan, two countries with similar profiles characterized by heavy dependence on the industrial sector, very low carbon prices, and weak environmental performance. Cluster 4, represented in orange, is concentrated in Western and Northern Europe, including Sweden, Norway, Denmark, the Netherlands, and Switzerland. This concentration highlights the dominance of Europe as the core region of countries with high carbon prices, strong environmental governance, and robust economic capacity. Finally, Cluster 5, depicted in yellow, encompasses non-European advanced economies such as Canada, Australia, Singapore, Iceland, and Luxembourg. Countries in this cluster exhibit high income and massive energy consumption but have yet to establish carbon prices as high as their European counterparts.

From a regional and geo-economic perspective, a clear fragmentation can be observed in Europe. Countries such as Germany, France, and Austria fall into Cluster 1, whereas Sweden, Norway, and the Netherlands are classified under Cluster 4. This highlights differences in the depth of carbon fiscal policies despite their shared membership in the European Union. Latin America is predominantly represented by Cluster 2, consistent with its middle-income economic capacity and reliance on fossil energy. Asia displays wide disparities, with Japan and China belonging to Cluster 1, Israel and parts of the Asia-Pacific included in Cluster 2, and Indonesia placed in Cluster 3. Oceania and North America exhibit the pattern of advanced energy-intensive economies, as reflected in Australia and Canada, which are grouped in Cluster 5. Africa is represented by South Africa, which falls into Cluster 2, underscoring its status as a transition economy facing significant decarbonization challenges.

In terms of policy implications, countries in Cluster 4 can serve as global role models, maintaining high carbon price ranges of approximately USD 100–150 per ton of CO_2. Cluster 5 countries, such as Canada, Australia, and Singapore, should raise their carbon prices to the range of USD 50–90 per ton of CO_2 to close the gap with Europe, particularly in the energy sector. Cluster 2, comprising Latin America and South Africa, requires a gradual approach with carbon prices ranging between USD 20–50 per ton of CO_2, alongside efforts to strengthen fiscal and institutional capacities. Cluster 1, covering Central–Eastern Europe and East Asia, may adopt transitional carbon pricing of USD 30–60 per ton of CO_2, supported by green technology to safeguard industrial competitiveness. Meanwhile, Cluster 3, consisting of Indonesia and Kazakhstan, requires low initial carbon tax schemes below USD 15 per ton of CO_2, combined with international support in the form of energy transition financing and emissions trading mechanisms.

DISCUSSION

Carbon tax as a fiscal instrument is rooted in Pigouvian Tax theory (Pigou, 1920), which emphasizes the importance of internalizing the negative externalities of greenhouse gas emissions through a carbon price that reflects the marginal social cost. In this context, the findings reveal pronounced spatial differentiation across countries in determining carbon prices. For instance, countries in Cluster 4 (Sweden, Norway, Denmark, the Netherlands, Switzerland) have adopted high carbon prices (100–150 USD/ton CO_2), consistent with their strong economic capacity and high environmental performance. This affirms that the implementation of carbon taxation cannot be standardized globally but must instead be tailored to the economic structure, fiscal capacity, and environmental performance of each jurisdiction.

From a spatial autocorrelation perspective (Tobler, 1970; Anselin, 1988), the results demonstrate consistent spatial patterns: Europe dominates the cluster of countries with high carbon taxes, while Latin America and Africa are concentrated in clusters with moderate rates, and Asia (e.g., Indonesia, Kazakhstan) emerges as an outlier with extremely low carbon prices. This supports the thesis that carbon tax policy is not merely fiscal-economic in nature but also geo-economic, with spatial distributions that carry significant implications for the equity of the global energy transition.

The integration of machine learning and spatial clustering in this study advances the literature (J. Wang & Zhuang, 2022; Jemeļjanova et al., 2024) by introducing a non-linear analytical framework capable of identifying multivariate economic–environmental patterns. Accordingly, this research contributes theoretically by proposing a hybrid approach that bridges Pigouvian Tax theory, spatial econometrics, and data-driven ML, thereby enabling a more adaptive design of carbon tax policies.

Previous studies have exhibited notable limitations. Misiuk & Brown, (2023) highlight the challenge of spatial autocorrelation, which is often overlooked in ML-based modeling, whereas Barrage, (2019) and Y. T. Chan, (2020) focus primarily on macroeconomic frameworks without adequately accounting for spatial heterogeneity. This study addresses these gaps by integrating spatial clustering across 38 countries, thereby capturing the complexity of interactions among carbon pricing, GDP, carbon emissions, energy consumption, industrial structure, EPI, and climate change indices.

In addition, prior studies such as Rahmati et al. (2023) and C. Kim et al. (2024) have primarily emphasized carbon supply chain optimization, whereas this research extends the scope by determining the optimal carbon price range across country clusters. The practical contribution of this study lies in providing differentiated policy recommendations tailored to the economic–environmental profiles of each cluster. Middle-income industrial countries in Cluster 1 are advised to implement a phased carbon tax of USD 30–60 per ton of CO_2, supported by green technology adoption. Cluster 2, comprising transition economies such as Latin America and South Africa, is more suited to a moderate range of USD 20–50 per ton of CO_2 while simultaneously strengthening institutional capacity. Cluster 3, which includes Indonesia and Kazakhstan, requires a relatively low rate below USD 15 per ton of CO_2, contingent upon international support. Advanced European economies in Cluster 4 are recommended to adopt a higher rate of USD 100–150 per ton of CO_2, whereas Cluster 5 is projected to align with a range of USD 50–90 per ton of CO_2, with a strong emphasis on energy decarbonization.

Table 3 Research Results Clusters, Economic-environmental Characteristics, Carbon Price Range Recommendations, and Policy Implications

Cluster	Economic-environmental Characteristics	Optimal Carbon Tax Range (USD/ton CO_2)	Policy Implications
C1	High-middle GDP, moderate emissions, large industrial structure, relatively high EPI	30 – 60	A gradual transition is needed; focus on energy efficiency, green technology, and regional policy harmonization
C2	Transitional countries, limited fiscal capacity, moderate energy consumption, varying EPI	20 – 50	Apply moderate tariffs; institutional strengthening and international funding support are needed
C3	Low-medium GDP, high carbon intensity, fossil fuel-based energy consumption, low EPI	< 15	Low tax rates; need for energy transition subsidies, international assistance, and emissions trading mechanisms
C4	Developed country, high GDP, excellent EPI, low emissions, efficient energy consumption	100 – 150	Become a global role model; promote climate leadership, harmonization of high tariffs in the European region
C5	High GDP, massive energy consumption, good EPI, but high energy intensity	50 – 90	Gradually increase carbon tariffs; prioritize energy decarbonization, technological innovation, and industrial compensation

Source: Data compiled by researchers, 2025

Table 3 demonstrates that countries in cluster C1, encompassing major industries in Europe and East Asia, are currently in a transitional phase; therefore, a moderate carbon tax rate is considered sufficient to maintain competitiveness while simultaneously promoting energy efficiency. Cluster C2, which consists of transitional economies in Latin America and Africa, requires more extensive fiscal adaptation, implying that moderate tax rates must be accompanied by institutional strengthening and international financial support. Meanwhile, Indonesia and Kazakhstan, categorized within cluster C3, emerge as critical outliers that necessitate a low carbon tax scheme with international assistance in order to avoid impeding economic growth. Northern and Western European countries in cluster C4 have successfully implemented high carbon taxes and are well-positioned to serve as global pioneers in advocating for the establishment of an international minimum tax rate. Finally, cluster C5, comprising advanced non-European economies, requires a gradual tax increase toward European levels in order to sustain the credibility of their global climate leadership.

Furthermore, the spatial heterogeneity of carbon pricing identified in this study resonates with the principle of Common but Differentiated Responsibilities and Respective Capabilities (CBDR-RC) under the UNFCCC framework. Advanced economies in Cluster 4 exhibit greater fiscal capacity, technological readiness, and historical emissions responsibility, thereby justifying their higher recommended carbon tax levels. Conversely, countries in Cluster 3, such as Indonesia and Kazakhstan, possess limited institutional and financial capability, indicating the need for lower carbon tax regimes supported by international assistance mechanisms. The clustering evidence thus reinforces that carbon taxation must incorporate differentiated economic burdens to ensure fairness, prevent development setbacks, and promote equitable transitions. Integrating CBDR-RC perspectives strengthens the global legitimacy of carbon pricing policies and aligns national actions with principles of distributive climate justice.

The findings of this study carry dual implications. From a practical perspective, the clustering results provide governments with a basis for formulating context-specific carbon tax policies that align with fiscal–economic capacity and environmental performance. For instance, countries in the low cluster (C3) require lower tax rates accompanied by international support, whereas those in the high cluster (C4) are expected to reinforce global leadership through more aggressive rates. From a theoretical standpoint, this study enriches the literature by introducing a framework for spatially informed carbon tax policy design, which has not been explicitly integrated into prior research.

CONCLUSION

The findings of this study underscore that carbon tax policies cannot be designed through a uniform approach but must instead account for the spatial heterogeneity of economic–environmental performance across jurisdictions. By employing hierarchical clustering with a Ward linkage method, 38 countries were classified into five distinct groups with clear characteristics. Western European and Scandinavian countries (Cluster 4), characterized by high economic capacity, strong environmental performance, and the adoption of aggressive carbon pricing, are recommended to implement a tax of USD 100–150 per ton of CO_2 in order to sustain their global leadership in climate mitigation. In contrast, transitional economies in Latin America and Africa (Cluster 2) are better suited to a moderate tax range of USD 20–50 per ton of CO_2, accompanied by institutional strengthening and international financial support. Middle and lower income countries such as Indonesia and Kazakhstan (Cluster 3) are realistically positioned to begin with a low tax of less than USD 15 per ton of CO_2 to avoid constraining growth, while still being directed toward a sustainable energy transition. The practical implication of these findings is the necessity of adopting differentiated policies based on fiscal capacity and environmental performance, complemented by global redistribution mechanisms, technology transfer, and international cooperation frameworks to ensure a just climate transition.

From a theoretical perspective, this study enriches the literature by integrating three foundational pillars: Pigouvian Tax theory as the fiscal basis, spatial autocorrelation as the spatial framework, and machine learning as a data-driven analytical tool. The primary contribution lies in the development of a spatially informed carbon tax policy design framework, which has been scarcely explored in prior research. By linking spatial analysis, economic-environmental indicators, and the determination of optimal carbon tax ranges, this study offers a novel conceptual model for designing adaptive and context-specific climate policies. Future research directions may focus on expanding the temporal dimension (spatio-temporal modeling) to capture the dynamics of emission changes and carbon prices over time, as well as integrating with dynamic macroeconomic models to evaluate fiscal distributional impacts and intergenerational equity. Furthermore, sectoral-level exploration (energy, industry, and transportation) is equally crucial to ensure greater precision and effectiveness of carbon tax policies. Thus, this study not only provides practical contributions to policy formulation but also opens avenues for more integrative theoretical advancements in the fields of environmental economics, taxation, and data science.

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