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Multidimensional Spatiotemporal Clustering – An Application to Environmental Sustainability Scores in Europe

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ABSTRACT

The assessment of corporate sustainability performance is extremely relevant in facilitating the transition to a green and low-carbon intensity economy. However, companies located in different areas may be subject to different sustainability and environmental risks and policies. Henceforth, the main objective of this paper is to investigate the spatial and temporal pattern of the sustainability evaluations of European firms. We leverage a large dataset containing information about companies' sustainability performances, measured by MSCI ESG ratings, and geographical coordinates of firms in Western Europe between 2013 and 2023. By means of a modified version of the Chavent et al. (2018) hierarchical algorithm, we conduct a spatial clustering analysis, combining sustainability and spatial information, and a spatiotemporal clustering analysis, which combines the time dynamics of multiple sustainability features and spatial dissimilarities, to detect groups of firms with homogeneous sustainability performance. We are able to build cross-national and cross-industry clusters with remarkable differences in terms of sustainability scores. Among other results, in the spatio-temporal analysis, we observe a high degree of geographical overlap among clusters, indicating that the temporal dynamics in sustainability assessment are relevant within a multidimensional approach. Our findings help to capture the diversity of ESG ratings across Western Europe and may assist practitioners and policymakers in evaluating companies facing different sustainability-linked risks in different areas.

1 | Introduction

As the world is facing a path toward a more sustainable, greener, and less carbon-intensive economy, Environmental, Social and Governance (ESG) practices are becoming more and more relevant from the company perspectives in mitigating sustainability-linked risks. Since the Paris Agreement of 2015, great attention has been paid to corporate sustainability performance, especially on environmental aspects such as Greenhouse Gas (GHG) emission levels.

According to the World Health Organization (WHO), almost all of the global population breathes air that exceeds WHO guideline limits and contains high levels of pollutants. Moreover, air quality is closely linked to the earth's climate and ecosystems globally. Many of the drivers of air pollution (that is, combustion of fossil fuels) are also sources of greenhouse gas emissions. Policies to reduce air pollution, therefore, offer a win-win strategy for both climate and health, lowering the burden of disease attributable to air pollution as well as contributing to the mitigation of climate change.

In this context, firms contribute significantly to the emission of polluting gases with respect to households. In Germany, the Environment Agency of the German Government UBA (2024) shows that companies produced more than 85% of the CO_2 emissions in the last years. In the UK, the Department for Energy Security and Net Zero (DESNZ 2023) affirms that in 2022, household emissions account only for 17% of the total. Moreover, the Italian National Institute of Statistics (Istat 2022) shows that in the last 20 years, the overall volume of CO_2 has decreased by around 30%, but the emissions from companies still represent around 70% of the total.

Within this framework, Environmental, Social, and Governance issues have become crucial topics for companies' operations and stakeholders' engagement and activism. Companies have begun to put sustainability practices as a core aspect of their operations and to disclose more and more information on their commitment to Environmental, Social, and Governance issues. Stakeholders have started to take ESG ratings and scores into consideration to make financial decisions, preferring to have relationships and interactions with companies that respect sustainability principles. ESG ratings and scores are synthetic evaluations from a specialized rater on a company's sustainability performance from many different points of view, broadly grouped under the three pillars E, S, and G. As a result, empirical evidence highlights that companies that achieve good ESG ratings are able to obtain better financial conditions, e.g., lower cost of capital and easier access to capital markets.

In this paper, we aim to investigate the spatial pattern and the time dynamics of sustainability scores assigned to firms in Western Europe. We first trace the spatial pattern of Western European firm evaluation on three different sustainability levels, that is, the overall sustainability-ESG score, the Environmental score, and the Carbon Emission performance using a tailored version of the hierarchical spatial clustering algorithm by Chavent et al. (2018), which allows for detecting homogeneous groups of companies combining sustainability and spatial information. Furthermore, we examine the temporal dynamics of ESG-Environmental-Carbon emission evaluations in the last ten years by combining the spatial information and the similarity across the temporal series of multiple sustainability-related evaluations. The latter constitutes a multidimensional spatiotemporal extension of the spatial clustering methodology by Chavent et al. (2018).

Our findings prove that both space and time dimensions are relevant in ESG performance evaluations. The initial spatial analysis, which was carried out for ESG ratings in 2023, provided evidence of the presence of cross-national and cross-industrial groups of companies with remarkable differences in the levels of environmental performance. Specifically, clusters are differentiated according to ESG scores, and the analysis brings out a cluster of companies with very poor sustainability performance, which belong to several European countries and are mainly classified in the manufacturing and mining industries. Other clusters are less transnational and composed mainly of companies engaged in the tertiary and service sectors. Regarding the spatiotemporal clustering, the identified groups are more prone to spatial overlapping, suggesting that the ESG scores' temporal aspect is relevant to our multidimensional approach.

The remainder of the paper is structured as follows. In Section 2, we briefly review the current literature on ESG evaluation and patterns in the ESG scores. Then, we describe the dataset and the data collection procedure in Section 3. In Section 4, we introduce two multidimensional hierarchical clustering algorithms, the first for the purely spatial framework and the second for the spatiotemporal case. Thereby, we focus on techniques to efficiently select the hyper-parameters (that is, weighting parameters and the number of clusters) by proposing two tailored algorithms. In Section 5, we summarise the results of the cluster analyses and provide an interpretation and discussion of the identified clusters. Eventually, in Section 6, we sum up the main contents of the paper and provide concluding remarks and future research perspectives.

2 | Background

Evaluating the sustainable commitment of companies is a very complex task and the final result and its interpretation may depend on the metrics chosen and the methodology applied, as well as on the information availability. Over the years, several data providers have managed to improve methodologies, follow similar standards, and increase the coverage of companies evaluated also by exploiting other sources of information. The academic literature in the economic-financial field provides increasing evidence about factors that impact firms' ESG performance and the beneficial effects that ESG commitment has on companies and stakeholders. Given its relevant role, researchers have recently begun analyzing ESG patterns to provide the basis for more specific studies on this phenomenon.

2.1 | The Challenge of ESG Assessment

Evaluating the sustainable commitment of companies and assigning scores regarding their impact on the different aspects that make up sustainability is a very complex task, which could be carried out following a multitude of approaches, and using different types of information systems. Considering 9 ESG rating agencies Billio et al. (2022), offer a comprehensive description and comparison of their approaches and methodologies. Furthermore, they provide a table to offer a quick comparison of the different methodologies used by the various agencies for calculating ESG ratings. Appendix B contains a summary of the table.

Following this direction, a recent branch of academic literature is in fact focusing on the analysis of agreement and disagreement across different ESG rating providers Berg, Kölbel, and Rigobon (2022); Christensen, Serafeim, and Sikochi (2022). provide a deeper understanding of the divergences in the ESG rating composition Gucciardi et al. (2024), and examine the common factors in the Environmental Pillar score of different rating providers. According to their description and comparison in Billio et al. (2022), we decided to use the MSCI ESG rating in our analysis because it provides ESG rating for more than 10 years, it covers a large number of companies and the data provider has not been subject to mergers and acquisitions that may have substantially changed the methodologies underlying the data provided. Moreover, the MSCI evaluations are standardized for each industry using company-specific adjustments, according to the exposure and the challenges that each company has to face. MSCI collects available data from company disclosure, government agencies, non-governmental organizations (NGOs) and media sources monitored daily (MSCI 2023a). As regards the carbon emission score, MSCI relies on the voluntary self-declaration provided by companies (MSCI 2023b). While in the academic literature, it is often discussed about the importance of providing corporate sustainability disclosure, especially with regard to carbon emission (Bolton et al. 2021; Bastos Neves and Semmler 2022; Bolton, Halem, and Kacperczyk 2022; Aldy et al. 2024), for the moment the institutions do not impose that it is mandatory for all enterprises, as it is necessary to define before the standardized guidelines. Although the number of companies providing such information is still very small, about a quarter according to Aldy et al. (2024), these are generally the largest in terms of size, and therefore represent the majority of economic activity in terms of total asset and sales. An accurate description of the methodology used by MSCI for the allocation of carbon emission score is given in Appendix C, together with a table showing the percentage of companies that in 2022 provided the non-mandatory sustainability report and were then assigned an ESG rating.

2.2 | The Important Role of ESG Evaluation for Firms and Stakeholders

First of all, companies' commitment to sustainability principles seems to be closely linked to environmental policies. In fact Zhang (2022) demonstrate that environmental regulation pushes companies to pay more attention to product quality and sustainability principles in production and Chen et al. (2022a) find positive effects of environmental regulation on firm environmental investment. Also Chen et al. (2022b); Qian and Yu (2024); Xue, Wang, and Bai (2023), observe a positive effect of green finance policy on ESG performance and Wang, Elahi, and Khalid (2022) show that green finance policy encourages enterprises to develop and adopt green products and technologies. Other research focuses on the Environmental Protection Tax Law in China, finding a positive effect on ESG performance and green technological innovation (Li and Li 2022), particularly for heavily polluting firms (He, Jing, and Chen 2023a; He, Zhao, and Zheng 2023b). Moreover Wu and Tham (2023), show that executive green incentives and top management team characteristics positively impact the corporate ESG performance and Zhang, Meng, and Zhang (2023) suggest that the disruption of environmental subsidies significantly positively affects them. Furthermore, the literature provides evidence of a positive impact of regional environmental transparency (Chen et al. 2023a), digital transformation (Zhao and Cai 2023) and digital finance (Mo, Che, and Ning 2023) on ESG performance.

Among the evidence on the effects of ESG performance Fu and Li (2023), found that it positively and significantly affects corporate financial performance, and digital transformation drives this promoting effect Alfalih (2023), show that social and governance dimensions of ESG influence companies' financial performance across the two measures of a firm's financial performance (ROA and Tobin's Q), while environmental dimension is significant with the Tobin's Q measure. Also Yu and Xiao (2022), find a significantly positive relationship between ESG composite performance and firm value and Panda and Ray (2023) describe the positive effect of Corporate Sustainability expenditure on share prices Ángeles López-Cabarcos et al. (2023). demonstrate that the absence of CO2 equivalent emissions, the absence of incentives, and the presence of environmental investment have an impact on stock market returns. Moreover, the academic literature provides evidence of significant positive impact of ESG commitment on listed companies' stock liquidity (Chen et al. 2023b), on productivity (Ma, Gao, and Sun 2022), on foreign investment flows (Chipalkatti, Le, and Rishi 2021), on green innovation (Lian, Li, and Cao 2023; Mukhtar, Shad, and Woon 2023; Zheng et al. 2023) and a negative impact on company over-indebtedness (Lai and Zhang 2022).

The above-mentioned research highlights the relevance of ESG performance and, consequently, the fundamental role that disclosure of ESG assessments plays.

2.3 | Pattern of Firms' ESG Evaluation

The recent academic literature provides interesting examples of how researchers have traced and mapped different patterns of businesses of their ESG assessments throughout a cluster analysis or other methodologies for classification, sometimes considering specific aspects of sustainability or including variables related to specific features of the activities carried out by the companies themselves. In particular Ronalter, Bernardo, and Romaní (2023), consider a sample of firms from Europe, East Asia and North America to perform a hierarchical cluster analysis including ESG indicators, and they carry out independence tests to compare the quality management systems and environmental management systems of firms with different ESG evaluation Gonzaga et al. (2024). employed the Kohonen Self-Organizing Map for clustering developing market companies, providing valuable evidence of the changes in ESG scores over the course of the COVID-19 pandemic. Using the same methodology Iamandi et al. (2019), examine the sustainability profile of European companies, considering the ESG score, the scores of the pillars, and the scores of the indicators composing them.

Moreover Wang (2023), investigates the dynamics of three pillars of ESG scores among banks and observes a convergence of the evaluations in separate clusters in recent years, exploiting a specific panel data model proposed by Phillips and Sul (2007, 2009) to represent the behavior of economies in transition, formulated as a non-linear time-varying factor model Saraswati et al. (2024). use a sample of Indonesian firms and perform a K-means cluster analysis on ESG score pillars' score to clarify differences between ESG sustainability and practice and show the relationship among the distinct aspects of ESG performance. The authors identify three clusters using the Elbow method, the silhouette, and the Gap Statistical Method.

Focusing on the environmental aspect Amores-Salvadó, Martin-de Castro, and Albertini (2023), consider a sample of public industrial firms from Europe, the United States, and Canada, they classify them according to a four-position matrix based on the dichotomy environmental performance-disclosure, then they perform ANOVA tests showing differences in the groups according to nationality and sector. Ishizaka, Lokman, and Tasiou (2021) propose a new hierarchical multi-criteria clustering based on PROMETHEE, they take into account uncertainty and imprecision making use of the Stochastic Multiobjective Acceptability Analysis (SMAA) and cluster ensemble methods, and they provide an interesting application on a sample US banks, considering financial variable and ESG pillar scores. Ortas et al. (2015) exploit a multidimensional HJ-Biplot technique finding evidence of how different country-specific social and institutional schemes influence ESG evaluation in a sample of firms located in Spain, France and Japan. Sariyer, and Taşkimath;n, D. (2022) consider a sample of companies listed in the (Borsa Istanbul) BIST sustainability index and, based on their ESG pillars scores, they perform a K-means++ algorithm which accounts for a smart centroid initialization method by assigning the first centroid randomly then selecting the rest of the centroids based on the maximum squared distance. Using the silhouette score, the authors identify heterogeneous clusters in terms of ESG evaluation and also in terms of size and profitability.

To the best of our knowledge, only Wang (2023) explicitly account for the temporal component in the clustering algorithm. In the other research, in which data are observed in several years, the authors repeat the same analysis considering separately the different years and then interpret the evolution of clusters over time (Ortas et al. 2015; Gonzaga et al. 2024). As regards the spatial component, although some studies have identified clusters with different compositions according to the country of origin of the companies (Ortas et al. 2015; Amores-Salvadó, Martin-de Castro, and Albertini 2023; Ronalter, Bernardo, and Romaní 2023), but including spatial information into the clustering algorithm is still an open question.

The primary innovation of our paper lies in the integration of spatial and temporal components to trace the patterns of ESG (Environmental, Social, and Governance) evaluations of companies. Specifically, we aim to incorporate spatial and temporal data into the clustering algorithm, ensuring that companies within the same cluster are not only geographically proximate but also exhibit similar trends over time. This approach is motivated by two main reasons. Firstly, existing literature has highlighted that sustainability commitments vary significantly based on geographical regions (e.g., see Ortas et al. 2015; Ronalter, Bernardo, and Romaní 2023; Gonzaga et al. 2024) and overtime (e.g., see Wang 2023; Gonzaga et al. 2024). For example, studies have demonstrated that different regions may have varying degrees of sustainability challenges and opportunities, influenced by local laws, resource availability, and cultural perspectives on sustainability. Companies situated in different areas encounter distinct environmental challenges due to these factors. By incorporating spatial and temporal data, we can better capture these regional variations and temporal trends, providing a more nuanced understanding of ESG evaluations. Secondly, our study serves as a preliminary step for future research aimed at comparing firms' environmental commitments with their actual environmental impacts. This comparison is crucial for evaluating the effectiveness of corporate sustainability initiatives. For instance, by considering air quality, soil and water pollutants, and waste production—factors often described by spatiotemporal models—we can assess whether companies' commitments to reducing CO2 emissions translate into tangible environmental benefits. This aspect of the study is particularly important, as ESG assessments typically rely on self-reported data from companies, which may not always reflect actual environmental performance. Moreover, the existing literature often focuses on the discrepancies between ratings from different ESG rating providers. However, our research takes a step further by investigating whether companies' efforts to reduce CO2 emissions are yielding measurable results in terms of air pollution reduction. By analyzing the spatial and temporal patterns of companies' environmental impact assessments, we aim to identify specific regions, time periods, and sectors that require further scrutiny. This analysis will help pinpoint areas where companies' sustainability efforts are most effective, and where additional efforts may be needed. In summary, the inclusion of spatial and temporal components in ESG evaluation clustering not only enhances our understanding of regional and temporal variations in corporate sustainability but also lays the groundwork for future research that links corporate environmental commitments with actual environmental outcomes. Through this approach, we hope to contribute to the ongoing efforts to assess and improve the effectiveness of corporate sustainability initiatives.

3 | Data Collection and Descriptive Statistics

We use a unique dataset covering companies from 15 European countries. This dataset includes assessments of companies' sustainability performance and their geographical location.

3.1 | MSCI ESG Rating and Carbon Emission Methodology

Companies' ESG performance is measured through ESG ratings. We collect this information on the companies' ESG rating and its components from MSCI ESG Ratings. ESG ratings are firm-level observations of their sustainability performance using different types of data, including, among others sustainability reports, media sources, and specific surveys to the clients. MSCI provides ESG ratings for more than 10k companies at the worldwide level, resulting in an overall evaluation system[1] with classes (that is, AAA, AA, A, BBB, BB, B, CCC in order from best to worst), a numerical overall score that ranges between 0 (worst) and 10 (best). The overall score is a weighted average of the scores on the three main pillars (Environmental, Social, and Governance). MSCI also provides information on key issues under the three pillars, e.g., relevant to our analysis, the carbon emission scores MSCI (2023a). The methodology that determines the aggregate pillar score from specific items, as well as the aggregation of the three pillars, E, S, and G, in the overall score and rating, are based on industry weights, reflecting the idea that valuation on key parameters is different according to the industry in which firms operate. As an example, the Environmental Pillar will weigh more on the final overall score for utilities than for firms in the Media & Entertainment industry. Lastly, ESG scores mainly cover listed firms, which are the ones that are most frequently under the attention of society, investors, and policymakers regarding sustainability issues.

Henceforth, ESG ratings are not just climate ratings. If a company's greenhouse gas emissions pose significant financial risks, its ESG rating will reflect that. For example, direct emissions pose a significant risk to power and steel companies, while emissions from their products after they have left the factory gate can pose a significant risk to automobile companies. However, for industries such as health care, the most financially relevant risks lie elsewhere, so emissions have less influence on a company's rating. In Appendix C, we report further details on the methodology used by MSCI for the computation of Carbon Emission scores and the number of companies providing the voluntary disclosure of the necessary information.

3.2 | Sample Description

Since this research focuses on the environmental aspects of sustainability scores, we include in our sample the overall ESG score, the Environmental Pillar score, and the Carbon Emission score, which are the three indicators in the set of sustainability scores that consistently draw attention from both scholars and professionals in the field. We consider observations from 2013 to 2023, and we select only companies with a weight of Carbon Emission score greater than zero, that is, companies whose activity involves the emission of greenhouse gases. We match the ESG rating database with the Orbis BvD database to link companies' ESG scores to their location. Initially, we collect the address of the Registered Office and NACE sector classification of listed companies located in Western European countries (Austria, Belgium, Denmark, France, Germany, Gibraltar, Ireland, Italy, Luxembourg, Malta, Netherlands, Portugal, Spain, Switzerland and United Kingdom). We include both active and inactive companies so that we do not exclude observations from companies that may have had an ESG rating in past years but recently have been the subject of mergers or acquisitions or have left the market.

The focus on Western Europe is to avoid problems in the translation of companies' addresses from different alphabets since the algorithm could miss-locate firms in these cases. This henceforth excludes companies from Eastern Europe, Greece, and Scandinavian countries.

In Figure 1, we provide an overview of the sample size, in particular considering the number of firms by year and the number of firms by country in the last year. In our spatial clustering, we are using only data from 2023, thereby considering 617 companies. In the spatiotemporal cluster analysis, we use a sample of 460 companies, since we need companies with at least six observations in the time window considered, as described in the methodology section. We exclude observation from 2012 and earlier, because of the small number of available ratings.

4 | Methodology: Hierarchical Spatial and Spatiotemporal Clustering

The main goal of this paper is to investigate both the spatial and temporal patterns of the sustainability evaluations of Western Europe firms between 2013 and 2023. To do so, we carry out a spatial and spatiotemporal clustering analysis based on the methodology proposed by Chavent et al. (2018), which combines socio-economic features, temporal dynamics and geographical information. Specifically, we implement a modified version of their Ward-like hierarchical algorithm (Ward 1963) that, in addition to detecting homogeneous groups under geographical constraints, selects the clustering hyperparameters such that the total proportion of explained inertia is maximized. The algorithm is then employed in a spatial framework combining cross-sectional socio-economic features and spatial information and in a spatiotemporal framework leveraging on the time dynamics of multiple sustainability distances and spatial dissimilarities.

4.1 | Spatial Hierarchical Clustering

Let $D = [d_{ij}]_{i,j=1,\dots,n}$ be the dissimilarity matrix of the observations and let w_i be the weight of the i-th firm for $i = 1, \dots, n$. Without prior information, it is commonly set to $w_i = 1/n$. Alternatively, the Ward hierarchical clustering approach starts with an initial partition in n clusters of singletons, and at each step, the algorithm aggregates the two clusters such that the new partition has minimum within-cluster inertia, which measures the degree of heterogeneity within each cluster. We define $\mathcal{P}_K = (C_1, \dots, C_K)$ a partition of the dataset into K clusters and the pseudo-inertia of cluster C_K is computed as follows:

$$I(C_K) = \sum_{i \in C_K} \sum_{j \in C_K} \frac{w_i w_j}{2 \sum_{i \in C_K} w_i} d_{ij}^2 \tag{1}$$

The pseudo-within-cluster inertia of the partition is computed as the sum of the pseudo-inertia of each cluster. We point out that the pseudo-inertia is a generalization of the inertia when the dissimilarities can be non-Euclidean. From here on, we will always refer to pseudo-inertia, but for simplicity, we will call it inertia.

The spatial component is included by considering for the sample of n units two $n \times n$ dissimilarity matrices, namely $D_0 = [d_{0,ij}]_{i,j=1,\dots,n}$ and $D_1 = [d_{1,ij}]_{i,j=1,\dots,n}$, referring to euclidean distances matrix of socio-economic variables under consideration and the geodetic distances matrix, respectively. Notice that, since the distances in the D_0 and D_1 matrices may belong to two very different measurement scales (e.g., socioeconomic distance in currency and physical distances in kilometers), it is necessary to scale the dissimilarity matrices to their maximum values so that the distances across observations take values between 0 and 1.

For a given mixing parameter $\alpha \in [0, 1]$, it is possible to obtain a convex combination of the dissimilarity matrices $D(\alpha) = (1 - \alpha)D_0 + \alpha D_1$ and thus perform the hierarchical clustering algorithm. Notice that α states the importance of geographical and socio-economic information in determining the clusters. Indeed, as one set $\alpha = 0$, the geographical dissimilarities are not taken into account, while when $\alpha = 1$, the socio-economic distances are ignored, and the clusters are defined according to geographical distances only.

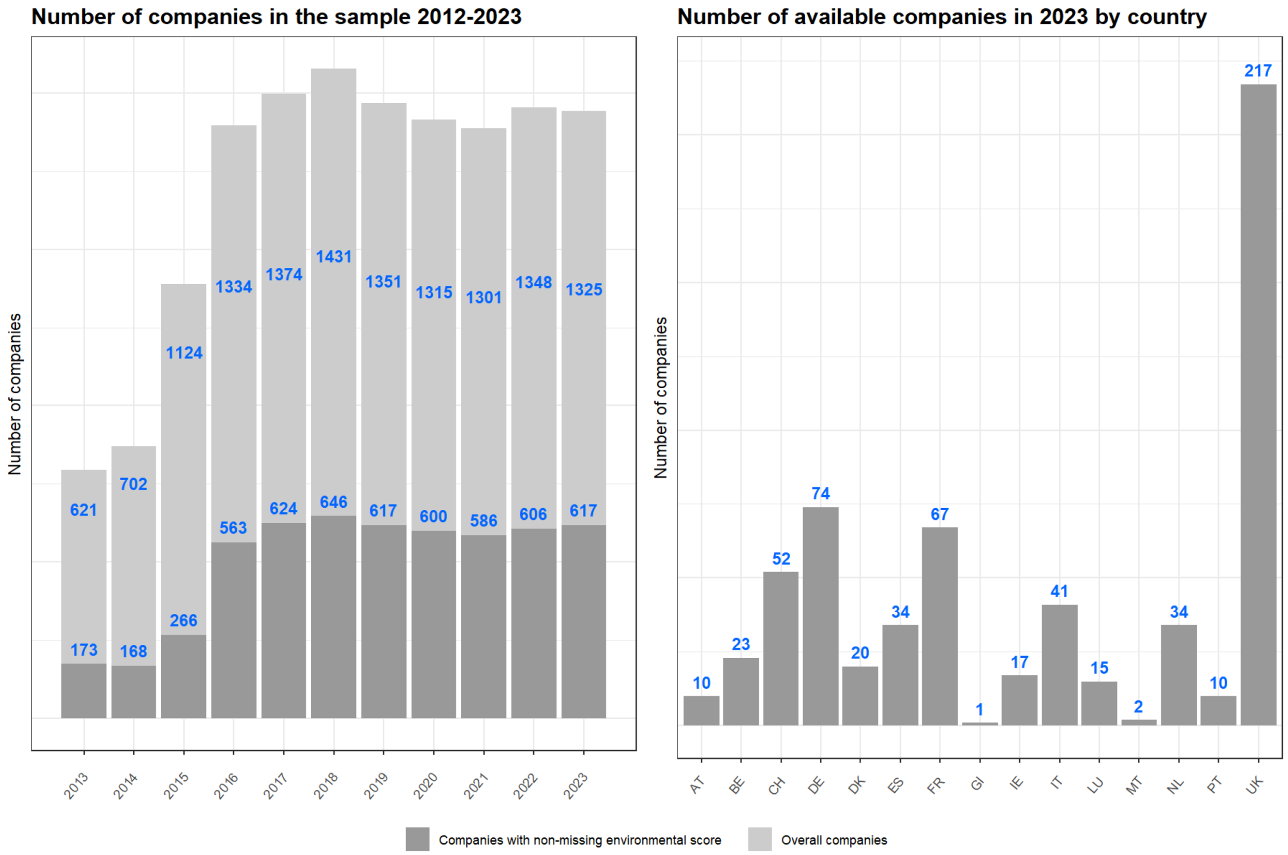

FIGURE 1 | Left panel: Number of observations per year between 2013 and 2023. We report the total number of observations and the number of observations with a positive weight of the Carbon Emission score, which represents the observations included in our sample. Right panel: number of companies per country in 2023 with a positive Carbon Emission score weight.

Given the partition $\mathcal{P}_K^\alpha = (C_1^\alpha, \dots, C_K^\alpha)$, the mixed inertia for cluster C_K^α is defined as the convex combination between the attribute inertia, and the inertia of the spatial component

$$I(C_K^\alpha) = (1-\alpha)\sum_{i\in C_K}\sum_{j\in C_K}\frac{w_i w_j}{2\sum_{i\in C_K} w_i} d_{0,ij}^2 + \alpha \sum_{i\in C_K}\sum_{j\in C_K}\frac{w_i w_j}{2\sum_{i\in C_K} w_i} d_{1,ij}^2 \tag{2}$$

and the mixed within-clusters pseudo inertia is computed as the sum of the mixed pseudo inertia of its clusters, that is,

$$W_\alpha(\mathcal{P}_K^\alpha) = \sum_{k=1}^{K} I_\alpha(C_k^\alpha) \tag{3}$$

Recall that the smaller the pseudo-inertia within the cluster, the more homogeneous the partition into K clusters. Therefore, in the spirit of Ward's criterion, at each iteration of the aggregation, the obtained cluster partition is the one that minimizes $W_\alpha(\mathcal{P}_K^\alpha)$.

4.2 | Spatial Hierarchical Clustering: Choice of the Parameters

The main issue in such a hierarchical clustering approach is the choice of the parameters α and K Chavent et al. (2018). suggest setting a prior value for K and then providing a criterion to choose α such that it allows to explanation of the same proportion of the dissimilarities from both matrices, to the cases in which the clusters are obtained considering only the feature matrix or the spatial matrix. They introduce the notion of the proportion of the total pseudo inertia explained by partition $\mathcal{P}_K^\alpha$ in K clusters as:

$$Q_\beta(\mathcal{P}_K^\alpha) = 1 - \frac{W_\beta(\mathcal{P}_K^\alpha)}{W_\beta(\mathcal{P}_1)} \tag{4}$$

where β can be either D_0 or D_1, depending on which dissimilarity matrix is used as a benchmark. Specifically, $Q_{D_0}(\mathcal{P}_K^\alpha)$ quantifies the proportion of socio-economic pseudo inertia (that is, $W_{D_0}(\mathcal{P}_1)$) explained by partition $\mathcal{P}_K^\alpha$, while $Q_{D_1}(\mathcal{P}_K^\alpha)$ quantifies the amount of geographical pseudo inertia (that is, $W_{D_1}(\mathcal{P}_1)$) explained by partition $\mathcal{P}_K^\alpha$.

To account for potential scale issues in $Q_{D_0}(\mathcal{P}_K^\alpha)$ and $Q_{D_1}(\mathcal{P}_K^\alpha)$, the $Q_\beta(\mathcal{P}_K^\alpha)$ metrics are then normalized to the baseline case of purely-geographical or purely-socio-economic clustering, that is, by computing the following ratios:

$$\tilde{Q}_{D_0}(\mathcal{P}_K^\alpha) = \frac{Q_{D_0}(\mathcal{P}_K^\alpha)}{Q_{D_0}(\mathcal{P}_K^0)} \qquad \tilde{Q}_{D_1}(\mathcal{P}_K^\alpha) = \frac{Q_{D_1}(\mathcal{P}_K^\alpha)}{Q_{D_1}(\mathcal{P}_K^1)} \tag{5}$$

This relative formulation allows for a straightforward interpretation of the values. For instance, by considering $\tilde{Q}_{D_0}(\mathcal{P}_K^\alpha)$, for a given K and a given mixing parameter α, one is expressing the percentage improvement in the explained proportion of pseudo inertia obtained by using a mixture of geographical and socio-economic feature to generate the partition $\mathcal{P}_K^\alpha$ (that is, $Q_{D_0}(\mathcal{P}_K^\alpha)$) to the proportion of pseudo inertia it would be explained by only using socio-economic feature to generate the partition $\mathcal{P}_K^\alpha$ in K clusters (that is, $Q_{D_0}(\mathcal{P}_K^0)$). Conversely, if one considers $\tilde{Q}_{D_1}(\mathcal{P}_K^\alpha)$, the resulting value for a specific pair of K and α expresses the improvement obtained by mixing the two dimensions instead of using a purely-geographical partitioning algorithm. Being α a measure of the trade-off between the loss of socio-economic homogeneity and the gain of geographic homogeneity, for a fixed K, increasingly values of α will correspond to higher $\tilde{Q}_{D_1}(\mathcal{P}_K^\alpha)$ and lower $\tilde{Q}_{D_0}(\mathcal{P}_K^\alpha)$. For a technical discussion about the properties of these quantities, we refer the readers to section 3 in Chavent et al. (2018).

Chavent et al. (2018) suggest to choose α such that the normalized proportion of the explained pseudo inertia from D_0 and D_1 are as similar as possible, that is,

$$min_\alpha |\tilde{Q}_{D_0}(\mathcal{P}_K^\alpha) - \tilde{Q}_{D_1}(\mathcal{P}_K^\alpha)| \tag{6}$$

which means to identify α such that socio-economic and geographical information return as similar as a possible proportion of explained pseudo inertia to proportion it would be explained by only using the socio-economic feature or spatial features to generate the partition. Consequently, the number of clusters can be chosen according to the dendrogram or elbow criteria. Following a similar rationale Mattera and Franses (2023), set an initial number of clusters K_0 considering the partition associated with D_0, then they determine α as in Chavent et al. (2018), and finally they define the optimal number of clusters based on the combined dissimilarity matrix. Notice that this selection method does not always allow to identify α such that it captures the highest possible overall dissimilarity in the data. To address such drawback Jaya et al. (2019), start finding α according to Mattera and Franses (2023) while choosing a different mixing parameter in order to explain better the normalized proportion of inertia in one matrix, with a relatively small reduction of the normalized proportion of inertia from the other matrix.

Hereafter, we propose an algorithm to select the clustering hyperparameters, that is, the mixing coefficient α and the number of clusters K, that generalizes the aforementioned approaches by optimizing the *weighted average of the explained mixed pseudo inertia*, which can be expressed in several ways:

$$\begin{aligned}\overline{Q}(\mathcal{P}_K^\alpha) &= \frac{Q_{D_0}(\mathcal{P}_K^\alpha)\cdot W_{D_0}(\mathcal{P}_1) + Q_{D_1}(\mathcal{P}_K^\alpha)\cdot W_{D_1}(\mathcal{P}_1)}{W_{D_0}(\mathcal{P}_1) + W_{D_1}(\mathcal{P}_1)} \\ &= \left[1 - \frac{W_{D_0}(\mathcal{P}_K^\alpha) + W_{D_1}(\mathcal{P}_K^\alpha)}{W_{D_0}(\mathcal{P}_1) + W_{D_1}(\mathcal{P}_1)}\right]\end{aligned} \tag{7}$$

In particular, conditioning on a given K, the optimal α is given by the maximizer of $\overline{Q}(\mathcal{P}_K^\alpha)$, that is,

$$max_\alpha \overline{Q}(\mathcal{P}_K^\alpha) \tag{8}$$

Thus, while Chavent et al. (2018) defined the optimal α as the one balancing the explained inertia from socio-economic and geographical features, we are proposing to select the α, which jointly maximizes the amount of pseudo inertia explained

ALGORITHM 1 | Hierarchical Spatial Clustering: grid for choice of α and K.

Define as $D_0 = [d_{0,ij}]_{i,j=1,\dots,n}$ the feature dissimilarity matrix
Define as $D_1 = [d_{1,ij}]_{i,j=1,\dots,n}$ the spatial dissimilarity matrix
Define as K_{max} the maximum number of clusters
Define as $\Delta\alpha$ the increment of α
for $K = 1, \dots, K_{max}$ **do**
  for $\alpha \in [0, 1]$, by $\Delta\alpha$ **do**
    Compute the linear combination of the two dissimilarity matrices $D(\alpha) = (1-\alpha)D_0 + \alpha D_1$;
    Compute the $\mathcal{P}_K^\alpha$ = partition in K clusters according to Ward hierarchical algorithm on the combined matrix D;
    Compute the weighted average of the explained mixed pseudo inertia $\bar{Q}(\mathcal{P}_K^\alpha)$
  end for
  Select the best α for each K such that $\alpha_K^* = argmax_\alpha \bar{Q}(\mathcal{P}_K^\alpha)$
end for
Choose K^* (evaluated at the corresponding α_K^*) according to one or more hierarchical clustering criteria, such as the first difference in the weighted average proportion of explained pseudo inertia or the Silhouette index.

from both the socio-economic and the geographical information (i.e., $Q_{D_0}(\mathcal{P}_K^\alpha)$ and $Q_{D_1}(\mathcal{P}_K^\alpha)$), weighted by the cumulated spatial and socio-economic pseudo inertia embedded the data (that is, $W_{D_0}(\mathcal{P}_1) + W_{D_1}(\mathcal{P}_1)$). Further details about $\overline{Q}(\mathcal{P}_K^\alpha)$, in particular, its relationship with the other metrics presented above, are provided in Appendix A.

The proposed algorithm works as follows. Having fixed a given value of K, the hierarchical clustering is performed for a sequence of α values on a regular grid from 0 to 1, with a specified constant increment $\Delta\alpha$. For any K, the best α_K^* is chosen such that the total proportion of explained inertia is maximum. The computation is iteratively repeated considering a range of K up to a defined maximum, that is, $K = 1, 2, \dots, K_{max}$. In this way, we obtain an optimal weighting α_K^*, conditional on K, which we then optimize across a range from $K = 1, \dots, K_{max}$. Then, the optimal number of clusters K^* (evaluated at the optimal α_K^*) is determined according to one or more suitable criteria for hierarchical clustering (Kaufman and Rousseeuw 1990). For instance, consider computing the increments in the weighted average proportion of explained pseudo inertia (which can be interpreted as the increase of the explained variability) induced by a unitary increase in the number of groups or computing the values of the Silhouette index (synthesizing the average homogeneity of units within each cluster). According to the former, the optimal number of groups will match the largest value of K guaranteeing a relevant increment in the weighted average explained inertia, while according to the latter, higher Silhouette values indicate that, on average, the units are properly matched within their cluster. The proposed algorithm is summarized in Algorithm 1.

4.3 | Spatiotemporal Hierarchical Clustering

As regards the spatio-temporal clustering, several authors proposed to adapt the methodology proposed by Chavent et al. (2018)

to the case of georeferenced time series data by combining the dissimilarity matrix computed on the n time series and the spatial dissimilarity component.

To the best of our knowledge, even considering different fields of application, the literature considered time series related to only one socio-economic variable (Bucci, Ippoliti, and Valentini 2023; Deb and Karmakar 2023; Mattera and Franses 2023). We aim to extend this framework by combining together multiple dissimilarities matrices corresponding to several time series of socio-economic features in addition to the spatial distances. Specifically, we combine the four dissimilarity matrices referring to the time series of the overall ESG score, the Environmental Pillar score and Carbon emission score, and the spatial component.

The distances among time series are computed adopting the Dynamic Time Warping (DTW) distance algorithm implemented in the function `diss.DTWARP()` from `TSclust` package in `R` Montero and Vilar (2014). The Dynamic Programming approach using a warping function has been introduced by Sakoe and Chiba (1971, 1978) in spoken word recognition field as a time-normalization algorithm Berndt and Clifford (1994). have implemented DTW distance to detect patterns in time series. DTW is a distance-minimizing temporal alignment between two-time series that allows us to compute a dissimilarity measure among time series that could have different lengths and/or missing observations during the period, but have at least one overlapping time stamp. Let us consider two time series, namely $x_t(t = t_{x_1}, \dots, T_x)$ and $y_t(t = t_{y_1}, \dots, T_y)$, such that $t_{x_1} \gtreqless t_{y_1}$ and $T_x \gtreqless T_y$ but $T_x \geq t_{y_1}$ and $T_y \geq t_{x_1}$. Let us compute the distance between two points $d(x_s, y_r) = |x_s - y_r|$ as the DTW distance between x and y up to points s and r, which is given by the optimal alignment minimizing the following the distance:

$$\Delta(s, r) = d(x_s, y_r) + \min[\Delta(s-1, r-1), \Delta(s-1, r), \Delta(s, r-1)]$$

As shown by Berndt and Clifford (1994), the usage of DTW distance is equivalent to minimizing the Euclidean distance between aligned time series, thus in one dimension, under all admissible temporal alignments. Therefore, time series with similar shapes will be considered similar, even if the deformation appears in different time stamps. This appears to be a proper choice in our analysis for two reasons. First of all, we know that the ESG performance of companies has varied over time, according to different events and factors, and certainly we can not assume that these follow a linear trend over time (we recall that DTW allows us to account for similar non-linear dynamics of the time series). Secondly, the time variability of ESG scores and subscores is very low; thus, we do not expect to observe time series with many fluctuations as there may be companies that have improved in the first period and then remain stable later or move toward the opposite direction; other companies could show a U shaped or U-inverted shape in their sustainability assessments. In any case, we do not impose that these potential changes in the ESG score happened for every company at the same moment, but simply that the shape of the dynamics is similar for companies belonging to the same group.

Once computed, the dissimilarity matrices $D_p = [d_{p,ij}]_{p=1,\dots,P; i,j=1,\dots,n}$, where $P-1$ is the number of variables included and D_P refers to the spatial dissimilarity matrix obtained computing the geodetic distances across the observations, we can proceed in finding the parameters K and α_p for the linear combination $D(\alpha_p) = \sum_{p=1}^{P} \alpha_p D_p$. Note that $\alpha_1, \dots, \alpha_{p-1}$ are the coefficients for the temporal dissimilarity matrices, while $\alpha_P = 1 - \sum_{p=1}^{P-1} \alpha_p$ represents the weight for the spatial component. We recall that dissimilarity matrices are normalized to their maximum value.

We adopt the criterion proposed in Algorithm 1 for the spatial clustering by choosing the vector α_p maximizing the weighted average of the explained mixed pseudo inertia induced by partition $\mathcal{P}_K^{\alpha_p}$.

Similarly to Algorithm 1, for a fixed number of groups K, we consider all the possible combinations for a grid of $\alpha_p (p = 1, \dots, P)$ with a constant increase of each α_p equal to $\Delta\alpha$ and such that $\sum_{p=1}^{P} \alpha_p = 1$. Then, we identify the clustering partition according to the Ward hierarchical algorithm on the combined distance matrix $\boldsymbol{D}$. In particular, we adapt the criterion proposed in Algorithm 1 for the spatial clustering by choosing the vector α_p maximizing the weighted average of the explained mixed pseudo inertia induced by partition $\mathcal{P}_K^{\alpha_p}$, given by the following generalization of the Equation (8):

$$\overline{Q}(\mathcal{P}_K^{\alpha_p}) = 1 - \frac{\sum_{p=1}^{P} W_{D_p}(\mathcal{P}_K^{\alpha_p})}{\sum_{p=1}^{P} W_{D_p}(\mathcal{P}_1^{\alpha_p})} \tag{9}$$

At this point, conditioning on K, we select the values of α_p for which $\overline{Q}(\mathcal{P}_K^{\alpha_p})$ is maximum. We iterate this step for a defined range of potential candidates $K = 1, 2, \dots, K_{max}$ evaluated at the corresponding optimal $\alpha_{K,p}^*$. Finally, we select the number of clusters according to the same criteria defined for the spatial clustering, that is, the increments in the weighted average proportion of explained inertia and the Silhouette index. The proposed algorithm is summarized in Algorithm 2.

5 | Empirical Findings

In this section, we discuss the empirical evidence offered by the spatial and spatiotemporal clustering algorithms, motivating the choice of parameters and interpreting the results.

5.1 | Spatial Clustering

For the Spatial clustering, we considered the sample of 617 European firms with available ESG, Environmental and Carbon Emission scores for 2023. We recall that we obtained the dissimilarity matrices D_0 and D_1 from the Euclidean distances of the ESG-related variables and the geodetic distances of the coordinates of the firms, respectively.

5.1.1 | Choice of K^* and α_K^*

We carry out the spatial cluster analysis by setting $\Delta\alpha = 0.1$ and $K_{max} = 20$. We compute the optimal hyperparameters α^* and K^* considering both the Chavent et al. (2018) procedure and the proposed Algorithm 1. As shown in Figure 2, our algorithm leads

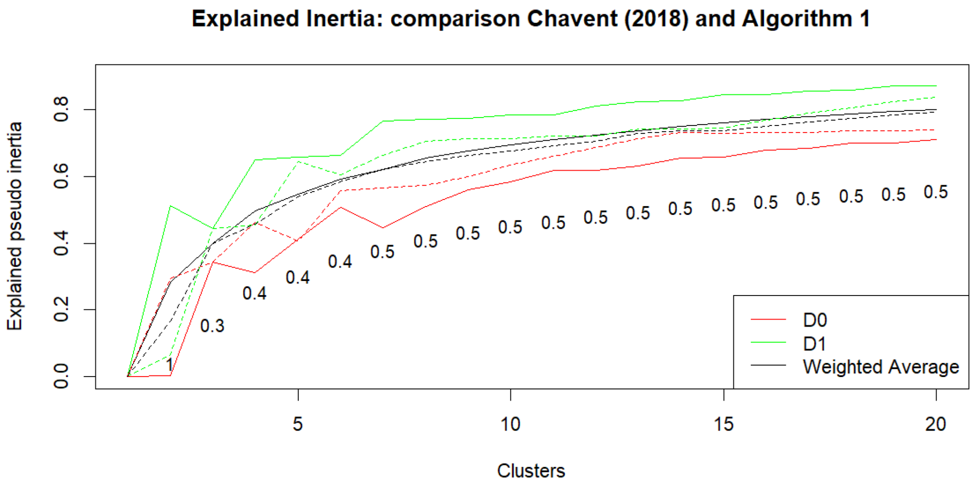

FIGURE 2 | Comparison of proportion of explained pseudo inertia from each dissimilarity matrices D_0 and D_1 and their weighted average, using Chavent et al. (2018) method (dashed line), and Algorithm 1 (solid line) for $K = 1, \dots, K_{max} = 20$. The values underlying the curves indicate the optimal α^*_K for Algorithm 1.

ALGORITHM 2 | Hierarchical Spatiotemporal Clustering: grid search of $\alpha_p (p = 1, \dots, P)$ and K.

Define as $D_p = [d_{p,ij}]_{p=1,\dots,P; i,j=1,\dots,n}$ the feature dissimilarity matrices
Define as K_{max} the maximum number of clusters
Define as $\Delta\alpha$ the increment of α_p
for $K = 1, 2, \dots, K_{max}$ **do**
  for $\alpha_p (p = 1, \dots, P) \in [0, 1]$ by $\Delta\alpha$ such that $\sum_{p=1}^{P} \alpha_p = 1$ **do**
    Compute the linear combination of the dissimilarity matrices $D(\alpha_p) = \alpha_1 D_1 + \alpha_2 D_2 + \dots + \alpha_P D_P$
    Compute the partition $\mathcal{P}_K^{\alpha_p}$ in K clusters according to Ward hierarchical algorithm on the combined matrix D
    Compute the weighted average of the explained mixed pseudo inertia $\bar{Q}(\mathcal{P}_K^{\alpha_p})$ for each partition
  end for
  Select the best α_{Kp} for each K such that $\alpha^*_{Kp} = argmax_{\alpha_p (p=1,\dots,P)} \bar{Q}(\mathcal{P}_K^{\alpha_p})$
end for
Choose K^* (evaluated at the corresponding α^*_{Kp}) according to one or more hierarchical clustering criteria, such as the first difference in the weighted average proportion of explained pseudo inertia or the Silhouette index.

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to a higher proportion of explained pseudo inertia in the spatial component and, as a consequence, the proportion of pseudo explained inertia is lower for the socio-economic features component. Overall, the weighted average proportion is higher than the proportion reached with the Chavent methodology, meaning that we are capturing better the overall variability embedded in the data.

As regards the choice of the parameters, we consider the increment in the weighted average proportion of the explained inertia associated with a unitary increase in the number of clusters, and the Silhouette index, where the dissimilarity matrices are linearly combined to α^*_K. The values of α^*_K are reported in Figure 2, while the aforementioned indices are described in Figure 3a,b.

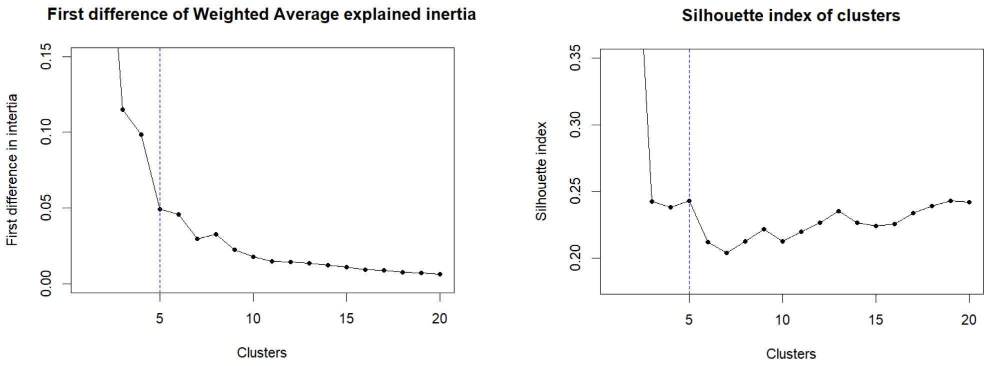
We select $K^* = 5$ because it seems a good compromise, able to gain a relevant increase in the weighted average explained inertia and a reasonable value of the Silhouette index. Consequently, we have $\alpha^*_{K=5} = 0.40$.

For a more exhaustive comparison between the results obtained by the two methods, in Table 1 are reported the inertia, the proportion of explained inertia and the normalized proportion of the explained inertia by the two dissimilarity matrices, considering $K^* = 5$ number of clusters. With respect to Chavent et al. (2018) approach, the proportion of explained inertia increases from 0.4070 to 0.4120 in the dissimilarity matrix D_0, and the gain in D_1 is from 0.6453 to 0.6567. Consequently, the normalized proportion of explained inertia obtained with α^*_5 is higher for both matrices.

5.1.2 | Resulting Spatial Clusters

Figure 4 maps the clusters produced by the spatial clustering for 2023 with parameters $K^* = 5$ and $\alpha^*_5 = 0.40$. Each point represents a company location, with different colors depending on the cluster to which the company is assigned. Also, Figure 6 summarizes the distribution of firms by country (left panel) and by industry (right panel) to understand the obtained categorization better.

In terms of number of companies and country representativeness, cluster 1 is definitely the largest group, with 273 companies located in 10 out of 15 countries in the sample, while the other clusters have fewer companies. Clusters 2 and 3 collect firms from 7 and 8 countries, respectively, while cluster 4 is composed only of companies from the Iberian Peninsula, and cluster 5 is mainly composed of UK and Irish companies (and one company from northern France). Moreover, cluster 3 and cluster 4 are the ones with the fewest companies, respectively 43 and 45. While cluster 4 includes all companies from Spain and Portugal (and one more from Gibraltar), the fact that cluster 3 is made up of companies from 8 countries suggests that there may be some common ESG factors that ultimately group these companies together.



(a) (b)

FIGURE 3 | Hyperparameters selection in spatial clustering. Left panel: increment in the weighted average proportion of explained inertia generated by a unitary increase in the number of clusters. Right panel: Silhouette index computed for each partition into K clusters. Recall that, for each K, we considered the best combination of the dissimilarity matrices according to the α_K^* found using the maximization inertia criterion according to Figure 2. (a) Gain in weighted average explained inertia; (b) Silhouette index.

TABLE 1 | Summary of the inertia (absolute, relative and normalized) returned by the spatial clustering.

		Chavent $\alpha_{K=5} = 0.50$			**Algorithm 1 $\alpha^*_{K=5} = 0.40$**		
	$W(\mathcal{P}_1)$	$W(\mathcal{P}_K^\alpha)$	$Q(\mathcal{P}_K^\alpha)$	$\tilde{Q}(\mathcal{P}_K^\alpha)$	$W(\mathcal{P}_K^\alpha)$	$Q(\mathcal{P}_K^\alpha)$	$\tilde{Q}(\mathcal{P}_K^\alpha)$
D_0	0.0473	0.0275	0.4070	0.5709	0.0271	0.4120	0.5780
D_1	0.0581	0.0221	0.6453	0.7802	0.0206	0.6567	0.7941

Note: Columns 3 to 5 report results according to Chavent et al (2018), that is, $K^* = 5$ and $\alpha^* = 0.50$. Columns 6 to 8 report results according to Algorithm 1, that is, $K^* = 5$ and $\alpha^* = 0.40$. $W(\mathcal{P}_1)$ is the total inertia from spatial dissimilarity (i.e., $W_{D_1}(\mathcal{P}_1)$) or socio-economic dissimilarity (i.e., $W_{D_0}(\mathcal{P}_1)$); $W(\mathcal{P}_K^\alpha)$ is the absolute within-cluster pseudo inertia from the mixed clustering; $Q(\mathcal{P}_K^\alpha)$ is the proportion of explained pseudo-inertia; $\tilde{Q}(\mathcal{P}_K^\alpha)$ is the normalized proportion of inertia.

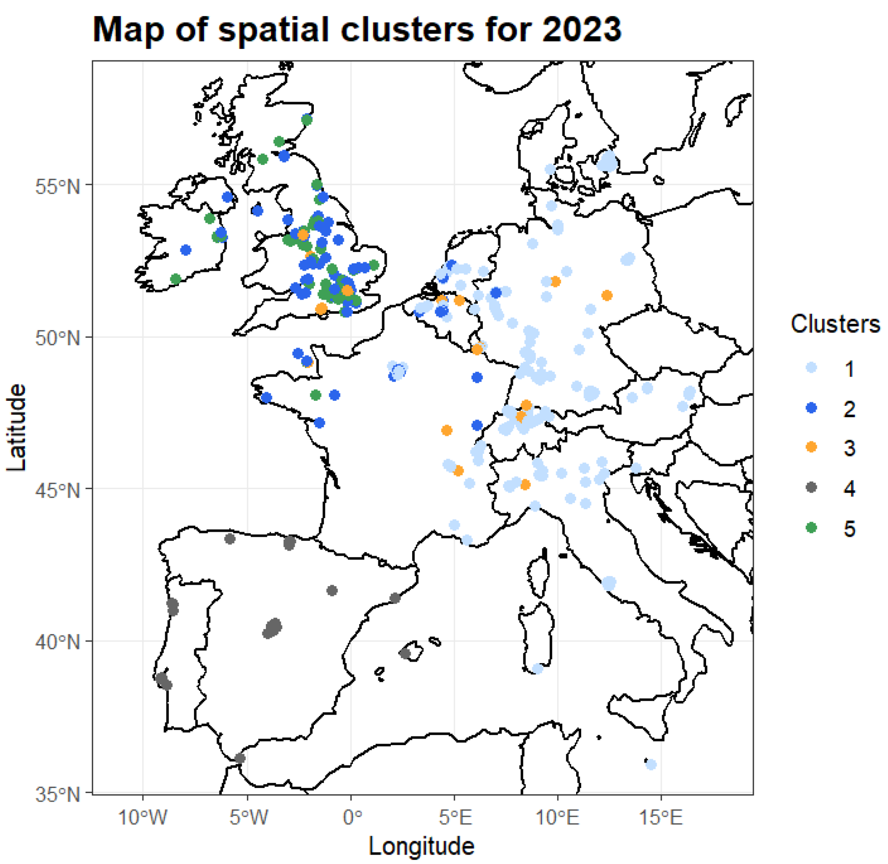


FIGURE 4 | Map of spatial clusters for 2023 using $K^* = 5$ and $\alpha_5^* = 0.40$. Clusters are computed using two dissimilarity matrices: Geodetic spatial distance and Euclidean distance of ESG, Environmental and Carbon Emission scores.

The above clustering shows some degree of overlap in space, except for Cluster 4, which consists only of companies located in Spain and Portugal. In this case, the geographical distance from the Iberian peninsula to the rest of Europe seems to prevail over the distance calculated on the ESG scores, and therefore the resulting cluster seems to absorb only the spatial information, ignoring the differences between variables. In order to better examine the role of the spatial component on cluster formation, we performed several robustness checks involving the non-spatial and the spatial settings with alternative spatial constraints. In particular, for data referring to 2023, we ran purely feature-based clustering (that is, without spatial components) and considered a Nearest Neighbour Distance Matrix to embed the spatial information. As expected, when ignoring the spatial component, the clusters appear to be more overlapped compared to the case of spatial clustering and the Iberian companies mixed-up with other European companies. In the case of spatial clustering based on the neighborhood matrix, although the Spanish and Portuguese companies do not form a perfectly compact cluster, it is still evident that most of them have very high ESG ratings and are homogeneous with each other. A full discussion of the two robustness checks and the corresponding results is reported in Appendix D.

Concluding, in terms of geographical overlap, cluster 1 and seems to overlap with cluster 2 mainly in Belgium, the Netherlands, and France and to a minimal extent with other clusters. Instead, clusters 2, 3, and 5 show a high degree of overlapping in the UK and Ireland, while cluster 4 does not seem to overlap with other clusters.

For the environmental assessment of each cluster, Figure 5 shows the descriptive statistics (mean, 25th and 75th percentile range) of the clusters in terms of Carbon Emission score (ce), Environmental Pillar score (env), and ESG score (esg).

Clusters 1, 4, and 5 have similar patterns of sustainability scores; in particular, they record above-average Carbon Emission scores and Environmental scores. As their ESG score is, on average, lower than their Environmental Pillar score, the companies in this cluster have better environmental practices than the Social and Governance Pillars. Cluster 5 seems to be the one with slightly larger mean scores than the other two. Cluster 2 shows a different pattern from the previous ones. Companies in this cluster seem to have higher carbon emissions than the environmental pillar scores, with their overall ESG score almost at the same level as Clusters 1 and 4. This indicates a disparity of ESG evaluation across clusters: companies in cluster 2 may lag in the overall environmental performance but exhibit relatively strong social and governance attributes, resulting in an ESG score comparable to other clusters, on average. Finally, cluster 3 seems to collect the companies with the lowest performance in terms of both carbon emissions score, environmental pillar score, and ESG score. This finding is relevant given the geographical distribution of clusters 2 and 3. Despite their considerable overlap, our algorithm is able to differentiate companies based on their environmental performance relative to the other two pillars.

Although ESG scores are industry-based, examining the distribution of sectors in the different clusters we obtain from the model is particularly relevant. Considering the distribution across industries (based on the NACE industrial classification), Figure 6 shows a remarkable cross-sectorial heterogeneity, that is, there are no industries that are fully concentrated in a few clusters. However, the concentration of industries can vary considerably between clusters. For example, while in clusters 1, 2, and 3 the

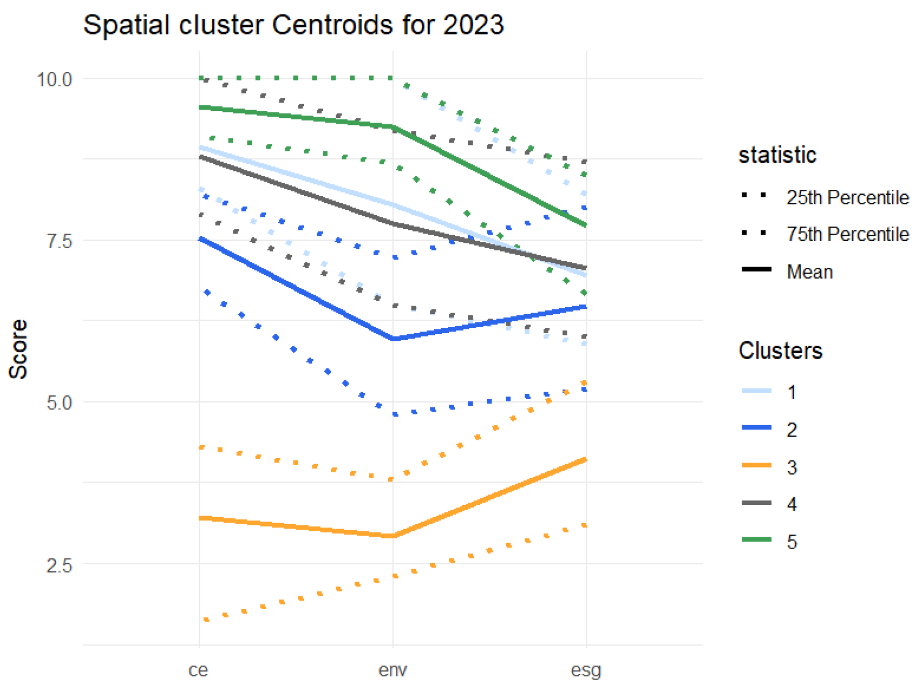


FIGURE 5 | Cluster-specific centroids of the three economic variables used to define the spatial clusters for 2023 using $K^* = 5$ and $\alpha_5^* = 0.40$. Recall that clusters are computed using two dissimilarity matrices: Geodetic spatial distance and Euclidean distance of ESG (esg), Environmental (env), and Carbon Emission (ce) scores. The solid lines represent the means of the variables; the dashed lines represent the two quartiles.

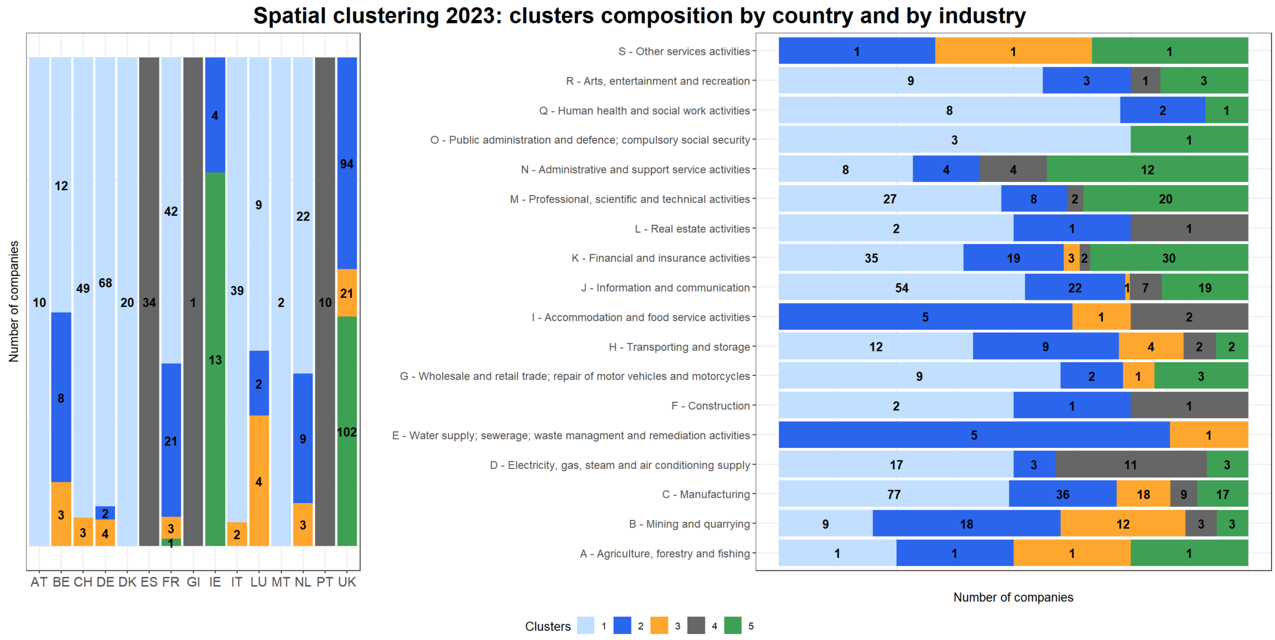


FIGURE 6 | Spatial clusters composition by country (specified using ISO code) and industry for 2023.

TABLE 2 | Average of the ESG (*ESG*), environmental pillar (*Env score*), environmental weight (*Env weight*), carbon emission score (*CE score*), carbon emission weight (*CE weight*), carbon emission exposure (*CE exp*), and carbon emission management score (*CE manag*) for each spatial cluster.

Cluster	ESG	Env score	Env weight	CE score	CE weight	CE exp	CE manag
All	6.797	7.419	21.24	8.324	9.269	3.521	5.579
1	6.949	8.047	19.08	8.93	8.707	3.043	5.768
2	6.476	5.961	25.71	7.536	10.07	4.307	5.113
3	4.116	2.921	39.49	3.212	14.86	7.765	3.974
4	7.067	7.76	29.13	8.787	11.31	3.400	6.56
5	7.719	9.239	11.08	9.565	6.759	2.172	5.909

manufacturing industry (NACE C) is the most relevant sector (in both absolute and relative number of firms), in cluster 4 there are more enterprises in electricity, gas, steam, and air conditioning supply (NACE D), while in cluster 5 manufacturing enterprises are outnumbered by companies in information and communication (NACE J), financial and insurance activities (NACE K) and professional, scientific and technical activities (NACE M). It is worth noting that cluster 3, which is composed of enterprises with poor environmental sustainability performance, includes enterprises from ten NACE sectors, although six of them are represented by only one enterprise.

It is well known that some sectors involve the emission of large quantities of CO_2, while other activities are less exposed to this risk. Considering the heterogeneity across cluster-sectors groups, it is interesting to observe for each cluster the Carbon Emission Exposure score and carbon Emission Management score, which measure respectively how much each firm's activity is linked to carbon emission and the effort of each firm toward this risk, without considering any sector adjustment. Moreover, we can use consider the Environmental Pillar weight and the Carbon Emission weight to understand the importance of this component within the overall ESG assessment. In Table 2 we show the average of the ESG, Environmental Pillar, Environmental weight, Carbon Emission, Carbon Emission weight, Carbon Emission exposure, and Carbon Emission management score for each spatial cluster. Additional details regarding the computation of the scores and the definition of each index are made available in Appendix C.

We can note that generally, companies with the worst performance in terms of carbon emissions are also those that should pay more attention to this factor, as more exposed to this risk, in particular cluster 3 has the lowest Carbon Emission score, and management score, with the highest exposure score. In line with the high exposure, the relevance of the Carbon Emission component and the Environmental Pillar is particularly high in the composition of the ESG score, which is also the lowest. Similarly, cluster 2 shows a higher exposure to Carbon Emission and lower performance than the average with the Environmental and Carbon weights slightly higher than the average. Clusters 1, 4, and 5 have an average lower exposure to carbon emission risk and higher management score. So the companies that should commit themselves more to the reduction of emissions because their activity involves the emission of large quantities of pollutants, are those that are most difficult to achieve good performance.

5.2 | Spatiotemporal Clustering

As regards spatiotemporal clustering application, by starting from the initial sample of 1045 companies with at least one rating between 2013 and 2023, we considered the subsample of 460 firms with at least six annual observations within the same window. This choice is necessary to use the DTW distance for time series, which requires, for each pair of companies, at least one overlapping time stamp. Thus, having considered a 11-years period, the minimum number of overlapping years must be set to six, that is, for every selected company we require a non-missing value for more than half of the entire period under consideration. We computed the dissimilarity matrices of the time series for the ESG score, Environmental Pillar score, and Carbon emission score, using the DTW algorithm described in Section 4.3, and the geodetic distances from the coordinates. Thus, we obtained the dissimilarity matrices named D_{esg}, D_{env}, D_{ce} and D_{sp}.

5.2.1 | Choice of K^* and α^*_{Kp}

To choose the optimal number of clusters K and the linear combination of weights α_p, we run the Algorithm 2 setting $K_{max} = 20$ and $\Delta\alpha = 0.05$. Having to choose a higher number of mixing parameters, we think it is more appropriate to use a smaller $\Delta\alpha$, so as to consider a greater number of combinations, including the case when the matrices all have the same weight (that is, $\alpha_p = 0.25 \quad \forall p = 1, \dots, P$). Notice that the latter combination would not be considered if we used a $\Delta\alpha = 0.1$ as in the purely spatial setting. In Figure 7, we show the results obtained for each number of clusters, both in terms of the proportion of explained inertia for each dissimilarity matrix and the weighted average proportion of explained inertia (top panel) and the best combination of mixing parameters.

From the plots, it is possible to notice that the spatial component is included when considering at least $K = 3$ groups. The dissimilarity matrix D_{esg} plays a less important role for a number of clusters lower than 8. For a higher number of clusters, the best combinations of the dissimilarity matrices provide similar weights. In Figure 8a,b, we compare the gain in the weighted average of explained inertia and the silhouette index from $K = 1$ up to $K_{max} = 20$, evaluating each K at the corresponding optimal combination $\alpha^*_{K,p}$. Both plots suggest that, when choosing a number of clusters equal to $K = 5$, we manage to increase the weighted average proportion of inertia by 0.0478, and we get a silhouette index equal to 0.1640, which represents one of the highest values among those shown. Although the value of the silhouette may not seem too high, with the increasing dimensionality of the

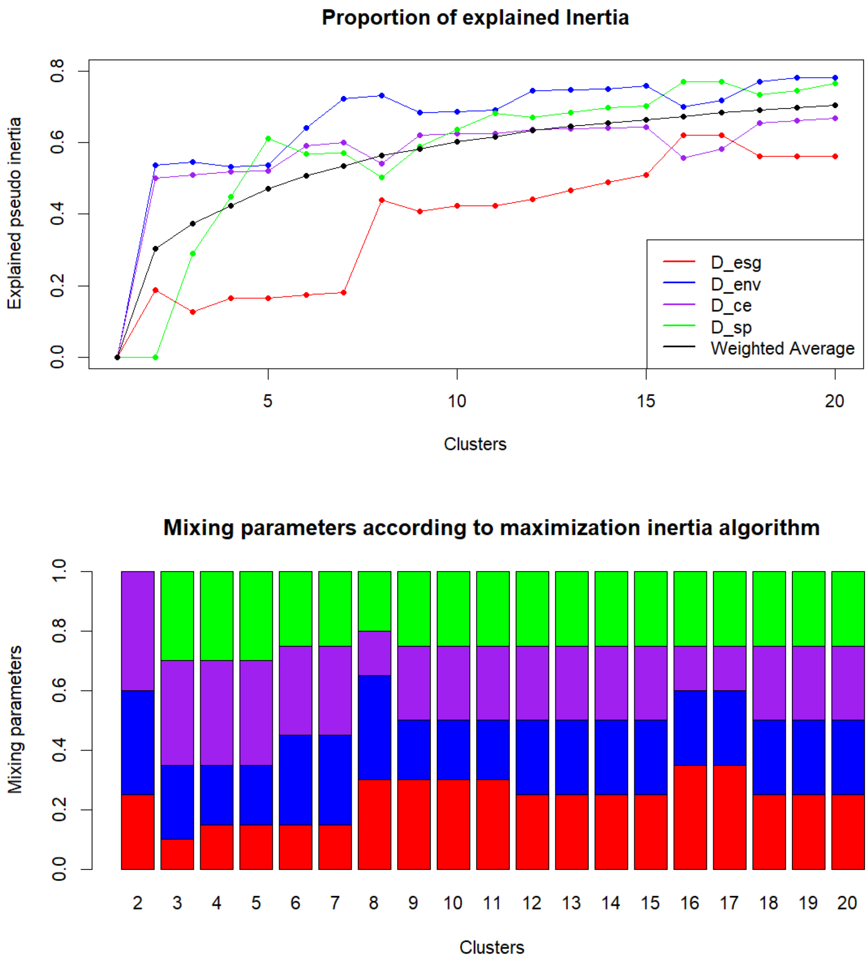
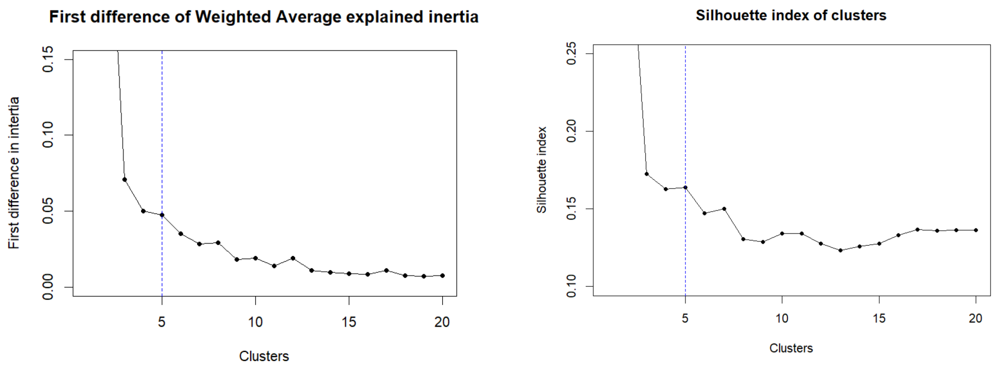


FIGURE 7 | Top panel: proportion of explained pseudo inertia contained in each dissimilarity matrix (colored lines) and weighted average proportion (black line). Values are computed considering for each K the optimal weighting combination $\alpha^*_{K,p}$ from Algorithm 2. Bottom panel: optimal weighting combination $\alpha^*_{K,p}$ from Algorithm 2. Colors refer to the four dissimilarity matrices used in the computation.



(a) (b)

FIGURE 8 | Hyperparameters selection in spatiotemporal clustering. Left panel: increment in the weighted average proportion of explained inertia generated by a unitary increase in the number of clusters. Right panel: Silhouette index computed for each partition into K clusters. Recall that, for each K, we considered the best combination of the dissimilarity matrices according to the α^*_{Kp} found using the maximization inertia criterion according to Figure 7. (a) Gain in the weighted average of explained pseudo inertia; (b) Silhouette index.

TABLE 3 | Summary of the inertia (absolute, relative, and normalized) returned by the spatiotemporal clustering at the optimal solution $K^* = 5$. $W(\mathcal{P}_1)$ is the total inertia provided by each dissimilarity matrix; $W(\mathcal{P}_K^{\alpha_p})$ is the absolute within-cluster pseudo inertia from the mixed clustering for each matrix; $Q(\mathcal{P}_K^{\alpha_p})$ is the proportion of explained pseudo-inertia; $\tilde{Q}(\mathcal{P}_K^{\alpha_p})$ is the normalized proportion of inertia.

	α_p	$W(\mathcal{P}_1)$	$W(\mathcal{P}_K^{\alpha_p})$	$Q(\mathcal{P}_K^{\alpha_p})$	$\tilde{Q}(\mathcal{P}_K^{\alpha_p})$
D_{esg}	0.15	0.0501	0.0418	0.1649	0.2195
D_{env}	0.20	0.0672	0.0311	0.5362	0.6411
D_{ce}	0.35	0.0456	0.0218	0.5206	0.6761
D_{sp}	0.30	0.0626	0.0242	0.6125	0.7453

data, it becomes difficult to achieve high values because of the curse of dimensionality as the distances become more similar.

Overall, we can state that using $K^* = 5$ clusters with weights $\alpha^*_{5,esg} = 0.15$, $\alpha^*_{5,env} = 0.20$, $\alpha^*_{5,ce} = 0.35$ and $\alpha^*_{5,sp} = 0.30$ represent the best solution. In Table 3, we report the absolute explained inertia, the proportion of explained inertia and the normalized proportion of explained inertia for each dissimilarity matrix, considering our choice of hyperparameters. Overall, through cluster analysis, we are able to explain more than 50% of inertia in the dissimilarity matrices D_{env}, D_{ce}, D_{sp}, but the proportion of explained inertia in D_{esg} is lower than 25%.

In order to achieve a substantially higher proportion of explained inertia in D_esg, it is necessary to choose a much higher number of clusters, but this would complicate the interpretation of the resulting clusters. In addition, the silhouette index assumes even lower values when the number of clusters is greater than 5, so the homogeneity of the resulting clusters seems to decrease. Thus, $K^* = 5$ is a reasonable choice in our spatiotemporal cluster analysis.

5.2.2 | Resulting Spatiotemporal Clusters

The spatiotemporal clustering produces substantially different groups to the spatial clustering results described in Section 5.1. Figure 9 represents the companies based on their location and on the final cluster to which they belong.

It is possible to notice a higher degree of overlap between the five clusters in the spatial clustering analysis. Even in the Iberian Peninsula, we observe the presence of two clusters, namely 3 and 4, whereas in the previous analysis, only one cluster was present. This implies that the specific temporal dynamics of ESG scores could be relevant to our multidimensional approach. In other words, the inclusion of the temporal component captures new information that was missed when only the spatial component was considered. In particular, different pairs (or sometimes even triplets) of clusters could be identified in different geographical areas. Clusters 1 and 2 overlap in Italy, Denmark, and Germany, and also with some enterprises from cluster 3, in Switzerland; clusters 2 and 3 overlap mainly in Belgium and the Netherlands, and they are also found together with cluster 5 in Paris; clusters 3 and 5 overlap significantly in the UK and Ireland; in Portugal there is an overlap between clusters 3 and 4, especially around the cities of Lisbon and Porto. For the environmental and sustainability assessment, we represent the mean, the 25th and the 75th percentile of the Carbon Emission Score, Environmental Pillar score, and ESG score in the period observed for the different clusters.

A synthesis of the results by country and by industry is reported in Figure 10. Similarly to the previous spatial analysis, the distribution of sectors across clusters is quite heterogeneous. Two results stand out. Once again, the manufacturing sector (NACE C) is not dominant in all clusters, but only in clusters 1, 2, and 3. In cluster 4, there are more enterprises in electricity, gas, steam, and

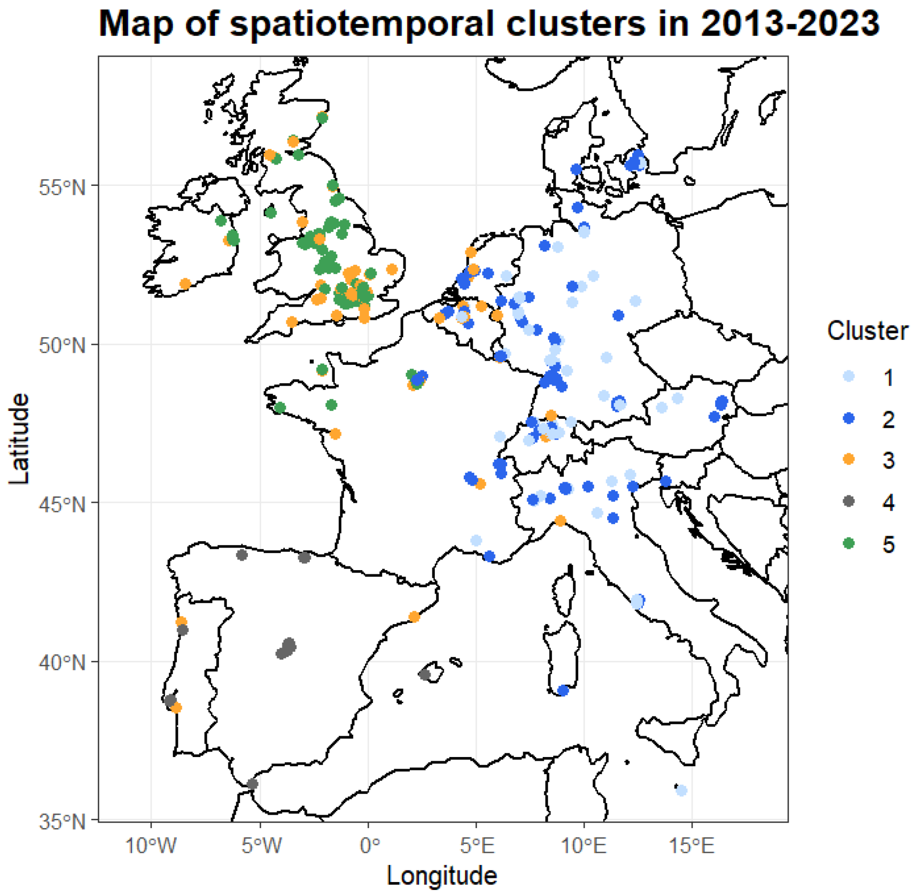


FIGURE 9 | Map of spatiotemporal clusters between 2013 and 2023. Clusters are computed using four dissimilarity matrices: Geodetic spatial distance, DTW distance of the overall ESG scores, DTW distance of the Environmental scores and DTW distance of Carbon Emission scores.

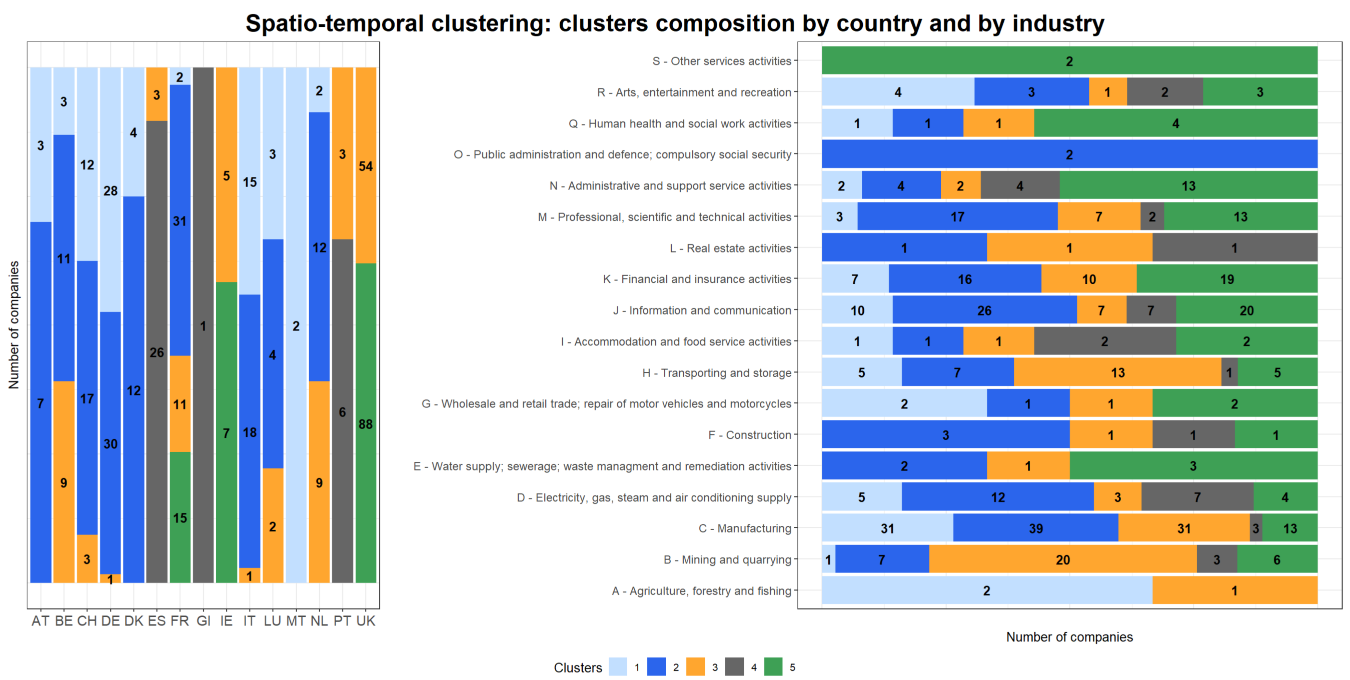


FIGURE 10 | Spatiotemporal clusters (from 2013 to 2023) composition by country (specified using ISO code) and industry.

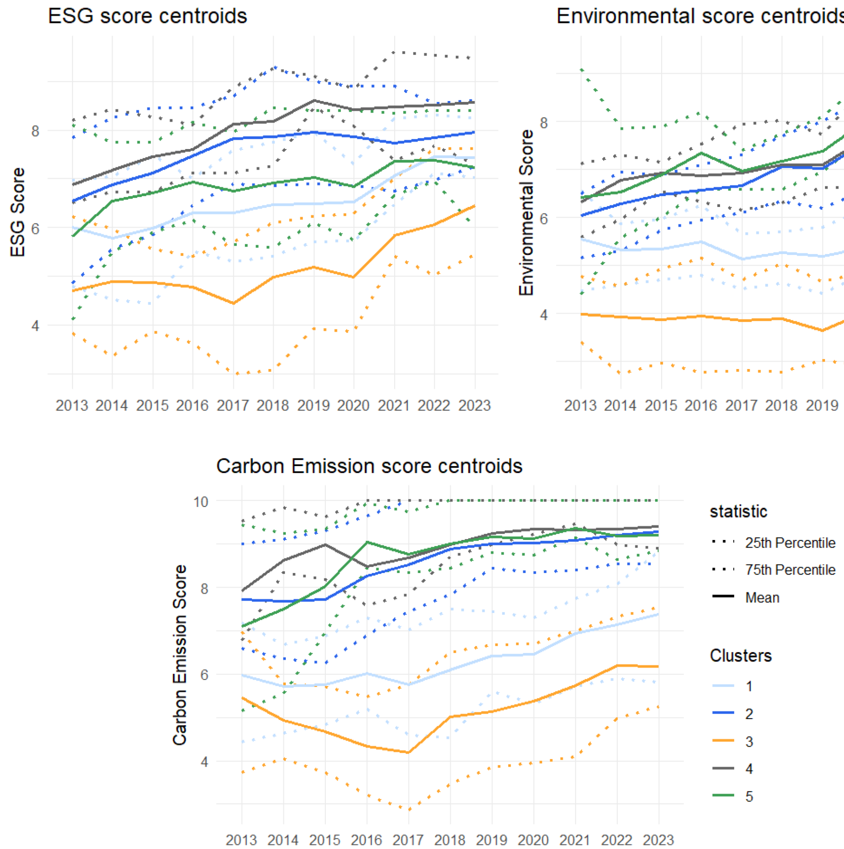


FIGURE 11 | Time series 2013–2023 of centroids (solid lines) and quantiles (dashed lines) of the socio-economic used for the spatiotemporal clusters.

air conditioning supply (NACE D), information and communication (NACE J), and administrative and support service activities (NACE N) than in manufacturing. In cluster 5, on the other hand, manufacturing is outnumbered by information and communication (NACE J) and finance and insurance (NACE K). Finally, cluster 3, the worst-performing cluster in terms of environmental sustainability, includes a large number of manufacturing enterprises and most of the enterprises in mining and quarrying (NACE B) and in transport and storage (NACE H).

As in the spatial clustering analysis, some clear paths can be identified in the individual clusters, as well as some common aspects between the clusters. As reported in Figure 11, clusters 2, 4, and 5 seem to contain the companies with the highest performance in all three variables considered. Their scores also seem to increase over time, albeit with different magnitudes. On the contrary, to the previous clusters, clusters 1 and 3 collect companies with visibly lower levels of environmental performance and carbon emission scores, with cluster 3 being the lowest-scoring cluster on average. While the pattern for the ESG score for the two clusters appears to be increasing throughout the period, as for the other three clusters, the pattern for the environmental score appears to be constant throughout the period. Instead, the two clusters observe a very different path for the carbon emission score. For cluster 3, this variable decreases on average between 2013 and 2017, while after 2017, it seems to increase until the end of the period. For cluster 2, on the other hand, the carbon emission score seems to be constant in the period 2013-2017 and then starts to increase until 2023.

6 | Conclusion

In this paper, we used spatial and spatiotemporal clustering methodologies to identify the main patterns that characterize the environmental performance of European companies. In particular, we examined the role of spatial location and temporal dynamics for European companies with ESG scores in the period between 2013 and 2023. For this reason, we developed a spatial and a spatiotemporal version of a hierarchical clustering technique accounting for multiple dimensions and providing alternative criteria to efficiently determine suitable values for the clustering hyperparameters, that is, the weighting combination between the considered variables and the optimal number of clusters.

Our findings suggest that both space and time matter when analyzing patterns of ESG performance. The spatial analysis for 2023 provided evidence of the presence of cross-national and cross-industrial groups of companies with remarkable differences in the levels of environmental performance. In particular, we were able to detect a subsample of companies with very poor environmental and ESG scores, which belong to several European countries and are mainly classified in the manufacturing and mining industries. Other clusters are mainly driven by companies engaged in the tertiary and service sectors, with a more regional and less transnational character (e.g., the clusters in the UK and the Iberian peninsula), with higher levels of sustainability performance. Regarding the space-time dynamic, the identified groups are more prone to spatial overlapping (e.g., two clusters in the Iberian peninsula), suggesting that the ESG scores' temporal aspect is relevant to our multidimensional approach. As for the purely spatial analysis, also in the spatiotemporal setting, the dualism between the manufacturing sector and tertiary sectors is a key element, with the manufacturers dominating the worst environmental-performing clusters.

Finally, another outcome of interest is the gap (in some groups, considerable gaps exist) between overall ESG score values and the scores in the environmental and carbon emissions pillars. In this sense, both approaches show a distance between environmental scores to the social and governance pillars. In other words, companies with better environmental and emissions scores perform worse on average in the social and governance categories, lowering the overall ESG score. In contrast, companies with low environmental scores perform better in terms of social and governance. This difference could be due to divergence in corporate strategies, leading to specialization in internal company practices as well, and thus diverse scores.

We believe our results can help identify how local regulations, cultural factors, and economic conditions influence ESG practices and provide insights into the effectiveness of environmental policies for companies and the impact of past regulations on ESG scores. Henceforth, the results of our study provide valuable insights for companies, practitioners, investors, and stakeholders. From a managerial perspective, by the means of the cluster analysis, firms can benchmark against peers to identify best practices and areas for improvement, aiding in strategic planning and setting realistic ESG targets. Additionally, these insights enhance stakeholder communication, promoting transparency and accountability.

Moreover, the results of our study provide valuable information for professionals and investors from two perspectives. On the one hand, identifying a cluster with poor environmental performance can help assess potential risks and vulnerabilities for investments. Through the cluster analysis, investors could assess whether firms in different clusters are exposed to different physical and transitional environmental risks. Investors can therefore use this information to reach regions or companies with better ESG and carbon performance and assess risks and vulnerabilities by making more informed decisions. On the other hand, companies that do not belong to the dominant cluster in their region are classified into other clusters based on their ESG performance. In other words, our proposed algorithm can isolate those companies for their exceptionally strong or weak sustainability performance compared to their regional counterparts. This is valuable to investors because it enables them to identify outliers in terms of ESG performance within specific regions. By isolating companies with notably high or low ESG performances, investors can make more informed decisions regarding sustainable investments in specific areas, potentially minimizing risk by avoiding companies with poor ESG records. This is also important for policymakers, especially regional authorities, who are trying to identify good and bad sustainability practices. With this regard, our proposed algorithm could be used by policymakers to design more effective and targeted actions with the aim of reducing corporate emissions and, thus, the overall environmental impact.

Lastly, in the academic literature, this research contributes by providing new insights into the spatial pattern and temporal dynamics of the Environmental performance of companies. The findings can help in developing new theoretical models and frameworks for understanding Environmental performance aiming to examine the relationship with other phenomena or changes due to significant events (e.g., policy changes, environmental incidents, economic crises), encouraging interdisciplinary research, combining environmental science, geography, economics, and data science.

In summary, the main take-home message of this paper is that the geographical location of firms is relevant for a comprehensive understanding of the time dynamics of ESG scores, particularly in explaining the ability of firms to achieve positive scores, especially in the environmental aspects of sustainability. Conversely, the transnational nature of groups, that is, the high degree of overlap between clusters, may pose a challenge when attempting to link cluster ESG performance to different national or supranational policies that influence firms' pursuit of sustainability practices.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

All results presented in this paper can be reproduced using the R software. The codes were developed entirely by the authors. The authors received the data on ESG ratings and scores from MSCI for research purposes under a non-disclosure agreement. Thus, actual data cannot be provided for replication. For reproducibility purposes, all the scripts and a simulated dataset with similar characteristics to the true one (including data not covered by non-disclosure agreements) are made available at the following GitHub folder https://github.com/PaoloMaranzano/CM_SB_PM_PO_ESG_Env2024.git.

Endnotes

[1] The assessments are not meant to be taken as absolute values, but need to be.

[2] See https://ghgprotocol.org/standards-guidance.

[3] We recall that MSCI provides methodological details upon request through a public procedure available at the following link: https://www.msci.com/esg-and-climate-methodologies.

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Appendix A

Further Details on the Average Proportion of Explained Mixed Pseudo Inertia $\overline{Q}(\mathcal{P}_K^\alpha)$

Let us consider a partition $\mathcal{P}_K^\alpha$ in K clusters obtained mixing the dissimilarity matrices D_0 and D_1 with the coefficient α. Also, let us denote its within-clusters mixed inertia as $W(\mathcal{P}_K^\alpha)$ and the corresponding proportion of the total pseudo inertia explained as

$$Q_0(\mathcal{P}_K^\alpha) = 1 - \frac{W_0(\mathcal{P}_K^\alpha)}{W_0(\mathcal{P}_1)} \qquad Q_1(\mathcal{P}_K^\alpha) = 1 - \frac{W_1(\mathcal{P}_K^\alpha)}{W_1(\mathcal{P}_1)}$$

where $W_0(\mathcal{P}_1)$ and $W_1(\mathcal{P}_1)$ are the total pseudo inertia under dissimilarity matrix D_0 and under dissimilarity matrix D_1, respectively.

The two previous expressions can be reformulated as follows:

$$Q_0(\mathcal{P}_K^\alpha) \cdot W_0(\mathcal{P}_1) = W_{D_0}(\mathcal{P}_1) - W_{D_0}(\mathcal{P}_K^\alpha)$$

$$Q_1(\mathcal{P}_K^\alpha) \cdot W_1(\mathcal{P}_1) = W_{D_1}(\mathcal{P}_1) - W_{D_1}(\mathcal{P}_K^\alpha)$$

Now, let us denote the *weighted average of explained mixed pseudo inertia for partition* $\mathcal{P}_K^\alpha$ as the following linear combination:

$$\overline{Q}(\mathcal{P}_K^\alpha) = \frac{Q_{D_0}(\mathcal{P}_K^\alpha) \cdot W_{D_0}(\mathcal{P}_1) + Q_{D_1}(\mathcal{P}_K^\alpha) \cdot W_{D_1}(\mathcal{P}_1)}{W_{D_0}(\mathcal{P}_1) + W_{D_1}(\mathcal{P}_1)}$$

In practice, we linearly combine the proportion of pseudo inertia explained by partition $\mathcal{P}_K^\alpha$ under dissimilarity D_0 (that is, $Q_{D_0}(\mathcal{P}_K^\alpha)$) and the share of pseudo inertia explained under dissimilarity D_1 (that is, $Q_{D_1}(\mathcal{P}_K^\alpha)$) weighting the values with the total pseudo inertia provided by the geographical information (that is, $W_{D_0}(\mathcal{P}_1)$) and the total pseudo inertia provided by the socio-economic features (that is, $W_{D_1}(\mathcal{P}_1)$).

Alternatively, the weighted average can also be expressed as a function of the total relative gain obtained by implementing a mixed partitioning instead of a purely-spatial or purely-socio-economic information approach, that is,

$$\overline{Q}(\mathcal{P}_K^\alpha) = \frac{[W_{D_0}(\mathcal{P}_1) - W_{D_0}(\mathcal{P}_K^\alpha)] + [W_{D_1}(\mathcal{P}_1) - W_{D_1}(\mathcal{P}_K^\alpha)]}{W_{D_0}(\mathcal{P}_1) + W_{D_1}(\mathcal{P}_1)}$$

where $W_{D_0}(\mathcal{P}_1) - W_{D_0}(\mathcal{P}_K^\alpha)$ is the discrepancy between the overall pseudo inertia using D_0 only and the pseudo inertia induced by partition $\mathcal{P}_K^\alpha$ in K clusters (that is, the gain in inertia obtained by using the combination of the two matrices instead of the D_0 matrix alone), while $W_{D_1}(\mathcal{P}_1) - W_{D_1}(\mathcal{P}_K^\alpha)$ is the discrepancy between the overall pseudo inertia using D_0 only and the pseudo inertia induced by partition $\mathcal{P}_K^\alpha$ in K clusters (that is, the gain in inertia obtained by using the combination of the two matrices instead of the D_1 matrix alone). This expression allows a further interpretation of the proposed criterion for selecting α, that is, we are maximizing the relative gain in terms of inertia induced by using a mixture of geographical and socio-economic information to cluster the observations instead of employing a purely spatial or purely socio-economic clustering.

Eventually, by rearranging the previous expression, one can rewrite $\overline{Q}(\mathcal{P}_K^\alpha)$ as a function of the within-cluster pseudo inertia as follows:

$$\begin{aligned}\overline{Q}(\mathcal{P}_K^\alpha) &= \frac{W_{D_0}(\mathcal{P}_1) + W_{D_1}(\mathcal{P}_1) - \left[W_{D_0}(\mathcal{P}_K^\alpha) + W_{D_1}(\mathcal{P}_K^\alpha)\right]}{W_{D_0}(\mathcal{P}_1) + W_{D_1}(\mathcal{P}_1)} \\ &= 1 - \frac{W_{D_0}(\mathcal{P}_K^\alpha) + W_{D_1}(\mathcal{P}_K^\alpha)}{W_{D_0}(\mathcal{P}_1) + W_{D_1}(\mathcal{P}_1)}\end{aligned}$$

Notice that, the last expression allows for an easy generalization to the case of $p = 1, 2, \ldots, P$ dissimilarity matrices $D_1, \ldots, D_p, \ldots, D_P$, as in the case of spatiotemporal clustering with multiple dimensions,

$$\overline{Q}(\mathcal{P}_K^{\alpha_p}) = 1 - \frac{\sum_{p=1}^P W_{D_p}(\mathcal{P}_K^{\alpha_p})}{\sum_{p=1}^P W_{D_p}(\mathcal{P}_1^{\alpha_p})}$$

Appendix B

Comparison Between Different ESG Rating Providers

In Table B1 we provide a comparison of ESG methodologies used by different data providers. It has been summarized from that reported by Billio et al. (2021).

Appendix C

MSCI Carbon Emission Score Methodology

Focusing on the Carbon Emission score, it evaluates the company's level of exposure to, and management of its risks, with regard to emissions whose sources are traceable to those indicated in scopes 1 and 2 of the Greenhouse Gas Protocol. Specifically, scope 1 emissions cover direct emissions over one year from establishments that are owned or controlled by the company, while scope 2 emissions come from the generation of purchased heat, steam, and electricity consumed by the company.[2] In the approach used by MSCI (2023b),[3] the Carbon Emission score is calculated by combining information on the Carbon Emission Exposure Score, which evaluates the company's exposure to risks on this Key Issue including industry-specific adjustments, and the Carbon Emissions Management Score which evaluates the company's ability to manage its exposure to Carbon Emission risk according to company disclosures.

As mentioned above, ESG assessments are only available for those companies that voluntarily publish the necessary information. In Table C1 we provide a comparison between the number of listed companies located in Western European countries included in our sample and those with ESG rating provided by MSCI.

According to the data collected from the Orbis dataset, we are considering only one-quarter of the companies but they represent 93% of the sum of the total assets and 88% of the sum of sales revenue. In other words, although we are considering less than half of active listed companies, these represent the majority of the invested capital and sales revenue.

Appendix D

The Role of Spatial Constraint in Cluster Analysis

In Section 5.1, the resulting spatial clusters show some degree of overlap in space, except for Cluster 4, which consists only of companies located in Spain and Portugal. In this case, the geographical distance from the Iberian peninsula to the rest of Europe seems to prevail over the distance calculated on the ESG scores, and therefore the resulting cluster seems to absorb only the spatial information, ignoring the differences between variables. In order to better examine the role of the spatial component on cluster formation, we report in this section the results obtained from cluster analysis in cases when using only the distance matrix D_0 obtained from the Euclidean distance of the ESG score, Environmental score and Carbon Emission score in 2023 for 617 companies and when combining it with the spatial information contained in the complementary matrix of the Nearest Neighbour Distance Matrix $D_1^{NNDc} = 1 - D_1^{NND}$. The latter is computed assigning $d_{1,ij}^{NND} = 1$ if firm i is one of the m closest firms to j or vice versa and 0 otherwise. In other words, D_1^{NNDc} can be interpreted as a simplified version of D_1, where m shorter distances are indicated with 0 and longer distances are equal to 1. In our case, we decide to set $m = n/K$.

Examining the first case, Figures D1 and D2 illustrate the map of firms belonging to different clusters and the centroids of the variables. Clusters 1, 2, and 3 refer to firms with higher sustainability performance, and they seem to be spread evenly throughout Europe. Considering firms with worse performance, Cluster 4 exhibits the lowest values for Carbon Emission and Environmental scores, while Cluster 5 shows the lowest centroid for ESG scores. Companies belonging to these clusters are mainly located in the northern, central, and eastern areas of the territory concerned, while just a few of them are located in the Iberian Peninsula. We can see from this that the spatial cluster of the Iberian peninsula described in section 5 is not only due to the long distances between Spanish and Portuguese companies compared with the rest of European companies, but also reflects the fact that companies show slightly better sustainability performance, in fact Iberian companies with particularly low sustainability scores are few.

Now, we observe the spatial clusters obtained by combining the Euclidean distance across the variables in 2023 with the complementary of the Nearest Neighbour distance matrix $D_1^{NNDc} = 1 - D_1^{NND}$, considering $m = n/K = 617/5 \approx 123$. We set $K = 5$ and $\Delta\alpha = 0.1$ and we find $\alpha_{K=5}^* = 0.1$ such that the combination of spatial and features information provides the maximum average weighted explained inertia of the dissimilarity matrices.

In Figures D3 and D4 it is possible to observe that the clusters obtained are quite similar to those shown in Section 5.1, where the spatial dissimilarity matrix contains geodetic distances calculated from the coordinates of firms. Also, in this case, a cluster with particularly low sustainability ratings is identified and its companies are mainly located in England and central Europe. As concerns the Iberian Peninsula, although there is no geographically separate cluster from all other companies, most Spanish and Portuguese firms belong to Cluster 3, which also extends into France, south of the UK and Belgium. This is a fairly compact group whose ESG, Environmental and Carbon Emission scores are higher than the other identified clusters.

TABLE B1 | Key Differences Between ESG Rating Agencies as Reported by Billio et al. (2021) in Table 1.

	MSCI	VIGEO	REFINITIV	Suatainalitics	ISS OEKOM	RobeccoSAM	ECPI	Bloomberg
RATING SCORE	CCC to AAA	− to ++	D- to A+	0 to 100	D- to A+	0 to 100	F to EEE	0 to 100
HISTORY	1990	1983	2002	1992	1985	1995	1997	2008
SOURCES	Company disclosure, 1600+ Media sources, 100+ specialized dataset	Company disclosure, Recommendation, Conventions	Company websites, Company reports, NGO Websites, Media and news, Stock Exchange filings	Public disclosure, Media and news, NGO reports	Publicly available information, Interviews with stakeholders, information on company policies and practices, company direct contact	Survey approach	Company reports, Company screening, Media and news, Regulatory data, Bloomberg and Thomson Reuters, University networks	Company reports, Company screening, Media and news, Regulatory data, Bloomberg and Thomson Reuters, University networks
MAIN RISK FACTORS	Environmental Climate Change, Natural Resources Pollution And Waste Mgmt. Environmental Opportunities Social Product Liability Human Capital Stakeholder Needs Social Opportunities Governance Corporate Behaviour Corporate Governance	Human Resources, Human Rights Environment Business Behaviour Community Involvement Corporate Governance	Environmental Resource Use, Emission, Innovation Social Workforce, Human Rights, Community, Product Responsibility Governance Mgmt., Shareholders, Csr Strategy	Industry-Specific indicators. Factors Change According To The Industrial Group To Which A Company Belongs	Environment Climate Change Strategy, Ecoefficiency, Energy Mgmt., Env. Impact of Product Portfolio, Env. Mgmt., Water Risk And Impact Social Equal Opportunities, Freedom of Association, Health and Safety, Human Rights, Product Responsibility, Social Impact of Product Portfolio, Supply Chain Mgmt., Taxes Governance Business Ethics, Compliance, Independence of The Board, Remuneration, Shareholder Democracy, Shareholder Structure	Industry- Specific Indicators Three Main Dimensions: Economic (38/100) Environmental (27/100) Social (35/100)	Environmental Strategy Policy Environmental Mgmt. Products Production Process Social and Governance Employees and Human Capital Community Relations Markets Corporate Governance and Shareholder	Environmental Carbon Emissions, Climate Change Effect, Pollution, Waste Disposal, Renewable Energy, Resource Depletion Social Supply Chain, Political Contributions, Discrimination, Diversity, Community Relations, Human Rights, Governance Cumulative Voting, Executive Compensation, Shareholders' Rights, Takeover Defence, Staggered Boards, Independent Directors

TABLE C1 | Comparison Between All Listed Firms Located in Western European Countries and Those With ESG Rating Provided by MSCI, Considering the Number of Firms, the Sum of the Total Asset in 2022 (In Billion of Euros), the Sum of the Sales Revenue in 2022 (In Billion of Euros) and Their Percentages With Respect to the Total. Note That Financial Data Refer to Year 2022, While ESG Ratings Have Been Assigned in 2023 Based on the Non-Financial Disclosure Available in the Previous Year, Thus Referring to 2022. Note That the Number of Firms With ESG Rating is Slightly Lower Than in Our Sample Because Here We can Consider Only Companies That Are Still Active and Still Listed in July 2024, While in the Sample Used in the Analysis, We Included Also Companies No Longer Listed and No Longer Active in Order to Keep as Many Observations as Possible.

	N. of firms	%	Total asset	%	Sales	%
All listed firms	4.848	1	27.815	1	9.871	1
Firms with ESG rating	1266	0.26	25.915	0.93	8.714	0.88

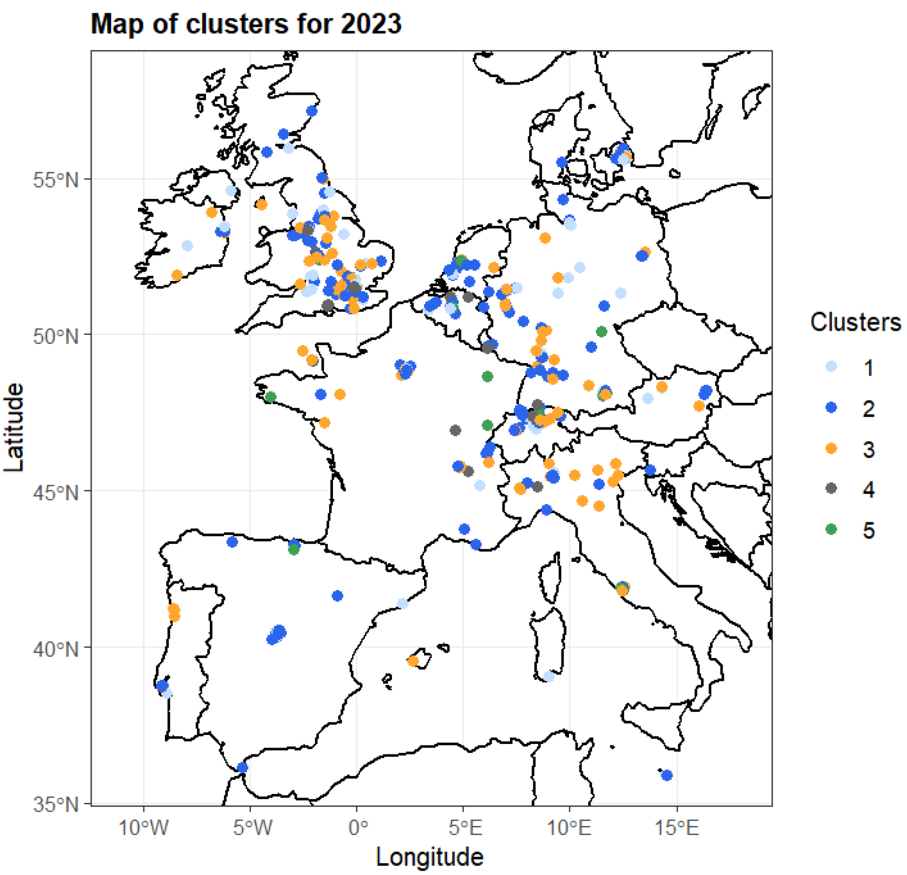

FIGURE D1 | Map of clusters for 2023 computed using Euclidean distance of ESG, Environmental and Carbon Emission scores.

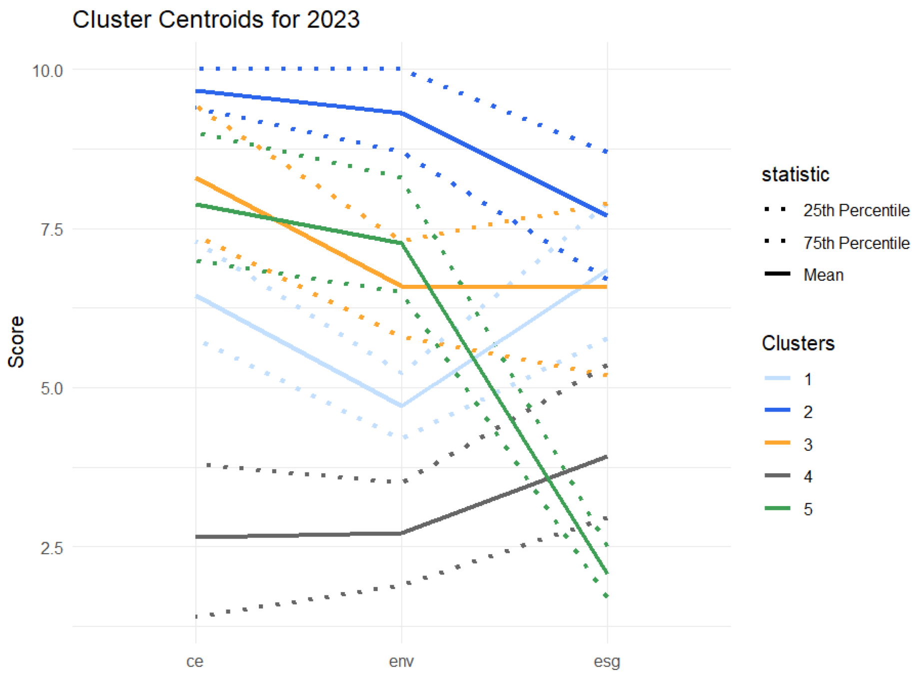

FIGURE D2 | Cluster-specific centroids of the three economic variables for 2023. Clusters are computed using Euclidean distance of ESG (esg), Environmental (env), and Carbon Emission (ce) scores. The solid lines represent the means of the variables, dashed lines represent the two quartiles.

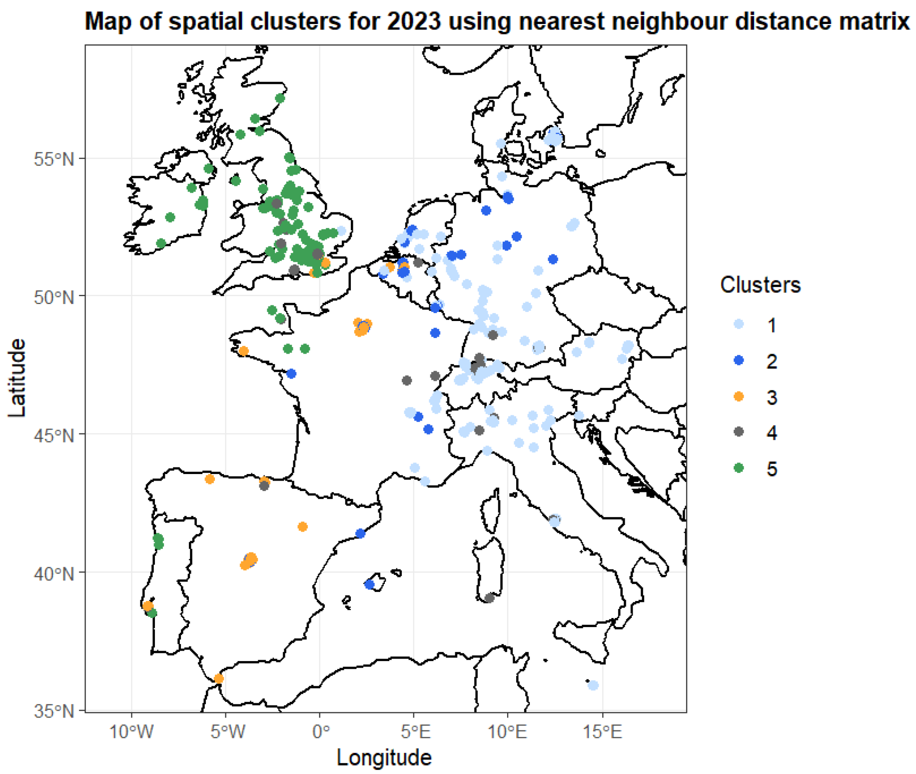

FIGURE D3 | Map of spatial clusters for 2023 computed using Euclidean distance of ESG, Environmental and Carbon Emission scores, and the complementary matrix of the Nearest Neighbour matrix of the location of firms.

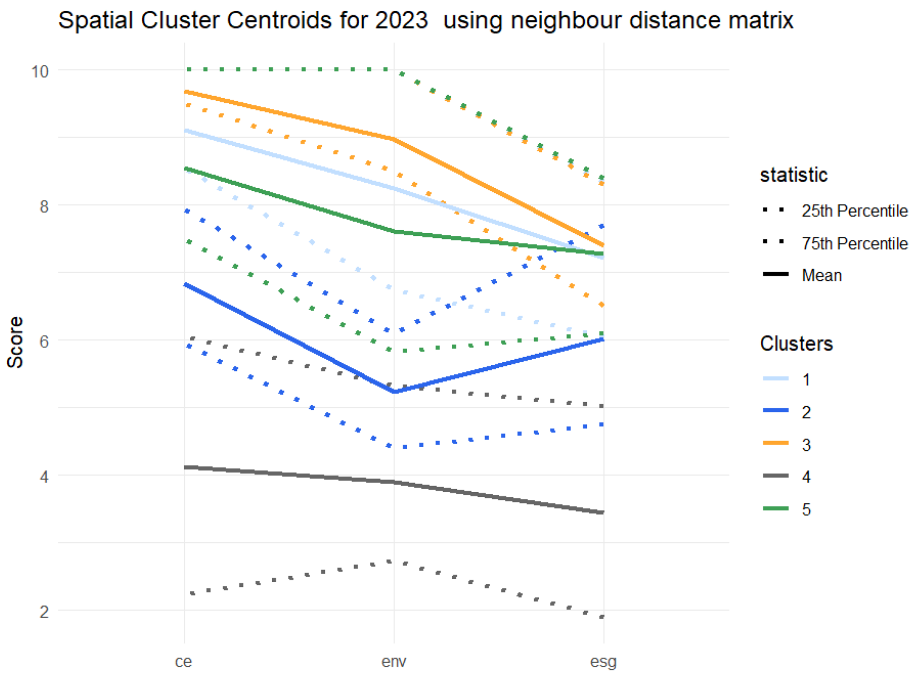

FIGURE D4 | Cluster-specific centroids of the three economic variables for 2023. Clusters are computed using Euclidean distance of ESG (esg), Environmental (env), and Carbon Emission (ce) scores. The solid lines represent the means of the variables, dashed lines represent the two quartiles.