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EXPLORATORY ASSESSMENT OF THE EUROPEAN UNION COUNTRIES CLIMATIC PROFILE

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Abstract. The paper subscribes to the broad strand of literature that examines the interplay between banking activity and climate risk, by particularly focusing on identifying and classifying European Union countries into similar, homogenous groups based on their intrinsic pattern related to climate vulnerability and readiness to cope with the negative effects of natural disasters. By applying an unsupervised learning clustering algorithm on a novel input dataset comprising six proxy indicators for the physical risk associated with climate challenges, we reveal the climate profile of the EU countries. A direct implication of our findings consists of ascertaining which banking systems are more exposed to environmental risks arising from physical sources in the home country they headquarter or in the host countries envisaged for the conduct of transnational financial activity. Results indicate that the least vulnerable EU countries to physical risks, being at the same time best performers in the process of climate risk adaptation, prevention, and management are Denmark, Luxembourg, Germany, Sweden, and Finland. Hence, their banking systems are less exposed to the adverse consequences of the physical risks. In contrast, banks operating in Bulgaria, Croatia, Poland, and Romania are the most exposed to the ripple effects of these risks, due to countries' increased vulnerability to climate risk and to the low degree of performance in implementing climate policies.

1. Introduction

In shed of the growing concerns related to the environmental degradation and climate change threat, many European and international institutions as well as national authorities (through the national adaptation actions developed and implemented under the EU Regulation on the Governance of the Energy Union and Climate Action) have started to design new environmental standards, guidelines and principles to be applied by both the business community and the financial sector. At the same time, the existing environmental standards have been tightened in order to facilitate the achievement of the sustainable development requirements, in addition to the adoption of clean production technology and the reallocation of capital to avoid unsustainable growth. There is the view that ignoring adverse environmental effects can impact not only a country's macroeconomic conditions but also financial stability (Huang et al., 2021).

Despite the growing interest of practitioners and researchers in the banking sector and its interaction with climate challenges, this relationship is mainly documented by previous literature from a theoretical point of view, while comprehensive analytical evidence is still lacking. According to the European Central Bank, environmental and climate risks represent the basic risk drivers of all existing categories of risk in the banking sector, being related to a widespread effect across sectors and geographical areas (European Central Bank, 2021). Another study explains that the focus on the impact exerted by environmental hazards on the financial

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sector was amplified by increasing awareness of the risks caused by climate change and other environmental hazards (Breitenstein et al., 2021). In the same vein, increasing awareness of environmental risk exposure can affect the willingness to develop businesses that address social and environmental failure (Middermann et al., 2020).

Climate change is affecting financial institutions through two channels. The first is the physical risk, which represents the adverse economic and financial effect of the expected increase in frequency and severity of natural hazards (Cortina and Madeira, 2023). It arises from the damage to infrastructure, land and property, assets and productivity. It can be acute if caused by hazards and extreme weather events such as floods, storms, and hurricanes, and chronic if it is caused by the gradual effect of global warming such as rising sea level. Physical risk mitigation needs timely adaptation and response measures, strategies, and policies to reduce vulnerability to the effects of climate change (Ferrazzi et al., 2021). The second channel represents the transition risk arising from changes in government policies, legislation, and regulation, changes in technology, and changes in market and customer sentiment that have the potential to generate, accelerate, slowdown, or disrupt the transition towards a low-carbon economy (Basel Committee on Banking Supervision, 2021). Transition risk appears from efforts to address environmental events or from technological changes or policies (Cambridge Institute for Sustainable Leadership, 2016).

The sound conduct of the banking business is twice impacted by the appearance of physical climate risks: i) a direct impact on the operational capabilities of a bank's territorial network; ii) an indirect impact, which affects the asset and liability side of the bank balance sheet, arising from the exposure of the bank to retail and corporate customers that were highly exposed to the adverse effects of natural hazards. Consequently, to uncover which banking systems are more prone to witness negative impacts on their balance sheets and profit and loss statements, generated by climate-physical risks, the paper focuses on identifying the geographical distribution of European Union countries that exhibit a similar degree of climate-risk vulnerability and readiness (preparedness in terms of government policies in place) against natural hazards.

Therefore, the main objective of the article is to empirically identify and classify EU countries in terms of their exposure and vulnerability to environmental risks.

One specific research implication, only theoretically substantiated by some previous studies, is that banks' exposure to environmental risks may be directly influenced by external factors such as natural disasters, geography, government policies, or economic conditions. The reason is that when a bank decides to carry out financial activities within a given country, it will be implicitly exposed to the specific environmental risks of that country. This argument was mentioned in an earlier report by Bank of England (2018) who uncovers that banks have started to incorporate vulnerabilities to physical risks (flood, drought, or the impact of extreme weather) and transition risks in their business models and risk management strategies.

Consequently, as an additional practical conclusion extracted from the exploratory analysis of the climatic profile of the EU countries, we can ascertain which banking systems are more exposed to environmental risks arising from exogenous sources, as enumerated above. Other sources of risk do not make the object of this analysis (for example, the environmental risk arising from bank customers that are vulnerable to these risks, or from bank's own activity, nor the transition risk).

Our contribution to the existing literature lies in three key novel areas. First, we attempt to uncover the climatic profile of EU countries using a statistical data mining method to perform an exploratory analysis and recognize intrinsic, latent data patterns. The existing approaches to shaping and updating the country profiles are twofold developed in economic literature. Some of them belong to international bodies and show a descriptive and graphical nature. For example, the World Bank Group is conducting a high-level assessment of physical climate risks for a selection of countries at the global level, known as the Climate Risk Country Profiles (Climate Change Knowledge Portal, 2023). The Climate Transparency Report, published annually since

2020, analyses climate adaptation and mitigation for the G20 countries and provides a meaningful and concise overview of key facts and figures on the state of climate performance of the G20, as well as on the transition path towards a net-zero-emissions economy. The European Commission and the European Environment Agency have jointly launched the Climate-ADAPT European Climate Adaptation Platform to monitor the current status of the national adaptation actions implemented by each EU country and to outline its country profile in terms of mitigation of transition risk. Other research directions gravitate around countries' environmental risks management (Freeman and Kunreuther, 2002; Finger et al. 2018; Huang, 2019), environmental sustainability and resilience (Shakil et al. 2019; Moghim and Garna, 2019), or environmental protection (Ascensão et al. 2018; Muganyi et al. 2021). To our knowledge, an empirically grounded paper that exhibits a similar endeavor of analyzing countries' climatic profile, but with a different methodology (by relying on past shocks of temperature anomalies and its relationship with temperature-induced sovereign risk) belongs to Boehm (2022).

Second, we adopt an exclusive and comprehensive focus on the physical dimension of the climate risk, by using a new database of six indicators collected from multiple sources. This research endeavor finds support in the report of the Basel Committee on Banking Supervision (2021) that advocates the use of a physical risk-based classification to categorize potential risk exposures using threshold indicators for proximity and vulnerability to physical hazards; this approach is deemed to simplify the mapping of physical risk exposure.

Third, we use an appropriate exploratory methodology to reveal the taxonomy of EU countries in terms of climate vulnerability and readiness. The unsupervised machine learning-based algorithm we apply is the cluster analysis algorithm, as it uncovers similar, homogeneous groups of countries exhibiting a common environmental profile. Additional findings will show which banking systems are exposed to a similar degree of physical risk, and hence are expected to follow a similar pattern of reaction in case this risk occurs.

The clustering is conducted for the most recent year with available data (2022), and additionally for the year 2015 (the official launch of the Paris Agreement international treaty on climate change), in order to make comparisons between the groups of countries identified, and to observe some changing patterns.

The remainder of the paper is organized as follows. Section 2 presents an overview of the issues related to climate risk exposure and vulnerability addressed by previous literature in the field. Section 3 discusses the specificity of the data and the method applied in our exploratory analysis. Section 4 presents the results and their interpretation, Section 5 evaluates the robustness of the initial findings through applying a series of complementary clustering algorithms while Section 6 concludes.

2. OVERVIEW OF THE RELATED LITERATURE

Understanding the nature of climate exposure and vulnerability is a prerequisite for any climate risk management framework. Trends in vulnerability and exposure act as key drivers of changes in disaster risk, which are important for designing suitable and reliable risk management strategies; in addition, appropriate risk communication is important for effective disaster risk management and effective adaptation (Cardona et al., 2012).

Historically, it was by the end of 1980 when North American banks first became aware of facing environmental risks, as a result of the US Comprehensive Environmental Response, Compensation and Liability Act, CERCLA adoption (Weber, 2012). At present, several complementary international guidelines, frameworks and principles coexist in order to facilitate the process of climate risk management, from its early identification to implementing corrective or adaptive measures.

According to the recent Sendai Framework for Disaster Risk Reduction, published in 2023 by the United Nations Office for Disaster Risk Reduction, the main three elements comprised of the risk of natural disasters are represented by hazard, exposure, and vulnerability.

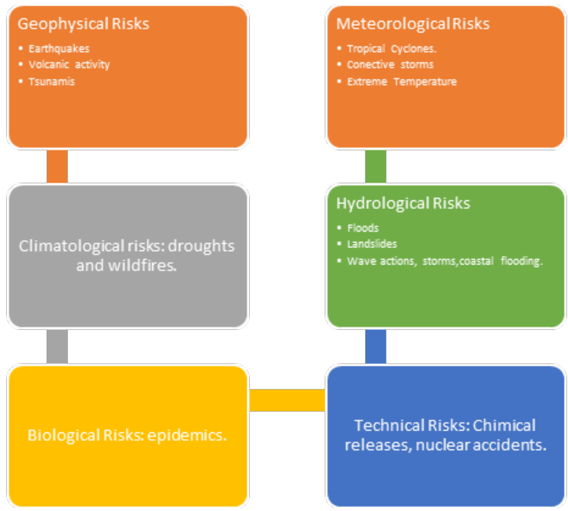

FIGURE 1. Typology of disaster risks

Source: prepared by the author, by relying on Poljansek et al., 2017.

i. Hazard is defined as a physical event caused by a natural phenomenon or human activity that potentially causes loss of life and adverse impacts on the environment such as degradation. The origins of the hazard may be natural (biological, geological, hydro meteorological), or caused by human activities and processes (technological hazards, environmental degradation through pollution) (United Nations, 2005). A similar definition refers to the possibility of the future occurrence of human or natural events which may exert adverse effects on exposed and vulnerable elements (Cardona et al., 2012).

ii. Exposure refers to the process that identifies and inventories the elements in a given area threatened by the event (hazard), such as people and the environment (Cardona et al., 2012; Poljansek et al., 2017). Exposures to disaster risks vary from country to country according to the income level (Grippa et al., 2019), despite it being determined that climate hazards represent a global phenomenon (Ferrazzi et al., 2021).

iii. Vulnerability is represented by unique characteristics that can make a society, system, or asset more susceptible to the negative effects of natural hazards (United Nations, 2016). These characteristics can be determined by physical, social, economic, environmental factors or processes that are intrinsically related to each community, system, or even individual level (Gabel et al., 2022), while the positive conditions and factors which increase the chance to cope with natural hazards are represented by the capacity and coping capacity (UNDRR, 2023).

Addressing vulnerability is perceived as the basic way for risk reduction measures, but it represents a 'holistic and systemic' concept closely related to resilience, in addition to adaptive capacity. In the same vein, identifying hazards that may affect a system or environment holds a core place in the disaster risk assessment framework (see Figure 1 for an overview of these risks).

The structured approach envisaged by the disaster risk assessment framework comprises several stages:

- Assess and analyze the probability that hazards might occur.
- Determine the exposure to the hazard.
- Estimate the vulnerability to the hazard in order to calculate the physical and/or financial impact.
- Estimate the potential financial or social consequences of the events (Poljansek et al., 2017).

An additional perspective rooted in the ESG criteria and corporate environmental performance points to the fact that environmental risk management should have two basic components. The first represents the hazard assessment, which addresses the identification of a potential adverse impact, while the second component refers to the environmental exposure assessment which identifies the direct/ indirect vulnerability to hazards (Breitenstein et al., 2021).

Vulnerability and exposure depend on many factors such as economic, social, geographic, environmental, governance, cultural, and demographic factors. They vary according to the spatial and temporal scale, therefore, we can argue that vulnerability and exposure are dynamic. Exposure and vulnerability to future climate events are related most of the time to a wrong and skewed management process (Cardona et al., 2012).

Environmental risk management must be aware and consider environmental hazards because financial institutions are directly exposed to this risk through their portfolio or even their invested capital (Boermans et al., 2019). A study by Caby et al. (2020) has identified the determinant factors for the voluntary commitment of banks to disclose climate change. Also, investors have started to pay more attention to this risk. A recent study by Ilhan et al. (2022) brings empirical evidence that institutional investors started to strongly demand and value transparent climate risk disclosure practices. Furthermore, the findings show a significant positive association between institutional ownership and better disclosure of climate risk.

Physical risks can materialize in direct or indirect ways in the activity of financial institutions: directly through exposures to countries/ companies/households that experience climate shocks, and indirectly through the effect of climate change on the financial system and the wider economy that may materialize through increased default rates or decreased assets values, while transition risk can materialize in the asset side of the bank balance sheet (Grippa et al., 2019).

Several recent studies that have addressed exposure and vulnerability to natural disasters followed different research objectives, focusing on specific types of risk that may arise from environmental risk and estimating the effects of adverse events or even environmental concerns on financial risks.

Shala and Schumacher (2022) studied the impact of natural disasters caused by climate change on banks, estimating the effect of 2013 floods on the impairment of the German banks' portfolio. Based on the estimation of difference in difference, the results showed that after 2013 German saving and cooperative banks in flood-affected regions achieved higher impairment compared to unaffected ones. This finding was related to the reason that most loans were concentrated in specific sectors and for specific destinations, such as agriculture. An additional result suggested that the profitability of banks in affected regions was significantly impacted by environmental factors.

Calice and Miguel (2021) found that the most important source of risk for the Latin America and Caribbean banking sector was exposure to floods. They estimated the exposure of Latin American and Caribbean banks to credit risk resulting from environmental risk (physical and transition) based on three different approaches. Starting from the provincial level, they compared the distribution of the non-financial corporate portfolios of banks with specific hazards to construct an indicator of the value at risk of the bank loan portfolios (only related to physical risks). Then, they narrowed the physical risk assessment only to the part of assets allocated for the purpose of home loan, while the last step was to study possible changes in the quality of banks' assets using geographical data for non-performing loans and information on natural disasters at the country-province level. Furthermore, the study focused on the exposure to highly CO_2-intensive and environmentally damaging assets and industries to estimate the exposure of credit risk to transition risks.

A study by Huang et al. (2021) assessed the risks arising from the transition to low-emission economy by using an environmental dynamic stochastic general equilibrium model to illustrate the reactions of financial institutions to the imposition of policy regulations. The study showed that tightening environmental regulations alters the balance sheets of banks and, consequently, threatens financial stability in the short term.

Pagliari (2023) proposed an approach to estimate the effect of adverse climate change events (river flooding phenomena) on the profitability of small banks in Europe. The study compared information on the performance of these banks (across regions with a low or high risk of floods) by building a database matching information like location and frequency of floods with balance sheet data of the banks that operated mainly in the area where they are headquartered. The results indicated that within the riskier areas, the loans decreased because of adverse events that lead to decreases in the ratio of return to assets.

In the same vein, Noth and Schüwer (2023) presented comprehensive evidence about the effects of weather disasters on the stability of the US banking sector. The study used the term weather-related disaster for meteorological, hydrological, and climatological disasters without taking into account geological disasters. The findings revealed that weather-related disasters can weaken the stability of banks operating in affected areas. In the short term, the results suggest a high probability of banks default and a significant adverse effect on banking stability and credit portfolio quality. Additional results indicate that banks have recovered their stability, profitability, and credit quality two years after the natural disaster.

On the contrary, a study by Blickle et al. (2021) found that natural disasters had small and insignificant effects on US banks' stability and performance. The study argued that the stability of the banking sector was not a mere reflection of aids, but it was endogenous stability in part due to knowledge and awareness of local predisposition to natural disasters, which may have mitigated the negative effects of disasters. The fewer effects on banks' performance were caused by the increase in the demand for loans after disasters, which has offset losses, as well as by the avoidance of banks when originating mortgage loans in areas where floods are more common. Curcio et al. (2023) have tested the reactions of the US banking sector to weather disasters and climate change and uncovered that some extreme events can increase the financial systemic risk.

Breitenstein et al. (2021) found that there is a possibility to reduce the exposure of financial institutions to environmental risk through environmental responsibility and performance, with high commitment from top management. Furthermore, an increasing desire to soundly assess environmental, climate-related financial risk motivates financial managers to adopt proactive environmental practices and policies.

In a broader perspective, Torinelli and Silva Junior (2021) discussed the physical and transition risks of climate of climate to which central banks are exposed when managing international reserves and showcased how central banks make use of environmental risk analysis strategies to better managing their international reserves.

3. METHODOLOGY AND DATA

3.1. **Cluster analysis features.** In this section, we present the methodological specificity of the cluster analysis technique that is used to identify and classify resembling EU countries in terms of their exposure and vulnerability to climate risks.

This unsupervised machine learning technique suits best the purpose of our paper, as it facilitates the identification of the geographical distribution of European Union countries that exhibit a similar degree of climate risk vulnerability and readiness in terms of government policies in place against natural hazards. The method was selected because of its ability to provide stakeholders (decision makers, national and European banking supervisors) with a useful and sound tool to gain this information and increase awareness of a country's climate risk profile, as well as of its peers. Additional findings will show which banking systems are exposed to a resembling degree of environmental risk and hence are expected to follow a similar pattern of reaction in case the environmental risk occurs.

Being considered one of the most important unsupervised techniques, cluster analysis has many fruitful applications in various fields of research (Cena and Gagolewski, 2020) such as pattern recognition (Sadeghi et al., 2022), bioinformatics (Rizvi et al., 2021), gene expressions (Bihari et al., 2019), data mining and information science (Djenouri et al., 2018; Lund and Ma, 2021), energy research (Kijewska and Bluszcz, 2016; Rybak et al., 2022), the environmental performance of countries (Aral and López-Sintas, 2023; Quatrosi, 2017) in addition to sustainability research (Repiská et al., 2022) to name just a few.

The geographical distribution of countries that exhibit a similar degree of environmental risk or common profiles has been assessed by some previous studies that apply cluster analysis. For example, the study of Crespi et al. (2023) employs cluster analysis at national level, for the identification of the main climate regions in Germany, while Lucio and Caiado (2022) apply it to study stock market volatility before and during the pandemic. Eligüzel et al. (2023) evaluate the climate risk of the countries and the climate risk indices using the K-means method; in the same vein, Kijewska and Bluszcz (2016) use cluster analysis to identify similar groups of EU countries in terms of greenhouse gas emissions.

From a methodological standpoint, the cluster analysis represents a multivariate method that gathers successive algorithms meant to group data by assessing and discovering if the data sets are similar to each other and different from other group. Moreover, it aims to classify data into a cluster according to a set of similarly measured variables (Cornish, 2007; Everitt et al., 2011) and helps to reach a reasonable, systematic grouping (Tryfos, 1997). Generally, clustering algorithms are classified into hierarchical algorithms and partitioned algorithms, with hierarchical algorithms that have a divisive or agglomerative nature. In the divisive algorithms, the clustering method starts with one large cluster containing all data points and then splits data into smaller homogenous clusters, whereas the agglomerative algorithms proceed on the contrary (Gan et al., 2007).

The most widely used clustering procedures are agglomerative algorithms because they provide a simple and intuitive way to showcase and segment the initial data set and generate a new structure of data for each nested partition. It starts with one data point in each cluster, and then the closest clusters are merged in each step, with respect of the distance measure chosen, allowing for obtaining high-quality partitions inside each hierarchical framework (Cena and Gagolewski, 2020). Subsequently, to merge the pairs of closest clusters we need to define the intra-cluster distance, which is also called a linkage function that acts as an extension of the point pairwise distance. Regardless of the distance measure and the linkage rule chosen, the most important issue of hierarchical clustering is that we do not need to specify the number of desired clusters in advance because it is automatically generated as a hierarchy of nested partitions and then depicted in the visual form of a tree diagram called a dendrogram (Gagolewski et al., 2023).

In our study, we use the agglomerative hierarchical method, in line with the majority of studies in the field. Our choice was guided by several reasons, such as we do not have to arbitrary pre-establish a given number of clusters to be generated by the algorithm, and the results will be displayed as a dendrogram which represents a simple and intuitive, easy to understand manner of the structure of clusters.

First, to group variables or observations into distinct and homogenous clusters, we need to estimate as an initial step the density of the data by calculating the distance between observations. It is worth mentioning that the similarity criterion may be represented either as distance (two objects belong to the same cluster if they are close to each other due to the distance) or as a common concept (when the cluster defines a common concept shared by the objects) (Kijewska and Bluszcz, 2016). According to Tryfos (1997), one needs to employ the familiar concept of distance when the grouping relies on quantitative measurable variables.

The theory has developed several distance measures such as the following: Euclidean Distance, Square Euclidean Distance, Manhattan Distance, Minkowski Distance, Hamming Distance, etc. Other measures such as correlation-based distances seem to be widely used. The reasoning is that every two observations are considered similar if their features or advantages are highly correlated even though the distance between them is far away according to the Euclidian distance, for example. The correlation-based distance is computed by subtracting the correlation coefficient from 1. The choice of the distance measure is very important, and because this study focuses on revealing the similarities between the features of EU countries, we rely on Pearson's correlation distance to measure how similar the observations are between countries.

Standardizing data (the mean 0 and the variance 1) represents another important step in preprocessing data before applying cluster analysis (Rizvi et al., 2021). Second, to calculate the distance between clusters it has to be defined a clustering method (Kijewska and Bluszcz, 2016), that consists of merging previously formed clusters according to a linkage rule which may be measured in many ways (Cornish, 2007; Kijewska and Bluszcz, 2016; Tryfos, 1997):

i) the nearest neighbor method (single linkage) which computes the distance between two clusters as the distance between the closest neighbors;

ii) the furthest neighbor method (complete linkage) that defines the distance between two clusters as the maximum distance between the members of each cluster;

iii) a compromise method called average linkage (between groups) which measures the distance between two clusters as the average of the distances of all pairs of observations;

iv) Ward's method tends to produce an equal size of clusters by maximizing the external separation between clusters and minimizing internal cohesion;

v) centroid method calculates the mean value of each observation (centroid) in each cluster, then the distance between centroids is used and clusters with the closest centroid will be further merged.

Each method of clustering has its pros and cons. Although single linkage represents a simple method, it does not take into account cluster structure. The complete linkage is based on the maximum distances, so it is strongly influenced by outliers, while in average linkage and centroid algorithms, the clusters generated exhibit relatively low cluster variance. In this respect, Everitt et al. (2011) synthesize some criteria that may help researchers make a good choice about the suitable method to be used: understanding the nature of the data, the scale of the data, and choosing a method which may ease the difficulty of the final results interpretation.

By relying on previous literature that employs hierarchical cluster analysis, it can be noticed that the linkage methods differ from study to study, being subordinated to the goal of the empirical analysis. In the study of Repiská et al. (2022) it is developed a comparison of three clustering methods (Ward, average and nearest neighbor) while in the study of Kijewska and Bluszcz (2016) they used complete linkage. In our study, we employ the average linkage (between groups linkage rule) as the method of clustering because we intend to emphasize the intrinsic structure of clusters without focusing on whether the size of the generated clusters is equal or not. According to this approach, the distance is defined by computing the arithmetic mean between all pairwise distances (Gagolewski et al., 2023).

3.2. **Presentation of the data and preliminary analysis.** The list of variables that are considered in this study as proxies for the climate-driven physical risk is described in table 1 below.

Table 1. Climate-driven physical risk indicators

Variable name	**Description**	**Source of the data**
Climate-related disasters frequency	Indicates the total number of climate-related natural disasters that have occurred in a given year. It comprises the following climate-related disasters: wildfire, storm, landslide, flood, extreme temperature, drought, fog, wave action, and glacial lake outburst.	IMF's Climate Change Indicators Dashboard https://climatedata.imf.org

Variable name	Description	Source of the data
Climate-driven INFORM Risk Index	Provides a global assessment of climate-driven risks and serves as a quantitative tool to support the decision-making at different stages of the disaster management cycle, specifically climate adaptation and disaster prevention, preparedness, and response. The index is calculated on a scale of 0 to 10. The higher the indicator level, the higher the risk faced by a country.	IMF's Climate Change Indicators Dashboard https://climatedata.imf.org
Environmental performance index (EPI)	The index values indicate which countries show the best performance in addressing the environmental challenges at the national level, across an array of critical sustainability issues including air and water pollution, waste management, biodiversity and habitat protection, and the transition to sources of clean energy. It shows whether a country is on track to meet its climate commitments.	Yale Center for Environmental Law and Policy https://epi.yale.edu/
Climate Change Performance Index (CCPI)	Evaluates and compares the climate policy performance of several countries, for identifying leaders and laggards in climate protection. The index estimates the progress in achieving the Paris Agreement goals transposed in countries' implementation policies, by monitoring 4 categories with a total of 14 indicators. These categories are: Greenhouse Gas Emissions (40% of the overall score), Renewable Energy (20%), Energy Use (20%), and Climate Policy (20%).	GermanWatch Institute, CAN International and the NewClimate Institute https://www.germanwatch.org/en/CCPI
Climate Risk Vulnerability Index (CRVI)	Measures a country's exposure, sensitivity, and capacity to adapt to the negative effects of climate change from a biophysical, natural hazards perspective. Higher index values signal a worse situation.	University of Notre Dame, Notre Dame Global Adaptation Initiative https://gain.nd.edu/our-work/country-index/
Climate Risk Readiness Index (CRRI)	Measures a country's ability or readiness to move into climate-friendly investment areas and promote sustainable investment climates, through a three-fold indicator composition: economic, governance and social. Higher values signal a better situation.	University of Notre Dame, Notre Dame Global Adaptation Initiative https://gain.nd.edu/our-work/country-index/

Data have been collected for each of the 27 European Union countries and focused on two years, namely the most recent data belong to the year 2022 while data for 2015 was used as a significant milestone in the process of adopting a global response to climate change, being the year of issuing and adopting the Paris Agreement. Therefore, our list of input variables can provide a more comprehensive view of the exposure and vulnerability to physical climate risk for each country. The clustering algorithm is conducted distinctly, for each of the two years, in order to classify countries with resembling risk features into homogenous groups or clusters, to allow comparisons between the groups identified, and to observe some changing patterns.

Before starting the cluster analysis, we display and discuss the main descriptive statistics related to the indicators of exposure and vulnerability to climate risk in EU countries in 2015 (table 2) and 2022 (table 3), in order to reveal some initial characteristics of our variables and observe potential changes in the level recorded in each study year.

Table 2. Descriptive statistics (2015 data)

	N	**Min**	**Max**	**Mean**	**Std. Dev.**
Climate-related Disasters Frequency	27	0	4	0.70	1.068
Climate-driven INFORM Risk Index	27	0.80	2.80	1.9630	0.5278
Environmental performance index	27	80.15	90.68	85.9122	2.9443
Climate Change Performance Index	27	50.69	71.19	59.7444	5.3246
Climate Risk Vulnerability Index	27	0.29	0.41	0.3373	0.0315
Climate Risk Readiness Index	27	0.44	0.80	0.6090	0.0986

The mean value of the frequency of climate-related disasters is 0.70 and the standard deviation is 1.068 which indicates that the values of the variable tend to be closer to the mean of the sample. The minimum value of the occurrence of natural hazards is 0 and is witnessed by Austria, Cyprus, Czechia, Denmark, Estonia, Finland, Germany, Hungary, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Slovakia, Slovenia, and Sweden, while the maximum value is in Italy.

The minimum value of the Climate-Driven INFORM Risk Index is 0.8 and is registered in Malta, while the maximum value is 2.8 being exhibited by Bulgaria and Romania. The standard deviation of the index of 0.52 indicates a low deviation of the values of the index around the mean of 1.96. The minimum value of the Environmental Performance Index is recorded in Belgium and the maximum one in Finland, the standard deviation of 2.944 indicates that the value of the index registered in EU countries is spread over a wider range of the mean.

The minimum value of the Climate Change Performance Index is registered in Austria, while the maximum one is in Denmark; the values of the index show large deviation from the mean value, which is 59.74.

The maximum value of the Climate Risk Vulnerability Index is 0.41 being registered in Romania, while the minimum is in Luxembourg (0.29). The value of the standard deviation is 0.031 which indicates that the value of the index tends to be very close to the mean in all EU countries. Hence, there is less data variability between countries.

The maximum value of the Climate Risk Readiness Index is 0.80 and belongs to Denmark, while the minimum value (0.44) is registered in Romania. The standard deviation of 0.098 indicates that all the index values tend to spread around the mean.

The mean value of the frequency of climate-related disasters is 1.14 and the standard deviation is 1.51, indicating that the values tend to be quite close to the mean of the sample. The minimum value is 0 and is recorded in Cyprus, Estonia, Finland, Hungary, Latvia, Lithuania, Luxembourg, Malta, Romania, Slovakia, Slovenia, and Sweden, while the maximum value is 6 natural hazards and is recorded in France. Compared to the 2015 data, it seems that the frequency of natural hazards has increased in 2022, a fact suggested by both the raw maximum

TABLE 3. Descriptive statistics (2022 data)

	N	Min	Max	Mean	Std. Dev.
Climate-related Disasters Frequency	27	0.00	6.00	1.1481	1.51159
Climate-driven INFORM Risk	27	0.80	3.40	2.2593	0.62527
Environmental performance index	27	50.40	77.90	61.5741	7.68403
Climate Change Performance Index	27	40.41	76.67	55.5852	9.28844
Climate Risk Vulnerability Index	27	0.27	0.40	0.3265	0.03286
Climate Risk Readiness Index	27	0.44	0.78	0.5897	0.09003

values and the sample average. The minimum value of the Climate-driven INFORM risk index is 0.8 being registered in Malta, while the maximum is 3.40 and is witnessed in Poland. The standard deviation of the index of 0.62 suggests a relatively small deviation of the index values around the mean. The comparison of the mean value of the sample for 2015 and 2022 indicates that individual countries face greater risks driven by climate at the end of 2022.

The minimum value of the Environmental Performance Index is 50.40 in Portugal and the maximum one is 77.90 in Denmark, and the standard deviation of 7.68 indicates that the value of the index registered in EU countries is largely spread out around the mean. The mean values of the index, as well as the minimum and maximum thresholds, have decreased significantly in 2022 compared to 2015. This is not a beneficial situation, as it is associated with a slower pace in addressing environmental challenges at the national level, stemming from air and water pollution, waste management, biodiversity and habitat protection, and the transition to clean energy.

The minimum value of the Climate Change Performance Index is registered in Hungary, while the maximum value is registered in Denmark (the same leading position as for 2015). In 2022 the mean value of the sample shows a small decrease compared to 2015 data, which means that the performance of climate policy has slowed in some EU countries.

The maximum value of the Climate Risk Vulnerability Index is 0.40 and is registered in Romania (same laggard positioning as in 2015), while the minimum value is in Czechia. The standard deviation value is 0.032 which suggests that the index values tend to spread closely to the mean. However, a small, negligible improvement can be noticed in 2022 compared with 2015 as the mean value has slightly decreased.

The maximum value of the Climate Risk Readiness Index is 0.78 being exhibited in Denmark while the minimum value (0.44) is registered in Romania. These two countries have the same positioning as in 2015. The mean value of 0.58 and the standard deviation of 0.090 indicate that the index values tend to be closer to the mean. The slight decrease in the mean value of the sample in 2022 suggests that some EU countries are deteriorating their ability to support sustainable, climate-friendly investments.

By comparing the historical path displayed by the six climate risk proxies in EU countries, the conclusion is straightforward: In 2022, the countries have witnessed an exacerbation of the occurrence of natural hazards (the sample's mean value had doubled in size), a higher propensity to climate-driven risks, overlapped with a lower performance to address environmental challenges and implement climate policies and climate-friendly investments. In the following, to gain a more granular view on the historical development of our climate variables across the EU countries, we realized a comparative graphical analysis (figures 2, 3, 4, 5 and 6, 7).

In 2015 Austria, Czechia, Cyprus, Denmark, Estonia, Finland, Germany, Hungary, Latvia, Netherlands, Lithuania, Luxembourg, Malta, Slovakia, Slovenia, and Sweden were the countries with a 0 frequency of climate-related disasters, while the highest number of natural hazards was in Italy followed by France. In 2022 the following countries maintained the rate of 0 for the Climate-Related Disasters Frequency: Cyprus, Estonia, Finland, Hungary, Latvia, Lithuania, Luxembourg, Malta, Slovakia, Slovenia, and Sweden. The number of natural hazards had

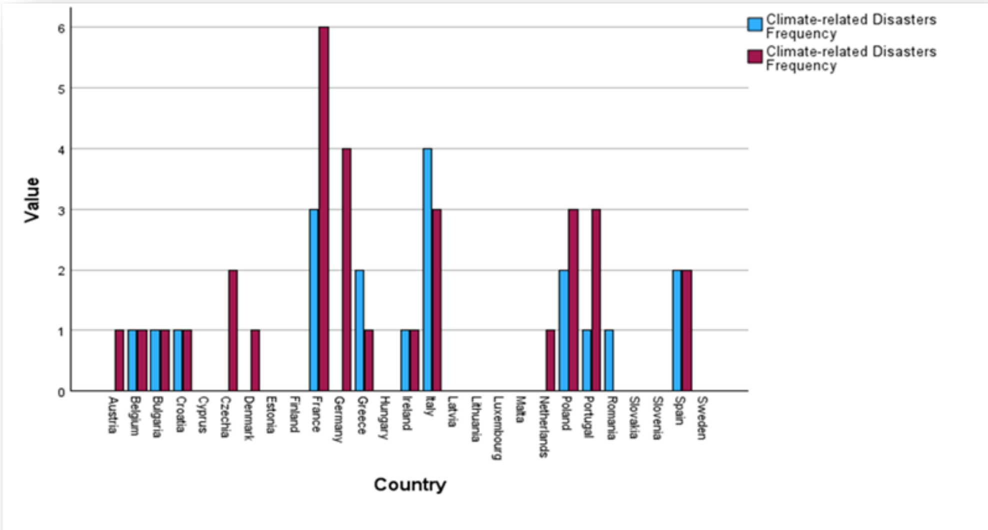

FIGURE 2. Comparative dynamics of the Climate- related Disasters Frequency

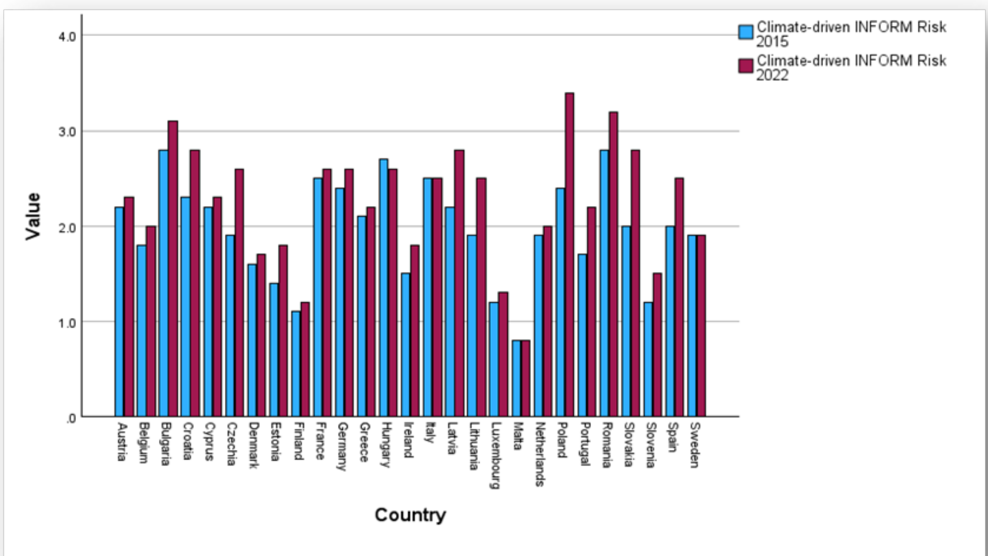

FIGURE 3. Comparative dynamics of the Climate-driven INFORM Risk index

increased in the countries: Austria, Czechia, Denmark, France, Germany, Netherlands, Poland, and Portugal, while it decreased in Greece, Italy, and Romania (here it decreased to 0). The maximum number was recorded by France, followed by Germany.

The value of the Climate-driven INFORM Risk Index increased in 2022 in all EU countries except Malta, which maintained the minimum value of the index, in addition to Italy and Sweden. The maximum value of the index in 2015 was in both Romania and Bulgaria and they

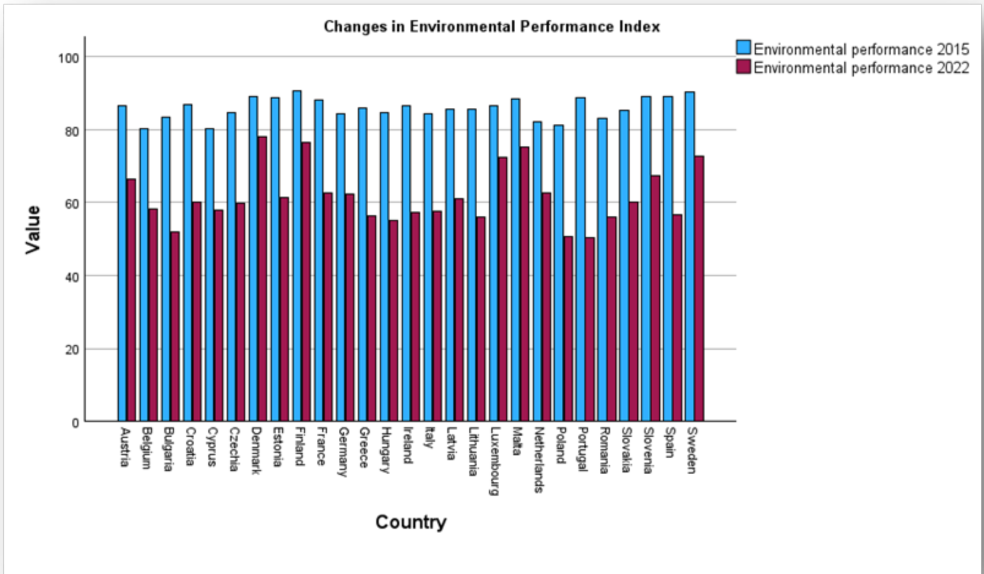

Figure 4. Comparative dynamics of the Environmental Performance Index

still had large values in 2022 as well (3.2 and 3.1), while Poland recorded the peak value of the index according to 2022 year measures (3.4).

Generally, there were big changes in the index values, and all EU countries witnessed a decrease in environmental performance in 2022. The best environmental performance in 2015 was in Finland, while in 2022 the best environmental performance was in Denmark, closely followed by Finland, Malta and Sweden. The minimum value of the index in 2022 was recorded in Portugal, while in 2015 it was registered in Belgium.

The Index of Climate Change Performance decreased in 2022 in the following countries: Belgium, Bulgaria, Croatia, Cyprus, Czechia, France, Hungary, Ireland, Italy, Latvia, Luxembourg, Poland, Romania, Slovakia and Slovenia reflecting a downgrade in the performance of each country to achieve the Paris Agreement goals, while in the remaining part of the EU countries it increased (Austria, Denmark, Estonia, Finland, Germany, Greece, Lithuania, Malta, Netherlands, Portugal, Spain, Sweden).

Denmark maintained the maximum value of the index in both years of study, reflecting a constant leading position and the best performance in the implementation of policies to achieve the Paris Agreement goals, while the minimum value belongs to Austria in 2015 and Hungary in 2022.

The index value decreased in 2022 in most EU countries except Cyprus, Denmark, Estonia, Italy, Luxembourg, Malta, the Netherlands, and Slovakia. The maximum value of the climate vulnerability index in both 2015 and 2022 was in Romania, while the minimum one was in Luxemburg in 2015 and in Czechia in 2022.

There was a decrease in the value of the index in all EU countries in 2022 compared with 2015, except in Greece, Italy, and Slovakia. Romania recorded the minimum index value in both years, suggesting the lowest progress in developing a sustainable investment climate. Denmark recorded the maximum value in both considered years, which means that this country has successfully implemented the best policies, reflecting its maturity and readiness to actively support a sustainable investment climate.

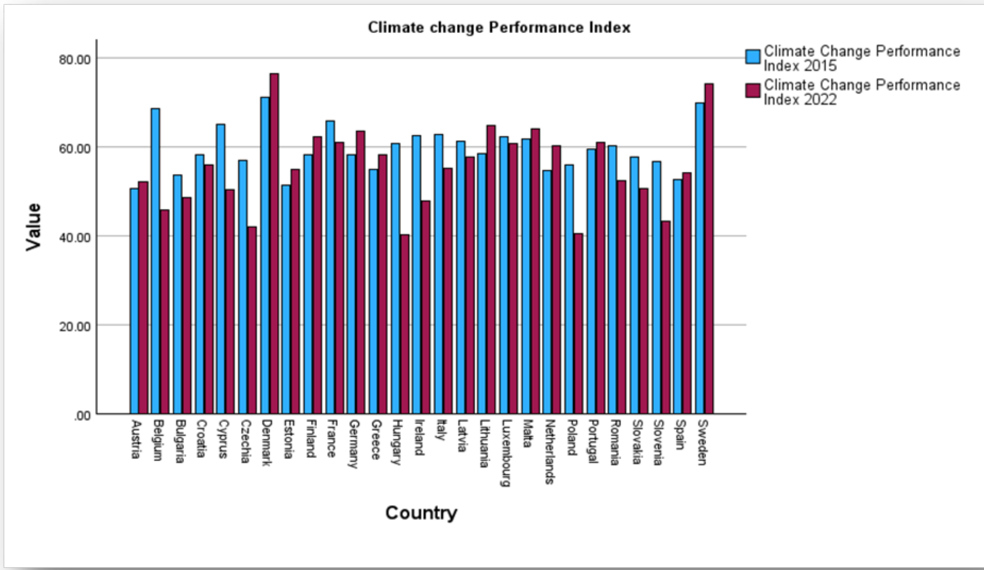

Figure 5. Comparative dynamics of the Climate Change Performance Index

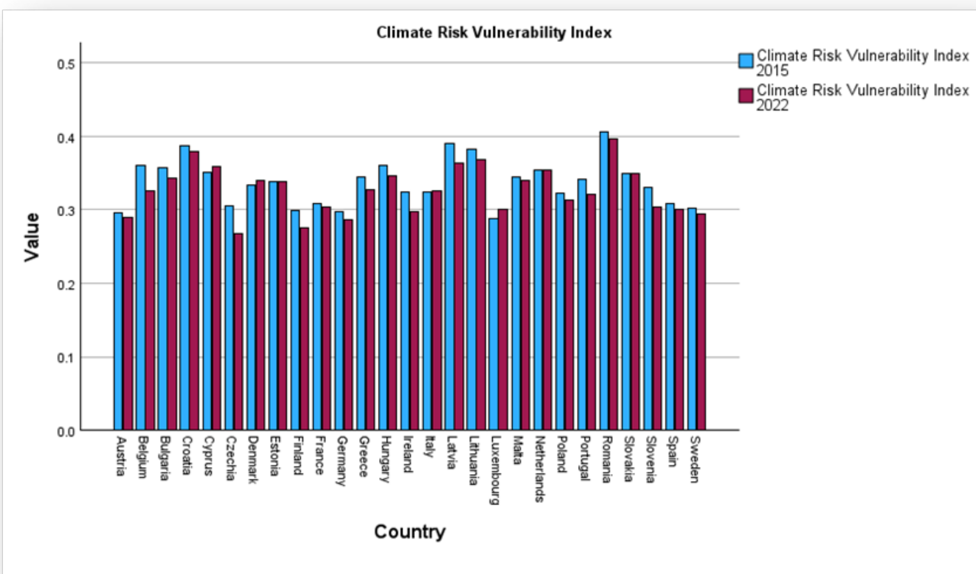

Figure 6. Comparative dynamics of the Climate Risk Vulnerability Index

4. RESULTS OBTAINED AND DISCUSSION

The clustering solution obtained for the distance range 5-10 is kept for further interpretation of the cluster membership, as it is the most meaningful. Hierarchical clustering for 2015 year (figure 8) shows the presence of six groups, each with its own distinctive features:

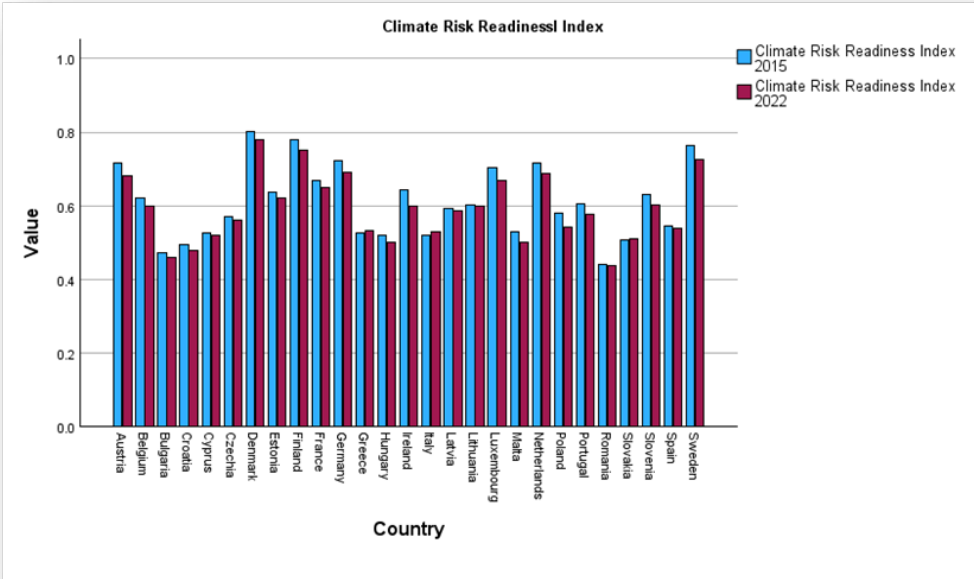

FIGURE 7. Comparative dynamics of the Climate Risk Readiness Index

1) Latvia, Lithuania, Croatia, Slovakia, Hungary, Bulgaria and Romania witnessed the occurrence of maximum one natural hazard, the highest values of the Climate-driven INFORM Risk Index and Climate Risk Vulnerability Index, average values of the Environmental performance index and Climate Change Performance Index, and the lowest values of the Climate Risk Readiness Index. Consequently, they seem not to be exposed to frequent occurrence of natural disasters, but they show the worse capacity to adapt to the negative effects of climate hazards if they occur, to disaster prevention and management, and to develop a climate-friendly business environment. However, these countries seem to achieve average performance in tailoring policies meant to achieve the broader goals of the Paris Agreement.

2) Belgium and Cyprus display the occurrence of maximum one natural hazard, average values of the Climate-driven INFORM Risk Index, Climate Risk Vulnerability Index, Climate Risk Readiness Index and Environmental performance index, and some of the highest values in the sample for the Climate Change Performance Index. Thus, they position among the leading countries in terms of compliance with the Paris Agreement scope, seem to be less exposed to natural hazards, and feature an average degree of vulnerability to the physical risks as well as of the performance in designing and implementing national climate policies.

3) Greece, Poland, Spain, France, and Italy record the largest number of natural disasters, some of the highest values of the Climate-driven INFORM Risk Index and of the Environmental performance index, close to average values for the Climate Change Performance Index, Climate Risk Vulnerability Index, and Climate Risk Readiness Index. These countries are the most exposed to physical climate risks and, at the same time, exhibit low capabilities for disaster prevention and management. In terms of policies for environmental protection, creating a climate-friendly business environment or achievement of the Paris Agreement goals, they register a close to average performance compared with the other EU countries.

4) Austria and Germany feature the lowest number of natural disasters (no hazards), above-average values of the Climate-driven INFORM Risk Index, close to average Environmental performance index and Climate Change Performance Index, one of the lowest Climate Risk

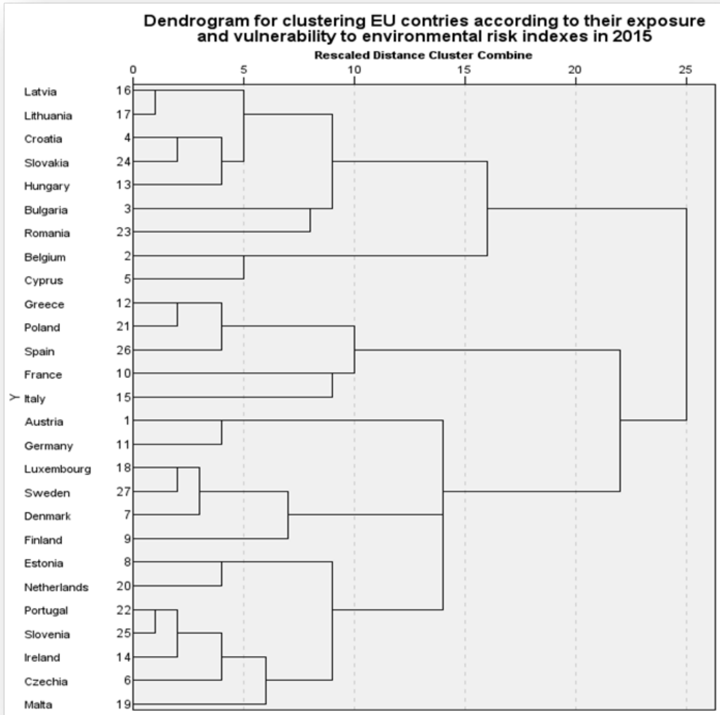

Figure 8. Dendrogram of the EU countries clustering in 2015

Vulnerability Index and one of the largest Climate Risk Readiness Index. Therefore, they are among the leaders in promoting a sustainable investment climate, exhibit good performance in implementing environmental policies and achieving the Paris Agreement goals, although the performance of the disaster management process and the ability to react to the negative effects of climate hazards seems to be slower. The predisposition to be adversely affected by natural hazards is one of the lowest in the entire sample.

5) Denmark, Finland, Luxemburg, and Sweden face the lowest number of natural disasters (no hazards), one of the smallest values of the Climate-driven INFORM Risk Index, the highest values of the Environmental performance index and the Climate Change Performance Index, the lowest values of the Climate Risk Vulnerability Index and the largest values for the Climate Risk Readiness Index. To sum up, the countries included in this group exhibit the best performance in terms of policy performance, of the ability to prevent, adapt and mitigate the harmful effects of the physical risks of climate, as well as the lowest vulnerability to the occurrence of natural disasters. They act as leaders for each of the six climate risk proxies.

6) Czechia, Estonia, Ireland, Malta, Netherlands, Portugal, and Slovenia display the occurrence of maximum one natural hazard, low values of the Climate-driven INFORM Risk Index, some of the highest values for the Environmental performance index and average values for the Climate Change Performance Index, the Climate Risk Vulnerability Index, and the Climate Risk Readiness Index. Therefore, they show moderate performance in managing physical risk exposure, but very good performance in addressing environmental challenges at national level arising mainly from pollution and environment preservation.

The hierarchical clustering for the year 2022 year (figure 9) identifies the presence of six groups, with the following features:

1) Estonia, the Netherlands, Ireland, Belgium, Greece, Spain, Italy, Cyprus, Latvia, Slovakia, Hungary, Lithuania, and Portugal face up to three natural disasters and around the average values for the remaining five climate proxy.

2) Bulgaria, Romania, and Croatia witness the occurrence of maximum one natural hazard, some of the highest values of the Climate-driven INFORM Risk Index, the largest values for the Climate Risk Vulnerability Index, above average values of the Environmental performance index, close to average values for Climate Change Performance Index, and the lowest values of the Climate Risk Readiness Index. Consequently, they seem to have a low exposure to the occurrence of natural disasters, but they depict the worst capacity to adapt to the negative effects of climate hazards if they occur, to disaster prevention and management and to develop a climate-friendly business environment. However, these countries seem to have achieved modest performance in achieving the goals of the Paris Agreement.

3) Poland is an outlier country exhibiting a number of three out of a maximum of six natural hazards, the highest value of the Climate-driven INFORM Risk Index, the smallest values in the entire sample for the Environmental performance index and the Climate Change Performance Index and below average values for the Climate Risk Vulnerability Index and the Climate Risk Readiness Index. It continues to be exposed to the physical risks of climate change and still exhibits low capabilities for disaster prevention and management, as in 2015. In terms of policies for environmental protection, creating a climate-friendly business environment or achievement of the Paris Agreement goals, it records one of the worst performance compared with the other EU countries.

4) France and Malta have large, above average values for the Environmental Performance Index, Climate Change Performance Index, and Climate Risk Readiness Index, close to the average value of the Climate Risk Vulnerability Index, and mixed evidence of the frequency of natural disasters. Therefore, although exposure to the physical risks and the predisposition to be adversely affected cannot be negligible, these countries seem to be well prepared in terms of policies in place and ability to react and manage the effects of the natural disasters.

5) Austria, Slovenia, and Czechia show a number of maximum two natural hazards, close to average values of the Climate-driven INFORM Risk Index, above-average values for the Environmental performance index and Climate Risk Readiness Index, modest values of the Climate Change Performance Index, the lowest values in the entire sample for the Climate Risk Vulnerability Index. This group witnesses a low exposure to the occurrence of the climate physical risks and to the propensity to be adversely impacted, on the background of moderate ability to cope with the challenges of managing the climate risks arising from natural disasters. At the same time, they show good performance in addressing environmental challenges arising from pollution and environmental preservation and in ensuring a climate-friendly investment approach.

6) Denmark, Luxembourg, Germany, Sweden and Finland record a frequency of maximum one natural hazard, below-average values for the Climate-driven INFORM Risk Index, the biggest values for the Environmental performance index, Climate Risk Readiness Index and the Climate Change Performance Index, and close to average Climate Risk Vulnerability Index. These countries achieved their best performance in terms of climate policy performance, the ability to prevent, adapt and mitigate the adverse effects of physical climate risks, and the moderate vulnerability to the occurrence of natural disasters.

5. ROBUSTNESS CHECK OF THE CLUSTERING PATTERNS

The two additional clustering methods employed for the robustness check of the stability of the initial findings are represented by the single linkage (the nearest neighbor method) and the complete linkage (the furthest neighbor method). They have been tested for 2022 year-end data and compared with the initial findings detailed in section four.

The hierarchical clustering illustrated in figure 10 identifies the presence of six groups and confirms the methodological expectation regarding the generation of long, chain-like clusters

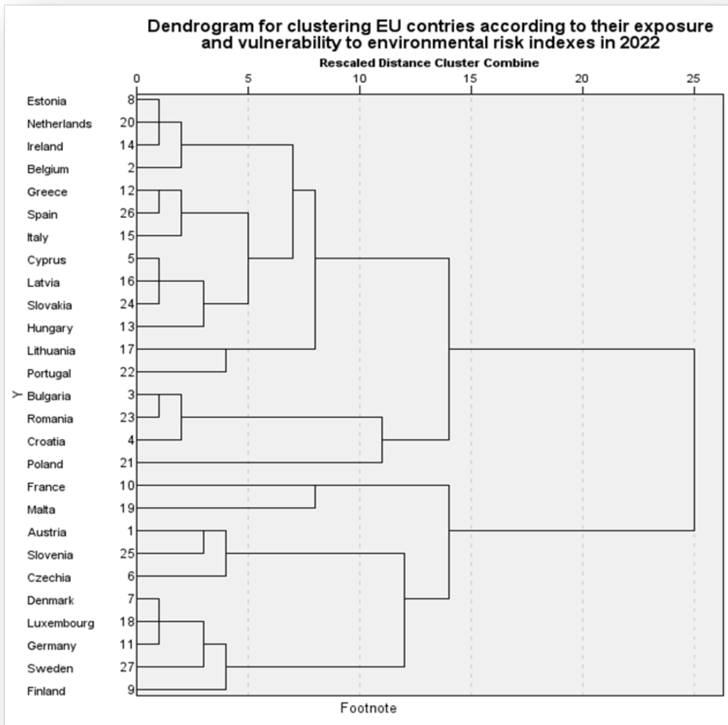

Figure 9. Dendrogram of the EU countries clustering in 2022

with a higher sensitivity to outliers. The clustering solution taken into consideration is the one generated for the distance range 5-10 as for the initial method used, in order to ensure the comparability of the results across the various clustering algorithms.

The number of clusters identified when employing the complete linkage method (figure 10) is of three, in line with the theoretical specificity of this method that appears to generate compact clusters, of a smaller number but gathering more entities within the cluster membership. The groups' composition is less sensitive to outliers and noise in the data.

In order to facilitate the comparison among the various findings, we draw a summarizing output (table 4).

Even if each clustering method leads to slightly different results by accounting for the same input data, due to the inherent features of the computational algorithm, there is evidence of a series of countries that are persistently placed in the same cluster regardless of the clustering method used. These countries are Belgium, Cyprus, Estonia, Greece, Ireland, Italy, Latvia, Lithuania, the Netherlands, Spain and Slovakia (always included in the first cluster identified) which represents a signal that they exhibit persistently similar climate features that gather them together regardless the computational algorithm used for evaluating the proximity or distance between them.

Other groups of countries showing resembling climate features and included in the same cluster by the various algorithms used for evaluating the distance between them are represented by: i) Denmark, Finland, Germany, Luxembourg, and Sweden; ii) Bulgaria, Romania, and Croatia; iii) Austria, Slovenia, and Czechia.

Some countries have been identified as outlier countries and hence included in a single cluster as they seem to exhibit distinguished climate features compared with the other EU ones. It is

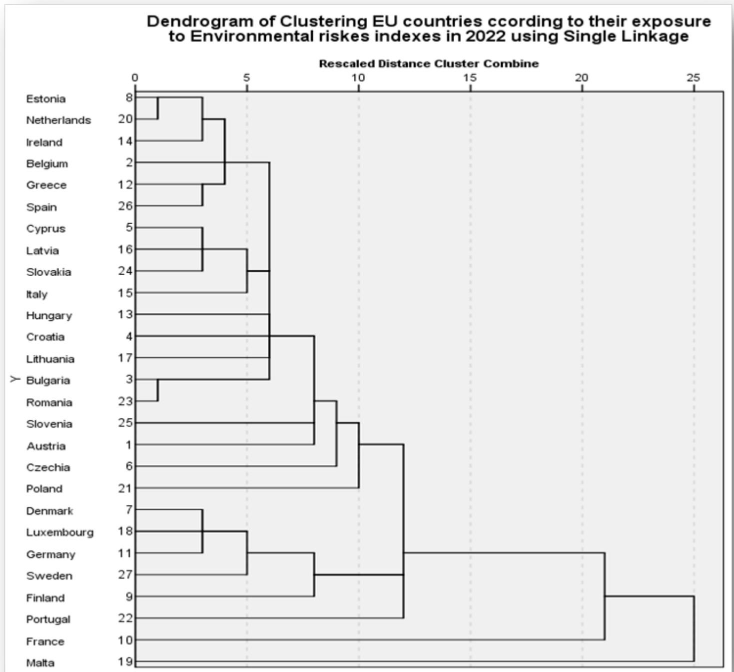

Figure 10. Dendrogram of the EU countries clustering in 2022 using the Single Linkage method

the case of Poland, Portugal, Malta and France. Overall, we can conclude that the clustering membership remained relatively unchanged when alternative estimation methods are used for checking the stability of findings.

6. Conclusions

The clustering solutions obtained for both years reveal the persistence of a relatively heterogeneity in terms of climate proxies across the European Union countries. In both cases six clusters were identified, with the main difference that in 2022 the number of similar countries varies significantly one group from another. This polarization indicates that some countries have evolved differently in the time span between the two years considered, either by improving or by deteriorating some climate variables.

Another interesting finding reveals that some countries were always included in the same group, a sign that they had evolved similarly. It is the case of: i) Denmark, Luxembourg, Sweden and Finland; ii) Bulgaria, Romania and Croatia; iii) Estonia, Netherlands, Ireland and Portugal; iv) Greece, Spain, and Italy; v) Latvia, Lithuania, and Slovakia.

According to the findings related to the most recent time period considered, it appears that the countries featuring the most favorable, milder climate profile for business development, including the banking activity, are represented by Denmark, Luxembourg, Germany, Sweden, and Finland. Good performance in addressing the environmental challenges coupled with a low frequency of natural hazards is witnessed also by Austria, Slovenia, and Czechia. Other examples of well-prepared countries in terms of managing the effects of natural disasters are those of France and Malta, although their exposure and vulnerability to the occurrence of the physical risks of climate are moderate.

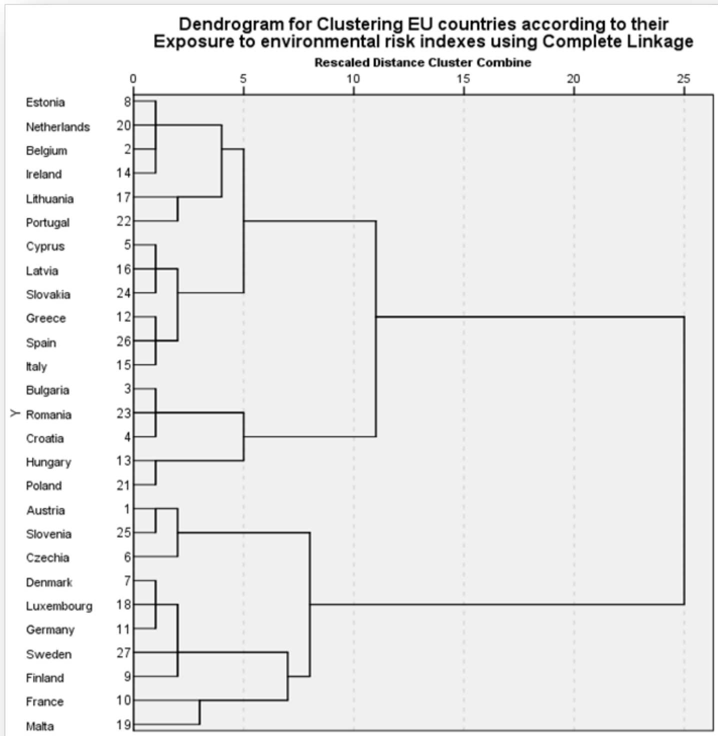

Figure 11. Dendrogram of the EU countries clustering in 2022 using the complete Linkage method

In the middle of the ranking it can be positioned Estonia, Netherlands, Ireland, Belgium, Greece, Spain, Italy, Cyprus, Latvia, Slovakia, Hungary, Lithuania, and Portugal, which witness up to three natural disasters and moderate, around the average values for the remaining five climate proxies.

In contrast, countries such as Bulgaria, Romania, Poland, and Croatia show low capabilities for natural disaster prevention and management, as well as modest to worst performance in terms of policies implemented for environmental protection, creating a climate-friendly business environment, or achieving the Paris Agreement goals.

Based on the above classification of European countries, one may naturally conjecture that the exposure of banking systems to physical climate risks should be lower if they establish headquarters and conduct financial operations in countries such as Denmark, Luxembourg, Germany, Sweden or Finland, closely followed by Austria, Slovenia, and Czechia. Findings indicate that these are the least vulnerable EU countries to physical risks, being at the same time good performers in the process of climate risk adaptation, prevention, and management. On the contrary, financial intermediaries operating in Bulgaria, Croatia, Poland and Romania are susceptible to be the most exposed to the ripple effects of these risks. Therefore, the statistical findings indirectly signal increasing understanding and awareness raising regarding the need to implement an active climate risk identification, assessment, and management strategy to counteract the vulnerability of the home country to climate risk and the low degree of readiness/performance in implementing climate policies.

In terms of the policy implications, the findings of the exploratory analysis developed in this paper can be further exploited by policymakers, financial supervisors, financial market players

TABLE 4. Comparative assessment of the cluster membership (2022 data)

Clusters identified	**Average linkage method**	**Single linkage method**	**Complete linkage method**
Cluster no. 1	Estonia, the Netherlands, Ireland, Belgium, Greece, Spain, Italy, Cyprus, Latvia, Slovakia, Hungary, Lithuania, and Portugal	Estonia, the Netherlands, Ireland, Belgium, Greece, Spain, Cyprus, Latvia, Slovakia, Italy, Hungary, Croatia, Lithuania, Bulgaria, Romania, Slovenia, Austria, Czechia	Estonia, Netherlands, Belgium, Ireland, Lithuania, Portugal, Cyprus, Latvia, Slovakia, Greece, Spain, and Italy
Cluster no. 2	Bulgaria, Romania, and Croatia	Poland	Bulgaria, Romania, Croatia, Hungary, and Poland
Cluster no. 3	Poland	Denmark, Finland, Germany, Luxembourg, Sweden	Austria, Slovenia, Czechia, Denmark, Luxembourg, Germany, Sweden, Finland, France, and Malta
Cluster no. 4	France and Malta	Portugal	
Cluster no. 5	Austria, Slovenia, and Czechia	France	
Cluster no. 6	Denmark, Luxembourg, Germany, Sweden, and Finland	Malta	

and the general public. They may gain a preliminary insight in terms of the most vulnerable countries to climate changes in order to ascertain which banking systems or economy sectors would be most exposed in case a natural hazard occurs and it overlaps a low preparedness stage of a country. Awareness of the climatic profile of the EU countries, in terms of exposure and vulnerability to environmental risks but also in terms of readiness to comply with these challenges and performance in climate policies implementation has become a matter of utmost importance at macroeconomic and microeconomic level. Financial regulators at European and international level are elaborating guidelines to facilitate financial intermediaries' understanding of the emerging climate risks, of the ESG challenges and how they are impacting the conduct of the banking business and the risk management process. One step further is made by the Network for Greening the Financial System, an association made up exclusively by central banks that jointly work to enhance the understanding and evaluation of climate risk exposure. One main outcome is the publication of a climate scenario framework. At the same time, financial supervisors started to develop and test new risk assessment tools at banking system level (an example is the climate stress test carried out by the European Central Bank, or by the Federal Reserve). The findings to be obtained are expected to serve a broader scope, in terms of safeguarding financial stability and including climate change considerations in the future monetary policy decisions.

Given the trend witnessed by the financial industry to develop into financial groups and conduct transnational (cross-border) financial activity, it is of utmost importance for financial market players to gain a comprehensive insight not only on the macroeconomic, governance and financial fundamentals specific to a country, but also on its climate pattern and related vulnerabilities when substantiating the decision to operate in a particular European country.

In addition, the broader framework represented by the smooth transition to the green economy and achievement of the Sustainable Development Goals (SDGs) actively involves the role of financial intermediaries in channeling financing to projects with positive added value not only from an economic and financial standpoint, but also from an environmental one. In view of the above, representatives of the European Central Bank (McCaul, 2023) emphasize that banks should make a priority from tackling climate-related and environmental risks, by incorporating them adequately within their business strategy, internal governance and risk management frameworks.

Future research directions may explore the impact to be exerted by various climate scenarios on banks' balance sheet, on their key indicators such as profitability, liquidity, adequacy of the capital to the risks with a particular emphasis on the credit portfolio quality and credit risk that may be exacerbated by the occurrence of the physical climate risks (natural hazards).

References

[1] Aral, Öykü H., and Jordi López-Sintas. 2023. "Environmental Behavior Patterns across Clusters of European Union Countries: Uncovering Heterogeneity in the Attitude-Behavior-Context Relationship." Journal of Cleaner Production 388. (February). https://doi.org/10.1016/j.jclepro.2023.135936.

[2] Ascensão, Fernando, Lenore Fahrig, Anthony P. Clevenger, Richard T. Corlett, Jochen A.G. Jaeger, William F. Laurance, and Henrique M. Pereira. 2018. "Environmental Challenges for the Belt and Road Initiative." Nature Sustainability. Nature Publishing Group. https://doi.org/10.1038/s41893-018-0059-3.

[3] Bank of England. 2018." Transition in thinking: the impact of climate change on the UK banking sector", Prudent. Regul. Auth. Rep.

[4] Basel Committee on Banking Supervision, 2021. "Climate-related financial risks – measurement methodologies", Bank for International Settlements, April 2021, https://www.bis.org/bcbs/publ/d518.pdf.

[5] Bihari, Anand, Sudhakar Tripathi, and Akshay Deepak. 2019. "Gene Expression Analysis Using Clustering Techniques and Evaluation Indices." In 2nd INTERNATIONAL CONFERENCE ON ADVANCED COMPUTING AND SOFTWARE ENGINEERING, 422–427. https://ssrn.com/abstract=3350332.

[6] Blickle, Kristian S, Sarah N Hamerling, and Donald P Morgan. 2021. 'How Bad Are Weather Disasters for Banks?' New York. file:///C:/Users/WafA/Downloads/SSRN-id3961081.pdf.

[7] Boehm, Hannes. 2022. "Physical Climate Change and the Sovereign Risk of Emerging Economies." Journal of Economic Structures 11 (1). https://doi.org/10.1186/s40008-022-00284-6.

[8] Breitenstein, Miriam, Duc Khuong Nguyen, and Thomas Walther. 2021. "Environmental Hazards And Risk Management In The Financial Sector: A Systematic Literature Review". Journal of Economic Surveys 35 (2): 512–38. https://doi.org/10.1111/joes.12411.

[9] Caby, Jerome, Ziane, Ydriss., and Lamarque, Eric. 2020. "The determinants of voluntary climate change disclosure commitment and quality in the banking industry". Technological Forecasting and Social Change, 161. https://doi.org/10.1016/j.techfore.2020.120282

[10] Cambridge Institute for Sustainable Leadership. 2016. "Environmental risk analysis by financial institutions-a review of global practice". www.unep.org/inquiry

[11] Calice, Pietro, and Faruk Miguel. 2021. "Climate-Related and Environmental Risks for the Banking Sector in Latin America and the Caribbean A Preliminary Assessment". 9694. http://www.worldbank.org/prwp.

[12] Cardona, Omar-Dario, Maarten K van Aalst, Jörn Birkmann, Maureen Fordham, Glenn McGregor, Rosa Perez, Roger S Pulwarty, et al. 2012. "Determinants of Risk: Exposure and Vulnerability". In: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. Cambridge, UK; New York, US: Australia. https://www.ipcc.ch/site/assets/uploads/2018/03/SREX-Chap2_FINAL-1.pdf.

[13] Cena, Anna, and Marek Gagolewski. 2020. "Genie+OWA: Robustifying Hierarchical Clustering with OWA-Based Linkages." Information Sciences 520 (May): 324–36. https://doi.org/10.1016/j.ins.2020.02.025.

[14] Climate Change Knowledge Portal. 2023. "Climate Risk Country Profiles", https://climateknowledgeportal.worldbank.org/country-profiles

[15] Climate Transparency. 2022. "Climate Transparency Report". https://www.climate-transparency.org/g20-climate-performance/g20report20221531904804037-423d5c88-a7a7

[16] Cornish, Rosie. 2007. "Statistics: 3.1 Cluster Analysis." Mathematics Learning Support Centre.

[17] Cortina, Magdalena, and Carlos Madeira. 2023. "Exposures to Climate Change's Physical Risks in Chile". Latin American Journal of Central Banking 4 (2): 100090. https://doi.org/10.1016/j.latcb.2023.100090.

[18] Crespi, Alice, Kathrin Renner, Marc Zebisch, Inke Schauser, Nora Leps, and Andreas Walter. 2023. "Analysing Spatial Patterns of Climate Change: Climate Clusters, Hotspots and Analogues to Support Climate Risk Assessment and Communication in Germany." Climate Services 30 (April). https://doi.org/10.1016/j.cliser.2023.100373

[19] Curcio, Domenico, Igor Gianfrancesco, and Davide Vioto. 2023. ‘Climate Change and Financial Systemic Risk: Evidence from US Banks and Insurers’. Journal of Financial Stability 66 (June). https://doi.org/10.1016/j.jfs.2023.101132.

[20] Djenouri, Youcef, Asma Belhadi, Philippe Fournier-Viger, and Jerry Chun Wei Lin. 2018. “Fast and Effective Cluster-Based Information Retrieval Using Frequent Closed Itemsets.” Information Sciences 453 (July): 154–67. https://doi.org/10.1016/j.ins.2018.04.008.

[21] Eligüzel, Nazmiye, Sena Aydoğan, and İbrahim Miraç Eligüzel. 2023. “Clustering Application and Evaluation of the Countries’ Word Risk and Climate Risk Indices.” International Journal of Applied Mathematics Electronics and Computers 11 (1): 13–19. https://doi.org/10.18100/ijamec.1217399.

[22] European Central Bank. 2021. “The state of climate and environmental risk management in the banking sector.”

[23] Everitt, Braian. S., Landau, Sabine., Leese, Morven., and Stahl, Daneil. 2011. “Cluster Analysis”, 5th Edition, WILEY SERIES IN PROBABILITY AND STATISTICS. A John Wiley and Sons.

[24] Finger, Maya, Gavious, Ilanit., and Manos, Ronny. 2018. “Environmental risk management and financial performance in the banking industry: A cross-country comparison”. Journal of International Financial Markets, Institutions and Money, 52, 240-261.

[25] Ferrazzi, Matteo, Fotios Kalantzis, and Sanne Zwart. 2021. “Assessing Climate Change Risks at the Country Level: The EIB Scoring Model”. 03. Economics. https://doi.org/10.2867/854649.

[26] Freeman, Paul K, and Howard Kunreuther. 2002. “Environmental Risk Management for Developing Countries.” The Geneva Papers on Risk and Insurance-Issues and Practice, 27, 196-214.

[27] Gabel, Friedrich, Kruger, Marco, Morsut, Claudia, and Kuran, Christian. 2022. “Bridging the Gap between Vulnerable Groups and Vulnerable Situations: Towards an Integrative Perspective on Vulnerability for Disaster Risk Reduction”. https://www.undrr.org/media/80258/download?startDownload=true.

[28] Gagolewski, Marek, Anna Cena, Simon James, and Gleb Beliakov. 2023. “Hierarchical Clustering with OWA-Based Linkages, the Lance–Williams Formula, and Dendrogram Inversions.” Fuzzy Sets and Systems 473 (December). https://doi.org/10.1016/j.fss.2023.108740.

[29] Gan, Guojun, Chaoqun Ma, and Jianhong Wu. 2007. “Data Clustering: Theory, Algorithms, and Applications”. Society for Industrial and Applied Mathematics. https://doi.org/10.1137/1.9780898718348.

[30] Grippa, Pierpaolo, Jochen Schmittmann, and Felix Suntheim. 2019. “Central Banks and Financial Regulators Are Starting to Factor in Climate Change”. file:///C:/Users/WafA/Downloads/climate-change-central-banks-and-financial-risk-grippa.pdf.

[31] Huang, Yanying. 2019. “Environmental risks and opportunities for countries along the Belt and Road: Location choice of China’s investment”. Journal of Cleaner Production, 211, 14-26.

[32] Huang, Bihong, Maria Teresa Punzi, Yu Wu, Xuefei Bai, Laurent Deville, Ulric Eriksson Von Allmen, Gianfranco Gianfrate, et al. 2021. “Do Banks Price Environmental Transition Risks? Evidence from a Quasi-Natural Experiment in a Chinese Province”, IMF Working Paper Monetary and Capital Market Department. https://www.imf.org/en/Publications/WP/Issues/2021/09/03/Do-Banks-Price-Environmental-Transition-Risks-Evidence-from-a-Quasi-Natural-Experiment-in-a-465065.

[33] Ilhan, Emirhan, Philipp Krueger, Zacharias Sautner, and Laura T Starks. 2022. “Climate Risk Disclosure and Institutional Investors”. http://ssrn.com/abstract_id=3437178www.ecgi.global/content/working-papers.

[34] Kijewska, Anna, and Anna Bluszcz. 2016. “Analysis of Greenhouse Gas Emissions in the European Union Member States with the Use of an Agglomeration Algorithm.” Journal of Sustainable Mining 15 (4): 133–42. https://doi.org/10.1016/j.jsm.2017.02.001.

[35] Lúcio, Francisco, and Jorge Caiado. 2022. “COVID-19 and Stock Market Volatility: A Clustering Approach for S&P 500 Industry Indices.” Finance Research Letters 49 (October). https://doi.org/10.1016/j.frl.2022.103141.

[36] Lund, Brady, and Jinxuan Ma. 2021. “A Review of Cluster Analysis Techniques and Their Uses in Library and Information Science Research: K-Means and k-Medoids Clustering.” Performance Measurement and Metrics 22 (3): 161–73. https://doi.org/10.1108/PMM-05-2021-0026.

[37] McCaul, Elizabeth. 2023. “Current risks and vulnerabilities in the European banking sector”, https://www.bankingsupervision.europa.eu/press/interviews/date/2023/html/ssm.in.230913_1 c6b319dd92.en.html

[38] Middermann, Laura H., Jan Kratzer, and Susanne Perner. 2020. “The Impact of Environmental Risk Exposure on the Determinants of Sustainable Entrepreneurship.” Sustainability (Switzerland) 12 (4). https://doi.org/10.3390/su12041534.

[39] Moghim, Sanaz, and Roja Kaveh Garna. 2019. “Countries’ Classification by Environmental Resilience.” Journal of Environmental Management 230 (January): 345–54. https://doi.org/10.1016/j.jenvman.2018.09.090.

[40] Muganyi, Tadiwanashe, Yan, Linnan, and Sun, Hua-ping. 2021. “Green finance, fintech and environmental protection: Evidence from China”. Environmental Science and Ecotechnology, 7, 100107.

[41] Noth, Felix, and Ulrich Schüwer. 2023. "Natural Disasters and Bank Stability: Evidence from the U.S. Financial System". https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2921000.
[42] Pagliari, Maria Sole. 2023. "LSIs' Exposures to Climate-Change-Related Risks: An Approach to Assess Physical Risks". International Journal of Central Banking, March. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3797137.
[43] Poljansek, K., F Montserrat, T. Groeve, and T. Clark. 2017. "Science for Disaster Risk Management. Knowing Better and Losing Less". Luxembourg. https://doi.org/10.2788/842809.
[44] Quatrosi, Marco. 2022. "Clustering Environmental Performances, Energy Efficiency and Clean Energy Patterns: A Comparative Static Approach across EU Countries." http://www.sustainability-seeds.org/.
[45] Repiská, Radka, Nora Grisáková, and Peter Štetka. 2022. "Hierarchical Clustering Based on International Sustainability Indices of EU Countries." Ekonomické Rozhl̆ady – Economic Review 51 (2): 149–70. https://doi.org/10.53465/er.2644-7185.2022.2.149-170.
[46] Rizvi, Syeda Amna, Muhammad Umair, and Muhammad Aamir Cheema. 2021. "Clustering of Countries for COVID-19 Cases Based on Disease Prevalence, Health Systems and Environmental Indicators." Chaos, Solitons and Fractals 151 (October). https://doi.org/10.1016/j.chaos.2021.111240.
[47] Rybak, Aurelia, Aleksandra Rybak, Jarosław Joostberens, and Spas D. Kolev. 2022. "Cluster Analysis of the EU-27 Countries in Light of the Guiding Principles of the European Green Deal, with Particular Emphasis on Poland." Energies 15 (14). https://doi.org/10.3390/en15145082.
[48] Sadeghi, Mehrdad, Reza Naghedi, Kourosh Behzadian, Amiradel Shamshirgaran, Mohammad Reza Tabrizi, and Reza Maknoon. 2022. "Customisation of Green Buildings Assessment Tools Based on Climatic Zoning and Experts Judgement Using K-Means Clustering and Fuzzy AHP." Building and Environment 223 (September). https://doi.org/10.1016/j.buildenv.2022.109473.
[49] Shala, Iliriana, and Benno Schumacher. 2022. "The Impact of Natural Disasters on Banks' Impairment Flow Evidence from Germany". No. 36/2022.
[50] Shakil, Mohammad. H., Mahmood, Nihal., Tasnia, Mashyat, and Munim, Ziaul Haque. 2019. "Do environmental, social and governance performance affect the financial performance of banks? A cross-country study of emerging market banks". Management of Environmental Quality: An International Journal, 30(6), 1331-1344.
[51] Torinelli, Viviane Helena, and Antônio Francisco de Almeida da Silva Júnior. 2021. "Environmental Risk Analysis (ERA) in the Strategic Asset Allocation (SAA) of the International Reserves (IRs) Managed by Central Banks (CBs)". Latin American Journal of Central Banking 2 (1): 100021. https://doi.org/10.1016/j.latcb.2021.100021.
[52] Tryfos, Peter. 1997. "Chapter 15 Cluster analysis".
[53] United Nations. 2005. "Building the Resilience of Nations and Communities to Disasters", Extract from the Final Report of the World Conference on Disaster Reduction (A/CONF.206/6). In Hyogo Framework for Action 2005-2015, 01–28. Hyogo- Japan. https://www.unisdr.org/files/1037_hyogoframeworkforactionenglish.pdf.
[54] United Nations. 2016. "A/71/644 Seventy-first session Agenda item 19 (c) Sustainable development: disaster risk reduction". http://www.preventionweb.net/drr-framework/open-ended-working-group/
[55] United Nations Office for Disaster Risk Reduction. 2023. "Sendai Framework for Disaster Risk Reduction", https://unfccc.int/documents/628865?gclid=CjwKCAjw1t2pBhAFEiwA_-A-NJQOUjMWnmJXblzkwvZTp5-MSV3WHCJRAFVN-AEG86RWC25fw5__gRoCzPcQAvD_BwE.
[56] Weber, Olaf. 2012. "Environmental Credit Risk Management in Banks and Financial Service Institutions". Business Strategy and the Environment 21 (4): 248–63. https://doi.org/10.1002/bse.737.