climate

Article

Using Machine Learning Clustering to Build an ESG-Based Taxonomy of Heat Vulnerability

Angelo Leogrande [1,*], Carlo Drago [2], Massimo Arnone [3] and Alberto Costantiello [1]

[1] Dipartimento di Management, Finanza e Tecnologia, LUM University Giuseppe Degennaro, Strada Statale 100 km 18, 70010 Casamassima, Italy; costantiello@lum.it
[2] Dipartimento di Scienze Economiche, Psicologiche, della Comunicazione, della Formazione e Motorie, Niccolò Cusano University, Via Don Carlo Gnocchi, 3, 00166 Rome, Italy; carlo.drago@unicusano.it
[3] Dipartimento di Scienze Politiche, University of Catania, Palazzo Pedagaggi Via Vittorio Emanuele II, 49, 95131 Catania, Italy; massimo.arnone@unict.it
* Correspondence: leogrande.cultore@lum.it

Abstract

HI35, defined as the mean annual number of days on which apparent temperature exceeds 35 °C, is introduced in this paper as a country-level heat exposure metric. Unlike vulnerability indicators, HI35 is treated as an exogenous climatic exposure variable and not as a direct measure of vulnerability or as an endogenous outcome. By combining HI35 with World Bank Environmental, Social, and Governance (ESG) indicators, this study applies unsupervised clustering algorithms to derive an exposure–vulnerability typology of countries. The Environmental, Social, and Governance pillars are analyzed separately through dedicated clustering procedures, supported by robustness checks and an additional country taxonomy based on principal component analysis and hierarchical clustering. The results identify heterogeneous country profiles in which similar levels of heat exposure coexist with different ESG-based vulnerability conditions, including environmental pressures, fragility, institutional capacity, innovation, water access, nutrition, and governance quality. Conversely, countries with relatively low heat exposure may display differentiated social or institutional vulnerability profiles. The empirical evidence suggests that heat exposure and ESG-based vulnerability are conceptually distinct but jointly relevant dimensions for classifying climate-risk profiles. No causal relationship is inferred between ESG indicators and HI35; the analysis is descriptive, classificatory, and based on unsupervised learning. Conceptually, HI35 captures the occurrence of extreme heat events, while ESG indicators describe the environmental, social, and institutional conditions associated with sensitivity, resilience, and adaptive capacity.

Keywords: heat 35 index; climate vulnerability; ESG indicators; country clustering; taxonomies

Academic Editor: Md Saidul Islam

Received: 19 March 2026
Revised: 22 May 2026
Accepted: 23 May 2026
Published: 3 July 2026

1. Introduction

Climate change is a systemic phenomenon, and ESG factors have gained importance as a framework for examining the environmental, social, and institutional conditions under which societies face climatic stress [1]. In this research, we consider HI35, defined as the annual number of days on which apparent temperature exceeds 35 °C. HI35 reflects heat exposure and is not treated as a proxy for a country's vulnerability to climate change. Countries with similar levels of heat exposure may display different ESG-based vulnerability profiles, depending on environmental pressures, societal sensitivity, institutional quality, and adaptive capacity. Therefore, the research question of this paper is as

 https://doi.org/10.3390/cli14070138

follows: how can HI35 and ESG indicators be jointly used to differentiate country-level exposure–vulnerability profiles? From a methodological perspective, we apply cluster analysis to an integrated country-level dataset including HI35 and ESG indicators. The method is descriptive and classificatory in nature, as it aims to identify groups of countries with similar heat-exposure conditions and ESG-based vulnerability-related profiles. No causal relationship is inferred between ESG indicators and HI35. The twofold contribution of the research is, first, to advance the classification of climate-risk profiles by jointly considering climatic exposure and the socio-institutional conditions under which exposure occurs. Second, the study shifts attention from firm-level ESG performance to cross-country ESG-based vulnerability profiles, an area that remains underexplored in the climate-risk literature.

This paper is structured as follows. Section 2 reviews the literature on ESG, heat exposure, and climate vulnerability. Section 3 presents the data, variables, aggregation procedure, cleaning strategy, and country-level unit of analysis. Section 4 explains the empirical framework, distinguishing HI35 as climatic exposure from ESG-based vulnerability. Sections 5–8 report the clustering results for the Environmental, Social, and Governance dimensions, including sensitivity analyses and robustness checks. Section 9 develops an integrated country taxonomy using PCA and hierarchical clustering, with macroeconomic and institutional interpretation. Section 10 discusses the empirical findings, while Section 11 derives policy implications for climate governance and heat resilience. Section 12 concludes this paper. Appendices A–C provide descriptive statistics and diagnostics for Environmental, Social, and Governance indicators. Appendix D reports long-term HI35 trends from 2000 to 2022.

2. Literature Review

Extreme heat events are becoming more prevalent, prompting policymakers, investors, and academics to reconsider how sustainability and climate risks are assessed. HI35, defined as the annual number of days on which apparent temperature exceeds 35 °C, is used in this study as an indicator of climatic heat exposure. However, HI35 is not treated as a direct vulnerability metric. The key challenge of the analysis is to understand how this exogenous exposure variable is associated with environmental, social, and governance conditions that describe vulnerability-related country profiles, without implying any causal relationship between ESG indicators and HI35.

Previous research shows a positive link between ESG performance and resilience to heat stress. The bulk of available literature focuses on individual companies or industrial sectors. Refs. [2,3] found that Chinese firms with higher ESG ratings showed greater resilience, as evidenced by lower volatility during extreme heat. At the same time, studies by [4,5] highlight the importance of ESG-based actions in reducing the impacts of heat exposure on economies. Nonetheless, the existing literature has failed to shed light on how ESG systems function as national vulnerability structures.

A similar strand of academic discourse explores reliability issues of ESG and climate exposure metrics. For instance, Refs. [6,7] suggest that ESG indicators might lose validity and consistency without solid institutional and data structures. Refs. [8–10] highlight the benefits of HI35 and similar indicators for sustainability planning and institutional ESG structures. Still, exposure indicators are inconsistently used in ESGs, and discrepancies between ESG data providers can lead to different interpretations of climate risks [11–13].

Moreover, the social and governance sides of heat vulnerability are understudied. Extreme temperatures cause severe health outcomes, impact workers' productivity, alter nutrition, exacerbate inequality, hinder access to public utilities, and contribute to migration. However, these risks are frequently neglected when evaluating ESG factors [14–18]. Similarly, the influence of governance on adaptive capacity, regulatory coordination, and climate-risk management requires further analysis since there is currently no comparative analysis of institutional profiles across countries at different heat exposures [19–25].

Innovation and data infrastructure also play important roles. Both ESG investments and R&D can improve adaptation, especially when they concern energy and technological sectors [26–31]. At the same time, reliable ESG data, geospatial information, and comparability become necessary for climate-risk assessment [7,32–34].

This paper addresses the following four gaps: (i) the prevalence of firm- or sector-level analyses; (ii) the patchy use of heat indicators in ESG frameworks; (iii) the lack of operationalized social and governance vulnerability indicators; and (iv) the absence of systematic cross-country taxonomies. In particular, the author uses HI35 and other ESG indicators in a joint analysis with machine learning techniques. Thus, exposure–vulnerability clusters are described without assuming causality. See Table 1.

Table 1. Synthesis of the literature review.

Problem-Oriented Literature Stream	Key Authors/Studies	What the Literature Shows	Remaining Limitation	How This Study Addresses the Gap
Firm-level ESG resilience to heat stress	[4,6,7,35,36]	Firms with stronger ESG profiles often show greater resilience to heat shocks, lower operational volatility, and stronger sustainability responses under extreme heat.	The evidence remains mainly firm-level and does not explain how ESG systems operate as national vulnerability structures under climatic exposure.	The study shifts the analysis from firms to countries and uses clustering to identify macro-level exposure–vulnerability profiles combining HI35 and ESG indicators.
Integration of climatic exposure into ESG frameworks	[7–9,12,13,36]	HI35 and related heat indicators are increasingly relevant for sustainability planning, ESG assessment, data comparability, resource management, and institutional response.	Climatic exposure indicators remain unevenly integrated into ESG systems, while inconsistencies in ESG data infrastructures limit cross-country comparability.	The study treats HI35 as an exogenous exposure indicator and integrates it with ESG variables in a coherent cross-country exposure–vulnerability clustering framework.
Social vulnerability under heat exposure	[14–18,31]	Extreme heat interacts with social inequality, nutrition, displacement, labor stress, and access to basic services.	The social pillar of ESG is often discussed conceptually but is rarely operationalized through measurable national indicators linked to heat exposure.	The study combines HI35 with social indicators such as fertility, access to safely managed drinking water, and undernourishment to identify social exposure–vulnerability profiles.
Governance and institutional adaptive capacity	[9,13,20,22–24]	Strong governance, regulatory capacity, and institutional coordination improve adaptive capacity under repeated heat shocks.	Existing studies do not provide a systematic cross-country taxonomy showing how governance profiles differ under comparable or different levels of heat exposure.	The study combines HI35 with governance indicators to identify institutional vulnerability profiles and compare countries by adaptive capacity.

Table 1. *Cont.*

Problem-Oriented Literature Stream	Key Authors/Studies	What the Literature Shows	Remaining Limitation	How This Study Addresses the Gap
Sectoral innovation and adaptive investment	[25–28,37,38]	ESG investment, green innovation, and R&D can support adaptation to climate stress, especially in energy and technology sectors.	The evidence is mostly sectoral or firm-oriented and does not explain how innovation capacity contributes to national exposure–vulnerability regimes.	The study incorporates innovation-related ESG indicators within a country-level clustering framework to compare adaptive-capacity profiles.
Heat indicators for policy and planning	[39,40]	Heat indicators can support urban planning, adaptation strategies, and local climate policy.	Policy-oriented studies often lack a unified empirical framework that compares vulnerability types across countries.	The study uses unsupervised clustering to derive exposure–vulnerability taxonomies that support differentiated adaptation strategies and resource allocation.

Note. This table reorganizes the literature around problem-oriented research streams, highlighting what previous studies show, their remaining limitations, and how the present study addresses these gaps through a cross-country ESG–HI35 exposure–vulnerability framework.

Despite being originally designed as an instrument for assessing sustainability and risk in corporate investments, the extension of ESG to the analysis of national characteristics requires re-conceptualizing the theory [41,42]. This paper does not consider the ESG framework as a measure of corporate sustainability, nor as a national ranking based on firm-level assessment principles. Rather, ESG is regarded as a macro-sustainability approach for describing nation-specific conditions associated with vulnerability-related profiles and adaptive capacity under exogenous climatic exposure [43,44]. Thus, the three main components of the ESG concept are considered as structural dimensions through which country-level climate vulnerability profiles can be classified. Specifically, the environmental pillar includes ecological pressures, depletion of natural resources, energy dependence, greenhouse gas emissions, and cooling stresses. The social pillar concerns population sensitivity to health, nutrition, demographics, and the provision of basic service parameters. Finally, the governance pillar accounts for issues of regulatory quality, rule of law, political stability, accountability, human rights protection, innovation capability, and the overall state of macroeconomic governance [43,44]. Clearly, the above taxonomy does not intend to create an all-inclusive development index but rather defines the boundaries within which national conditions associated with climate vulnerability are analyzed. HI35 is viewed as an exogenous index of climatic exposure, while the ESG variables represent national characteristics associated with sensitivity, resilience, and adaptive capacity under climate exposure [44]. GDP growth is used because it is contained in the World Bank database and viewed as an element of macroeconomic governance. Future development of the taxonomy should be focused on GDP per capita, income groups, fiscal capacity, and urbanization factors [43,44].

3. Data Architecture and Variable Framework

We have used the following data from the World Bank Database (Table 2).

Table 2. Variables used to construct the HI35–ESG exposure–vulnerability framework.

Macro	Variable	Acronym	Definition
	Heat Index 35 New	HI35	It is the number of days in a year when the apparent temperature, a perceived measure that combines ambient temperature and humidity, surpasses 35 °C. This variable indicates the occurrence of extreme heat that can affect health conditions, productivity, and ecosystems.
E-Environment	Adjusted savings: natural resources depletion (% of GNI)	NRD	Measures the economic cost of depleting natural resources, such as forests, minerals, and fossil fuels, expressed as a percentage of a country's Gross National Income (GNI). This indicator reflects the long-term impact of resource extraction on a nation's wealth, considering sustainability and future economic potential.
	Adjusted savings: net forest depletion (% of GNI)	NFD	Quantifies the economic cost associated with the loss of forest resources, expressed as a percentage of Gross National Income (GNI). This measure reflects the financial and environmental impact of deforestation on a country's long-term sustainability and natural wealth.
	Energy imports, net (% of energy use)	EIN	Represents the percentage of a country's total energy consumption that is met through imported energy sources, after accounting for any energy exported. This metric highlights a country's reliance on foreign energy, indicating its vulnerability to external energy supply and price fluctuations.
	Energy intensity level of primary energy (MJ/$2017 PPP GDP)	EIL	Measures the amount of primary energy consumed per unit of economic output, expressed in megajoules per dollar of GDP adjusted to 2017 purchasing power parity (PPP). This indicator reflects the efficiency of a country's energy use in relation to its economic productivity, with lower values indicating higher energy efficiency.
	Fossil fuel energy consumption (% of total)	FFEC	Indicates the proportion of a country's total energy consumption that is derived from fossil fuels, including coal, oil, and natural gas. This metric helps gauge a nation's reliance on non-renewable energy sources, with higher percentages indicating greater dependence on fossil fuels and associated emissions.
	Methane emissions (metric tons of CO_2 equivalent per capita)	ME	Represents the average methane emissions per person in a country, converted to their equivalent impact in metric tons of CO_2 for comparative purposes. This measure reflects the contribution of methane, a potent greenhouse gas, to overall greenhouse gas emissions on a per capita basis.
	Nitrous oxide emissions (metric tons of CO_2 equivalent per capita)	NOE	Quantifies the average emissions of nitrous oxide per person in CO_2-equivalent metric tons, allowing for comparison with other greenhouse gases. This metric captures the impact of nitrous oxide, a potent greenhouse gas primarily emitted from agricultural and industrial activities, on a per capita basis.
S-Social	Fertility rate, total (births per woman)	FR	Represents the average number of children a woman is expected to have over her lifetime based on current birth rates. This metric is a key demographic indicator that helps assess population growth and reproductive trends within a country.

Table 2. *Cont.*

Macro	Variable	Acronym	Definition
S-Social	People using safely managed drinking water services (% of population)	PUSM	Refers to the percentage of a population with access to drinking water that is located on-site, available when needed, and free from contamination. This metric is a key indicator of public health and infrastructure quality, reflecting access to essential safe water services.
	Prevalence of undernourishment (% of population)	POU	Measures the percentage of a population whose daily food intake is insufficient to meet minimum dietary energy requirements. This indicator reflects food insecurity and is used to assess hunger levels and nutritional deficiencies within a population.
G-Governance	GDP growth (annual %)	GDPG	Represents the yearly percentage increase in a country's Gross Domestic Product, reflecting the overall economic growth of a nation. This metric is widely used to assess economic health, indicating how rapidly an economy is expanding or contracting over a given year.
	Political Stability and Absence of Violence/Terrorism	PS	Is an indicator that measures the likelihood of political unrest, violence, or terrorism affecting a country, reflecting the stability of its political environment. Higher values on this indicator suggest a more stable, secure setting for citizens and investors, whereas lower values indicate greater risks of political or violent disruptions.
	Ratio of female to male labor force participation rate (%) (modeled ILO estimate)	RFTM	Compares the percentage of women participating in the labor force to that of men, showing gender parity in workforce involvement. A higher ratio indicates closer levels of labor force engagement between women and men, reflecting gender equality in employment opportunities.
	Regulatory Quality	RQ	Assesses the ability of a government to implement policies and regulations that promote private sector development while maintaining fair and efficient market standards. Higher values indicate effective regulations that support business growth and protect public interests, whereas lower values suggest regulatory challenges or inefficiencies
	Research and development expenditure (% of GDP)	RDE	Measures the percentage of a country's Gross Domestic Product invested in research and development activities, reflecting its commitment to innovation and technological advancement. Higher values indicate a stronger emphasis on R&D, which can drive economic growth and competitiveness.
	Rule of Law	RL	Measures the extent to which a society enforces laws fairly, protects individual rights, and upholds contracts and property rights. Higher values indicate a strong legal framework where laws are applied consistently, contributing to social stability and trust in institutions, while lower values suggest weaker legal enforcement and potential governance challenges.
	School enrollment, primary and secondary (gross), gender parity index (GPI)	SEPS	Measures the ratio of female to male students enrolled at primary and secondary levels, reflecting gender equality in educational access. A GPI closer to 1 indicates balanced enrollment between genders, while values further from 1 suggest disparities favoring either male or female students.

https://doi.org/10.3390/cli14070138

Table 2. *Cont.*

Macro	Variable	Acronym	Definition
G-Governance	Scientific and technical journal articles	STJA	Refers to the number of peer-reviewed publications produced within a country, often used as an indicator of research output and intellectual activity in science and technology fields. Higher counts signify robust academic and research engagement, contributing to innovation and knowledge development across various disciplines.
	Strength of legal rights index (0 = weak to 12 = strong)	SLRI	Measures the degree to which a country's legal system protects borrowers' and lenders' rights, with scores ranging from 0 (weak) to 12 (strong). Higher scores indicate stronger legal protections for accessing credit, which can enhance economic activity by making it easier for businesses and individuals to secure loans.
	Voice and Accountability	VA	Measures the extent to which citizens of a country are able to participate in selecting their government, as well as their freedom of expression, association, and access to a free media. Higher scores indicate a more democratic and open society, where people have greater influence over governance and civil liberties are better protected.

Source: for HI35 https://data360.worldbank.org/en/indicator/WB_ESG_EN_CLC_HEAT_XD Accessed 10 December 2024; for ESG variable https://esgdata.worldbank.org/?lang=en Accessed 10 December 2024.

The countries (Afghanistan, Albania, Algeria, Angola, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahrain, Bangladesh, Barbados, Belarus, Belgium, Belize, Benin, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Canada, Central African Republic, Chad, Chile, China, Colombia, Congo Dem. Rep., Congo Rep., Costa Rica, Cote d'Ivoire, Croatia, Cuba, Cyprus, Czechia, Denmark, Djibouti, Dominica, Ecuador, Egypt Arab Rep., El Salvador, Equatorial Guinea, Eritrea, Estonia, Eswatini, Ethiopia, Fiji, Finland, France, Gabon, Gambia The, Georgia, Germany, Ghana, Greece, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hungary, Iceland, India, Indonesia, Iran Islamic Rep., Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Kiribati, Korea Dem. People's Rep., Kuwait, Kyrgyz Republic, Lao PDR, Latvia, Lebanon, Lesotho, Liberia, Libya, Liechtenstein, Lithuania, Luxembourg, Madagascar, Malawi, Malaysia, Maldives, Mali, Malta, Marshall Islands, Mauritania, Mauritius, Mexico, Micronesia Fed. Sts., Moldova, Monaco, Mongolia, Montenegro, Morocco, Mozambique, Myanmar, Namibia, Nauru, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, North Macedonia, Norway, Oman, Pakistan, Palau, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russian Federation, Rwanda, Samoa, San Marino, Sao Tome and Principe, Saudi Arabia, Senegal, Serbia, Seychelles, Sierra Leone, Singapore, Slovak Republic, Slovenia, Solomon Islands, Somalia, South Africa, South Sudan, Spain, Sri Lanka, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, Sudan, Suriname, Sweden, Switzerland, Syrian Arab Republic, Tajikistan, Tanzania, Thailand, Timor-Leste, Togo, Tonga, Trinidad and Tobago, Tunisia, Turkiye, Turkmenistan, Tuvalu, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Uzbekistan, Vanuatu, Venezuela RB, Viet Nam, Yemen Rep., Zambia, Zimbabwe.) included in this analysis are represented in the following map. Data cover the period from 1999 to 2023. See Figure 1.

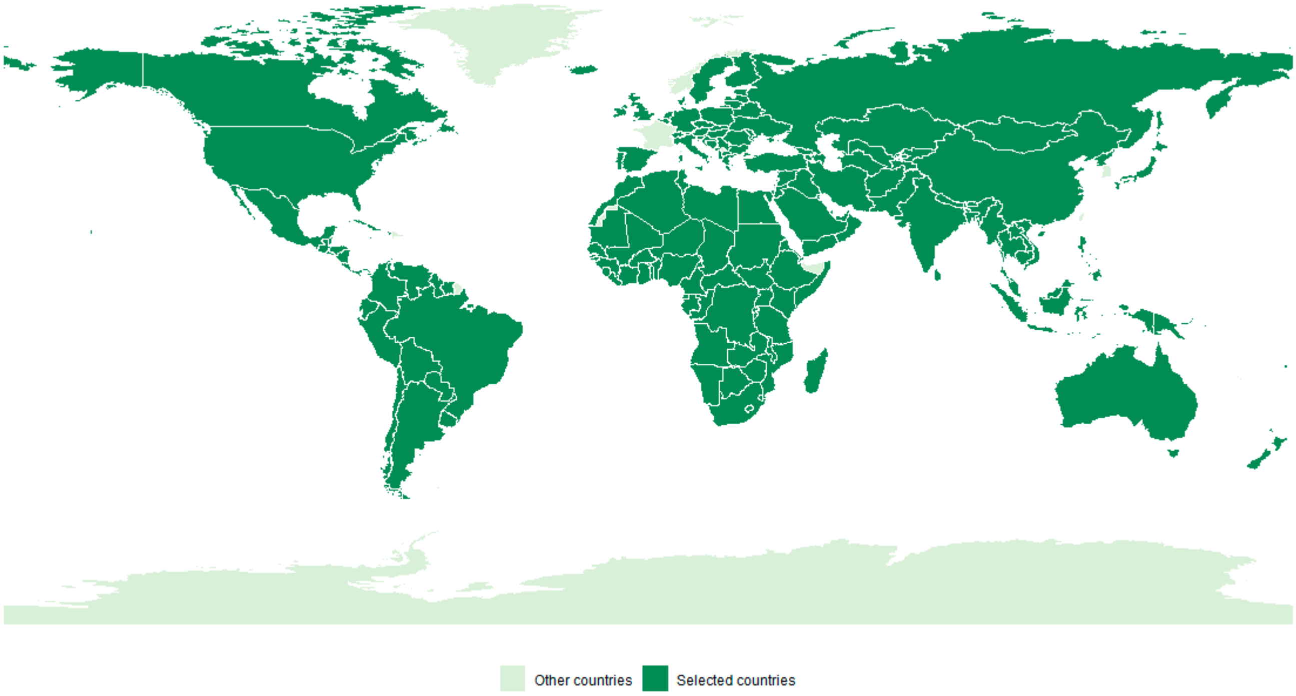

Figure 1. Geographic Distribution of Countries Included in the ESG–HI35 Analysis. Note. The figure displays countries included in the ESG–HI35 dataset used for clustering analysis. Selected countries cover the 1999–2023 period and represent diverse climatic, environmental, social, and governance conditions worldwide.

3.1. Temporal Scope and Aggregation Procedure

The data come from the World Bank ESG database and consist of yearly observations of all indicators for each country, over the longest available period for each indicator. Given the imbalance in data availability over time and space, we use an unbalanced panel [45,46]. To conduct clustering, we take the annual mean to form cross-sectional data at the country level. That is, for each country and each indicator, we aggregate annual observations by averaging them, resulting in one average value per country for HI35 and ESG indicators. The use of the mean was justified, as our research aims to identify countries' long-run exposure and vulnerability profiles rather than year-by-year dynamics or fluctuations. Observations with missing values, as well as outliers that will be identified during plausibility testing conducted next, will not be included when forming country means. As a result, country-level means will be computed only from valid values. Thus, after temporal aggregation, we end up with a set of observations, where each country is characterized by a single observation that includes its long-run HI35 mean and ESG variables. Therefore, our clusters should be viewed as long-run exposure and vulnerability profiles at the country level [45,47]. Additional information on the temporal variation in countries' HI35 values will be presented in Appendix D. The time series themselves will not be used in clustering algorithms, but they will provide insight into long-run heat exposure variation [46].

3.2. Data Cleaning and Plausibility Checks

Before conducting temporal aggregation and clustering, a structured data-cleaning and plausibility-check procedure was implemented to identify physically impossible observations, coding errors, missing records, and inconsistencies in indicator scales. This screening was conducted separately for each variable used in the analysis because all environmental, social, governance, and HI35 indicators have physically and/or conceptually admissible ranges. For indicators with upper and lower bounds, admissible ranges were defined according to each indicator's substantive meaning and measurement scale. Percentage indicators were checked for physical feasibility, while counts, rates, and index variables were assessed to detect negative values, out-of-range records, or implausible observations. Missing observations, physically impossible values, and inconsistent records were not imputed before clustering; instead, they were excluded from the computation of country-level means. As a result, temporal aggregation was based only on valid observations, reducing the risk that data anomalies would distort the construction of long-run exposure–vulnerability profiles.

3.3. Unit of Analysis and Aggregation Rationale

For the present investigation, countries are used as the unit of analysis to develop a cross-national typology of exposure and vulnerability situations based on ESG scores [43,47]. This choice reflects the nature of the World Bank ESG database, which computes environmental, social, governance, and HI35 indicators at the country level. Using countries as the unit of analysis will enable cross-national comparisons and facilitate comparisons of institutional capacity, public service provision, environmental pressure, and national resilience within a unified metric system [44,45].

Analytically speaking, using countries as the unit of analysis is quite relevant for several reasons. Many of the ESG dimensions discussed above are defined primarily in terms of national policies and institutions. Thus, the quality of governance, institutional capacity, rights and freedoms, stability, research support, public healthcare systems, social provisions, and environmental management are largely national phenomena [43,45]. As a result, using a country as the unit of analysis enables researchers to identify exposures and vulnerabilities that are essential for national adaptation efforts and ESG assessments [44,47].

At the same time, this choice entails some limitations. First, each country exhibits some degree of heterogeneity, and using country averages as the unit of analysis may ignore relevant subnational variation. In particular, this problem becomes especially acute when it comes to very big and diverse countries like China, the US, India, and Brazil, where various climate zones exist alongside one another and where urbanization, infrastructure development, institutional capacity, social vulnerability, and climatic exposure may vary significantly across a single nation [44].

Thus, in this regard, the study's findings cannot be interpreted as a map of heat risks [44]. Instead, it is supposed to deliver a typology of countries according to their exposure–vulnerability relations [43,47]. While using a country as the unit of analysis may be appropriate for cross-national comparisons of national indicators of ESG and exposures, it is associated with aggregation problems that may mask subnational variation in exposure and vulnerability to heat. Future investigations will need to develop methods to measure the impacts of heat risk within metropolitan regions [44,45].

4. Empirical Framework and Methodological Rationale: Classifying ESG–Heat Exposure Vulnerability Profiles

This section presents the empirical framework used to construct the ESG–HI35 exposure–vulnerability taxonomy. The framework clarifies how climatic exposure and ESG-based vulnerability are analyzed together while remaining conceptually distinct. HI35 is treated as an exogenous climatic exposure indicator, not as a direct measure of vulnerability. ESG variables are used to describe environmental, social, and governance-related conditions associated with sensitivity, resilience, and adaptive capacity. The section also explains the clustering strategy and the boundary conditions for interpreting the resulting taxonomy. The clustering analysis is applied to the temporally aggregated country-level dataset described in previous sections. Therefore, the empirical framework does not model year-by-year variation, dynamic temporal relationships, or panel effects. Instead, it classifies countries according to their long-run average combinations of climatic exposure and ESG-based vulnerability conditions. No parametric regression models are estimated in this study. Accordingly, no variable is specified as dependent or independent in an econometric sense. HI35 is included in the clustering space as an exogenous climatic exposure indicator. ESG variables are included as descriptors of environmental, social, and governance-related vulnerability and adaptive-capacity conditions. The analysis is therefore entirely unsupervised and cluster-based.

4.1. Distinguishing Climatic Exposure from ESG-Based Vulnerability

The methodological framework is designed with a clear separation between climatic exposure and vulnerability. Specifically, the ESG approach is first broken down into its three essential pillars: Environment, Society, and Governance. This framework allows the identification of institutional, social, and environmental conditions associated with vulnerability and adaptability to high temperatures. According to the research conceptual framework, HI35 is neither a measure of vulnerability nor a vulnerability outcome. Indeed, HI35 is an external measure of climatic exposure, reflecting the number of days when apparent temperature exceeds 35 degrees centigrade [48,49].

Vulnerability is defined as the interaction between exposure, sensitivity, and adaptive capacity. As a result, ESG variables can help identify the institutional and structural factors that affect nations' vulnerability and adaptation to extreme heat. The methodological framework will include the definition of two levels of exposure: climatic exposure, represented by HI35 and determined primarily by geographical and atmospheric factors; and systemic vulnerability, which can be measured through various ESG variables, such as environmental pressures, social vulnerabilities, institutional quality, and governmental capacity. ESG indicators cannot be used as factors determining the existence of the HI35 phenomenon; nor can they be considered explanatory of its occurrence.

Secondly, the research will rely on different unsupervised clustering models to detect the emergence of configurations involving both HI35 and ESG. Specifically, a variety of models will be analyzed: Density-Based clustering, Fuzzy C-Means, Hierarchical clustering, Model-Based clustering, K-Means, and Random Forests Proximity clustering. Different measures will be used to evaluate model quality, including R^2, silhouette scores, the Calinski–Harabasz ratio, AIC, BIC, and entropy criteria. Given the unsupervised nature of clustering, models will be selected based on statistical performance, geographical spread, cluster balance, semantic meaning, and clarity of exposure–vulnerability regimes [50].

Thirdly, after technical classification, the taxonomy of exposure–vulnerability regimes will be established based on the identified clusters. Clusters will be interpreted as specific exposure–vulnerability regimes combining different features of exposure (HI35) and socio-institutional structures. In other words, the analysis will demonstrate that countries with the same climatic exposure can exhibit different vulnerabilities due to their environmental, social, and institutional conditions. Therefore, the regime taxonomy will not state the causal relationship between HI35 exposure and ESG structures, but will show how countries differ in terms of adaptive capacity.

The research methodology uses a descriptive, classificatory approach. Namely, this study will analyze the pattern of co-variation between HI35 and ESG indicators to classify countries into clusters. Such an approach will avoid any causal inference and treat HI35 as independent of ESG measures. ESG indicators will include resource depletion, population pressure, innovation capacity, institutional quality, and governance efficiency.

In conclusion, the methodology proposed in this paper provides a systematic approach to examining climatic exposure and systemic vulnerability. Specifically, the methodology explains that HI35 reflects exposure to heat, while ESG variables capture the environmental, social, and institutional structures that determine the extent to which nations may be vulnerable to extreme climate conditions.

4.2. Boundary Conditions and Scope of Applicability

This classification needs to be understood within clear boundary conditions. This is applicable to macro-level comparative analyses, such as comparing countries, benchmarking countries' sustainability, conducting international climate risk assessments, and assessing national adaptations to climate change, but not for local heat risk mapping [43,47]. The outcomes will depend on the selected indicators, the World Bank ESG dataset framework, the timespan, and the method used to perform the cluster analysis; using other datasets or geographical units could yield different vulnerability clusters [43,44]. The classification is only descriptive and used to categorize exposure–vulnerability clusters.

5. Clustering Framework and Empirical Results

Building on the exposure–vulnerability framework presented in Section 4, this section reports the clustering results for the Environmental, Social, and Governance dimensions. HI35 is used as the climatic exposure indicator, while ESG variables represent socio-institutional and environmental conditions related to sensitivity, resilience, and adaptive capacity. The analysis identifies groups of countries characterized by different combinations of heat exposure and ESG-based vulnerability. Since the indicators are temporally averaged at country level, the clusters should be interpreted as structural classifications rather than year-specific outcomes or temporal trajectories.

Three separate clustering analyses were conducted, one for each ESG pillar. In each case, countries were grouped according to their ESG characteristics and corresponding HI35 values. This strategy allows the identification of exposure–vulnerability configurations and comparison of countries that may experience similar climatic exposure but differ in environmental fragility, social sensitivity, health-related conditions, institutional quality, or governance capacity.

Six unsupervised clustering algorithms were applied to each ESG dimension: Density-Based, Fuzzy C-Means, Hierarchical, Model-Based, K-Means, and Random Forest proximity clustering [51–53]. Algorithm performance was evaluated through a multi-metric framework combining clustering quality, parsimony, and interpretability. R^2, Silhouette, and Calinski–Harabasz scores were maximized, while AIC, BIC, and entropy were minimized. All indicators were normalized using Min–Max scaling, with inversion applied to minimization metrics to ensure comparability.

Using multiple algorithms strengthens robustness by reducing method-specific bias, since different approaches rely on different assumptions about cluster shape, density, variance, and distance structure. However, model selection was not based mechanically on a single metric. The final choice combined statistical performance, cluster balance, substantive interpretability, and coherence with the exposure–vulnerability framework. Solutions with high internal validity but highly unbalanced clusters were not preferred, as they offered limited value for constructing an interpretable country taxonomy.

Although the same selection protocol was applied across all ESG pillars, the preferred algorithm may differ because each dataset has distinct statistical properties. The procedure therefore followed the same sequence: exclusion of degenerate solutions, comparison of normalized metrics, assessment of cluster-size balance through the HH index, and final evaluation of interpretability. Cluster means were computed using the original, non-standardized variables and are reported in their original scales. Additional diagnostics are provided in Appendices A–C.

6. Comparative Evaluation of Clustering Algorithms for the Environmental Dimension

The chosen clustering algorithm is K-Means, as it provides the best performance across all criteria, including balance between statistics, interpretation, parsimony, and cluster size [54,55]. Even though the best Silhouette of 0.84 can be reached in Density-Based clustering, along with high Pearson's γ and low entropy, the method fails to generate a solution that would be considered balanced. The number of clusters is large, yet nearly all observations cluster into one large cluster, with a few others containing only a few objects. As a result, the HH Index is very high (0.9734), with 16 noise points identified. Therefore, this method cannot be used for interpretative taxonomy [56,57]. Hierarchical clustering shows good results on some metrics (R^2, Silhouette, max diameter), but it is not balanced, as the observations mostly cluster into a single large cluster. As a result, the HH Index value is quite high—0.9149 [56,58]. At the same time, K-Means achieves the best R^2 (0.804), CH index, and the lowest AIC and BIC. The Silhouette is positive, and the HH Index equals 0.1881, meaning that the algorithm generates a more diverse cluster structure. See Table 3.

Table 3. Comparative Performance of Clustering Algorithms for the Environmental Dimension.

Statistics	Density Based	Fuzzy C-Means	Hierarchical	Model Based	K-Means	Random Forest
Maximum diameter	24.23	22.955	7.561	24.23	19.367	21.315
Minimum separation	1.201	0.007	0.583	0.003	0.023	0.011
Pearson's γ	0.853	0.121	0.766	0.216	0.283	0.185
Dunn index	0.05	3.233×10^{-4}	0.077	1.125×10^{-4}	0.001	5.039×10^{-4}
Entropy	0.129	2.129	0.26	1.6	1.861	1.908
Calinski-Harabasz index	574.997	87.921	469.363	268.74	852.534	388.528
Clusters	3	10	10	6	10	10
N	1876	1876	1876	1876	1876	1876
R^2	0.509	0.215	0.694	0.418	0.804	0.652
AIC	5811.19	10,693.3	4755.86	8824.26	3094.33	5379.33
BIC	5944.07	11,136.25	5198.81	9090.03	3537.28	5822.29
Silhouette	0.84	0.06	0.59	0.07	0.31	−0.11
Clusters	3	10	10	6	10	10
Size	1835; 11; 14	212; 355; 283; 72; 237;44; 112; 123; 344; 94	1794; 11; 4; 10; 4; 4; 14; 2; 30; 3	423; 444; 61; 590; 192; 166	225; 240; 388; 30; 4; 54; 574; 253; 52; 56	197; 779; 101; 45; 38; 157; 137; 151; 133; 138
Noise points	16					
HH Index	0.9734	0.1333	0.9149	0.2251	0.1881	0.2166

Note. The table compares six clustering algorithms using validity, fit, parsimony, and balance metrics. Although Density-Based clustering has the highest Silhouette, K-Means provides the best overall trade-off between explanatory power and cluster balance.

A total of ten different cluster configurations of environmental variables were identified through the analysis. All variables are reported using their original measurement scales. As such, HI35 refers to the average number of days per year when the temperature exceeds 35 °C, and the ESG variables refer to their own unit of [44,47]. Clusters 1 and 2 display low-to-medium profiles. In particular, Cluster 1 shows a negative NFD value and other environmental variables close to zero. Cluster 2 shows similar characteristics, with an increased NRD value and negative ME and N2O values. Cluster 3 is characterized by an intermediate profile, as indicated by positive NRD and NFD values and negative ME and N2O values [43,45]. Cluster 4 shows a highly unusual profile, characterized by very high values of HI35, EIN, EIL, FFEC, and ME and negative NFD and N2O values. The high structural density of this cluster is indicative of a high-intensity environment or productive structure, but it does not correlate with increased N2O emissions. In turn, Cluster 5 is primarily represented by HI35, which has the highest value in the dataset. Positive values are recorded for EIL and ME, while neither EIN nor FFEC is significantly increased [44,47]. Cluster 6 shows a very low NRD but high N2O, indicating a very critical environmental profile marked by a serious depletion of resources coupled with emissions stress [59,60]. In contrast, Cluster 7 appears better, with positive NRD and NFD and negative ME and N2O values. Cluster 8 combines positive NFD and EIL together with positive N2O. Cluster 9 features negative NFD, high ME, and N2O [46,61]. Finally, Cluster 10 is characterized by the highest EIL, with moderate values for the other variables. In summary, clusters 4, 5, and 6 seem the most extreme clusters, while clusters 3, 7, and 10 represent a relatively balanced cluster profile. See Table 4.

Table 4. Environmental Cluster Profiles Based on HI35 and ESG Indicators.

Cluster	HI35	NRD	NFD	EIN	EIL	FFEC	ME	N2O
1	−0.111	0.108	−1.655	−0.129	−0.248	−0.112	0.03	−0.078
2	−0.116	0.398	−0.65	−0.128	−0.279	−0.116	−0.211	−0.506
3	−0.116	0.34	0.116	−0.126	−0.211	−0.114	−0.222	−0.364
4	4.884	0.196	−2.136	7.752	4.725	6.967	6.913	−0.588
5	15.009	0.214	−2.223	0.106	1.219	−0.071	1.331	−0.589
6	−0.117	−4.108	−0.865	−0.129	0.183	−0.115	0.073	3.424
7	−0.115	0.429	0.786	−0.134	−0.218	−0.114	−0.228	−0.416
8	−0.112	−1.113	0.954	−0.106	0.419	−0.116	−0.213	1.074
9	−0.063	0.05	−1.887	−0.13	−0.192	−0.118	1.962	2.067
10	−0.08	−0.071	0.156	−0.133	1.378	−0.078	−0.06	−0.451

Note. The table reports mean values for the ten environmental clusters. HI35 measures heat exposure, while NRD, NFD, EIN, EIL, FFEC, ME, and N2O capture resource depletion, energy dependence, energy intensity, fossil-fuel use, and emissions.

Figure 2 reports the Silhouette plot associated with the Environmental K-Means clustering solution. The graph provides an assessment of cluster cohesion and separation by measuring the Silhouette coefficient for each observation across the ten identified environmental clusters. Positive Silhouette values indicate that observations are, on average, more similar to members of their own cluster than to observations belonging to neighboring clusters, thus supporting the internal consistency of the environmental taxonomy. See Figure 2.

Overall, the figure shows that the K-Means clustering provides an acceptable and rather consistent solution. In the majority of cases, Silhouette scores are positive and exceed zero. Furthermore, the average value across several clusters is close to, or even higher than, the global average Silhouette score (marked with a dashed red line). Thus, the results confirm that the selected environmental taxonomy captures relevant differences in the environmental exposure–vulnerability profile of countries worldwide. Moreover, there is considerable heterogeneity between different clusters. Specifically, Cluster 9 proves to be rather stable, given its large size and consistently positive Silhouette values. Therefore, one may state that such clustering is caused by a relatively large environmental regime characterized by environmental homogeneity. Clusters 4 and 5 demonstrate internal coherence as well, although their members exhibit highly adverse environmental characteristics, including high HI35, high energy intensity, reliance on fossil fuels, and methane emissions. However, their separation from the rest of the clusters further supports the presence of two distinct dimensions of environmental vulnerability: heat exposure and energy stress. On the other hand, the small clusters have negative or near-zero Silhouette scores, indicating that their borders overlap to some degree. As a consequence, some countries fall into the hybrid environmental regime category, as they share traits with both regimes. This tendency was expected because exposure to climate change, resource depletion, emissions intensity, and energy dependence develops differently across countries within the framework of the selected ESG-HI35 approach.

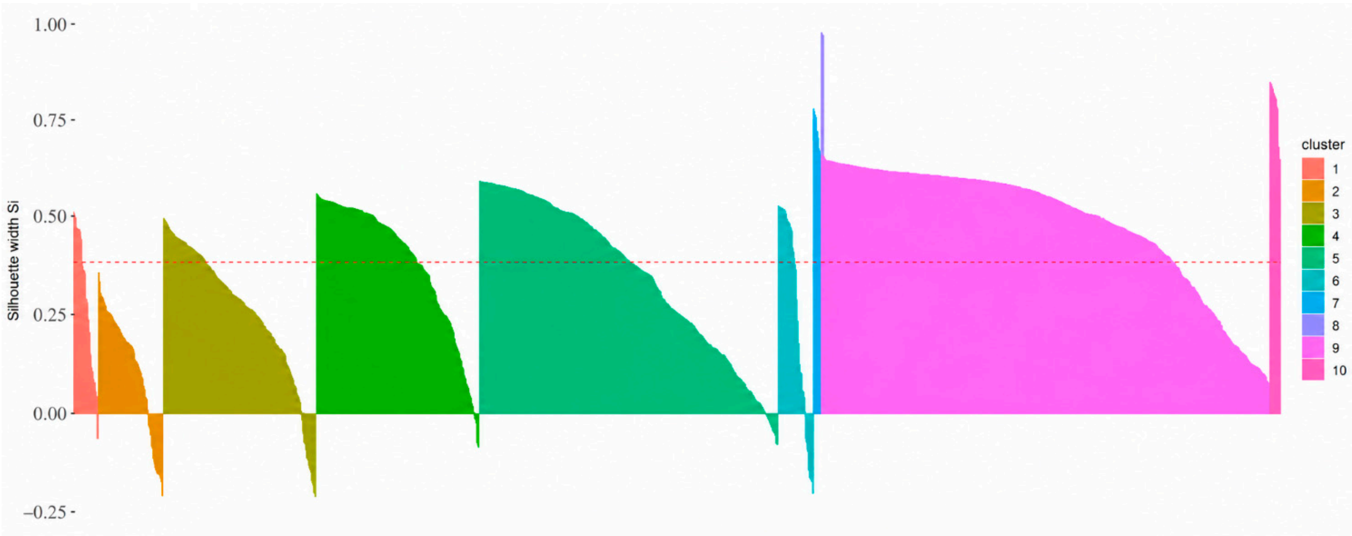

Figure 2. Silhouette plot for the Environmental K-Means clustering solution. Note. The figure reports silhouette coefficients for the Environmental K-Means clustering solution. The red dashed line indicates the average silhouette width across all observations and is used as a reference threshold for evaluating the overall quality of the clustering solution. Values above the red line indicate observations with stronger-than-average cluster cohesion and separation, while values below the line indicate weaker-than-average clustering fit. Positive values indicate acceptable cluster separation and cohesion, whereas negative values identify borderline observations with partially overlapping environmental vulnerability profiles.

The illustration in Figure 3 represents the outcomes of the environmental clustering for the ESG-HI35 scheme. There are three panels: Panel A provides model selection criteria. Panel B represents a two-dimensional cluster map, and Panel C illustrates cluster means of HI35, NRD, NFD, EIN, EIL, FFEC, ME, and N2O in their raw scale [44,47]. Thus, the reported values can be considered true means, as they were not transformed to z-scores. See Figure 3.

As shown in Panel A, alternative clustering solutions are evaluated using AIC, BIC, and WSS. The point denoted by red color shows that 10 clusters have the smallest BIC value. It is reasonable to assume that there is an optimal balance between explanatory power and simplicity, since BIC incorporates both [60,61].

From the analysis of Panel B, one can conclude that clusters overlap to some extent, but there are some clearly distinguishable regions. Clusters occupying central locations suggest common environment-related characteristics of countries or regions; those located peripherally may reflect specific configurations of the five aforementioned variables [43,45].

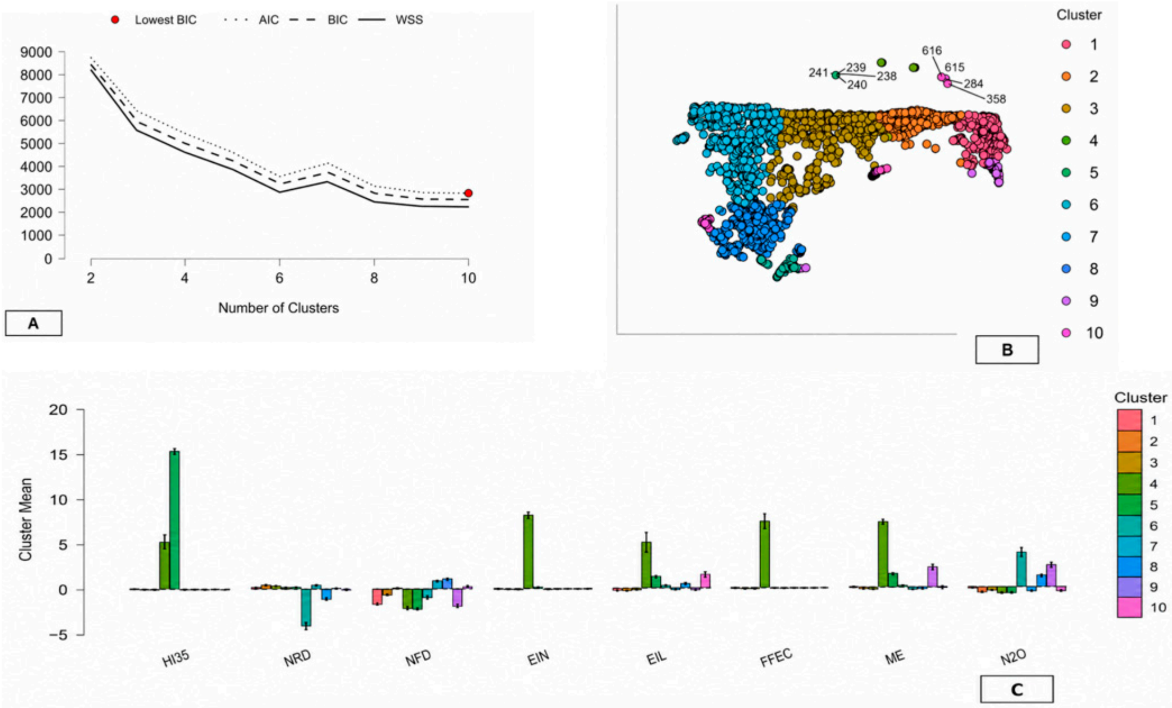

Figure 3. Environmental Clustering Results for the ESG–HI35 Framework. Note. The figure summarizes environmental clustering results: Panel (**A**) reports model selection criteria, Panel (**B**) shows cluster distribution, and Panel (**C**) presents cluster means for HI35, resource depletion, energy dependence, and emissions.

Panel C provides substantive interpretations of the findings. HI35 is the mean annual number of hot days when the air temperature exceeds 35 °C; all other indicators are explained in their native terms. The findings provide additional evidence that climatic exposure does not exhaust the concept of environmental vulnerability. Some clusters show high levels of HI35, while others are defined by indicators such as imports/consumption of energy or fossil fuel production/consumption, greenhouse gas emissions, etc. [59,60].

Thus, in conclusion, the illustrated results justify the use of the heterogeneous 10-cluster taxonomy and prove that climatic exposure and environmental pressure form separate but related constructs [43,44,47,61].

6.1. Sensitivity Analysis and Validation of Environmental Clusters

The sensitivity analysis uses a restricted sample to assess the robustness of the clustering results to structural missingness. The baseline dataset includes 185 countries over the period 1999–2023, while the robustness exercise excludes countries with complete absence of data for at least one variable in the ESG pillar analyzed. As a result, the sample decreases from 185 to 131 countries, excluding 54 cases. This restriction does not remove occasional missing observations, which are common in unbalanced panels, but only countries with structural data gaps. The procedure verifies whether the clustering results remain stable in a more information-complete dataset, thereby strengthening the methodological reliability of the ESG–HI35 taxonomy. This robustness check directly assesses whether structural missingness affects the stability and interpretability of the baseline clustering results. See Figure 4.

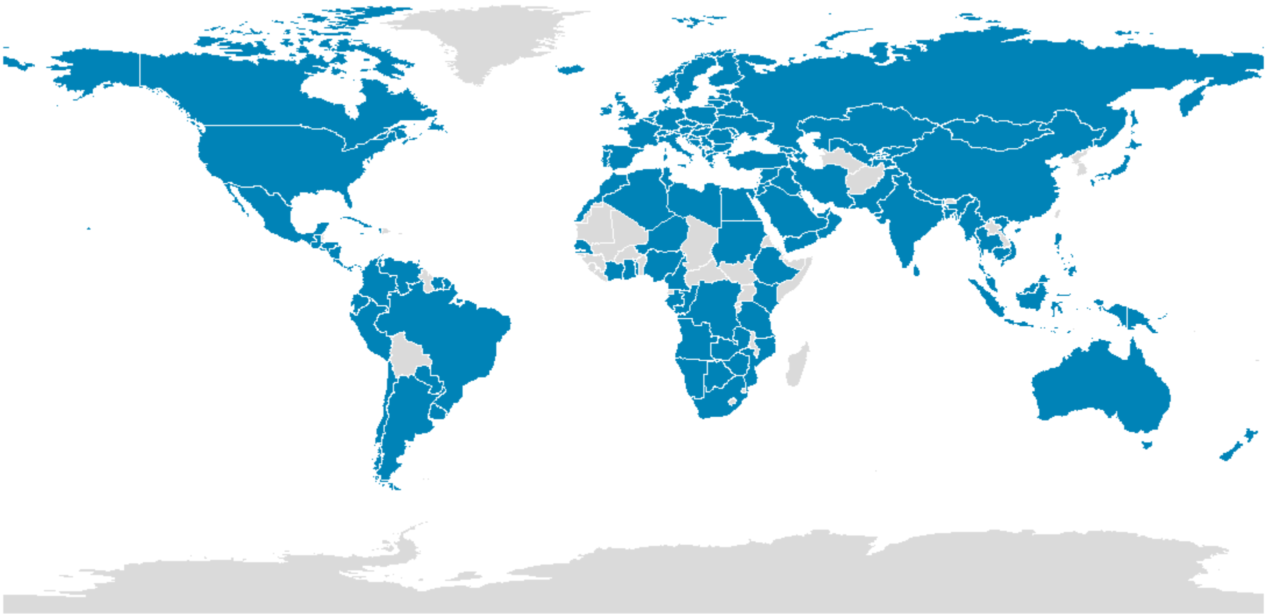

Figure 4. Geographic Distribution of the Restricted Sample Used in the Sensitivity Analysis. Note. Countries are Albania, Algeria, Angola, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahrain, Bangladesh, Barbados, Belarus, Belgium, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Cambodia, Cameroon, Canada, Chile, China, Colombia, Congo, Dem. Rep., Congo, Rep., Costa Rica, Cote d'Ivoire, Croatia, Cuba, Cyprus, Czechia, Denmark, Ecuador, Egypt, Arab Rep., El Salvador, Estonia, Ethiopia, Finland, France, Gabon, Georgia, Germany, Ghana, Greece, Guatemala, Haiti, Honduras, Hungary, Iceland, India, Indonesia, Iran, Islamic Rep., Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Kuwait, Kyrgyz Republic, Latvia, Lebanon, Libya, Lithuania, Luxembourg, Malaysia, Mauritius, Mexico, Moldova, Mongolia, Montenegro, Morocco, Mozambique, Myanmar, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, North Macedonia, Norway, Oman, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russian Federation, Saudi Arabia, Senegal, Serbia, Singapore, Slovak Republic, Slovenia, South Africa, Spain, Sri Lanka, Sudan, Suriname, Sweden, Switzerland, Syrian Arab Republic, Tajikistan, Tanzania, Thailand, Togo, Trinidad and Tobago, Tunisia, Turkiye, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Uzbekistan, Venezuela, RB, Viet Nam, Yemen, Rep., Zambia, and Zimbabwe.

The optimal clustering result was achieved by assessing its multidimensional properties, including validity, model fit, and even cluster sizes [55,56,58]. Although the best silhouette coefficient and the lowest entropy are offered by Density-Based Clustering, its results are significantly imbalanced. Most cases belong to the same cluster, which is shown by the high HH value of 0.9732. Excessive concentration leads to poor discrimination performance and low interpretability [56,57].

On the other hand, Neighborhood-Based Clustering demonstrates the best combination of the results. First, it shows the largest R^2 (0.835), indicating the best explanatory capacity among all methods. Second, it has the highest Calinski-Harabasz score (1172.505) and the lowest AIC (2595.07) and BIC (2993.11) values, thus indicating good separation, compactness, and parsimony [54,58].

Third, the HH of this method is rather low (0.2411). Its cluster concentration is lower than that of the Density-Based and Hierarchical models. While Model-Based and Fuzzy C-Means yield smaller HH values, their validity scores are poorer. In light of the aforementioned arguments, Neighborhood-Based Clustering can be recommended, as it ensures statistical validity, strong explanatory power, cluster balance, and interpretability [55,56]. See Table 5.

Table 5. Sensitivity Analysis of Environmental Clustering Algorithms.

Statistics	Density Based	Fuzzy C-Means	Hierarchical	Model-Based	Neighborhood-Based	Random Forest
Maximum diameter	24.141	19.99	7.539	21.262	19.99	21.262
Minimum separation	1.199	0.011	0.581	0.002	0.033	0.011
Pearson's γ	0.859	0.137	0.767	0.181	0.338	0.201
Dunn index	0.05	5.297×10^{-4}	0.077	9.782×10^{-5}	0.002	5.033×10^{-4}
Entropy	0.127	1.995	0.259	2.06	1.658	1.909
Calinski-Harabasz index	575.644	111.663	466.687	337.054	1172.505	412.969
Clusters	3	9	10	10	9	10
N	1860	1860	1860	1860	1860	1860
R^2	0.509	0.3	0.694	0.62	0.835	0.668
AIC	5768.79	10,174.98	4707.5	5793.93	2595.07	5102.44
BIC	5901.47	10,573.02	5149.77	6236.19	2993.11	5544.71
Silhouette	0.85	0.01	0.59	−0.12	0.38	−0.06
Clusters	3	9	10	10	9	10
Size	1820; 11; 14	179; 338; 208; 59; 146; 107; 516; 70; 237	1779; 11; 4; 10; 4; 3; 14; 2; 30; 3	248; 246; 296; 113; 190; 488; 37; 124; 66; 52	467; 700; 54; 220; 253; 20; 39; 93; 14	325; 712; 101; 45; 147; 37; 114; 152; 76; 151
Noise points	15	—	—	—	—	—
HH Index	0.9732	0.1599	0.9152	0.1504	0.2411	0.2059

Note. The table compares clustering algorithms under the restricted environmental sample. Neighborhood-Based clustering shows the best balance between explanatory power, information criteria, cluster distribution, and interpretability, despite Density-Based clustering achieving the highest Silhouette value.

From the analysis of these profiles, we can conclude that there is considerable heterogeneity regarding the correlation between extreme heat exposure and environmental issues. HI35 is not always positively correlated with other environmental indicators, which supports the understanding that exposures to heat, resource stress, energy dependency, and emissions intensity are independent dimensions of climate risk [44,47]. The profile of Cluster 5 is highly dominated by heat exposure because its HI35 level is at its peak, reaching the value of 14.947. None of the other variables reaches extreme values, except for energy intensity and methane emissions, which surpass the region average. Thus, one may assume that it is extreme-heat days that are the determining variable, and there is no imbalance within the environment. Adaptation should focus on improving heat and health safety, developing cooling solutions, providing access to drinking water, building robust infrastructure, and managing emergencies [43,44]. A somewhat worse situation can be observed in Cluster 3 where HI35 is accompanied by energy imports, fossil fuel use, methane emissions, and environmental pressure. Compound vulnerability emerges here because heat exposure is combined with energy dependency on carbon-based and fragile energy supplies. Thus, the adaptation strategy should be integrated into the energy transition process [47,54,61]. Likewise, Cluster 6 is characterized by relatively high pressure resulting mainly from energy dependency, energy intensity, fossil fuels, and methane emissions. Therefore, priority measures that should be taken in relation to Cluster 6 include improvements in energy efficiency, energy diversification, reductions in carbon intensity, and technological upgrades [40,61]. Clusters 1, 2, and 4 have moderate values, while Clusters 7, 8, 9, and 10 demonstrate rather focused vulnerabilities related to NRD, NFD, methane emissions, and energy intensity [54]. To sum up, high heat exposure does not correlate with the same environmental burden across countries. The findings provide further evidence for using differentiated approaches in addressing climate-related risks associated with heat, energy, emissions, and resource constraints [40,44,47]. See Table 6.

Table 6. Environmental Cluster Profiles under Sensitivity Analysis.

Cluster	HI35	NRD	NFD	EIN	EIL	FFEC	ME
1	−0.115	0.431	0.774	−0.134	−0.221	−0.115	−0.23
2	−0.116	0.389	−0.689	−0.129	−0.269	−0.116	−0.216
3	7.416	0.184	−2.292	8.705	0.575	9.939	6.066
4	−0.116	0.345	0.073	−0.127	−0.113	−0.111	−0.223
5	14.947	0.209	−2.216	0.105	1.221	−0.072	1.324
6	1.947	0.198	−1.944	6.59	9.472	3.506	7.819
7	−0.117	−4.104	−0.86	−0.13	0.185	−0.115	0.071
8	−0.112	−1.079	0.967	−0.108	0.485	−0.113	−0.213
9	−0.025	0.051	−2.03	−0.133	0.165	−0.117	2.359
10	−0.111	0.094	−1.646	−0.129	−0.246	−0.113	0.088

Note. The table reports the standardized mean values of environmental clusters in the restricted sample. HI35, resource depletion, energy dependence, fossil-fuel use, energy intensity, and methane emissions define distinct environmental vulnerability profiles.

Sensitivity analysis in relation to the E-Environment category shows that the environmental grouping structure remains stable for a subset of countries with higher data coverage [62,63]. As seen from Panel A, AIC, BIC, and WSS values decline as the number of clusters rises, achieving the lowest value of BIC for ten clusters. Hence, the optimal number of groups seems to be greater than two or three in a classification. This conclusion is supported by Panel B, which presents the distribution of observations in distinct geographical regions. Some overlap is expected because the model belongs to the ESG-environmental category, according to which some countries are similar regarding certain parameters but differ in others. Peripheral observations can help us identify some surprising combinations of HI35, energy dependence, forest loss, and emissions intensity [63,64]. Panel C provides the most essential interpretation. Standardized cluster means show that all ten clusters are characterized by the dominance of different environmental variables. While some groups have high HI35 levels, other groups are influenced mostly by the energy system and/or emissions. Thus, it cannot be stated that high heat exposure necessarily indicates environmental vulnerability [65,66]. All things considered, the sensitivity analysis demonstrates the reliability and interpretability of the proposed environmental taxonomic system. Environmental vulnerability is multivariate and determined by high heat exposure combined with resource depletion, forest loss, energy dependence, fossil fuel consumption, energy intensity, and greenhouse gas emissions [63,66,67]. See Figure 5.

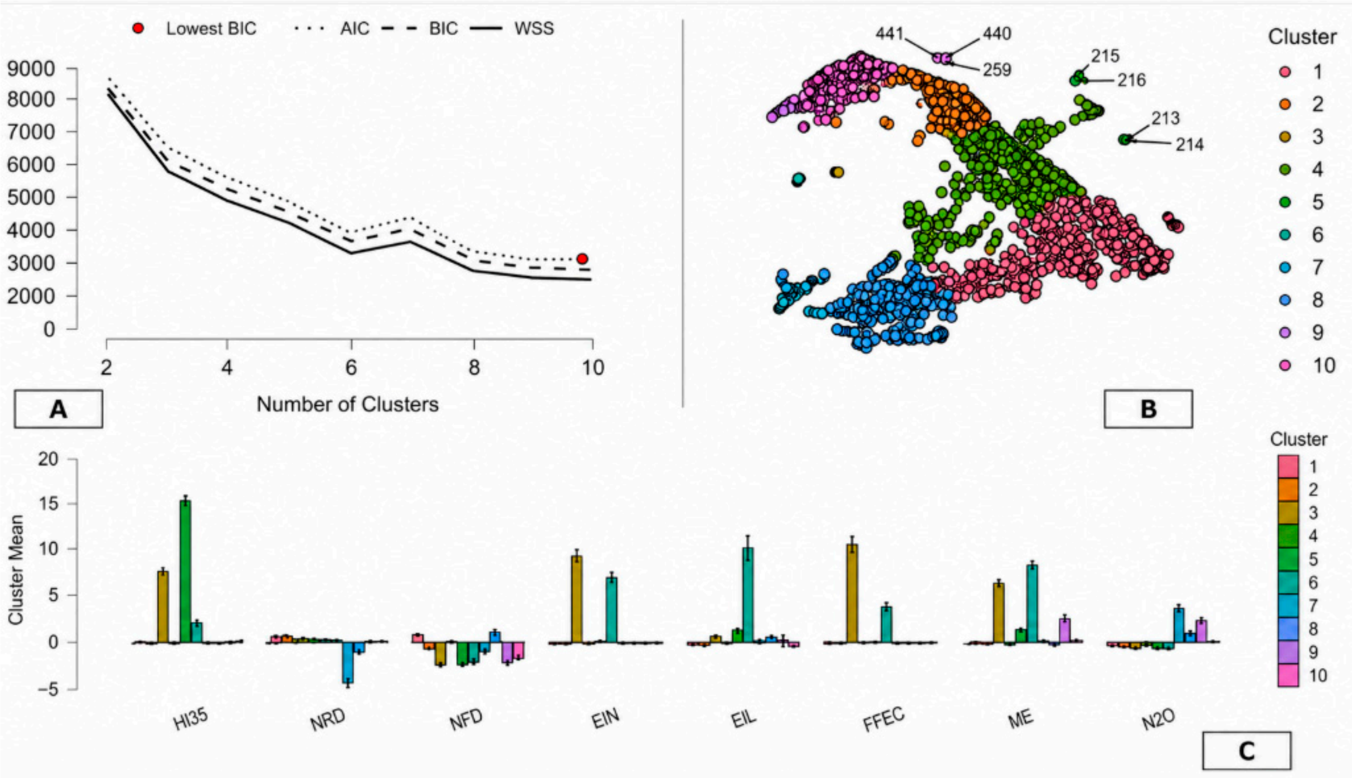

Figure 5. Sensitivity Analysis of Environmental Clustering Results under the Restricted ESG–HI35 Sample. Note. The figure summarizes the environmental sensitivity-analysis clustering results. Panel (**A**) reports AIC, BIC, and WSS values across alternative cluster solutions, where red points identify the minimum BIC and the preferred 10-cluster specification. Panel (**B**) illustrates cluster distribution, while Panel (**C**) presents standardized cluster means.

6.2. Comparison Between Baseline and Sensitivity Environmental Clustering Results

The comparison of the standard Environmental model with sensitivity analysis supports the validity of the ESG-HI35 taxonomy [68,69]. The standard model uses a larger sample size, including countries for which data are partially available, while the sensitivity analysis relies only on 131 countries with complete data on the E-Environment. Thus, the sensitivity analysis will test whether the taxonomy remains relevant even with structurally complete datasets. It appears that the clustering structure in the two cases is similar. In particular, the standard model suggests using K-Means because it offers the best trade-off between high explanatory power and balanced clusters. The sensitivity analysis results confirm the existence of 10 clusters using BIC. Thus, we can state that countries show various combinations of heat exposure, resource depletion, forest loss, energy dependence, energy intensity, fossil fuel use, and emissions [70]. From a statistical perspective, the result shows significant robustness as well. Specifically, the output of K-Means in the standard model shows R^2 = 0.804, AIC = 3094.33, BIC = 3537.28, and HH Index = 0.1881, indicating high explanatory power but no excessive clustering. Sensitivity analysis confirms that the reduced sample size still allows distinguishing clusters without reducing them to a single residual cluster [71,72]. Finally, substantively, both models highlight heat-dominated clusters and profiles with high energy or emission intensity. This result proves that HI35 constitutes an independent dimension of vulnerability and does not overlap with fossil fuel dependency and energy/emission intensity [68,73]. As a consequence, a multidimensional taxonomy of the environment is necessary, and it will require approaches such as heat adaptation, energy transition, and emission reduction [68–70,72]. See Table 7.

Table 7. Comparison between Baseline and Sensitivity Environmental Clustering Models.

Dimension of Comparison	Ordinary Environmental Model	Sensitivity-Analysis Environmental Model	Interpretation for the ESG–HI35 Framework	Policy and ESG Implications
Sample structure	Baseline country sample, including countries with partial data availability across the historical period.	Restricted sample of 131 countries, obtained by excluding countries with complete absence of information for at least one E-Environment variable.	The sensitivity model tests whether the environmental taxonomy is dependent on countries with structurally incomplete data.	If similar profiles emerge in both models, the ESG–HI35 classification is more reliable for international comparison and policy screening.
Preferred algorithm	K-Means is selected as the best compromise between explanatory power, information criteria, and cluster balance.	The sensitivity analysis identifies a structured multi-cluster solution, with the lowest BIC reached at 10 clusters.	Both models support an articulated taxonomy rather than a simplified binary classification of countries.	Environmental vulnerability should not be treated as a single homogeneous condition; differentiated policy responses are required.
Number of clusters	10 clusters in the preferred K-Means specification.	10 clusters according to the BIC-optimal sensitivity solution.	The persistence of a ten-cluster structure suggests that environmental heterogeneity remains visible after restricting the sample.	The robustness of the cluster structure strengthens the use of the taxonomy for ESG benchmarking and climate-risk classification.
Model fit and parsimony	K-Means reports the lowest AIC = 3094.33 and BIC = 3537.28 among the ordinary models, indicating strong parsimony.	Panel A shows decreasing AIC, BIC, and WSS, with the lowest BIC at 10 clusters.	Both models support the view that a relatively complex but parsimonious partition is necessary to capture the environmental structure of the data.	Policymakers should avoid overly aggregated classifications that obscure differences in exposure, energy dependence, and emissions intensity.
Explained variance	K-Means has the highest $R^2 = 0.804$, indicating strong explanatory capacity.	The figure confirms clear differentiation across cluster means, especially for HI35, EIN, EIL, FFEC, ME, and N2O.	The environmental clustering captures meaningful variation across countries rather than random statistical separation.	The taxonomy can support prioritization of countries according to dominant environmental pressures.
Cluster balance	K-Means has an HH Index = 0.1881, showing a relatively diversified distribution across clusters.	The sensitivity model visually preserves multiple identifiable groups and does not collapse into one dominant cluster.	Both results contrast with Density-Based and Hierarchical solutions, which are excessively concentrated in one large cluster.	Balanced clustering improves the operational usefulness of the taxonomy for ESG policy design, as it avoids classifying most countries into a single residual group.
Problem with alternative algorithms	Density-Based has high Silhouette but extreme concentration: HH Index = 0.9734 and cluster sizes 1835; 11; 14. Hierarchical also shows excessive concentration, with HH Index = 0.9149.	The sensitivity analysis confirms the need to assess interpretability and cluster structure, not only formal fit indices.	Strong separation metrics are insufficient when the resulting taxonomy lacks discriminatory capacity.	ESG classifications should not be based only on technical performance; they must also produce meaningful and usable country groups.
Heat-exposure profile	One cluster is dominated by HI35, with a standardized value of 15.009, while other environmental variables are less extreme.	The sensitivity analysis reproduces a heat-dominated cluster, with HI35 remaining the most distinctive variable in one group.	Heat exposure remains an autonomous dimension of environmental vulnerability and is not reducible to energy or emissions indicators.	Countries in heat-dominated clusters require direct adaptation measures: heat-health systems, cooling infrastructure, urban resilience, water security, and emergency planning.

Table 7. *Cont.*

Dimension of Comparison	Ordinary Environmental Model	Sensitivity-Analysis Environmental Model	Interpretation for the ESG–HI35 Framework	Policy and ESG Implications
Energy-dependence profile	Cluster 4 combines high HI35, EIN, EIL, FFEC, and ME, indicating a structurally energy-intensive and emissions-intensive configuration.	The sensitivity model similarly identifies a profile combining high HI35 with high EIN, FFEC, and ME.	This confirms the presence of compound environmental vulnerability, where climatic exposure coexists with fossil-fuel dependence and emissions pressure.	These countries require integrated adaptation–mitigation strategies, combining heat adaptation with energy transition and fossil-fuel reduction.
Energy-intensity profile	Cluster 10 is mainly characterized by high EIL = 1.378, while Cluster 4 also shows high energy intensity.	The sensitivity model identifies a cluster dominated by very high EIL, together with elevated energy and emissions indicators.	Energy intensity remains a stable discriminating factor across model specifications.	Policy priorities include energy-efficiency investments, technological upgrading, industrial modernization, and productivity-oriented decarbonization.
Emissions profile	Cluster 6 is defined by high N2O = 3.424, while Cluster 9 combines high ME = 1.962 and N2O = 2.067.	The sensitivity analysis confirms that emissions-related variables differentiate specific clusters independently from HI35.	Greenhouse-gas vulnerability is not always associated with the highest heat exposure.	Mitigation policies should be tailored to the dominant emissions source, including methane reduction, agricultural emissions control, and sector-specific decarbonization.
Resource and forest depletion	Several clusters are differentiated by NRD and NFD, including profiles with strongly negative NFD or selective forest-related pressures.	The sensitivity model also shows that NRD and NFD contribute to the differentiation of moderate and selective environmental profiles.	Resource depletion and forest depletion remain relevant but do not always coincide with heat or energy-related pressures.	ESG strategies should distinguish between climate adaptation, energy transition, and natural-capital preservation.
Interpretability of clusters	The ordinary model identifies heat-dominated, energy-intensive, emissions-intensive, and mixed environmental profiles.	The sensitivity analysis confirms the persistence of heterogeneous and interpretable environmental regimes.	The main substantive taxonomy remains stable after excluding countries with structurally incomplete data.	The classification can be used as a robust basis for ESG risk screening, climate-risk comparison, and differentiated policy intervention.
General conclusion	The ordinary model provides a strong and balanced environmental taxonomy, with K-Means as the preferred algorithm.	The sensitivity analysis supports the robustness of the taxonomy on a more information-complete sample.	The comparison shows that the results are not merely an artifact of missing-data patterns or sample composition.	The ESG–HI35 framework provides a credible basis for identifying country groups requiring different combinations of adaptation, mitigation, energy reform, and environmental protection.

Note. The table compares the ordinary and sensitivity-analysis environmental taxonomies. Results confirm the robustness of the ESG–HI35 framework, showing persistent heat, energy, emissions, and resource-depletion profiles across alternative samples and clustering specifications.

6.3. Robustness to Missingness and Imputation Choices

To further assess the potential impact of missingness and imputation choices on cluster stability, the analysis deliberately avoids imputing missing observations before clustering. This choice prevents artificially generated values from influencing distances between countries and altering cluster assignments. Instead, baseline country-level means are computed only from valid observations, while robustness is assessed through restricted-sample sensitivity analyses excluding countries with structural data gaps. The comparison between baseline and restricted-sample results shows that the main exposure–vulnerability patterns remain interpretable and broadly stable, suggesting that the proposed ESG–HI35 taxonomy is not primarily driven by missing-data structure. Nevertheless, because missingness is uneven across countries and indicators, the results should be interpreted as robust descriptive classifications rather than as exact partitions unaffected by data availability.

7. Comparative Evaluation of Clustering Algorithms for Social Indicators

Based on the results above, there appear to be unique cluster profiles for the environmental parameters. Since all values are presented in their natural units of measurement, HI35 indicates the average number of days with temperatures above 35 °C per year. The environmental stressors (ESG) parameters, on the other hand, are measured using their respective units [44,47]. Clusters 1 and 2 fall into the low-to-moderate profile category. More precisely, Cluster 1 appears to be dominated by a negative NFD value, whereas the remaining indicators show no significant departure from zero. Likewise, Cluster 2 features negative ME and N2O values, with a positive NRD, but smaller than those in Cluster 1. The third cluster depicts a mid-range profile, featuring positive NRD and NFD, along with negative ME and N2O values [40,43]. The fourth cluster stands out as the one having the most distinct characteristics, including relatively high values of HI35, EIN, EIL, FFEC, and ME, together with very low NFD and N2O. Cluster 5 can be characterized as one having a significantly high HI35, coupled with relatively high EIL and ME but not EIN and FFEC [44,47]. On the other hand, Cluster 6 features extremely low NRD and high N2O, indicating a very crucial case [54,61]. The seventh cluster indicates more favorable conditions, characterized by positive NRD and NFD, and negative ME and N2O. Cluster 8 captures an ambiguous situation, whereas Cluster 9 includes a negative NFD value alongside very high ME and N2O values [41]. Lastly, Cluster 10 is marked by EIL. It is imperative to note that Clusters 4, 5, and 6 constitute critical instances. See Table 8.

Table 8. Comparative Performance of Clustering Algorithms for the Social Dimension.

Algorithm	Density Based	Fuzzy C-Means	Hierarchical	Model Based	K-Means	Random Forest
Maximum diameter	8.659 (0.855)	40.102 (0.000)	3.848 (0.986)	6.838 (0.905)	3.341 (1.000)	39.060 (0.028)
Minimum separation	37.726 (1.000)	0.003 (0.000)	0.104 (0.003)	0.016 (0.000)	0.011 (0.000)	3.437×10^{-4} (0.000)
Pearson's γ	0.625 (1.000)	0.275 (0.284)	0.578 (0.904)	0.493 (0.730)	0.444 (0.630)	0.136 (0.000)
Dunn index	4.357 (1.000)	6.283×10^{-5} (0.000)	0.027 (0.006)	0.002 (0.000)	0.003 (0.001)	8.799×10^{-6} (0.000)
Entropy	0.004 (1.000)	2.099 (0.000)	1.298 (0.382)	1.591 (0.242)	1.856 (0.116)	1.989 (0.053)
Calinski-Harabasz index	491.341 (0.144)	539.122 (0.166)	1718.704 (0.718)	890.861 (0.330)	2319.401 (1.000)	184.365 (0.000)
HHI	0.999 (0.000)	0.130 (1.000)	0.366 (0.729)	0.313 (0.789)	0.198 (0.922)	0.176 (0.947)
No. clusters	1	9	9	9	10	10
Cluster sizes	2094	206, 83, 394, 317, 184, 248, 262, 313, 88	213, 564, 1110, 31, 83, 42, 11, 1, 40	120, 106, 1106, 137, 141, 123, 111, 250, 1	81, 282, 1, 379, 71, 214, 736, 126, 181, 24	230, 682, 384, 216, 152, 88, 47, 96, 69, 131

Note. The table compares clustering algorithms for Social indicators using normalized validity, separation, entropy, and balance measures. K-Means and Random Forest provide more interpretable cluster structures than highly concentrated Density-Based alternatives.

Figure 6 reports the Silhouette plot associated with the Random Forest clustering solution for the Social dimension of the ESG–HI35 framework. The figure evaluates the internal consistency and separation of the ten identified social clusters by displaying the Silhouette coefficient for each observation. Positive values indicate that observations are more similar to members of their own cluster than to neighboring clusters, whereas negative values suggest partial overlap or ambiguous classification. See Figure 6.

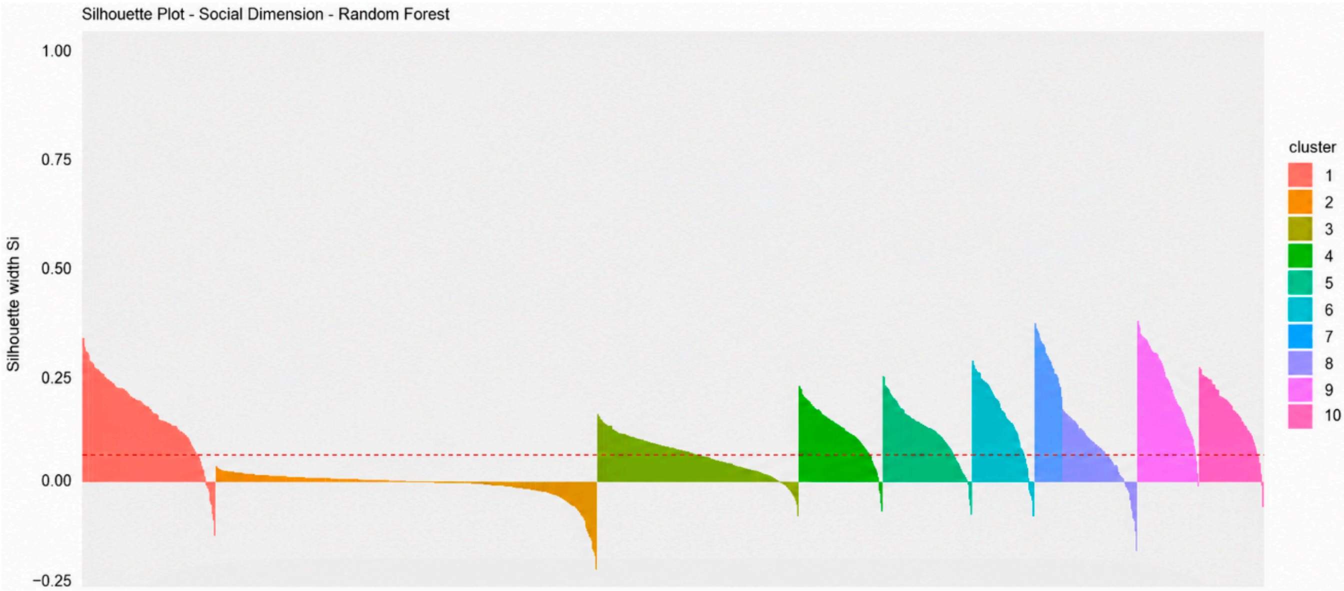

Figure 6. Silhouette Plot for the Social Random Forest Clustering Solution. Note. The figure reports silhouette coefficients for the Random Forest social clustering model. The red dotted line represents the average silhouette width across all observations and serves as a reference threshold for assessing the overall quality of the clustering solution. Positive values indicate acceptable cohesion and separation, while negative coefficients identify partially overlapping or intermediate social exposure–vulnerability profiles across countries.

All in all, based on the Silhouette analysis, it can be noted that there is greater heterogeneity in the Social clustering structure than in the Environmental one. It is worth noting that several clusters have low mean Silhouette values close to zero, indicating that the observed social vulnerability profiles largely overlap across countries. This conclusion corroborates the multivariate character of social vulnerability, as factors such as demographic pressure, water access, undernourishment, and climatic exposure can interact in different combinations and forms. For instance, Clusters 1, 7, 9, and 10 have comparatively high consistency, as many observations in these clusters have positive coefficients above the dashed red line. Specifically, Cluster 7 could be considered particularly coherent, as it represents a profile with strong cohesion and a high separation degree, associated with very high HI35 values, along with access to safely managed drinking water and minimal undernourishment. At the same time, Cluster 10 shows positive Silhouette coefficients even with a more complex combination of high fertility rates and heat exposure. On the contrary, Clusters 2 and 3 imply a significant number of observations with low Silhouette coefficients, close to zero or even negative, indicating that countries in them share intermediate social characteristics and can overlap with adjacent clusters. This is reasonable, since social vulnerability and resilience usually develop gradually without any clearly defined regimes. As shown in the figure, the distribution of cluster sizes varies significantly; both large and small clusters exhibit high and low cohesion. Consequently, it can be concluded that regimes of social exposure–vulnerability are unevenly distributed across countries. Based on the performed Silhouette analysis, the Random Forest clustering solution is shown to be interpretable and stable.

Social clustering profiles standardized after Random Forest modeling are presented in the table. The chosen modeling method is characterized by its balance and interpretability. The social cluster models consider such variables as HI35 as a climatic exposure indicator and FR, PUSM, and POU as social vulnerability indicators. With standardization taken into account, positive scores indicate values above average, whereas negative scores indicate values below average. In other words, the clusters present profiles in terms of relative vulnerability to climate change as a function of exposure and social capacity [74]. Clusters 1 and 7 stand for profiles with high exposure and resilience. Specifically, in Cluster 1, high HI35 coexists with very high PUSM and very low POU, indicating high heat exposure and adequate basic service provision and nutrition [75,76]. In turn, Cluster 7 shows an extreme situation in which both HI35 and PUSM have the highest values, and POU has the lowest, indicating extreme heat exposure and relatively high social capacity [74]. Conversely, Clusters 4, 5, 6, 8, and 9 feature below-average HI35, along with below-average PUSM and above-average POU, indicating that low heat exposure may be accompanied by social vulnerability [75,77]. Clusters 2 and 3 demonstrate a combination of values near the average. Moreover, Cluster 10 stands out with above-average HI35 and fertility rates, suggesting a demographic burden on service provision [78]. In general, HI35 and social vulnerability indicators do not correlate with movement [74,76]. See Table 9.

Table 9. Social Cluster Profiles Based on HI35 and Vulnerability Indicators.

Cluster	HI35	FR	PUSM	POU
1	0.875	−0.183	1.676	−1.536
2	−0.139	−0.072	−0.127	0.192
3	−0.076	0.288	0.054	−0.387
4	−0.471	−0.378	−0.716	0.737
5	−0.417	−0.378	−0.716	1.048
6	−0.492	−0.378	−0.716	1.119
7	1.936	−0.378	1.684	−1.793
8	−0.293	−0.378	−0.716	0.976
9	−0.379	−0.378	−0.716	1.128
10	0.721	1.775	0.350	−1.019

Note. The table reports standardized Social cluster profiles from the Random Forest model. HI35 captures heat exposure, while fertility, water access, and undernourishment identify distinct social vulnerability and resilience configurations across countries.

The Mean Decrease in Gini Index measures the importance of the variables for clustering. The larger values correspond to greater importance of the variables in distinguishing the clusters created from the random forest algorithm. The variable that comes out on top of the list is PUSM, with a value of 703.491, indicating that the presence of safe drinking water is the most important determinant for the clusters. FR takes second place with a value of 614.094, meaning that the fertility rate is an important variable in distinguishing demographic pressure clusters. See Table 10.

The diagram shows results from Random Forest clusters regarding Social dimensions. According to panel A, the value of AIC, BIC, and WSS decreases with the increase in the number of clusters, and the value of BIC reaches its minimum point at ten clusters, thus indicating the point at which there is an ideal trade-off between goodness of fit and complexity of the model. Panel B illustrates the clusters in two dimensions, distributed in a curved pattern, with gradual rather than clear-cut differences among them. See Figure 7.

Table 10. Variable Importance in the Random Forest Social Clustering Model.

	PUSM	FR	POU	HI35
Mean decrease in Gini Index	703.491	614.094	480.401	221.003

Note. The table reports Mean Decrease in Gini values for Social clustering variables. PUSM and fertility rate contribute most to cluster separation, while HI35 plays a smaller but still relevant discriminating role.

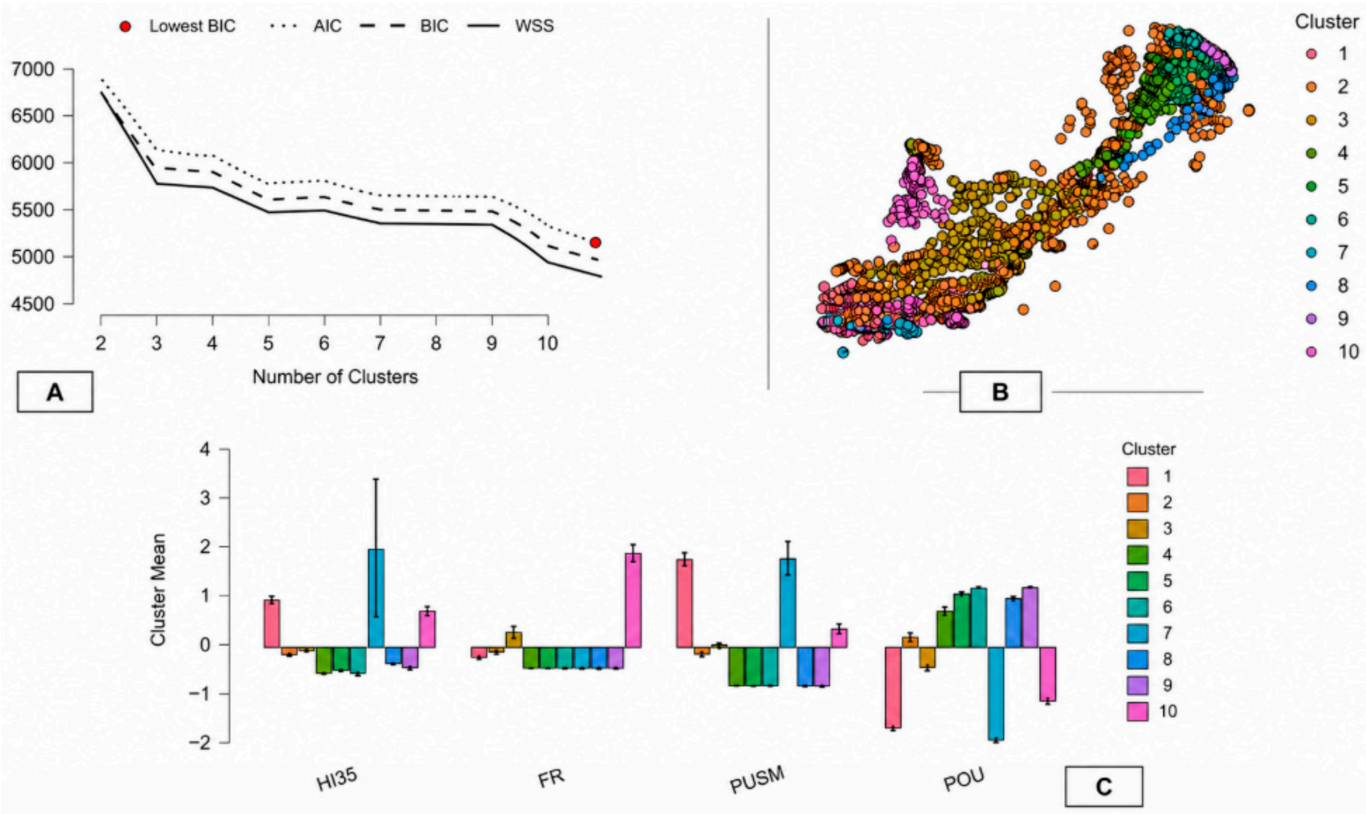

Figure 7. Social Clustering Results for the ESG–HI35 Framework. Note. The figure summarizes Random Forest social clustering results. Panel (**A**) reports AIC, BIC, and WSS values across alternative cluster solutions, where red points identify the minimum BIC and the preferred 10-cluster specification. Panel (**B**) shows cluster distribution, while Panel (**C**) presents standardized cluster means for HI35, fertility, water access, and undernourishment.

7.1. Sensitivity Analysis of Social Exposure–Vulnerability Clusters

A sensitivity analysis was conducted to test the robustness of the Social clustering results under substantial missing data. Since some Social variables had limited empirical coverage, the analysis was repeated on a re-duced sample, excluding countries with completely missing information for HI35, fertility rate, access to safely managed drinking water, or undernourishment. This conservative approach reduces the influence of poorly supported country profiles. The aim is not to replace the main specification, but to verify whether the Social taxonomy remains statistically meaningful and interpretable under stricter data conditions. The analysis compares algorithms using validity metrics, cluster sizes, and the HHI. See Figure 8.

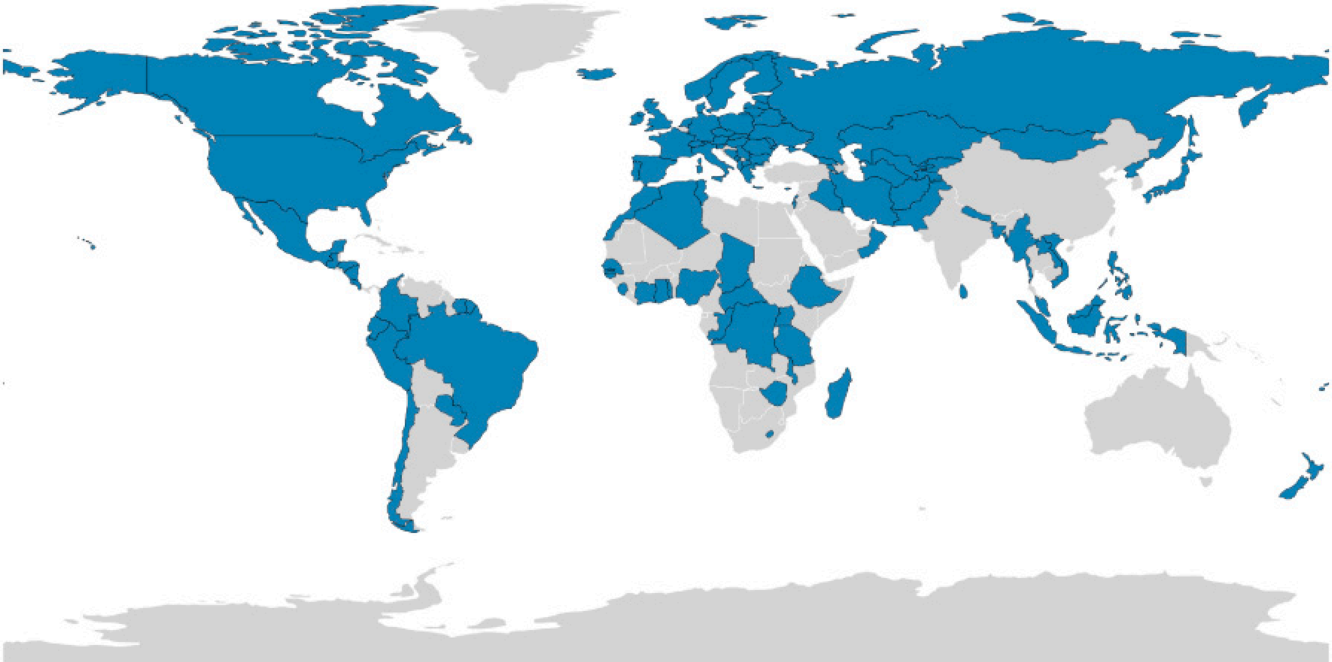

Figure 8. Geographic Distribution of the Restricted Sample for Social Sensitivity Analysis. The colored countries are those that were used for the analysis carried out. Note. Countries are: Afghanistan; Albania; Algeria; Armenia; Austria; Bangladesh; Belarus; Bosnia and Herzegovina; Brazil; Bulgaria; Canada; Central African Republic; Chad; Chile; Colombia; Congo, Dem. Rep.; Congo, Rep.; Costa Rica; Cote d'Ivoire; Cyprus; Czechia; Denmark; Ecuador; Estonia; Ethiopia; Fiji; Finland; France; Gambia, The; Georgia; Germany; Ghana; Greece; Guatemala; Guinea-Bissau; Honduras; Hungary; Iceland; Indonesia; Iran, Islamic Rep.; Iraq; Ireland; Israel; Italy; Japan; Kazakhstan; Kiribati; Korea, Dem. People's Rep.; Kuwait; Kyrgyz Republic; Lao PDR; Latvia; Lesotho; Lithuania; Luxembourg; Madagascar; Malawi; Malaysia; Malta; Mexico; Moldova; Mongolia; Montenegro; Morocco; Myanmar; Nepal; Netherlands; New Zealand; Nicaragua; Nigeria; North Macedonia; Norway; Oman; Pakistan; Paraguay; Peru; Philippines; Poland; Portugal; Romania; Russian Federation; Samoa; Sao Tome and Principe; Senegal; Serbia; Sierra Leone; Slovak Republic; Slovenia; Spain; Sri Lanka; Suriname; Sweden; Switzerland; Tajikistan; Tanzania; Togo; Tunisia; Turkmenistan; Uganda; Ukraine; United Kingdom; United States; Uzbekistan; Viet Nam; Zimbabwe.

From the comparison of clustering techniques, it can be concluded that a single statistical parameter alone will not allow the identification of the optimal solution. A reliable clustering solution should be characterized by compactness, separation, explanatory power, information criteria, and balanced cluster membership [79–81].

The hierarchical clustering performs well according to the internal validity criteria. For instance, it shows the best maximum diameter, the lowest separation, Pearson's γ, Dunn index, entropy, and the highest Silhouette value, which equals 0.490. Therefore, the solution involves compact, well-separated clusters [80,81]. Nevertheless, it is highly unbalanced since only one cluster accounts for 1452 observations out of 2087. Hence, its Herfindahl–Hirschman Index equals 0.5020, the highest among the compared algorithms, indicating excess concentration [82,83].

Conversely, K-Means provides a balanced solution and shows a combination of the highest parameters. Specifically, this technique yields the highest Calinski-Harabasz value, the highest R^2 (0.885), and the best AIC and BIC values. They speak of high explanatory power and efficiency. Additionally, its Silhouette value is relatively high at 0.390. Finally, the Herfindahl–Hirschman Index equals 0.1871, which is lower than for hierarchical clustering [79,83]. See Table 11.

Table 11. Sensitivity Analysis of Social Clustering Algorithms.

Statistics	Fuzzy C-Means	Hierarchical	Random Forest	Model Based	K-Means
Number of clusters	9	10	8	10	10
Cluster numerosity	51; 688; 140; 598; 265; 32; 74; 63; 176	120; 210; 82; 1452; 31; 48; 11; 93; 31; 9	117; 220; 810; 240; 93; 101; 270; 47; 117; 72	196; 127; 285; 96; 181; 539; 150; 100; 413	142; 101; 78; 118; 194; 221; 61; 85; 348; 739
HHI	0.2215	0.5020	0.2040	0.1541	0.1871
Maximum diameter	6.478 (0.360)	3.400 (1.000)	8.165 (0.010)	4.645 (0.741)	8.212 (0.000)
Minimum separation	0.007 (0.048)	0.126 (1.000)	0.008 (0.056)	0.036 (0.280)	0.001 (0.000)
Pearson's γ	0.487 (0.516)	0.779 (1.000)	0.269 (0.154)	0.550 (0.620)	0.176 (0.000)
Dunn index	0.001 (0.024)	0.037 (1.000)	9.278×10^{-4} (0.022)	0.008 (0.213)	1.296×10^{-4} (0.000)
Entropy	1.755 (0.274)	1.176 (1.000)	1.899 (0.093)	1.973 (0.000)	1.928 (0.056)
Calinski-Harabasz index	977.641 (0.468)	836.791 (0.375)	452.744 (0.121)	1781.660 (1.000)	269.578 (0.000)
R^2	0.792 (0.731)	0.784 (0.708)	0.601 (0.179)	0.885 (1.000)	0.539 (0.000)
AIC	1823.550 (0.728)	1883.730 (0.707)	3369.350 (0.193)	1036.850 (1.000)	3928.480 (0.000)
BIC	2026.720 (0.736)	2109.470 (0.707)	3549.940 (0.209)	1262.590 (1.000)	4154.220 (0.000)
Silhouette	0.170 (0.448)	0.490 (1.000)	0.020 (0.190)	0.390 (0.828)	−0.090 (0.000)

Note. The table compares Social clustering algorithms under restricted data conditions. K-Means offers strong explanatory power, favorable information criteria, acceptable balance, and interpretable cluster membership.

The table shows the social profiles generated using K-Means clustering. These include HI35, fertility rate (FR), access to safely managed drinking water (PUSM), and prevalence of undernourishment (POU). Any positive value indicates an above-average level, while a negative value indicates a below-average level. Thus, the clusters depict relative exposure–vulnerability profiles and not actual situations in a given country [74]. Cluster 4 represents the clear case of an exposure-resilient cluster. This has the highest HI35 value (2.267) alongside very high PUSM and the lowest POU value. Although there is high heat exposure, the condition regarding access to safe water and nutrition is better than in other countries [75,76]. Cluster 5 represents a situation that is somewhat similar but not extreme. On the other hand, Cluster 8 shows a high HI35 value combined with a very high fertility rate, suggesting greater pressure in the future [74,78]. Clusters 1 and 2 represent more moderate yet resilient clusters that feature average or moderate HI35 levels, good water access, and below-average POU values. Cluster 6 features a mixed profile with positive but weak access to water. Cluster 3 depicts the combination of low exposure with higher fertility levels [77]. The two socially fragile clusters include Clusters 9 and 10. These two represent a below-average HI35 level alongside poor water supply and higher undernourishment. Cluster 10 is important because it features the lowest HI35 value and the highest POU and PUSM. Thus, this highlights that social fragility and maximum exposure are unrelated [75,77]. See Table 12.

Table 12. Social Cluster Profiles under Sensitivity Analysis.

Cluster	HI35	FR	PUSM	POU
1	0.012	−0.221	0.788	−0.492
2	0.393	−0.303	2.335	−0.810
3	−0.150	0.815	−0.367	−0.236
4	2.267	−0.189	2.297	−1.751

Table 12. *Cont.*

Cluster	HI35	FR	PUSM	POU
5	1.581	−0.128	0.729	−1.470
6	0.159	−0.233	−0.237	−0.750
7	−0.053	4.388	−0.205	0.461
8	1.318	2.322	0.485	−0.848
9	−0.560	−0.326	−0.571	0.360
10	−0.748	−0.345	−0.689	1.010

Figure 9 summarizes the results of the sensitivity analysis of the S-Social component obtained using K-Means clustering. The figure shows the K-Means clustering results for the Social component using a reduced sample, excluding countries with completely missing values.

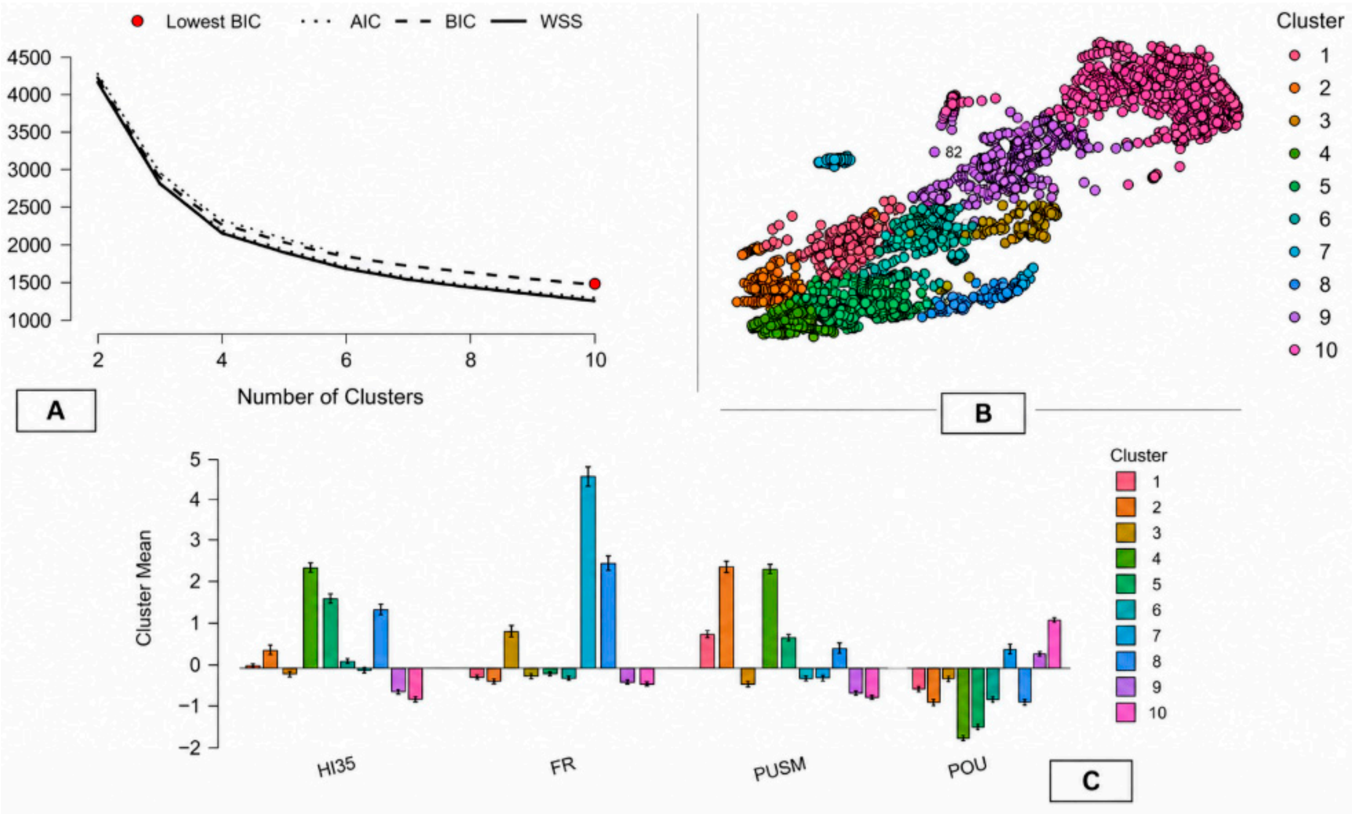

Figure 9. Sensitivity Analysis of Social K-Means Clustering Results. Note. The figure summarizes the Social sensitivity-analysis results. Panel (**A**) reports AIC, BIC, and WSS across alternative cluster solutions; the red point identifies the minimum BIC, supporting the preferred 10-cluster specification. Panel (**B**) shows the spatial distribution of observations according to the Social K-Means clustering solution, with colors indicating cluster membership. Panel (**C**) reports the mean values of the social indicators for each cluster, allowing comparison of the cluster profiles across HI35, FR, PUSM, and POU.

It combines cluster-number selection, two-dimensional visualization, and interpretation of social profiles. Figure 9A shows WSS, AIC, and BIC across alternative cluster numbers. The curves decline between 2 and 4 clusters sharply, then more gradually. The lowest BIC is reached at 10 clusters, supporting a detailed social exposure–vulnerability taxonomy. Figure 9B displays the observations in reduced-dimensional space. Several groups are reasonably separated, although some overlap remains, as expected with heterogeneous social and climatic indicators. This suggests that K-Means identifies meaningful differentiated profiles rather than artificial partitions [78,84]. Figure 9C shows standardized means for HI35, FR, PUSM, and POU. The results confirm that high heat exposure may coexist with favorable social conditions, while lower HI35 may coexist with higher social fragility [77,84,85].

7.2. Robustness Assessment of Social Clustering Models Within the ESG–HI35 Framework

The comparison of the standard and sensitivity analysis versions of the S-Social models provides a robustness check for the Social model component of the framework ESG-HI35 [74,75]. While the standard model applies to the entire database, regardless of partial data availability, the sensitivity analysis considers only those countries where all HI35, fertility rate, access to safely managed drinking water, and undernourishment data are available. Such an exclusion test whether the taxonomy of the ESG-HI35 framework would hold under structurally incomplete data. A notable change concerns the algorithmic preference, which switches from the Random Forest approach in the standard model to K-Means in the sensitivity analysis model. Such a shift does not undermine the results, as it shows that algorithmic preference depends on data and structure, not on the underlying categorization itself. In this regard, either version of the model represents a compromise between the algorithm's ability to provide explanations, generate quality clusters, and allow for interpretation. The primary result that stands out in both models is the maintenance of the ten clusters' pattern. It means that social vulnerability to heat is multifaceted and cannot be characterized as vulnerable or non-vulnerable. Interactions among HI35, water access, and undernourishment lead to different types of vulnerability [74,86]. Substantively, both models identify similar groups of countries. Thus, some of the identified clusters have high HI35 with strong water access and low levels of undernourishment, meaning resilience against climatic conditions despite high levels of vulnerability, while others have low HI35 but poor water access and high levels of undernourishment, demonstrating that social vulnerability persists irrespective of climatic vulnerability [77,87]. See Table 13.

Table 13. Comparison between Baseline and Sensitivity Social Clustering Models.

Dimension of Comparison	Ordinary S-Social Model	Sensitivity-Analysis S-Social Model	Interpretation for the ESG–HI35 Framework	Policy and ESG Implications
Sample structure	Full Social-component dataset, including countries with partial data availability across the historical period.	Reduced sample obtained by excluding countries with completely missing values for HI35, FR, PUSM, or POU.	The sensitivity analysis tests whether the Social taxonomy is affected by structurally incomplete information.	If similar social profiles persist, the classification is more reliable for ESG-based vulnerability screening.
Preferred algorithm	Random Forest is selected because it offers the best compromise between cluster balance, interpretability, and avoidance of single-observation clusters.	K-Means is selected because it combines strong explanatory power, favorable information criteria, acceptable Silhouette, and reasonable cluster balance.	The preferred algorithm changes, but both models prioritize interpretability and balanced classification rather than a single technical metric.	Model choice should reflect the objective of producing meaningful exposure–vulnerability profiles, not only maximizing statistical scores.
Number of clusters	10 clusters in the Random Forest solution.	10 clusters in the K-Means sensitivity solution, supported by the lowest BIC.	The persistence of a 10-cluster structure indicates that the Social component contains heterogeneous vulnerability regimes.	Social vulnerability should not be reduced to a binary distinction between vulnerable and non-vulnerable countries.

Table 13. *Cont.*

Dimension of Comparison	Ordinary S-Social Model	Sensitivity-Analysis S-Social Model	Interpretation for the ESG–HI35 Framework	Policy and ESG Implications
Cluster balance	Random Forest produces clusters ranging from 47 to 682 observations, with HHI = 0.176, avoiding both single-observation clusters and one dominant cluster.	K-Means produces a more concentrated but still acceptable distribution, with HHI = 0.1871 and cluster sizes ranging from 61 to 739 observations.	Both solutions provide relatively balanced classifications compared with Density-Based or Hierarchical alternatives.	Balanced clusters improve the operational usefulness of the taxonomy for targeting social adaptation policies.
Problem with alternative algorithms	Density-Based collapses the sample into one dominant cluster of 2094 observations, with HHI = 0.999. Hierarchical and Model-Based also produce dominant clusters or single-observation groups.	Hierarchical performs strongly on compactness and separation but is highly concentrated, with one cluster of 1452 observations and HHI = 0.5020.	Good internal validity metrics are insufficient when cluster numerosity is too imbalanced for meaningful interpretation.	ESG classifications must avoid technically strong but substantively weak solutions that fail to distinguish social vulnerability profiles.
Model fit and explanatory capacity	Random Forest is not the strongest on classical statistical indicators, but it provides the most usable taxonomy in the full-sample model.	K-Means performs strongly in the reduced sample, with high explanatory capacity and favorable model-selection criteria.	The sensitivity model shows that, under stricter data availability, a more conventional partitioning method can produce a robust Social taxonomy.	The Social taxonomy remains useful even when the empirical sample is restricted to countries with stronger data coverage.
Key discriminating variables	Mean Decrease in Gini shows that PUSM is the most important variable, followed by FR, POU, and HI35.	The K-Means profiles also show strong differentiation through PUSM, POU, and FR, while HI35 separates high-exposure groups.	Social vulnerability is driven more by access to safe water, demographic pressure, and undernourishment than by heat exposure alone.	Social adaptation policies should prioritize basic services, water security, nutrition, and demographic-pressure management.
High heat–high social capacity profile	Clusters 1 and 7 combine high HI35 with strong PUSM and very low POU. Cluster 7 has HI35 = 1.936, PUSM = 1.684, and POU = −1.793.	Clusters 4 and 5 show similar profiles. Cluster 4 has HI35 = 2.267, PUSM = 2.297, and POU = −1.751.	Both models show that high heat exposure does not necessarily imply high social vulnerability.	Countries in this profile require heat adaptation, but their stronger social infrastructure may reduce immediate vulnerability.
Low heat–high social fragility profile	Clusters 4, 5, 6, 8, and 9 show below-average HI35, low PUSM, and high POU. Cluster 6 has the lowest HI35 but high undernourishment.	Clusters 9 and 10 show below-average HI35, weak PUSM, and high POU. Cluster 10 combines HI35 = −0.748, PUSM = −0.689, and POU = 1.010.	Social fragility may be severe even where extreme heat exposure is not high.	Development and ESG strategies should not allocate resources only according to climatic exposure; social deprivation requires independent attention.
Demographic-pressure profile	Cluster 10 combines above-average HI35 with very high fertility: HI35 = 0.721, FR = 1.775.	Cluster 8 combines high HI35 and high fertility, while Cluster 7 is dominated by very high fertility: FR = 4.388.	Fertility identifies countries where future demand for water, food, health, and social infrastructure may increase vulnerability over time.	Policy priorities include reproductive health, education, public-service expansion, and long-term adaptation planning.

Table 13. *Cont.*

Dimension of Comparison	Ordinary S-Social Model	Sensitivity-Analysis S-Social Model	Interpretation for the ESG–HI35 Framework	Policy and ESG Implications
Interpretability of profiles	The Random Forest model distinguishes socially resilient high-exposure profiles, socially fragile lower-exposure profiles, intermediate profiles, and demographic-pressure profiles.	The K-Means sensitivity model reproduces the same broad categories, despite changes in the algorithm and reduced sample.	The core Social taxonomy remains substantively stable across specifications.	The framework can support country grouping for climate adaptation, social protection, water access, nutrition, and ESG risk assessment.
General conclusion	The ordinary model supports Random Forest as the most interpretable full-sample Social clustering solution.	The sensitivity analysis supports K-Means as the strongest reduced-sample solution.	Although the preferred algorithm changes, the main substantive conclusion remains stable: HI35 and social vulnerability indicators do not move uniformly together.	Effective ESG and climate-risk policy must combine heat-exposure analysis with social indicators of adaptive capacity, especially water access, nutrition, and demographic pressure.

Note. The table compares ordinary and sensitivity-analysis Social taxonomies. Results confirm the robustness of the ESG–HI35 framework, identifying persistent exposure–vulnerability profiles related to heat, water access, undernourishment, and demographic pressure.

8. Governance-Based Clustering Framework and Empirical Results

In this study, six machine learning algorithms were compared with the aim of assessing their performance across multiple evaluation metrics. To ensure consistency and comparability, the data were normalized, allowing each algorithm to be evaluated on the same scale. This comparative approach provides the basis for identifying the most suitable algorithm in terms of overall performance without privileging any single method a priori (Table 14).

Table 14. Normalized Performance of Clustering Algorithms Applied to the G-Governance Dimension of the ESG Framework.

Metric	Density Based	Fuzzy C-Means	Hierarchical	Model Based	K-Means	Random Forest
R^2	0.01	0.01	0.00	0.01	0.01	0.01
AIC	0.12	0.04	0.13	0.05	0.02	0.05
BIC	0.13	0.03	0.14	0.06	0.02	0.06
Silhouette	0.00	0.00	0.00	0.00	0.00	0.00
Maximum Diameter	0.62	0.18	0.34	0.30	0.10	0.22
Minimum Separation	0.03	0.00	0.06	0.00	0.00	0.01
Pearson's γ	0.02	0.01	0.02	0.01	0.00	0.00
Dunn Index	0.00	0.00	0.00	0.00	0.00	0.00
Entropy	0.03	0.03	0.01	0.04	0.02	0.04
Calinski-Harabasz Index	1.00	1.00	1.00	1.00	1.00	1.00

Note: All metrics were normalized using Min–Max scaling (0–1). Normalization was applied to ensure comparability across indicators with different scales and ranges, allowing for a fair statistical performance comparison among clustering algorithms.

A ranking of the clustering algorithms was generated through a multi-indicator statistical evaluation based on metrics designed either to be maximized or minimized. This procedure reflects the multidimensional nature of clustering performance, since no single metric is sufficient to evaluate the quality of an unsupervised classification on its own. Instead, overall performance depends on a trade-off among several statistical indicators capturing cohesion, separation, compactness, and model parsimony [88]. In line with the conceptual framework of the study, this ranking is used only to evaluate the ability of each algorithm to classify observations into coherent exposure–vulnerability profiles. It is not intended to assess whether ESG variables explain, determine, or generate HI35. HI35 remains an exogenous climatic exposure indicator, while governance-related ESG variables are interpreted as institutional and socio-economic conditions that may influence adaptive capacity and vulnerability under heat exposure. Indicators such as R^2, Silhouette, Minimum Separation, Pearson's γ, Dunn Index, and the Calinski–Harabasz Index were considered criteria to be maximized, since they reflect internal coherence, inter-cluster separation, and overall partitioning quality. By contrast, metrics such as AIC, BIC, Maximum Diameter, and Entropy were considered criteria to be minimized, as lower values indicate greater parsimony, lower dispersion, and more compact cluster formations [89,90]. All indicators were normalized on a common scale to allow direct comparison across metrics. Subsequently, the indicators designed for minimization were inverted so that all measures could be interpreted in the same direction, with higher normalized values corresponding to better performance. Each algorithm was then evaluated using two components: the arithmetic mean of the normalized indicators to be maximized and the arithmetic mean of the inverted indicators to be minimized. The final score was calculated as the average of these two components, providing a balanced assessment of clustering quality and model simplicity. According to this procedure, K-Means achieved the highest overall score, followed by Fuzzy C-Means and Random Forest. These algorithms therefore offered the most balanced statistical trade-off between partition quality and model parsimony in this specific classification exercise [62,91]. This systematic approach reduces the risk of relying on a single metric and allows a more comprehensive comparison among competing clustering algorithms. Importantly, the ranking should be interpreted as a methodological tool for selecting the most appropriate clustering solution. It does not imply a causal relationship between governance indicators and the occurrence of extreme heat. Rather, it supports the identification of country groups characterized by different combinations of exogenous heat exposure, measured by HI35, and governance-related conditions that may shape vulnerability, resilience, and adaptive capacity (Table 15).

Table 15. Trade-Off Evaluation of Clustering Algorithms Based on Maximization and Minimization Indicators.

Rank	Model	Maximize Avg	Minimize Avg	Total Score
1	K-Means	0.17	0.96	0.56
2	Fuzzy C-Means	0.17	0.93	0.55
3	Random Forest	0.17	0.91	0.54
4	Model Based	0.17	0.89	0.53
5	Hierarchical	0.18	0.85	0.51
6	Density Based	0.18	0.78	0.48

Note: The column Maximize Avg reports the average of normalized metrics to be maximized (R^2, Silhouette, Minimum Separation, Pearson's γ, Dunn Index, Calinski–Harabasz Index). The column Minimize Avg is the average of inverted normalized metrics (1—value) for those to be minimized (AIC, BIC, Maximum Diameter, Entropy). Total Score is computed as the mean of these two averages, providing a balanced overall ranking across both groups of indicators.

While statistical performance provides an important basis for comparing clustering procedures, it cannot by itself determine the best solution, especially in unsupervised learning, where no ground-truth validation is available [92]. For this reason, statistical indicators must be complemented by criteria such as interpretability, structural balance, and coherence in line with the research objective. In this study, clustering is used as a classificatory tool to identify country profiles based on the joint distribution of exogenous heat exposure and ESG-related vulnerability conditions. The purpose is not to test whether ESG variables determine HI35. HI35 is treated as a climatic exposure indicator, primarily shaped by geographical and atmospheric factors, while ESG dimensions describe institutional, social, and environmental conditions that may influence vulnerability, resilience, and adaptive capacity. Therefore, it is not sufficient to rely exclusively on aggregate statistical indicators. The internal composition and size distribution of the clusters must also be evaluated. Some algorithms may perform well statistically but produce highly imbalanced cluster structures, in which a few large groups contain most observations while several marginal clusters remain underpopulated. Such a pattern limits the usefulness of the classification because it reduces the ability to distinguish meaningful exposure–vulnerability profiles across countries. This issue is particularly evident in Density-Based and Hierarchical clustering solutions, where a small number of very large clusters include the overwhelming majority of observations, while the remaining clusters contain only a limited number of cases. This raises concerns about the granularity and discriminatory capacity of these classifications. In contrast, the Model-Based clustering algorithm, although not always the best-performing method according to aggregate statistical scores, produces a more balanced and homogeneous distribution of cluster sizes. This improves the identification of latent structures in the data and supports clearer comparisons across country groups [93]. Such balance is especially important for the purposes of this study. A more even cluster distribution improves interpretability, facilitates inter-cluster comparison, and reduces the risk that the analysis is dominated by overrepresented groups or outlier-driven classifications. Accordingly, the preferred solution is not necessarily the one that maximizes statistical performance alone, but the one that provides internally coherent, interpretable, and relatively balanced country groupings. This approach is consistent with good practice in unsupervised classification. The objective is not statistical optimization for its own sake, nor the estimation of a causal effect from ESG variables to HI35. Rather, the objective is to obtain meaningful segmentations that are theoretically and empirically consistent with the distinction between climatic exposure, measured by HI35, and ESG-based vulnerability or adaptive-capacity conditions (Table 16).

Table 16. Cluster Size Distributions and Comparative Rankings of Clustering Algorithms.

Cluster	Density Based	Fuzzy C-Means	Hierarchical	Model Based	K-Means	Random Forest
Noise points	25					
Size Cluster 1	395	88	423	82	51	75
Size Cluster 2	7	45	4	109	21	64
Size Cluster 3	7	53	1	81	99	84
Size Cluster 4	7	30	7	31	45	57
Size Cluster 5	6	7	7	70	46	42
Size Cluster 6	5	114	17	7	14	58
Size Cluster 7	4	23	1	14	79	23

Table 16. *Cont.*

Cluster	Density Based	Fuzzy C-Means	Hierarchical	Model Based	K-Means	Random Forest
Size Cluster 8	7	8	4	53	8	19
Size Cluster 9	8	46	7	7	7	35
Size Cluster 10		59		7	101	14
Ranking Statistical Performance	6	2	5	4	1	3
Rank Cluster Structure	6 (Worst)	4	5	1 (Best)	2	3

Note. The table compares clustering algorithms considering both statistical performance and the distribution of elements across clusters. A more balanced cluster structure, with sizes closer to each other, indicates greater heterogeneity and interpretability. Model-Based clustering shows the most homogeneous distribution of cluster sizes, while Density-Based and Hierarchical methods result in highly unbalanced structures dominated by a single large cluster.

The model-based clustering analysis highlights substantial heterogeneity in the joint distribution of HI35 and governance-related ESG variables. In line with the conceptual framework of the study, HI35 is not interpreted as an outcome influenced or determined by governance conditions. Rather, HI35 is treated as an exogenous climatic exposure indicator, while governance variables describe institutional conditions that may shape vulnerability, resilience, and adaptive capacity under heat exposure. Clusters with lower or negative HI35 values, such as Clusters 1, 4, 7, 8, and 10, represent country profiles characterized by lower levels of heat exposure together with specific governance configurations. In several of these clusters, weaknesses emerge in indicators such as political stability, rule of law, and regulatory quality. These patterns should not be interpreted as evidence that institutional fragility reduces or worsens HI35. Instead, they indicate that certain governance weaknesses may coexist with particular levels of climatic exposure and may affect the capacity of countries to manage the consequences of heat stress. Conversely, clusters with higher or positive HI35 values, such as Clusters 2, 3, 6, and 9, identify profiles in which stronger climatic exposure is combined with different governance conditions. For example, Cluster 6 records one of the highest HI35 values and also displays relatively strong regulatory quality and R&D expenditure, while at the same time showing imbalances in legal rights (SLRI) and voice and accountability (VA). This suggests that high heat exposure may coexist with uneven governance capacity: some institutional dimensions may support adaptation and response, while weaknesses in other governance areas may limit overall resilience. Therefore, the clustering results do not suggest that governance effectiveness shapes the physical occurrence of extreme heat. Rather, they show that countries exposed to different levels of HI35 may differ substantially in institutional capacity, regulatory quality, legal protection, political stability, innovation capacity, and accountability. These governance conditions are relevant because they may influence how societies prepare for, absorb, and respond to heat-related risks. Overall, the analysis underscores the multidimensional role of governance in differentiating exposure–vulnerability profiles. HI35 captures exogenous climatic exposure, whereas governance-related ESG variables capture institutional and socio-economic conditions that may mediate the consequences of such exposure. The results therefore support the construction of a taxonomy of governance-related heat vulnerability profiles, without conflating climatic exposure with institutional determinants or implying that ESG structures generate HI35 outcomes (Table 17).

Table 17. Cluster Means of Governance Indicators and HI35 Values.

Cluster	HI35	GDPG	PS	RFTM	RQ	RDE	RL	SEPS	STJA	SLRI	VA
1	−0.378	−0.314	0.065	−0.421	−0.126	−0.287	−0.289	0.159	−0.873	−2.086	0.181
2	0.332	−0.216	−0.534	−0.867	−0.100	−0.888	−0.632	−0.031	−0.553	−0.363	−0.677
3	0.270	1.393	−0.986	−2.442	−1.170	−0.568	−0.735	0.394	−0.330	−0.137	−1.034
4	−0.611	−0.316	0.974	1.892	0.545	1.343	1.100	−0.407	0.025	0.316	1.034
5	0.098	−0.355	0.781	0.032	0.440	0.572	0.703	−0.050	0.866	−0.229	0.656
6	1.488	−0.050	−0.687	0.899	0.827	−0.830	−1.039	0.322	−0.554	−5.440	−2.215
7	−0.509	−0.339	1.063	1.208	1.035	1.579	1.426	1.804	−0.283	−0.129	1.270
8	−0.280	−0.103	−0.392	0.726	0.778	1.116	0.988	−0.140	−0.533	0.907	0.927
9	0.335	−0.311	−1.333	3.299	0.765	0.803	0.749	0.326	0.105	−0.239	0.305
10	−0.308	−0.271	0.338	1.702	0.578	1.141	0.937	−0.084	1.887	5.114	0.865

Note: The table presents governance-based clusters with associated HI35 means. Cluster 6 records the highest HI35, paired with strong regulatory quality and R&D but deficits in legal rights and accountability, illustrating governance's multidimensional influence. Balanced institutional development—combining stability, accountability, and regulatory strength—emerges as critical for reducing vulnerability to extreme heat stress.

Statistical measures may help assess various clustering techniques against each other, but are insufficient on their own in the unsupervised setting [94]. Since this research categorizes countries based on exogenous climatic exposure and ESG-based vulnerability, model selection should be guided by interpretability, cluster homogeneity, and thematic significance.

Model-Based Clustering seems to be the best approach among the selected techniques. The reason Model-Based Clustering stands out is not only for its statistical efficiency but also for producing balanced, homogeneous clusters with interpretative value. The ability will facilitate cross-cluster comparisons and identify governance profiles with HI35 and vulnerability-adaptive capacity.

It turns out there is significant variation in governance profiles across exposure levels. Nevertheless, no causal claims should be made, as HI35 exposure depends primarily on geography and atmospheric conditions, whereas governance characteristics relate to institutions that can affect readiness and adaptation to heat exposure.

Clusters with lower or negative HI35 values (Clusters 1, 4, 7, 8, and 10) often exhibit worse governance performance across political stability, regulatory quality, and the rule of law. This does not mean that a poor institutional environment leads to higher heat exposure, but rather that some HI35 values correlate with institutional vulnerabilities [95].

Cluster 6 is especially interesting because it features both the highest HI35 value and good regulatory performance and high R&D expenditure, alongside lower performance in the areas of legal rights and voice and accountability. High exposure coexists with uneven governance capacities in this case. Overall, good governance matters because it affects adaptive capacity [30].

Figure 10 demonstrates the Silhouette plot for the Governance K-Means clustering solution in the ESG–HI35 model. The figure shows the internal cohesion and separateness of the ten governance clusters using the Silhouette value for each observation. Positive Silhouette coefficients indicate that an observation is closer to its group members than to other nearby clusters, while negative coefficients indicate that a point is overlapping or unclearly placed between adjacent governance clusters. See Figure 10.

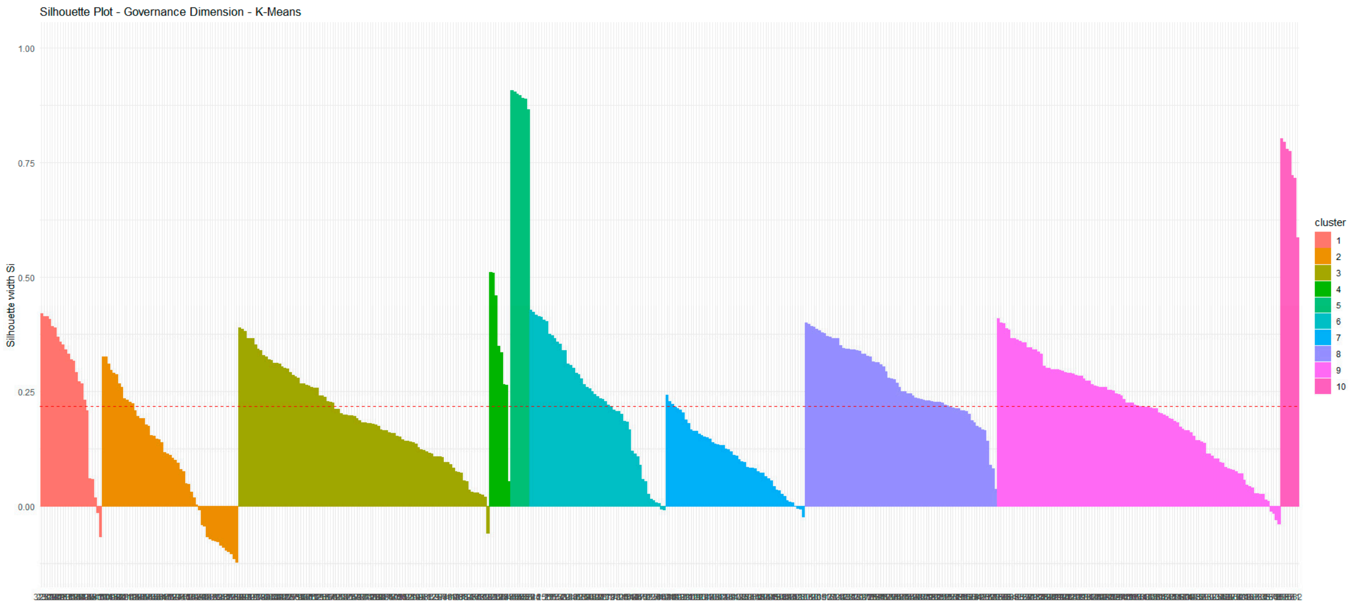

Figure 10. The figure reports silhouette coefficients for the Governance K-Means clustering model. The red dotted line represents the average silhouette width across all observations and serves as a reference threshold for assessing the overall quality of the clustering solution. Positive values indicate acceptable cohesion and separation, while negative values identify borderline observations and partially overlapping governance vulnerability profiles across countries.

In general, one can observe rather consistent clusters. As shown in Figure 10, the majority of observations have positive Silhouette values, with some clusters even having average values close to or exceeding the global mean, marked by a red dashed line. Therefore, the governance taxonomy proves statistically valid and interpretable. Compared to the previous Social clustering solution, the governance classification appears more distinct, suggesting that governance factors yield clear structural patterns. However, as shown in Figure 10, considerable differences exist among governance clusters. For instance, clusters 5 and 10 exhibit considerably higher Silhouette values, indicating internal consistency and distinct governance regimes. Thus, those clusters are represented by countries that share very similar institutional characteristics, such as regulation quality, rule of law, research intensity, accountability, and legal protection. The distance between the two clusters indicates that governance capacity constitutes a relatively stable macro-structural configuration. On the contrary, some clusters have moderate or even slightly negative Silhouette values at their borders. Such overlap occurs in clusters characterized by intermediate institutional quality or mixed governance. These observations may refer to countries experiencing governance transitions, which are associated with the development of various aspects, including economic growth, institutional capacity, and social inclusion. Therefore, the observed overlap in clusters seems quite realistic within the multidimensional ESG approach. One more factor to consider is heterogeneity. It should be noted that some clusters contain diverse observations with moderate cohesion, whereas others are characterized by lower density but with high consistency within a group. In other words, such an outcome shows that governance vulnerability is unevenly distributed and that some institutional configurations dominate over others. In summary, the results show that the Governance K-Means clustering solution produces an adequate taxonomy. Despite some observations near the borders of governance clusters, the overall result confirms the differentiation of vulnerability regimes in terms of governance issues.

8.1. Sensitivity Analysis of Governance Exposure–Vulnerability Clusters

As far as G-Governance is concerned, a sensitivity test was conducted on the robustness of the grouping pattern under an information-completed dataset. The time period (1999–2023) continues to be the same, but the number of countries is cut down from 185 to 125 since they have a complete lack of information for at least one governance criterion. This helps us in dealing with structural problems regarding missing data linked with factors like quality of institutions, political stability, capacity of regulations, innovations, accountability, and legal rights. The purpose here is not to exclude isolated cases of missing information but to verify the stability of the governance classification under improved data requirements. See Figure 11.

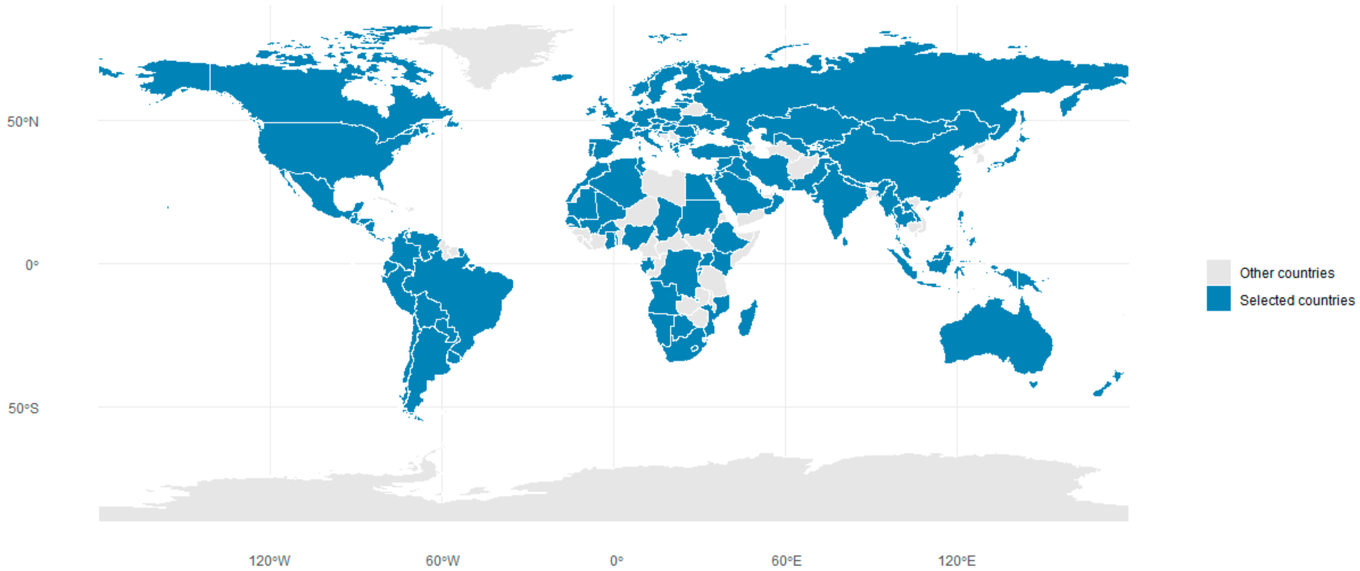

Figure 11. Geographic Distribution of the Restricted Governance Sample Used in the Sensitivity Analysis. Note. Countries are: Albania, Algeria, Angola, Argentina, Armenia, Australia, Austria, Bolivia, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Canada, Chad, Chile, China, Colombia, Congo, Dem. Rep., Costa Rica, Cote d'Ivoire, Croatia, Cyprus, Czechia, Denmark, Ecuador, Egypt, Arab Rep., El Salvador, Estonia, Eswatini, Ethiopia, Finland, France, Gabon, Gambia, The, Georgia, Germany, Ghana, Greece, Guatemala, Honduras, Hungary, Iceland, India, Indonesia, Iran, Islamic Rep., Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Kuwait, Kyrgyz Republic, Lao PDR, Latvia, Lesotho, Lithuania, Luxembourg, Madagascar, Malaysia, Mali, Malta, Mauritania, Mauritius, Mexico, Moldova, Mongolia, Montenegro, Morocco, Mozambique, Myanmar, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Nigeria, North Macedonia, Norway, Oman, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russian Federation, Rwanda, Saudi Arabia, Senegal, Serbia, Singapore, Slovak Republic, Slovenia, South Africa, Spain, Sri Lanka, St. Lucia, St. Vincent and the Grenadines, Sudan, Sweden, Switzerland, Syrian Arab Republic, Tajikistan, Tanzania, Thailand, Togo, Trinidad and Tobago, Tunisia, Turkiye, Uganda, Ukraine, United Kingdom, United States, Uruguay, Uzbekistan, Venezuela, RB.

Comparing the ordinary and sensitivity-analysis Social models provides valuable information regarding the robustness of the ESG–HI35 framework [74,75]. The ordinary version includes countries with some degree of data availability, whereas the sensitivity analysis excludes countries with completely missing data on at least one Social indicator. The aim is to see how sensitive the taxonomy's clustering structure is to structurally incomplete data. An interesting aspect pertains to the preferred algorithm. While in the ordinary Social model, Random Forest was selected to produce a balanced and understandable taxonomy, in the sensitivity analysis, K-Means prevails due to better interpretability, more favorable information criteria values, and sufficient cluster balance. It should be noted that such changes in methodology do not threaten the validity of the findings; on the contrary, they confirm the flexibility of methodological choice and the consistency of substantive classification. As in the previous case, both the ordinary and sensitivity versions of the model produce 10 clusters. It shows once again that vulnerability to heat stress is multidimensional and determined by a complex combination of variables, including HI35, access to water sources, levels of undernourishment, and population dynamics [74,86]. The findings of both analyses are very similar. They show that there exist clusters of high heat with social resilience, in which high HI35 occurs alongside high water access and the absence of undernourishment. Similarly, there are clusters of low heat with social fragility, indicating that the lack of basic services and food security can persist regardless of climatic conditions [77,87]. See Table 18.

Table 18. Sensitivity Analysis of Governance Clustering Algorithms.

Statistics	Density-Based Clustering	Fuzzy C-Means Clustering	Hierarchical Clustering	Model-Based Clustering	Neighborhood-Based Clustering	Random Forest Clustering
Number of clusters	9	6	9	10	10	8
N	471	471	471	471	471	471
R^2	0.319	0.549	0.326	0.51	0.665	0.462
AIC	3065.86	2864.01	3684.62	2753.87	1950.23	2957.88
BIC	3477.19	3138.23	4095.95	3205.91	2407.26	3323.5
Silhouette	0.08	0.16	0.3	0.12	0.19	0.05
Cluster sizes	395; 7; 7; 7; 6; 5; 4; 7; 8	44; 131; 109; 37; 37; 113	423; 4; 1; 7; 7; 17; 1; 4; 7	92; 109; 81; 31; 70; 7; 14; 53; 7; 7	22; 65; 71; 93; 37; 89; 8; 14; 21; 51	88; 63; 37; 81; 40; 33; 101; 28
Explained proportion within-cluster heterogeneity	0.980; 0.003; 0.003; 6.189×10^{-4}; 0.004; 0.003; 0.002; 3.973×10^{-4}; 0.004	0.113; 0.139; 0.199; 0.279; 0.098; 0.171	0.947; 0.008; 0.000; 0.002; 0.011; 0.031; 0.000; 7.723×10^{-4}; 3.268×10^{-4}	0.164; 0.205; 0.508; 0.017; 0.059; 0.003; 0.004; 0.039; 7.005×10^{-4}; 4.496×10^{-4}	0.043; 0.087; 0.178; 0.167; 0.107; 0.135; 0.048; 0.065; 0.082; 0.089	0.314; 0.124; 0.067; 0.106; 0.029; 0.068; 0.103; 0.188
Within sum of squares	2810.972; 8.531; 8.397; 1.775; 10.278; 9.542; 5.732; 1.139; 11.495	308.785; 380.017; 544.464; 761.997; 268.603; 468.142	3301.349; 26.948; 0.000; 8.531; 38.509; 107.451; 0.000; 2.693; 1.139	415.839; 519.692; 1287.133; 41.835; 149.118; 8.531; 9.546; 99.264; 1.775; 1.139	73.886; 150.776; 307.672; 288.694; 184.443; 234.285; 82.192; 112.688; 141.402; 154.188	873.402; 345.671; 186.569; 294.457; 81.752; 188.861; 287.362; 523.804
Maximum diameter	16.003	16.003	9.71	16.003	9.391	11.416
Minimum separation	0.953	0.311	1.969	0.248	0.138	0.799
Pearson's γ	0.624	0.423	0.654	0.288	0.411	0.306
Dunn index	0.06	0.019	0.203	0.015	0.015	0.07
Entropy	0.767	1.658	0.511	1.961	2.09	1.979
Calinski-Harabasz index	25.617	82.991	27.882	53.289	101.832	56.781
HH-Index	0.7861	0.2095	0.8087	0.1619	0.1397	0.1502

Note. The table compares alternative governance clustering methods using fit, compactness, separation, entropy, and balance indicators. Results confirm the robustness of multidimensional governance vulnerability profiles across different algorithmic specifications and restricted-sample conditions.

The Governance dimension, which emerges from the Neighborhood-Based Clustering, highlights significant disparities in regimes of governance vulnerabilities within the ESG framework. Specifically, the results suggest that economic development, institutional quality, innovation potential, and social inclusiveness are not inherently interrelated processes and do not develop in tandem in response to climate pressures and thermal stress [70,96]. The first and sixth clusters stand out as the most institutionally robust, with relatively high Regulatory Quality (RQ), Research and Development Expenditure (RDE), Rule of Law (RL), and Voice and Accountability (VA) scores, as well as strong female labor-force participation rates. Such governance systems should foster innovation, coordination, and climate adaptation. Good institutions could enable countries' investments in sustainable infrastructure development, technological innovations, and environmental management [97]. On the contrary, Clusters 5, 7, and 9 can be considered structural weak-governance regimes. First, Cluster 5 is characterized by highly negative RQ, RL, RDE, and VA values, indicating poor institutions and weak adaptive capacities [96,98]. In addition, Clusters 7 and 9 stand out for a combination of very high GDP growth and poor governance indicators. Thus, countries can experience rapid growth without achieving sustainable, resilient institutional performance [70]. Cluster 8 stands out for its extremely high protection of legal rights and scientific production, indicating well-developed legal and innovative systems. In conclusion, it is worth noting that governance quality is a key dimension of climate resilience and adaptability [70,96]. See Table 19.

Table 19. Governance Cluster Profiles under Sensitivity Analysis.

Cluster	HI35	GDPG	PS	RFTM	RQ	RDE	RL	SEPS	STJA	SLRI	VA
1	−0.23	−0.33	0.292	2.349	0.939	1.271	1.205	1.276	0.251	−0.208	0.962
2	0.279	−0.213	−0.213	−0.594	−0.265	−0.457	−0.159	0.27	1.163	−0.326	−0.223
3	0.267	−0.055	−0.866	−0.825	0.246	−1.118	−0.888	−0.267	0.18	−0.294	−0.996
4	0.354	−0.336	0.752	−0.12	0.287	0.515	0.546	0.099	−0.129	−0.275	0.653
5	0.461	0.01	−1.306	−0.691	−1.78	−1.212	−1.542	−0.026	−1.031	−0.245	−1.527
6	−0.455	−0.304	0.986	1.119	0.689	1.304	1.174	−0.129	0.101	0.144	0.985
7	0.149	2.863	−2.524	−0.912	−1.502	−1.349	−1.5	−4.891	−0.608	−0.329	−1.181
8	0.58	−0.16	−0.174	1.316	0.603	0.156	−0.051	0.129	0.462	5.277	−0.765
9	0.409	3.716	−0.505	−0.693	−1.846	−0.368	−0.755	0.622	−0.625	0.081	−0.865
10	−1.165	−0.307	−0.142	−0.273	−0.014	−0.423	−0.447	0.018	−0.81	−0.087	0.203

Note. The table reports standardized governance cluster profiles from Neighborhood-Based clustering. Indicators capture institutional quality, innovation, legal rights, accountability, gender inclusion, economic growth, and heat exposure across heterogeneous governance regimes.

Figure 12 shows the output of the Neighborhood-Based Clustering algorithm for the Governance component of the ESG–HI35 framework. According to Panel A, the smallest value of the Bayesian Information Criterion (BIC) is observed when there are ten clusters. Therefore, it can be stated that governance vulnerability is characterized by many structural arrangements rather than by a few homogeneous clusters. The distribution of observations in the lower-dimensional space is shown in Panel B; from this, it is clear that while some clusters are tightly knit, others are located at the periphery, indicating governance–economic regime heterogeneity. Finally, Panel C presents the standardized cluster means; it can be noted that clusters with high GDP growth do not necessarily have good governance quality. See Figure 12.

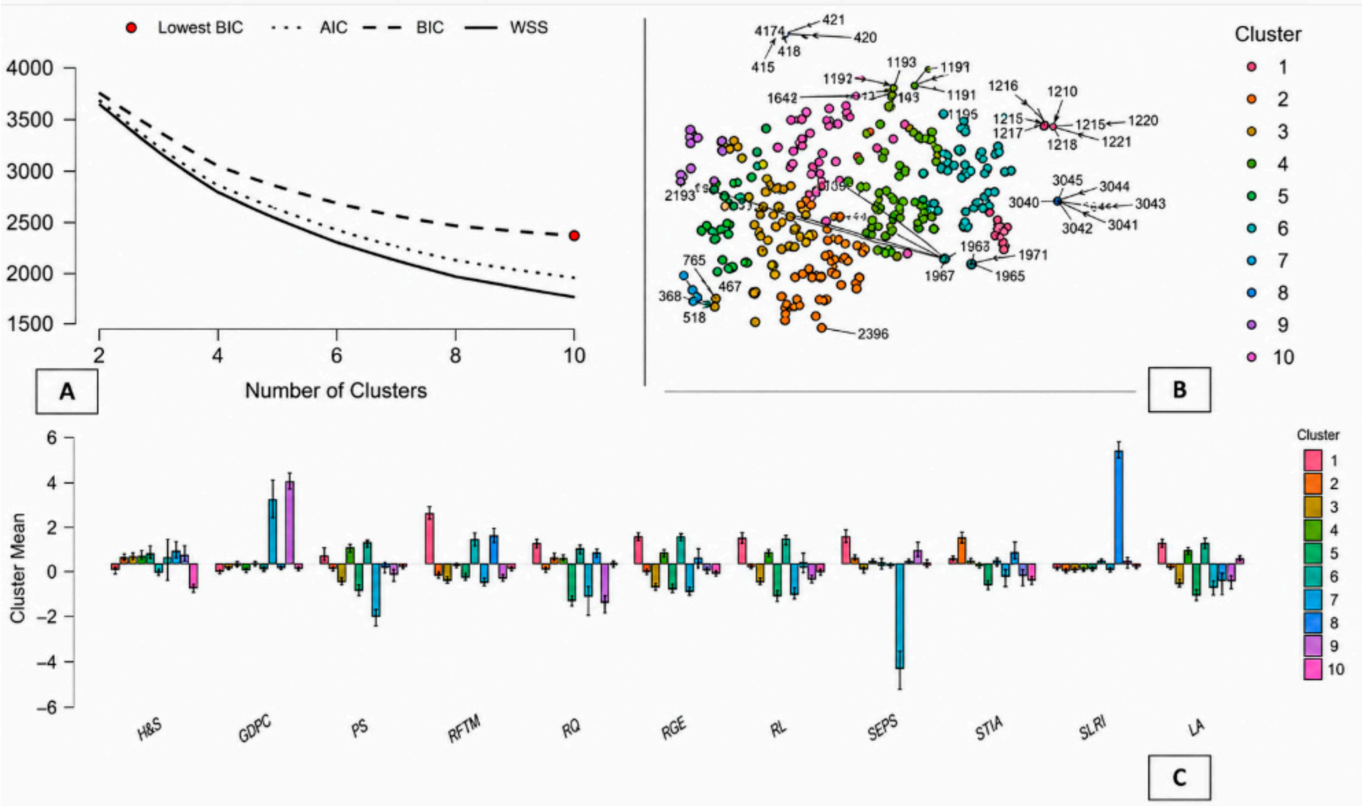

Figure 12. Governance Clustering Results under the Restricted ESG–HI35 Sample. Note. The figure summarizes Neighborhood-Based governance clustering results for the restricted sample. Panel (**A**) reports AIC, BIC, and WSS values across alternative cluster solutions, where the red point identifies the minimum BIC and supports the preferred 10-cluster specification. Panel (**B**) illustrates cluster distribution in reduced-dimensional space, while Panel (**C**) presents standardized governance cluster means across institutional, economic, and social indicators.

8.2. Institutional Resilience and Governance Vulnerability: A Robustness Analysis Within the ESG–HI35 Framework

The comparison between the ordinary and sensitivity-analysis Governance models confirms the robustness of the governance-based ESG–HI35 taxonomy [99,100]. The clustering structure remains broadly stable even after restricting the sample to countries with more complete governance data, suggesting that the results are not primarily driven by missing-data patterns but by consistent institutional differences. An important finding concerns the change in the preferred clustering algorithm. In the ordinary model, Model-Based Clustering is selected because it produces the most balanced and interpretable structure. In the sensitivity analysis, Neighborhood-Based Clustering becomes preferable due to stronger statistical performance and a lower HH-Index. This demonstrates that algorithm selection in unsupervised learning should not rely on a single metric, but on the capacity to generate meaningful and balanced governance profiles. The persistence of a ten-cluster structure across both models further supports robustness. Governance-related vulnerability appears highly heterogeneous, combining different levels of political stability, regulatory quality, innovation capacity, accountability, and legal protection [101,102]. Substantively, the results confirm the central role of governance quality in shaping climate-related vulnerability. Regulatory Quality, Rule of Law, Research and Development Expenditure, Voice and Accountability, and Strength of Legal Rights consistently emerge as key discriminating variables [103,104]. Overall, the findings indicate that economic growth alone is insufficient to ensure resilience without strong institutions, legal protection, and effective governance structures [100,102]. See Table 20.

Table 20. Comparison between Baseline and Sensitivity Governance Clustering Models.

Dimension of Comparison	**Ordinary G-Governance Model**	**Sensitivity-Analysis G-Governance Model**	**Interpretation for the ESG–HI35 Framework**	**Policy and ESG Implications**
Sample structure	Full Governance-component dataset, including countries with partial data availability across the historical period.	Reduced sample obtained by excluding countries with completely missing values for at least one G-Governance variable.	The sensitivity analysis tests whether the Governance taxonomy is affected by structurally incomplete information.	If similar governance profiles persist, the classification is more reliable for ESG-based vulnerability screening.
Preferred algorithm	Model-Based Clustering is selected because it provides the most balanced and interpretable cluster-size distribution.	Neighborhood-Based Clustering is selected because it combines strong statistical performance with the lowest HH-Index.	The preferred algorithm changes, but both models prioritize interpretability and cluster balance.	Model choice should support meaningful governance–vulnerability profiles, not only statistical optimization.
Number of clusters	10 clusters in the Model-Based solution.	10 clusters in the Neighborhood-Based sensitivity solution.	The persistence of a 10-cluster structure confirms strong heterogeneity in governance regimes.	Governance vulnerability should not be reduced to a simple strong/weak institutional distinction.
Cluster balance	Model-Based produces a relatively balanced structure, with HH-Index = 0.1619.	Neighborhood-Based produces the most balanced solution, with HH-Index = 0.1397.	Both solutions avoid excessive concentration in one dominant cluster.	Balanced clusters improve the usefulness of the taxonomy for comparative ESG and policy analysis.
Problem with alternative algorithms	Density-Based and Hierarchical models produce highly concentrated clusters, with HH-Index values of 0.7861 and 0.8087.	Density-Based and Hierarchical remain weak alternatives because they concentrate most observations in a single large group.	Strong separation metrics are not sufficient when the cluster structure is too unbalanced.	ESG classifications should avoid technically strong but substantively weak segmentations.
Model fit and explanatory capacity	Model-Based is not the strongest in all statistical indicators, but it provides the most interpretable full-sample governance taxonomy.	Neighborhood-Based achieves the best statistical performance, with R^2 = 0.665, AIC = 1950.23, and BIC = 2407.26.	The sensitivity model shows that, under stricter data availability, Neighborhood-Based becomes both statistically and structurally preferable.	The Governance taxonomy remains robust when incomplete data are removed.
Key discriminating variables	GDPG, RQ, RDE, RL, SLRI, and VA differentiate the governance profiles.	The same variables remain central, especially GDPG, RQ, RL, RDE, VA, and SLRI.	Governance vulnerability is driven by institutional quality, innovation capacity, legal strength, accountability, and economic growth patterns.	ESG policy should combine institutional reform, innovation investment, legal capacity, and accountability.
High growth–weak governance profile	Some clusters show high GDP growth but weak RQ, RL, RDE, and VA.	Clusters 7 and 9 show very high GDPG but weak governance indicators.	Economic growth does not automatically imply institutional resilience.	Growth-oriented strategies must be accompanied by governance strengthening and institutional upgrading.

Table 20. *Cont.*

Dimension of Comparison	Ordinary G-Governance Model	Sensitivity-Analysis G-Governance Model	Interpretation for the ESG–HI35 Framework	Policy and ESG Implications
Strong governance–moderate growth profile	Some clusters combine moderate GDP growth with strong RQ, RDE, RL, and VA.	Clusters 1 and 6 show strong governance capacity despite moderate or negative GDPG.	Institutional quality may support resilience even without rapid growth.	Countries with strong institutions are better positioned to manage heat-related socio-economic risks.
Legal-rights specialization profile	Model-Based identifies clusters with distinctive SLRI patterns.	Cluster 8 shows an exceptionally high SLRI value, indicating a specialized legal-rights profile.	Legal capacity can differ from broader governance quality.	ESG assessment should consider legal rights separately from general institutional indicators.
Interpretability of profiles	The ordinary model distinguishes balanced institutional profiles, weak-governance profiles, high-growth fragile profiles, and legal-specialization profiles.	The sensitivity model reproduces similar categories with stronger statistical support.	The core Governance taxonomy remains substantively stable across specifications.	The framework can support country grouping for governance reform, climate adaptation, and ESG risk assessment.
General conclusion	The ordinary model supports Model-Based Clustering as the most interpretable full-sample Governance solution.	The sensitivity analysis supports Neighborhood-Based Clustering as the strongest reduced-sample solution.	Although the preferred algorithm changes, the main conclusion remains stable: governance capacity and HI35 do not move uniformly together.	Effective ESG and climate-risk policy must combine heat-exposure analysis with institutional quality, innovation capacity, rule of law, accountability, and legal protection.

Note. The table compares ordinary and sensitivity-analysis Governance taxonomies. Results confirm stable governance vulnerability profiles, emphasizing institutional quality, innovation capacity, legal protection, accountability, and the limits of growth-based resilience.

9. Empirical Strategy: PCA and Hierarchical Clustering for Country Taxonomies

This section explains the empirical methodology used to develop the exposure–vulnerability taxonomy based on the ESG-HI35 indicators, using dimensionality reduction and clustering procedures. In other words, the goal is to turn the high-dimensional, noisy, and diverse dataset about environmental, social, governance, and climatic variables into a structured cross-country framework capable of identifying structural patterns of vulnerability. To be more specific, the section discusses how data from the original, unbalanced World Bank datasets were processed before applying Principal Component Analysis (PCA) and hierarchical clustering. There are multiple reasons to use such an empirical strategy. Firstly, processing and aggregation of data help turn raw data into a new, balanced, cross-sectional dataset at the country level, which serves as the basis for unsupervised learning tasks. Since there is no need to estimate causal relationships between variables or their time-series properties, given the focus on a long-term cross-country perspective, annual observations are aggregated to a country-average level from 1999 to 2023. Secondly, PCA is used to reduce redundancy and dimensionality of the ESG-HI35 data while preserving the information contained in most of the original variables. The use of principal components helps increase clustering robustness, reduce data noise, and make latent structures of vulnerability associated with environmental pressure, social problems, governance issues, and heat exposure easier to detect. Thirdly, the empirical strategy uses hierarchical clustering and the Gap Statistic to classify countries based on their exposure and vulnerability to climate change. Thus, countries' exposure–vulnerability regimes are intended to provide insights for comparative studies of climate risks rather than serve as a normative evaluation.

9.1. Data Aggregation and Preprocessing Framework

As such, a data preprocessing step was required to convert the original panel dataset into a country-level cross-sectional matrix suitable for multivariate clustering analysis [105,106]. The dataset comprised annual observations for 185 countries, including HI35 and ESG variables from the World Bank ESG database. Since the objective of this study is to analyze long-run exposure–vulnerability profiles rather than short-term volatility, annual observations were aggregated at the country level. For each country and each indicator, the arithmetic mean was computed, obtaining one long-run value per variable and country. This procedure reduces the influence of short-term shocks and year-specific fluctuations [107]. HI35 was treated as an exogenous measure of climatic exposure, while ESG variables were interpreted as descriptors of vulnerability-related structural conditions and adaptive capacity. The exclusion of cooling degree days was justified conceptually and statistically because of the potential redundancy between HI35 and CDD. Unlike the pillar-specific clustering analyses, the integrated PCA-based taxonomy required a complete country-by-variable matrix. Therefore, after country-level aggregation, the remaining missing values were addressed through variable-specific mean imputation in the integrated PCA and hierarchical-clustering exercise only. This limited imputation step was used to avoid excessive sample loss and retain the full set of 185 countries, while not affecting the pillar-specific baseline clustering results reported in the previous sections [108,109]. Finally, all variables were transformed into z-scores before PCA and hierarchical clustering. See Figure 13.

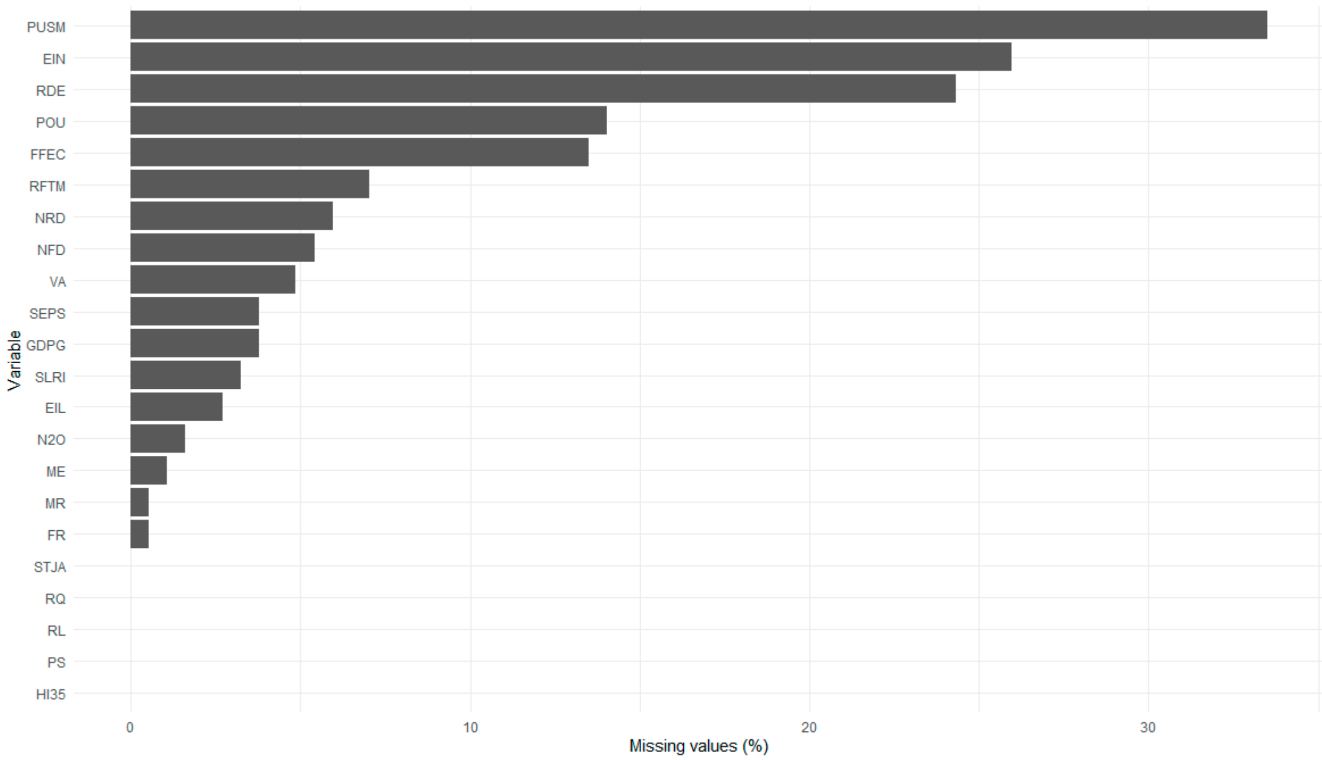

Figure 13. Percentage of Missing Values across ESG–HI35 Variables before Imputation. Note. The figure reports the percentage of missing country-level observations before imputation. Missingness is concentrated in selected ESG indicators, particularly PUSM, EIN, RDE, and POU, motivating the use of variable-specific mean imputation procedures.

9.2. Principal Component Extraction and Taxonomy Construction

Based on PCA, the ESG–HI35 taxonomy consists of several dimensions. More specifically, PC1 has an eigenvalue of 6.772, explaining 29.444% of the total variance. This suggests that the ESG-HI35 taxonomy is based on several latent factors, as confirmed by the presence of independent dimensions [110,111].

PC2 explains 15.909% of the variance, thereby increasing the explained variance rate to 45.353%. PC3 adds another 11.070%, raising the total explained variance to 56.433%. Overall, the first three principal components account for over 50% of the total variance. Further, the fourth, fifth, and sixth principal components explain 6.115%, 5.518%, and 4.896% of total variance, respectively. Consequently, when taken together, the first six principal components provide an explanation of 72.950% of variance, and hence they can be used as a basis for clustering because of their ability to convey a considerable amount of information provided by the initial 23 variables [112,113]. The explanatory power of the remaining principal components is lower and tends to decrease further as they add little to the explained variance. Still, PCA improves the clustering process by generating a more noise-free, non-redundant, and robust taxonomy [110,111]. See Table 21.

Table 21. Eigenvalues and Explained Variance of Principal Components.

Dimension	Eigenvalue	Explained Variance (%)	Cumulative Variance (%)
PC1	6.772	29.444	29.444
PC2	3.659	15.909	45.353
PC3	2.546	11.070	56.423
PC4	1.406	6.115	62.537
PC5	1.269	5.518	68.055
PC6	1.126	4.896	72.950
PC7	0.912	3.966	76.917
PC8	0.869	3.777	80.694
PC9	0.825	3.585	84.279
PC10	0.674	2.930	87.209
PC11	0.581	2.525	89.735
PC12	0.475	2.065	91.800
PC13	0.358	1.558	93.358
PC14	0.343	1.491	94.849
PC15	0.336	1.463	96.311
PC16	0.258	1.123	97.434
PC17	0.237	1.030	98.465
PC18	0.170	0.737	99.202
PC19	0.094	0.407	99.609
PC20	0.057	0.248	99.857
PC21	0.031	0.134	99.992
PC22	0.002	0.007	99.999
PC23	0.000	0.001	100.000

Note. The table reports PCA eigenvalues, individual variance, and cumulative variance for 23 components. The first six components explain 72.950% of total variance and support subsequent hierarchical clustering.

Figure 14 represents the percentage of variance explained by the first ten principal components of the standardized ESG–HI35 data set. The first principal component explains about 29.4% of the variance in the whole model, indicating a significant but incomplete latent structure. The second and third principal components, on the other hand, explain 15.9% and 11.1% of the variance, respectively. Therefore, the first three principal components account for over 50% of the dataset variance. The next components—fourth to sixth—still contribute significantly, leading to an accumulated variance of 73%. After the sixth component, further contributions become negligible. Thus, the lack of a clear elbow signifies the multidimensionality of the ESG–HI35 taxonomy. See Figure 14.

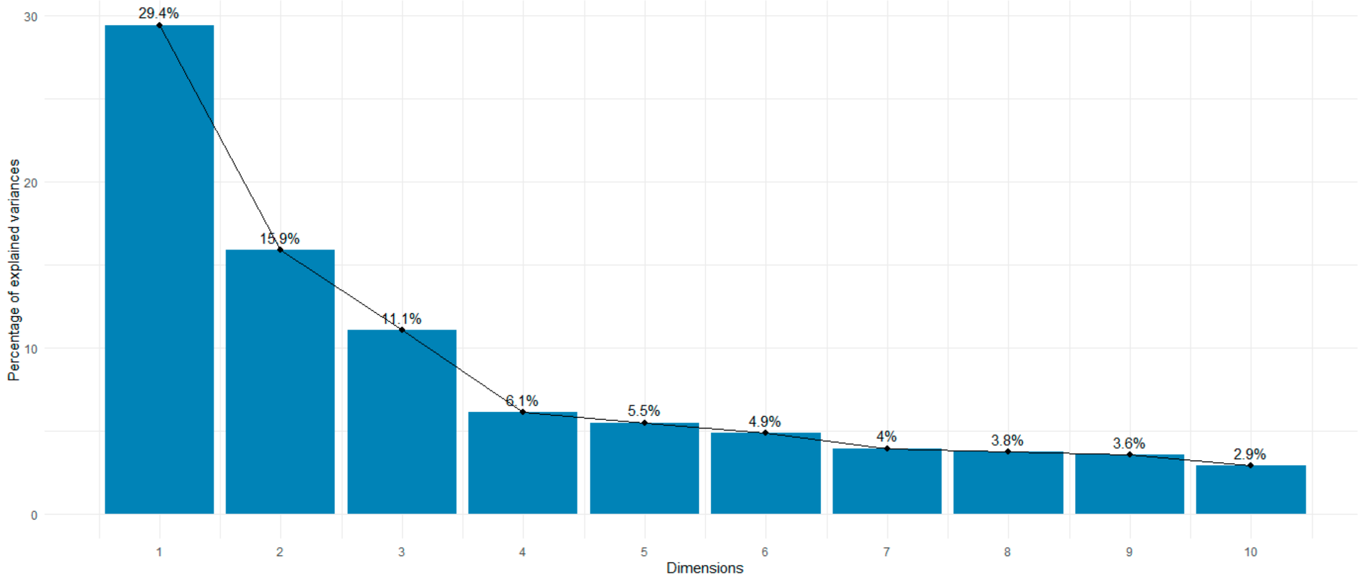

Figure 14. Scree Plot of Principal Components from the ESG–HI35 Dataset. Note. The figure reports the percentage of variance explained by the first ten principal components extracted from the standardized ESG–HI35 dataset. Percentages refer to individual explained variance contributions and are calculated from the eigenvalues of the correlation matrix after variable standardization.

9.3. Hierarchical Clustering and Gap Statistic Analysis of the ESG–HI35 Taxonomy

The graph above depicts the Gap Statistic for hierarchical clustering applied to the PCA-reduced ESG–HI35 dataset. The Gap Statistic compares the observed intra-cluster variance with a reference distribution generated under a null model; higher values indicate stronger clustering structure. The function increases from 1 to 30 clusters, with a substantial rise between 4 and 15 clusters, suggesting latent heterogeneity across climatic exposure, environmental pressure, social vulnerability, and governance dimensions. After approximately 15 clusters, the curve tends to flatten, with its maximum around k = 20. Accordingly, the k = 20 solution is selected as a high-resolution exploratory taxonomy rather than as the only possible country partition. Its purpose is to capture fine-grained heterogeneity across ESG–HI35 profiles. To address the trade-off between parsimony and interpretability, the k = 20 solution is compared with more parsimonious alternatives, particularly k = 10 and k = 12, which are used as robustness benchmarks to verify whether the main ESG–HI35 macro-patterns remain stable under less fragmented classifications. See Figure 15.

The dendrogram provides an explanation of the hierarchical clustering pattern developed from the ESG–HI35 dataset after applying PCA. It illustrates the result of applying the Gap Statistic analysis to determine the optimal number of clusters, yielding 20 clusters in the dataset. The level of linkage used indicates the degree of dissimilarity between clusters; low linkages indicate similar groups, while high linkages indicate dissimilar groups. This tree shows local and broad macro-clustering, indicating heterogeneity in exposure, pressure, governance, and vulnerability factors. Some branches remain independent at relatively high levels of linkage, suggesting different country profiles. See Figure 16.

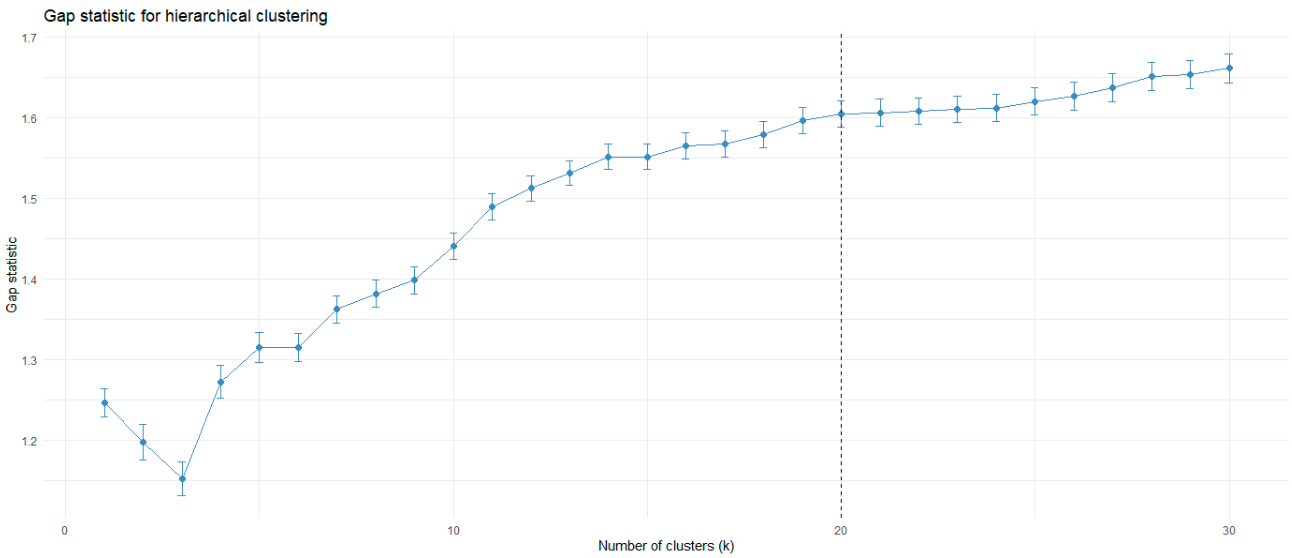

Figure 15. Gap Statistic for Hierarchical Clustering on the PCA-Reduced ESG–HI35 Dataset. Note. The figure reports the Gap Statistic values associated with hierarchical clustering solutions estimated on the first six principal components extracted from the standardized ESG–HI35 dataset. Error bars represent simulation-based standard errors used to evaluate clustering stability and partition quality across alternative numbers of clusters.

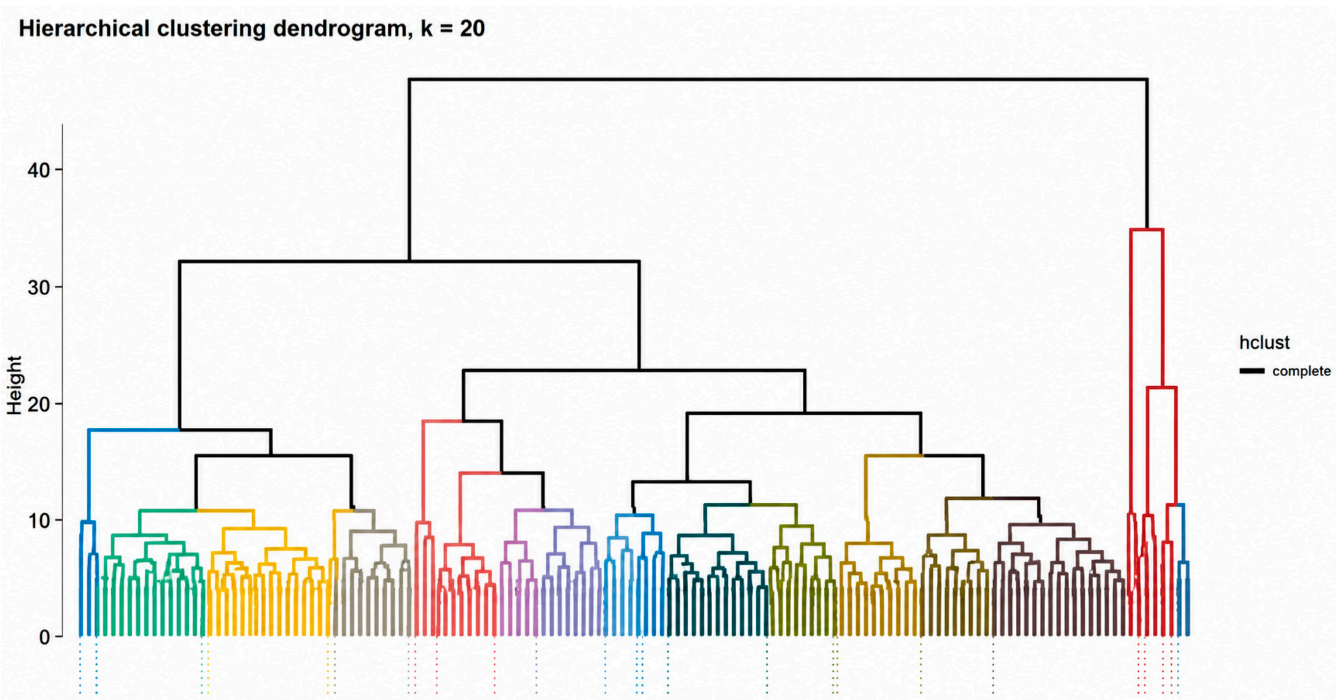

Figure 16. Hierarchical Clustering Dendrogram for the ESG–HI35 Dataset (k = 20). Note. The figure reports the hierarchical clustering dendrogram obtained from the first six principal components extracted from the standardized ESG–HI35 dataset using the Ward.D2 agglomerative method. The colored branches identify the 20 clusters selected through the Gap Statistic criterion. Different colors are used solely to distinguish cluster membership and do not indicate a ranking, intensity scale, or qualitative ordering among clusters. The vertical axis represents linkage distance (height), indicating the degree of dissimilarity at which clusters are merged during the hierarchical aggregation process.

9.4. Hierarchical Taxonomy of ESG–Heat Vulnerability Profiles

The table reports the classification of countries according to the clusters obtained from hierarchical clustering of the PCA-reduced ESG–HI35 dataset. The taxonomy shows considerable heterogeneity: some clusters include many countries, while others contain only a few observations or a single country. This structure indicates that the ESG–HI35 framework can identify both broad macro-regional vulnerability regimes and more specific country profiles. However, small and single-country clusters should be interpreted cautiously. They may reflect distinctive ESG–HI35 configurations, but in some cases they may also result from the higher granularity of the k = 20 exploratory taxonomy rather than from fully stable country types. Cluster 5 represents the largest group, with 40 observations, including advanced and upper-middle-income economies such as Australia, Italy, Spain, Singapore, and Uruguay. This cluster combines countries with relatively diversified economic structures, stronger institutions, and higher adaptive capacity. Cluster 2 includes 27 countries, many of which are emerging economies, such as Argentina, Colombia, Mexico, Peru, and Thailand, indicating intermediate exposure–vulnerability profiles. Cluster 1 includes densely populated and heat-exposed countries such as Bangladesh, India, Indonesia, Pakistan, Nigeria, and the Philippines. This group is particularly relevant because it combines demographic pressure, development challenges, and high exposure to heat. Some clusters also group countries with geographic or structural similarities. For instance, Cluster 3 includes hydrocarbon-intensive economies such as Saudi Arabia, Qatar, Kuwait, and the United Arab Emirates, reflecting exposure–vulnerability profiles associated with fossil-fuel dependence, arid climates, and high cooling demand. Cluster 19 mainly includes small island countries, whose profiles are associated with territorial constraints, geographic isolation, infrastructure fragility, and exposure to climate-related risks. Overall, the taxonomy should be interpreted as a descriptive classification of ESG–HI35 similarity patterns, while the robustness of small clusters is further assessed through alternative k solutions and sensitivity checks. See Table 22.

Table 22. Country Classification Based on the Hierarchical ESG–HI35 Taxonomy.

Cluster	Countries	N
1	Afghanistan, Bangladesh, Cote d'Ivoire, Djibouti, El Salvador, Eritrea, Eswatini, Guatemala, Guyana, Honduras, India, Indonesia, Maldives, Mauritania, Nepal, Nicaragua, Nigeria, Pakistan, Paraguay, Philippines, Sao Tome and Principe, Senegal, Seychelles, Sri Lanka, Sudan	25
2	Albania, Argentina, Armenia, Bolivia, Botswana, Burkina Faso, Colombia, Ecuador, Georgia, Ghana, Kazakhstan, Kyrgyz Republic, Malawi, Malaysia, Mali, Mexico, Moldova, Mongolia, Namibia, Nauru, Panama, Peru, Russian Federation, Suriname, Thailand, Trinidad and Tobago, Uzbekistan	27
3	Algeria, Iraq, Kuwait, Libya, Oman, Qatar, Saudi Arabia, United Arab Emirates, Venezuela, RB	9
4	Angola, Congo, Rep., Gabon, Norway, South Sudan	5
5	Australia, Belarus, Bosnia and Herzegovina, Brazil, Bulgaria, Chile, Costa Rica, Croatia, Cyprus, Czechia, Greece, Hungary, Ireland, Italy, Jamaica, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Mauritius, Micronesia, Fed. Sts., Monaco, Montenegro, Netherlands, New Zealand, North Macedonia, Palau, Poland, Portugal, Romania, San Marino, Serbia, Singapore, Slovak Republic, Slovenia, South Africa, Spain, Ukraine, Uruguay	40
6	Austria, Canada, Denmark, Estonia, Finland, France, Germany, Iceland, Israel, Japan, Sweden, Switzerland, United Kingdom	13
7	Azerbaijan	1
8	Bahrain	1
9	Barbados	1

Table 22. *Cont.*

Cluster	Countries	N
10	Belgium	1
11	Belize	1
12	Benin	1
13	Bhutan, Cameroon, Gambia, The, Guinea, Kenya, Lao PDR, Lesotho, Mozambique, Myanmar, Niger, Papua New Guinea, Rwanda, Tajikistan, Tanzania, Togo, Viet Nam, Zambia	17
14	Burundi, Chad, Congo, Dem. Rep., Ethiopia, Guinea-Bissau, Liberia, Sierra Leone, Somalia, Uganda	9
15	Cambodia	1
16	Central African Republic, Haiti, Korea, Dem. People's Rep., Madagascar, Zimbabwe	5
17	China, United States	2
18	Cuba, Egypt, Arab Rep., Iran, Islamic Rep., Jordan, Lebanon, Morocco, Syrian Arab Republic, Tunisia, Turkiye, Yemen, Rep.	10
19	Dominica, Fiji, Grenada, Kiribati, Marshall Islands, Samoa, Solomon Islands, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, Tonga, Tuvalu, Vanuatu	13
20	Equatorial Guinea, Timor-Leste, Turkmenistan	3

Note. The table reports the 20 country clusters derived from PCA-based hierarchical clustering. Cluster membership reflects similarities in heat exposure, ESG conditions, institutional capacity, development structure, and vulnerability profiles across countries.

In this case, the robustness test will determine whether China and the US remain in the same cluster as the number of clusters changes. In particular, it will be assumed that both states belong to the same cluster when k = 10, 12, 15, 18, and 20. It will be seen that these states share similar features in terms of size, technological development, and international engagement [63,103]. Nevertheless, their likeness disappears at k = 22, indicating that China and the US share traits only when viewed from a broader perspective. Cluster 17 may serve as an example in this regard [76]. See Table 23.

Table 23. Robustness of China–United States Co-Clustering across Alternative k Values.

k	China_Cluster	China_Cluster_Members	United_States_Cluster	United_States_Cluster_Members
10	10	China, United States	10	China, United States
12	11	China, United States	11	China, United States
15	14	China, United States	14	China, United States
18	15	China, United States	15	China, United States
20	17	China, United States	17	China, United States
22	18	China	22	United States
25	19	China	25	United States
30	21	China	30	United States

Note. The table tests whether China and the United States remain jointly classified across alternative cluster solutions. Co-clustering persists from k = 10 to k = 20, but disappears at higher resolutions.

Figure 17 illustrates the robustness of the hierarchically clustered results for both China and the United States across different numbers of clusters. If the segments are green, the two nations belong to the same cluster; if they are red or blue, the two countries are partitioned into different clusters. Both China and the United States will be in one cluster at k ranging from 10 to 20, indicating that the nations share structural similarities in terms of size, technology, global integration, and geographical disparities [63,103].

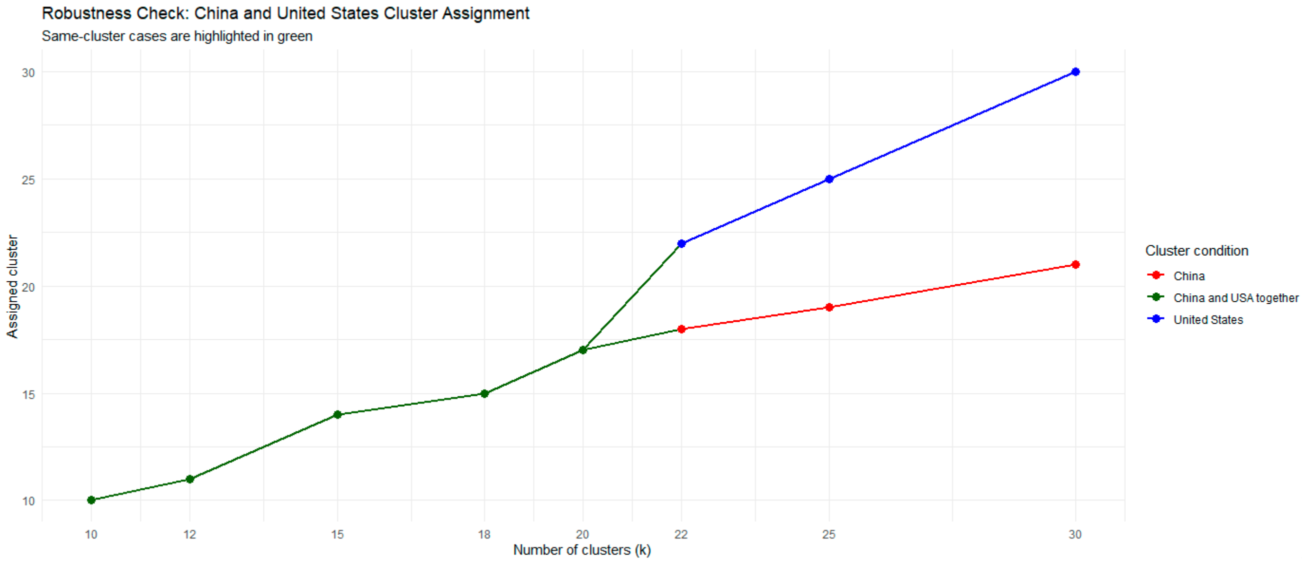

Figure 17. Robustness of China–United States Cluster Membership across Alternative Hierarchical Taxonomies. Note. The figure reports the cluster assignment of China and the United States across alternative values of k. Green segments indicate shared cluster membership, while red and blue segments identify separate classifications under higher-resolution taxonomies.

To further assess the robustness and parsimony of the hierarchical clustering results, we conducted an additional sensitivity analysis focused on single-country clusters. The aim was to verify whether the isolated country profiles observed in the main k = 20 taxonomy remained isolated when the dendrogram was cut at more aggregated levels, namely k = 10 and k = 12. The results show that the more parsimonious k = 10 and k = 12 solutions produce only one single-country cluster, represented by Belgium. In contrast, the higher-resolution k = 20 solution produces seven single-country clusters: Azerbaijan, Bahrain, Barbados, Belgium, Belize, Benin, and Cambodia. This evidence indicates that the 20-cluster taxonomy captures finer country-level heterogeneity, but also increases fragmentation. The persistence of Belgium across all three specifications suggests that it represents a stable outlier profile within the ESG–HI35 space. Conversely, the additional isolated countries that appear only in the k = 20 solution seem to reflect the greater granularity of the selected specification rather than fully stable structural separation. Accordingly, the k = 20 taxonomy is interpreted as a high-resolution exploratory classification, while the k = 10 and k = 12 solutions are used as more parsimonious robustness benchmarks. These results suggest that the main macro-taxonomy remains interpretable under more parsimonious specifications, while the k = 20 solution should be used mainly to capture finer within-taxonomy heterogeneity. See Table 24.

Table 24. Single-Country Clusters across Alternative Hierarchical Taxonomies.

Number of Clusters (k)	Number of Single-Country Clusters	Single-Country Cluster Members
10	1	Belgium
12	1	Belgium
20	7	Azerbaijan, Bahrain, Barbados, Belgium, Belize, Benin, Cambodia

Note. The table compares single-country clusters across k = 10, 12, and 20 solutions. Belgium remains isolated across specifications, while additional single-country clusters emerge only in the high-resolution taxonomy.

9.5. Macroeconomic and Institutional Interpretation of the ESG–HI35 Taxonomy

The cluster size distribution and representative country classification provide a holistic perspective on how the interplay among exposure to climate risks, ESG variables, institutional strength, and development conditions unfolds at the global level. In particular, the results show that vulnerability and resilience to climate change impacts are not randomly distributed across countries but instead coincide with identifiable macroeconomic and institutional regimes. This implies that the clustering approach has important implications for economic policy, fiscal management, financial stability, development planning, and climate governance. See Table 25.

Table 25. Macroeconomic and Policy Interpretation of ESG–HI35 Country Clusters.

Cluster	Representative Countries	Economic Profile	Institutional/Development Interpretation	Policy Implication
1	Bangladesh, India, Indonesia, Pakistan, Philippines, Sri Lanka, Sudan	Heat-exposed populous economies	High demographic pressure, infrastructure stress, and strong exposure of workers and households to heat risk	Public-health adaptation, urban cooling, water security, food security, and labor protection
3	Algeria, Iraq, Kuwait, Libya, Oman, Qatar, Saudi Arabia, United Arab Emirates	Hydrocarbon-intensive arid economies	Fossil-fuel dependence, high cooling demand, water scarcity, and resource-based development	Economic diversification, cooling efficiency, water management, and energy transition
5	Australia, Brazil, Chile, Italy, Netherlands, Portugal, Singapore, Spain, Uruguay	Diversified advanced and upper-middle-income economies	Stronger institutional capacity, developed infrastructure, and higher adaptive resources	Urban resilience, green innovation, energy-efficient adaptation, and climate-smart infrastructure
6	Austria, Canada, Denmark, Finland, France, Germany, Japan, Sweden, Switzerland, United Kingdom	Highly developed advanced economies	Strong governance, innovation capacity, advanced public services, and institutional resilience	Innovation-led adaptation, low-carbon transition, resilient urban systems, and infrastructure modernization
13	Cameroon, Kenya, Mozambique, Myanmar, Tanzania, Viet Nam, Zambia	Developing agrarian and lower-middle-income economies	Agricultural dependence, demographic growth, infrastructure gaps, and moderate institutional fragility	Agricultural resilience, food security, water management, rural adaptation, and institutional strengthening
14	Burundi, Chad, Congo Dem. Rep., Ethiopia, Liberia, Sierra Leone, Somalia, Uganda	Structurally fragile low-income economies	Weak institutions, limited fiscal resources, low adaptive capacity, and high social vulnerability	Basic services, public health, food security, water access, social protection, and capacity building
17	China, United States	Large systemic economies	Very large economic scale, technological capacity, global integration, and strong internal heterogeneity. However, their co-clustering is not stable across alternative k values	Multi-level climate governance, regional adaptation, urban heat planning, and innovation-led resilience
19	Fiji, Kiribati, Samoa, Solomon Islands, Tonga, Tuvalu, Vanuatu	Small island vulnerability economies	Geographic isolation, limited territorial scale, infrastructure fragility, and dependence on external climate finance	Climate finance, disaster preparedness, resilient infrastructure, and adaptation support

From a macroeconomic perspective, the largest clusters reflect broad structural development patterns within the ESG–HI35 taxonomy. Cluster 5 includes diversified advanced and upper-middle-income economies such as Australia, Italy, Singapore, Spain, and the Netherlands. These countries are characterized by stronger institutions, diversified productive systems, developed financial markets, and greater adaptive capacity [70,103]. Cluster

6 groups highly developed economies including Germany, Japan, Sweden, and the United Kingdom. Compared with Cluster 5, these countries exhibit even stronger governance quality and innovation systems, where climate policy increasingly overlaps with industrial competitiveness and technological leadership [70,114]. By contrast, Cluster 1 includes populous heat-exposed economies such as Bangladesh, India, Indonesia, Pakistan, and the Philippines. These countries combine demographic pressure, infrastructure deficits, and strong exposure to heat stress. Extreme heat may therefore reduce labor productivity, agricultural output, and urban economic activity [76]. Cluster 14 contains structurally fragile low-income economies such as Burundi, Chad, Somalia, and Uganda. Weak institutions, limited fiscal resources, and low adaptive capacity increase vulnerability to climate shocks and humanitarian crises [103,115]. Cluster 3 groups hydrocarbon-intensive economies such as Saudi Arabia, Qatar, and Kuwait, which combine high fiscal resources with significant transition risks linked to fossil-fuel dependence and water scarcity. Overall, the taxonomy highlights differentiated macroeconomic vulnerability regimes shaped by climate exposure, governance capacity, and structural development conditions. See Figure 18.

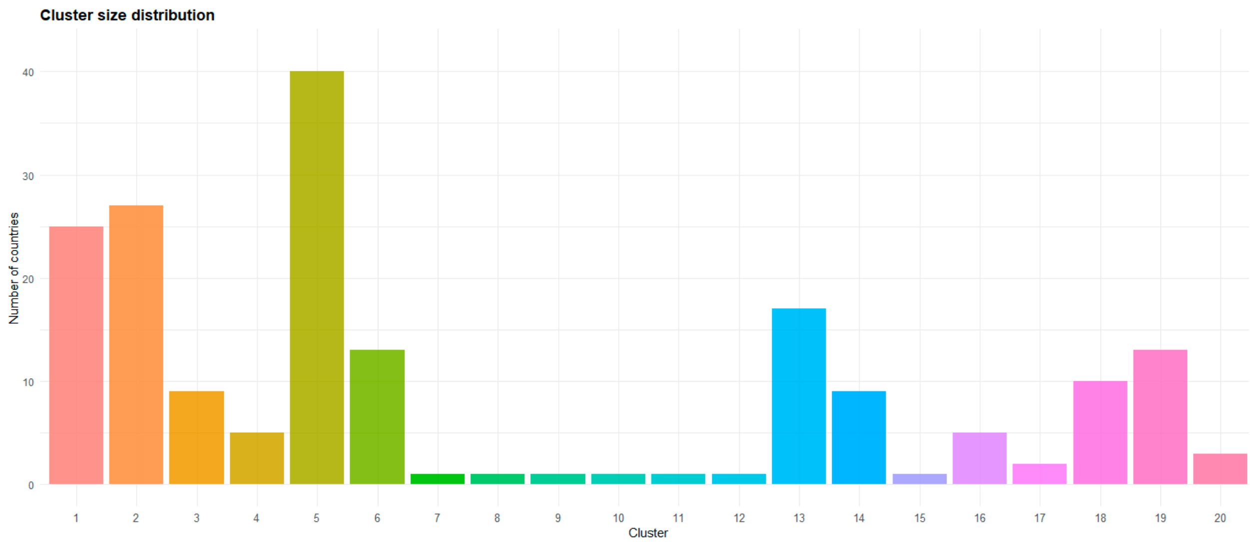

Figure 18. Distribution of Country Membership across the ESG–HI35 Hierarchical Clusters. Note. The figure reports the number of countries assigned to each of the 20 ESG–HI35 clusters. The distribution highlights substantial heterogeneity in cluster size, reflecting uneven global patterns of climatic exposure, governance, and structural vulnerability.

10. Empirical Result Analysis: Degradation, Demographics, and Governance in Climate Stress

The present study focuses on the combination of exposure to climatic heat events and vulnerability conditions related to ESG factors. HI35 is used as a measure of heat exposure, defined as the number of days when the apparent temperature exceeds 35 °C [74,116]. HI35 should be considered an independent climatic exposure measure without assuming any vulnerability characteristics or causal links between HI35 and an outcome variable produced by the ESG environment. As mentioned above, ESG variables include environmental, social, and governance factors contributing to climate vulnerability, resilience, and adaptive potential. Clustering methods are utilized to analyze the combination of exposure to HI35 and various ESG-related features. The analysis is purely descriptive, as this approach aims to establish a taxonomy of exposure–vulnerability profiles rather than examine causality. When considering the environmental dimension, NRD, EIL, ME, NOE, and FFEC help define clusters that combine heat exposure with resource pressures, energy dependence, and emission conditions. According to the findings, HI35 is not associated with greater pressure on the natural environment. Therefore, climatic exposure and ecological vulnerability can be viewed as distinct yet related concepts [117]. With regard to the social domain, HI35 will be combined with fertility rates, access to safely managed drinking water, and undernourishment. Thus, it is possible to find clusters where HI35 co-occurs with both high and low social resilience, suggesting the relevance of demographic and service pressures [118,119]. Heterogeneity will also be revealed in the cluster analysis of the governance domain, including factors such as institutional quality, innovation, legal rights, and accountability. See Table 26.

Table 26. Descriptive Taxonomy of ESG Conditions and HI35 Exposure–Vulnerability Profiles.

ESG Pillar	Key Variables	Role in the Exposure–Vulnerability Classification	Synthetic Interpretation	Clustering Evidence
Environment (E)	NRD, EIL, ME, NOE, FFEC	Captures environmental pressure, energy dependence, energy intensity, fossil-fuel reliance, and emissions-related conditions. These variables are not interpreted as determinants of HI35.	Environmental indicators describe ecological and structural conditions that coexist with different levels of heat exposure and may shape countries' vulnerability and adaptive capacity.	Clustering identifies heterogeneous environmental profiles, including clusters where high HI35 coexists with moderate environmental pressure and clusters where lower HI35 coexists with stronger energy and emissions pressure.
Social (S)	FR, PUSM, POU	Captures demographic pressure, access to safely managed drinking water, and nutritional fragility under different levels of heat exposure. These variables are not interpreted as causes of HI35.	Social indicators describe population sensitivity and basic-service conditions associated with different exposure–vulnerability profiles. HI35 remains an exogenous climatic exposure indicator.	Random Forest clustering shows that FR, PUSM, and POU differentiate social exposure–vulnerability profiles. Some high-HI35 clusters coexist with stronger water access and lower undernourishment, while others coexist with weaker social conditions.
Governance (G)	PS, RQ, RL, VA, GDPG, RDE, STJA, SLRI, gender-parity indicators	Captures institutional quality, regulatory capacity, rule of law, accountability, innovation capacity, legal rights, and macroeconomic context. These variables are not interpreted as causes of HI35.	Governance indicators describe institutional readiness and adaptive capacity associated with comparable or different levels of heat exposure.	Clustering reveals institutional heterogeneity, distinguishing profiles where heat exposure coexists with stronger governance conditions from profiles where heat exposure coexists with weaker or uneven institutional capacity.

Note: This table provides a descriptive and associative synthesis of the clustering results. ESG variables are not interpreted as determinants or causes of HI35. The table reports observed co-occurrences between ESG conditions and HI35 profiles within the clustering structure. It does not report causal effects, directional impacts, regression coefficients, confidence intervals, or hypothesis tests. HI35 is treated as an exogenous climatic exposure indicator, while ESG variables describe environmental, social, and governance conditions associated with vulnerability and adaptive capacity.

11. Climate Governance and Heat Resilience: Policy Lessons from ESG-Driven Analysis

These implications guide the development of climate policies based on adaptability to increasingly extreme weather events. As noted above, HI35, as an indicator of climatic exposure, is unsuitable both as an index of vulnerability and as an index of ESG-based variables. These, in turn, capture the environmental, social, and governance-related pressures leading to exposure, vulnerability, and resilience. It follows that climate adaptation policies should not depend on HI35 alone because even similar exposure levels can produce vastly different needs among countries. Concerning environmental pressures, policies need to focus on the development of cooling infrastructure, energy-efficient buildings, greening, afforestation, and technologies for water and ecosystem management [120,121]. For countries with high energy intensity, fossil fuel consumption, methane emissions, or nitrous oxide emissions, adaptation must involve policies of energy transition and low-carbon cooling [122]. Social vulnerabilities of a country can be defined through its PUSM index, followed by FR, POU, and HI35 indices, based on the results of a random forest classification model. It means that social vulnerability depends on a country's ability to provide basic services to the population, manage its demographic composition and ensure food security. Policy responses in this case include addressing water security issues and food security concerns, providing nutrition, managing the population, protecting people from social vulnerabilities, and developing heat-resistant public services [123,124]. As for governance capacity, the development of policies should be based on the strength of institutions. Countries with a robust system of the rule of law, regulations, accountability, and political stability can implement climate policies that would involve creating a climate risk dashboard and disclosing the information on ESG-based variables. The latter would also allow financing innovations in heat adaptation efforts [125–127]. With partially developed institutions, it is also necessary to develop climate and energy transition policies together with policies that would strengthen accountability and the rule of law [128]. To conclude, HI35 could be considered as an index for measuring exposure and included into the set of ESG variables for guiding policies. In this case, countries with high environmental pressures need to implement ecological adaptation policies. Countries with a high level of social vulnerability require policies focused on water and nutritional aspects. Countries with high governance pressure require institutional strengthening. Finally, countries with fragile or small-island economies require adaptation financing.

12. Conclusions

This research proposes a country-level taxonomy of vulnerability to extreme heat by combining HI35 with ESG indicators through clustering techniques. HI35 is not treated as a systemic vulnerability index or as an outcome generated by ESG structures. Instead, it is used as an exogenous climatic exposure measure, capturing the annual number of days with apparent temperature above 35 °C. ESG variables describe the environmental, social, and governance conditions that may influence how countries experience, absorb, and respond to heat exposure.

The country is used as the unit of analysis because the objective is to construct a comparable cross-national taxonomy. This choice is consistent with the World Bank ESG database, where HI35 and most ESG indicators are harmonized at the national level. It also allows comparison of institutional capacity, public-service provision, environmental pressure, social structure, and adaptive capacity across countries. However, national averages may conceal important subnational differences, especially in large or territorially heterogeneous countries. Therefore, the results should be interpreted as macro-comparative exposure–vulnerability profiles, not as local heat-risk maps.

The main contribution of the study is to place HI35 within a broader exposure–vulnerability framework. The clustering results show that countries with similar heat exposure may differ substantially in environmental degradation, access to basic services, institutional quality, social resilience, and governance capacity. Vulnerability is therefore not identified with HI35 alone but emerges from the interaction between exogenous climatic exposure and socio-institutional conditions.

From the environmental perspective, the analysis shows that energy intensity, fossil-fuel dependence, resource depletion, emissions pressure, and cooling demand are associated with differentiated profiles. These variables do not determine HI35; rather, they indicate the ecological and infrastructural contexts in which heat exposure occurs. Some countries combine lower HI35 with higher fossil-fuel or energy intensity, while others combine higher HI35 with weaker environmental-response conditions.

The revised Social dimension uses HI35 together with fertility rate, access to safely managed drinking water, and prevalence of undernourishment. Random Forest clustering provides a balanced and interpretable taxonomy. The results show that social vulnerability is shaped more strongly by water access, demographic pressure, and nutritional fragility than by HI35 alone. Some high-HI35 clusters have strong water access and low undernourishment, while some lower-HI35 clusters show greater social fragility.

Governance also differentiates vulnerability profiles. Political stability, rule of law, regulatory quality, accountability, innovation capacity, and institutional effectiveness matter because they shape preparedness and adaptive capacity under heat stress. Strong governance may support resilience, while partial or weak institutional structures may limit adaptation.

Overall, this study demonstrates that climate vulnerability is multidimensional. HI35 remains a heat-exposure indicator, while ESG variables capture the conditions that influence resilience and adaptive capacity. Future research should extend this framework using dynamic data, subnational observations, metropolitan areas, or gridded datasets.

Author Contributions: Conceptualization, A.L., C.D., A.C. and M.A.; Methodology, A.L., C.D., A.C. and M.A.; Software, A.L., C.D., A.C. and M.A.; Validation, A.L., C.D., A.C. and M.A.; Formal analysis, A.L., C.D., A.C. and M.A.; Investigation A.L., C.D., A.C. and M.A.; Resources, A.L., C.D., A.C. and M.A.; Data curation, A.L., C.D., A.C. and M.A.; Writing—original draft, A.L., C.D., A.C. and M.A.; Writing—review and& editing, A.L., C.D., A.C. and M.A.; Visualization, A.L., C.D., A.C. and M.A.; Supervision, A.L., C.D., A.C. and M.A.; Project administration, A.L., C.D., A.C. and M.A.; Funding acquisition, A.L., C.D., A.C. and M.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data used in this study are publicly available from the Sovereign ESG Data Portal maintained by the World Bank. The portal provides access to a comprehensive set of Environmental, Social, and Governance (ESG) indicators covering 213 economies and 171 indicators across 64 years. The data can be accessed freely at https://esgdata.worldbank.org/?lang=en (accessed 10 January 2025). For HI35 we have used the following link: https://data360.worldbank.org/en/indicator/WB_ESG_EN_CLC_HEAT_XD (accessed 10 December 2024).

Conflicts of Interest: The authors declare that there is no conflict of interest.

Appendix A. Descriptive Statistics and Distributional Analysis of HI35 and Environmental Sustainability Indicators

Table A1. Descriptive Statistics of HI35 and Environmental Sustainability Indicators.

	HI35	NRD	NFD	EIN	EIL	FFEC	ME	N2O
Valid	4070	3839	3878	2235	3798	2313	4033	3939
Missing	555	786	747	2390	827	2312	592	686
Mode	0	0	0	5.15	2.71	0	4.1	0
Median	0	1.012	0.011	18.971	4.42	70.238	1.026	0.348
Mean	57.346	4.485	2.74	−30.196	86.454	60.115	3.143	5.744
Std. Error of Mean	7.693	0.125	0.125	3.7	12.994	0.689	0.162	0.909
95% CI Mean Upper	72.429	4.73	2.985	−22.94	111.93	61.466	3.461	7.525
95% CI Mean Lower	42.264	4.241	2.494	−37.452	60.978	58.763	2.825	3.963

Table A1. *Cont.*

	HI35	NRD	NFD	EIN	EIL	FFEC	ME	N2O
Std. Deviation	490.788	7.728	7.793	174.925	800.786	33.145	10.304	57.021
95% CI Std. Dev. Upper	501.689	7.905	7.97	180.21	819.213	34.129	10.534	58.309
95% CI Std. Dev. Lower	480.354	7.559	7.623	169.944	783.175	32.217	10.084	55.789
MAD	0	1.002	0.011	36.006	1.41	22.181	0.429	0.163
IQR	2.507	5.781	0.953	78.966	3.33	57.434	1.142	0.36
95% CI Variance Upper	251,692.196	62.495	63.52	32,475.721	671,109.844	1164.798	110.965	3399.893
95% CI Variance Lower	230,739.763	57.145	58.109	28,880.872	613,362.645	1037.933	101.687	3112.398
Skewness	9.757	3.452	4.399	−4.081	11.966	−0.57	8.727	12.963
Std. Error of Skewness	0.038	0.04	0.039	0.052	0.04	0.051	0.039	0.039
Kurtosis	95.43	19.486	21.843	25.242	151.511	−1.07	87.182	181.671
Std. Error of Kurtosis	0.077	0.079	0.079	0.104	0.079	0.102	0.077	0.078
Shapiro-Wilk	0.089	0.616	0.397	0.59	0.078	0.891	0.233	0.07
p-value of Shapiro-Wilk	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Range	6306.54	102.891	57.842	2042.003	11,572.233	113.732	140.051	1054
Minimum	0	0	0	−1942.003	1.03	−13.732	0.049	0
Maximum	6306.54	102.891	57.842	100	11,573.263	100	140.1	1054
25th percentile	0	0.106	0	−26.987	3.27	30.973	0.672	0.211
50th percentile	0	1.012	0.011	18.971	4.42	70.238	1.026	0.348
75th percentile	2.507	5.887	0.953	51.979	6.6	88.407	1.813	0.571
Sum	233,398.85	17,219.254	10,624.36	−67,487.53	328,351.868	139,045.338	12,676.686	22,625.262

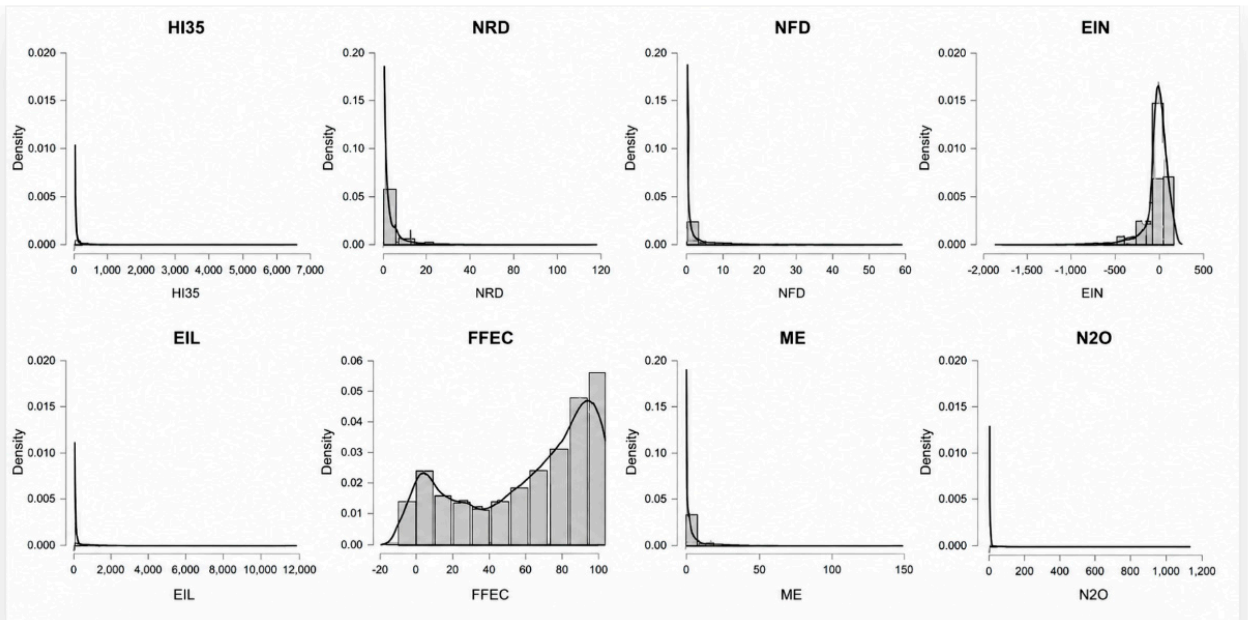

Figure A1. Distribution Plots of HI35 and Environmental Sustainability Indicators.

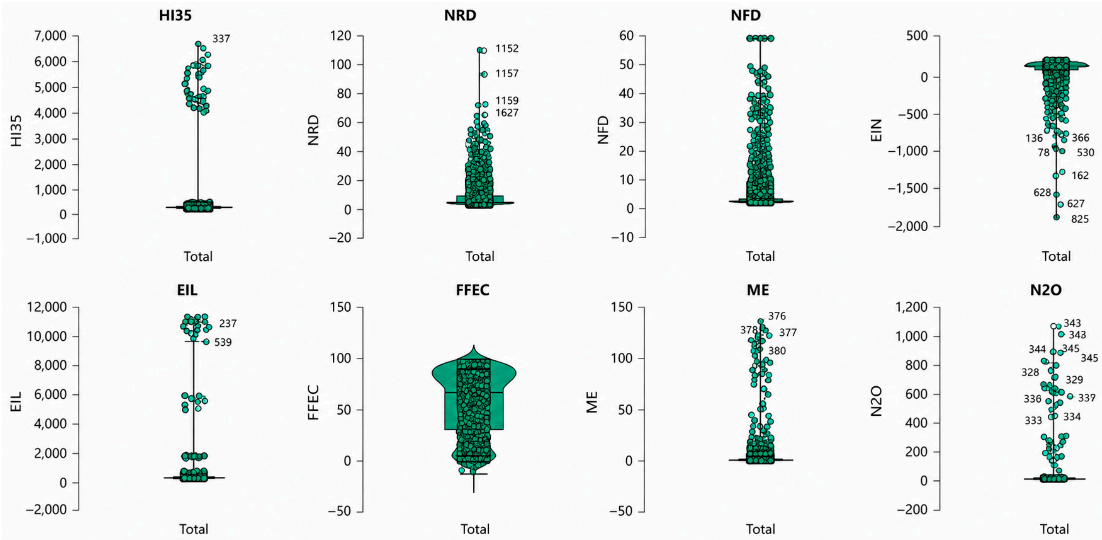

Figure A2. Boxplots and Violin Plots of Key Environmental and Energy Variables Related to Heat Exposure and Sustainability.

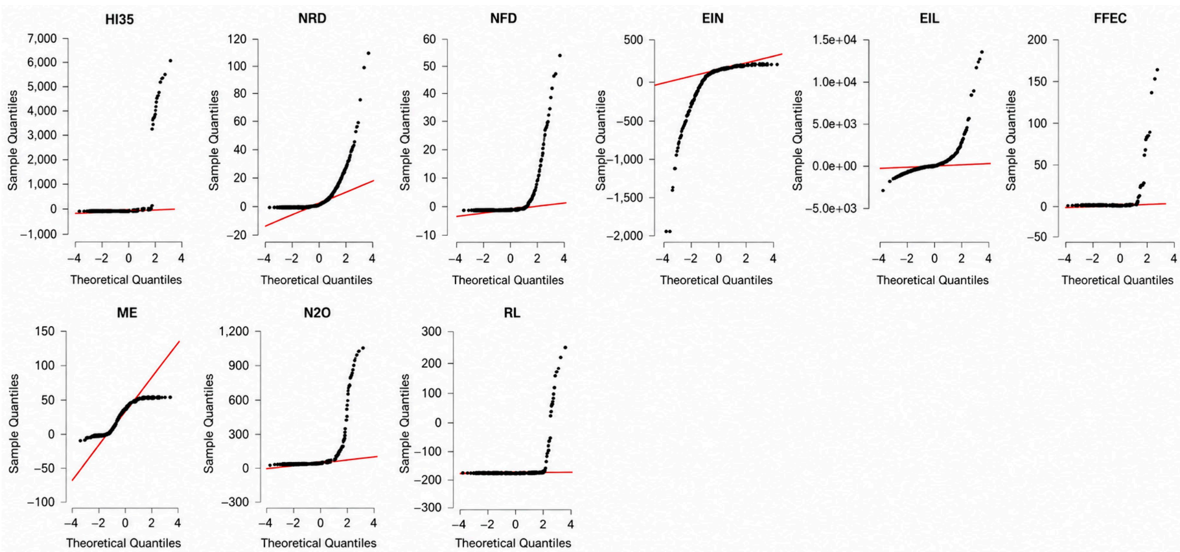

Figure A3. Q-Q Plots for Distributional Assessment of Environmental and Climate Variables.

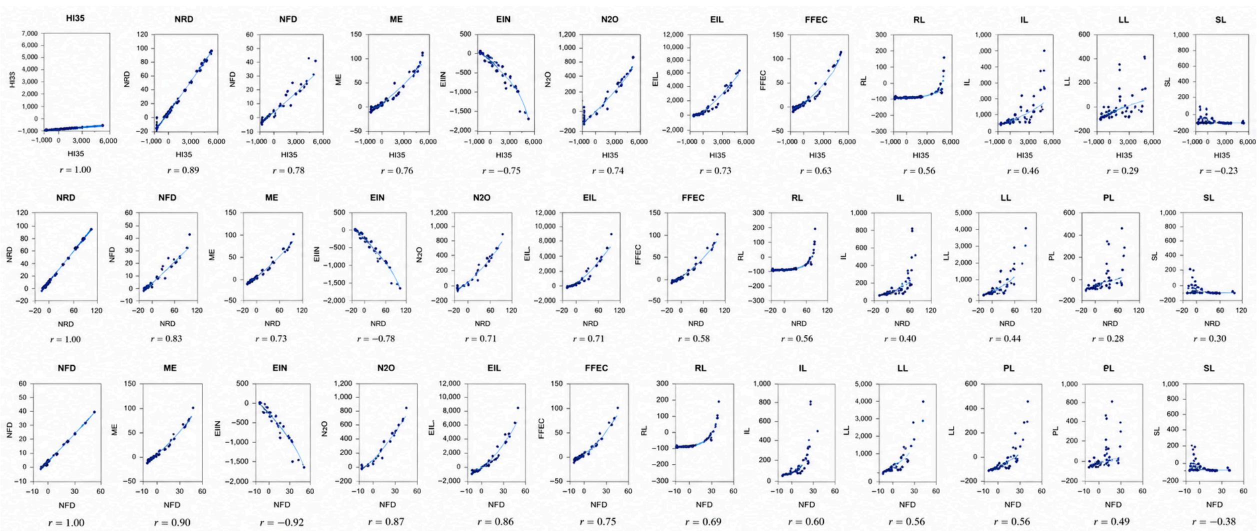

Figure A4. HI35 and ESG Dimension Interactions: Scatter and Density Plots.

Appendix B. Descriptive and Statistical Diagnostics of HI35 and Social Sustainability Indicators

Table A2. Descriptive Statistics of HI35 and Social Sustainability Indicators: Fertility, Water Access, and Undernourishment.

	HI35	FR	PUSM	POU
Valid	4070	4022	2785	3268
Missing	555	603	1840	1357
Mode	0.000	1.460	100.000	2.500
Median	0.000	2.603	72.927	6.400
Mean	57.346	6.610	64.482	11.884
Std. Error of Mean	7.693	0.285	0.605	0.212
95% CI Mean Upper	72.429	7.169	65.668	12.300
95% CI Mean Lower	42.264	6.051	63.297	11.467
Std. Deviation	490.788	18.082	31.911	12.140
95% CI Std. Dev. Upper	501.689	18.486	32.772	12.442
95% CI Std. Dev. Lower	480.354	17.695	31.095	11.853
Coefficient of variation	8.558	2.735	0.495	1.022
MAD	0.000	1.038	25.031	3.900
MAD robust	0.000	1.539	37.111	5.782
IQR	2.507	2.631	55.808	14.800
Variance	240,873.070	326.963	1018.331	147.389
95% CI Variance Upper	251,692.196	341.739	1074.018	154.806
95% CI Variance Lower	230,739.763	313.129	966.884	140.495
Skewness	9.757	5.056	−0.483	1.721
Std. Error of Skewness	0.038	0.039	0.046	0.043
Kurtosis	95.430	24.843	−1.173	3.359
Std. Error of Kurtosis	0.077	0.077	0.093	0.086
Shapiro-Wilk	0.089	0.262	0.886	0.779
p-value of Shapiro-Wilk	<0.001	<0.001	<0.001	<0.001
Range	6306.540	136.840	98.881	86.900
Minimum	0.000	0.850	1.119	2.500
Maximum	6306.540	137.690	100.000	89.400
25th percentile	0.000	1.750	39.378	2.500
50th percentile	0.000	2.603	72.927	6.400
75th percentile	2.507	4.381	95.185	17.300
Sum	233,398.850	26,586.556	179,583.090	38,835.400

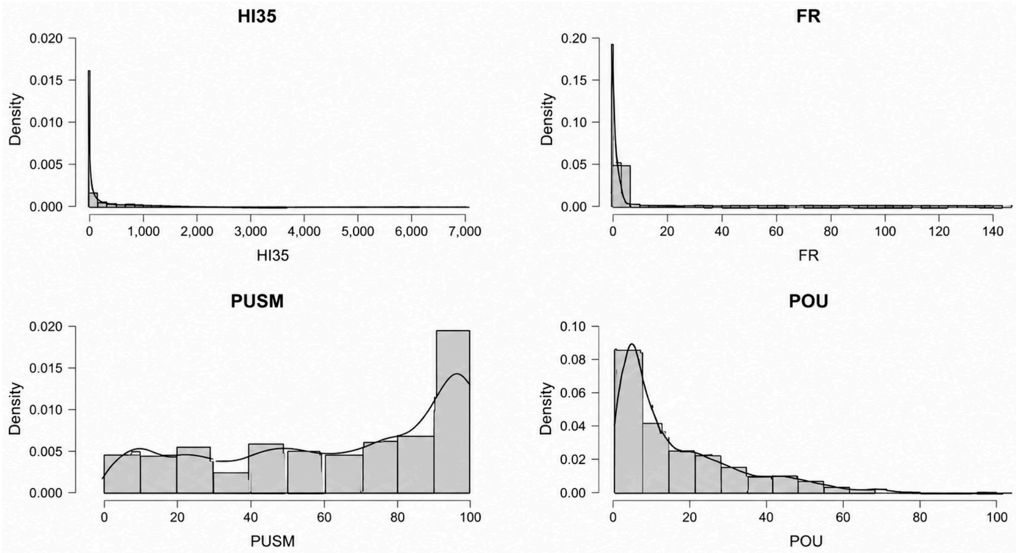

Figure A5. Distribution Plots of HI35 and Social ESG Indicators (FR, PUSM, and POU).

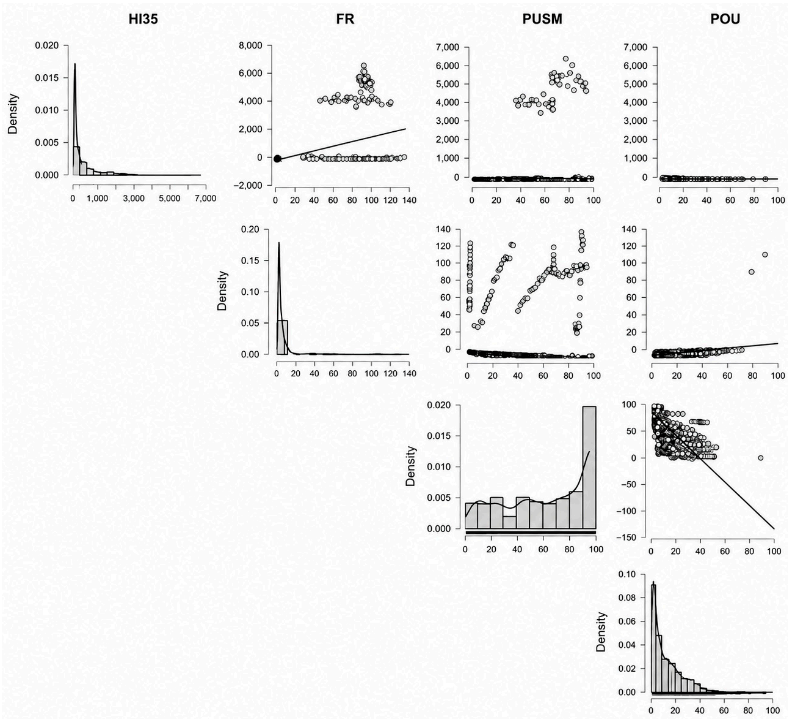

Figure A6. Scatterplot Matrix of HI35 and Social ESG Indicators (FR, PUSM, and POU).

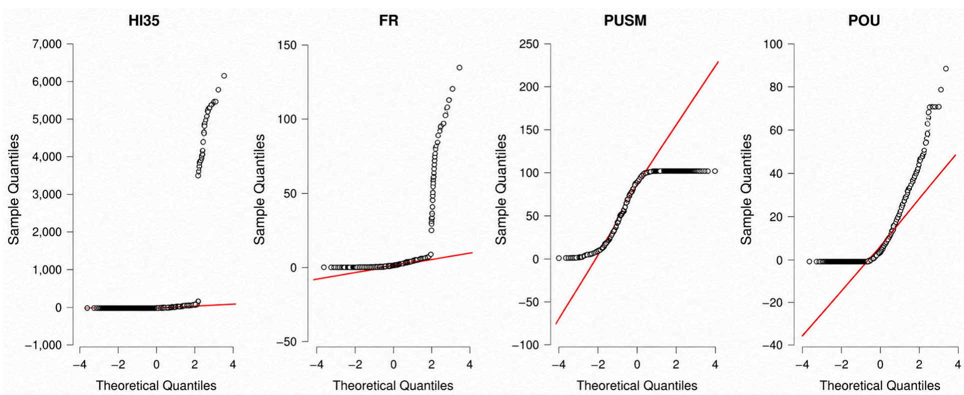

Figure A7. Q–Q Plots of HI35 and Social ESG Indicators (FR, PUSM, and POU).

Appendix C. Descriptive Analysis of Governance Structures and Climate Stress Exposure Across Nations

Table A3. Descriptive Statistics of HI35 and Leading Governance Indicators: Economic Growth, Political Stability, Gender Equality, Legal Strength, and Innovation Capacity.

	HI35	GDPG	PS	RFTM	RQ	RDE	RL	SEPS	STJA	SLRI	VA
Valid	4070	4147	4035	4277	3948	2045	4061	2814	4077	1246	3862
Missing	555	478	590	348	677	2580	564	1811	548	3379	763
Mode	0.000	4.500	1.170	61.619	0.000	0.199	0.834	0.992	0.000	6.000	1.123
Median	0.000	3.685	0.034	74.802	−0.196	0.559	−0.199	0.999	183.890	5.000	−0.021
Mean	57.346	3.458	0.171	67.416	0.306	0.877	4.024	117.542	9.551	5.484	−0.056
Std. Error of Mean	7.693	0.087	0.031	0.360	0.075	0.022	0.325	23.631	643.463	0.116	0.016
95% CI Mean Upper	72.429	3.629	0.232	68.123	0.453	0.920	4.661	163.877	10.813	5.711	−0.024
95% CI Mean Lower	42.264	3.288	0.110	66.710	0.160	0.835	3.387	71.207	8.290	5.256	−0.088
Std. Deviation	490.788	5.605	1.979	23.570	4.693	0.980	20.697	1253.543	41.086	4.097	1.007
95% CI Std. Dev. Upper	501.689	5.728	2.023	24.080	4.798	1.011	21.158	1287.182	41.997	4.264	1.030
95% CI Std. Dev. Lower	480.354	5.487	1.937	23.081	4.591	0.950	20.257	1221.629	40.213	3.942	0.985
Coefficient of variation	8.558	1.621	11.552	0.350	15.316	1.116	5.143	10.665	4.301	0.747	−17.976
MAD	0.000	2.271	0.776	12.029	0.686	0.429	0.747	0.026	182.810	3.000	0.864
MAD robust	0.000	3.367	1.150	17.834	1.016	0.636	1.108	0.038	271.034	4.448	1.281
IQR	2.507	4.532	1.549	27.586	1.434	1.083	1.596	0.053	2.689	5.000	1.724
Variance	240.873	31.417	3.917	555.542	22.021	0.960	428.385	1.571×10^6	1.688×10^9	16.784	1.015
Skewness	9.757	1.048	5.094	−1.146	13.203	1.196	4.870	11.673	8.744	2.002	−0.170
Std. Error of Skewness	0.038	0.038	0.039	0.037	0.039	0.054	0.038	0.046	0.038	0.069	0.039
Kurtosis	95.430	32.101	39.102	0.833	197.531	1.566	22.178	137.677	90.658	8.143	−0.982
Std. Error of Kurtosis	0.077	0.076	0.077	0.075	0.078	0.108	0.077	0.092	0.077	0.139	0.079
Shapiro–Wilk	0.089	0.797	0.606	0.899	0.196	0.891	0.231	0.066	0.226	0.844	0.969
p-value of Shapiro–Wilk Test	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Range	6.306	137.165	22.521	108.050	97.295	6.947	147.323	17.015	669.746	31.768	4.114
Minimum	0.000	−50.339	−3.313	−0.860	−2.548	−1.242	−2.591	0.000	−2.533	0.000	−2.313
Maximum	6.306	86.827	19.208	107.190	94.748	5.706	144.733	17.015	669.744	31.768	1.801
25th percentile	0.000	1.386	−0.711	56.369	−0.797	0.219	−0.819	0.970	15.240	2.000	−0.878
50th percentile	0.000	3.685	0.034	74.802	−0.196	0.559	−0.199	0.999	183.890	5.000	−0.021
75th percentile	2.507	5.918	0.838	83.954	0.637	1.301	0.777	1.023	2705.070	7.000	0.846

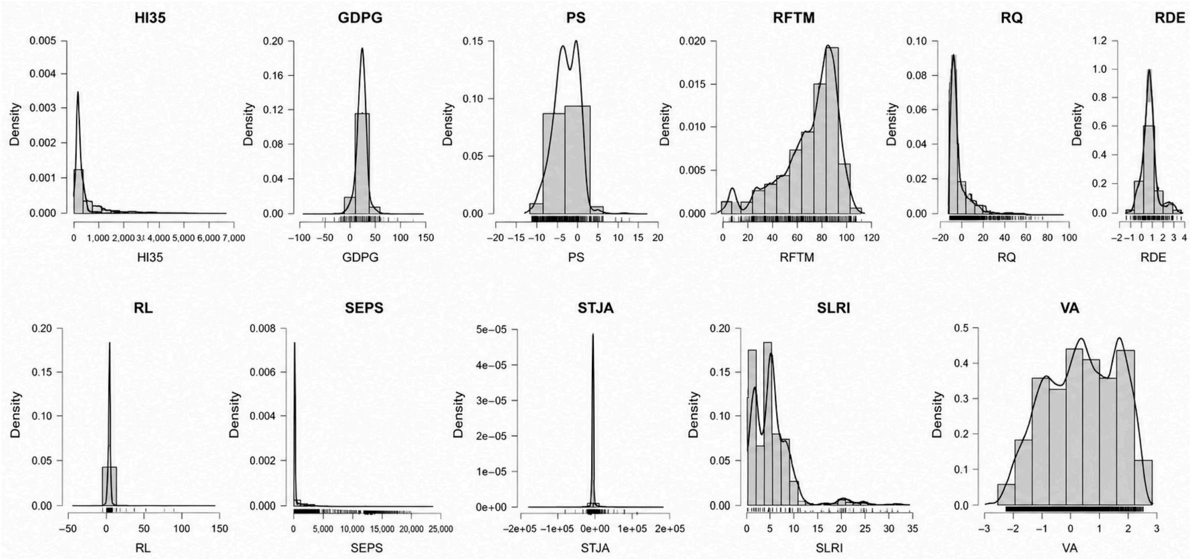

Figure A8. Distribution Plots of HI35 and Governance Indicators: Institutional Quality and Climate Stress Across Countries.

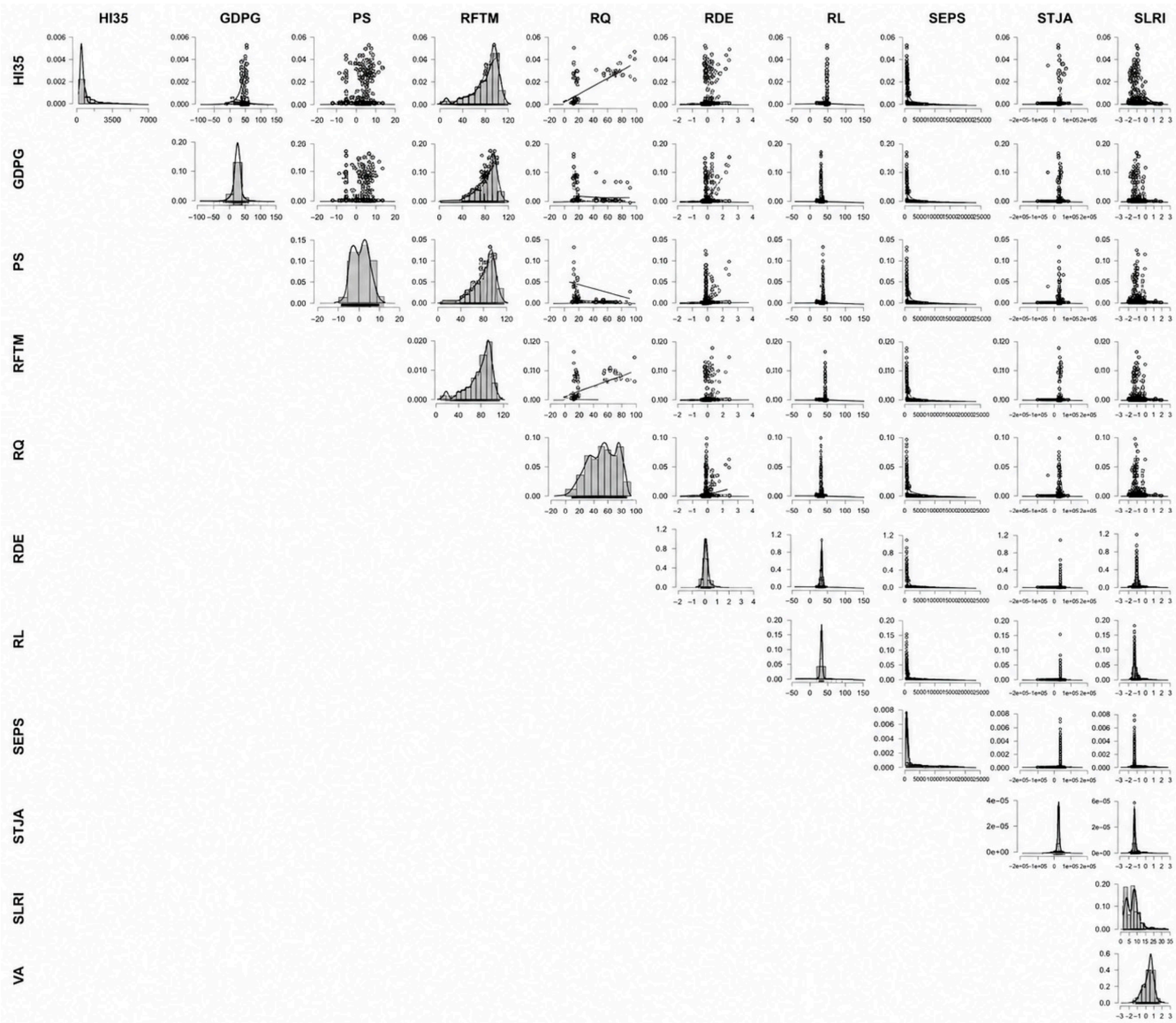

Figure A9. Correlation Scatterplot Matrix of HI35 and Governance Indicators.

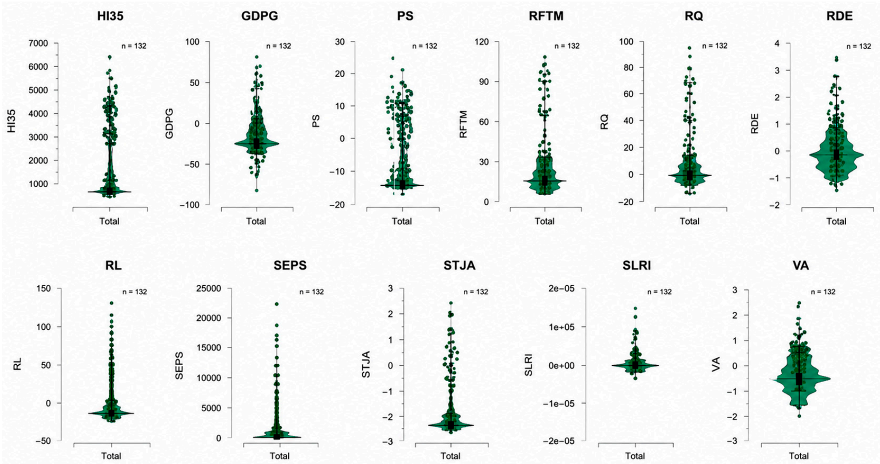

Figure A10. Boxplot Distribution of Climate Stress and Governance Indicators.

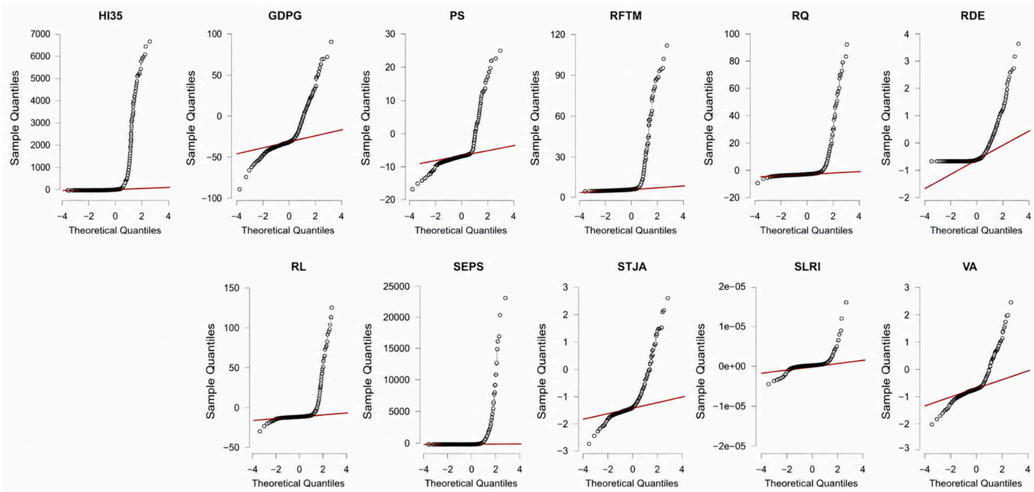

Figure A11. Q-Q Plots Assessing Normality of Climate Stress and Governance Indicators.

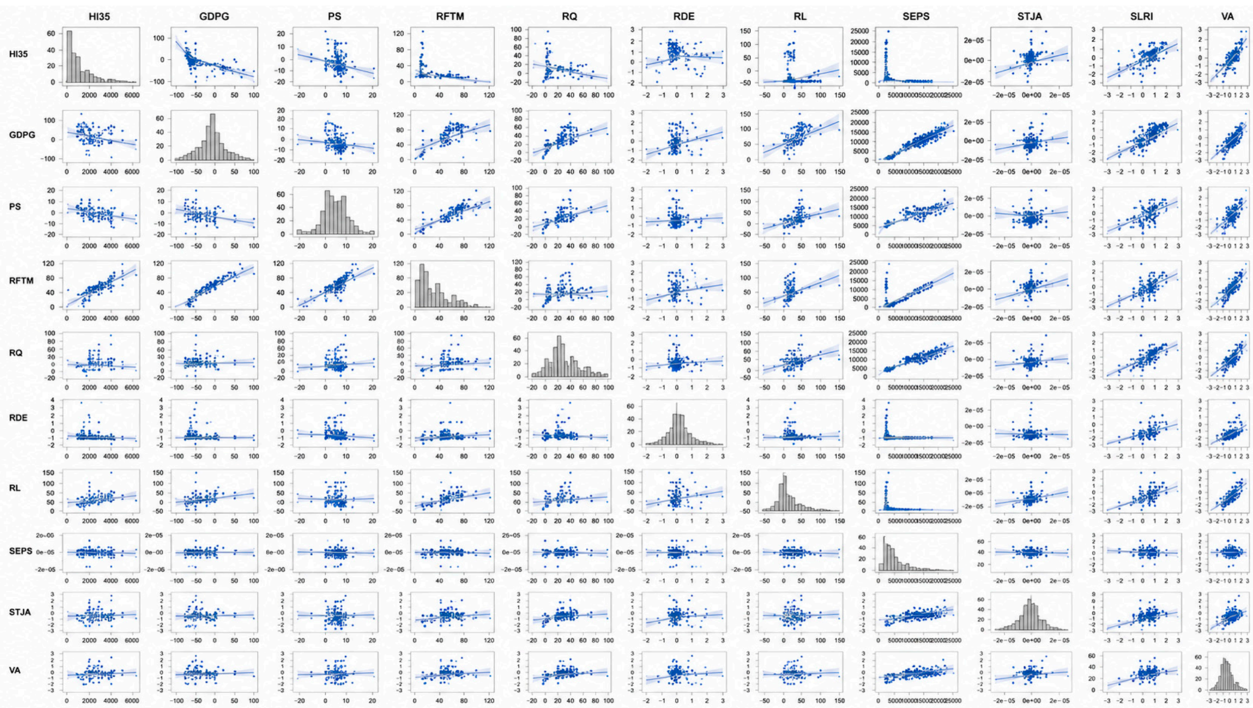

Figure A12. Governance and Climate Stress—Scatter Matrix of Institutional Interactions.

Table A4. Covariance Matrix of Climate Stress (HI35) and Governance Indicators: Institutional Quality, Scientific Capacity, and Legal Structures.

	HI35	GDPG	PS	RFTM	RQ	RDE	RL	SEPS	STJA	SLRI	VA
HI35	240.873	−69.363	688.645	−3.459	345.211	−45.517	5.337	597.278	−512.012	364.583	−3.969
GDPG	−69.363	31.417	−0.512	1.567	−0.454	−0.674	−2.040	−248.272	−5.333	0.569	−0.687
PS	688.645	−0.512	3.917	−12.402	2.696	0.160	27.057	2.117	−274.135	2.681	0.698
RFTM	−3.459	1.567	−12.402	555.542	−24.457	10.373	−272.344	−7.487	87.483	−9.415	5.012
RQ	345.211	−0.454	2.696	−24.457	22.021	−0.411	46.189	648.264	4.709	0.881	0.808
RDE	−45.517	−0.674	0.160	10.373	−0.411	0.960	−7.242	65.756	21.614	−0.660	0.510
RL	5.337	−2.040	27.057	−272.344	46.189	−7.242	428.385	12.283	−34.513	40.078	0.840
SEPS	597.278	−248.272	2.117	−7.487	648.264	65.756	12.283	1.571×10^6	-1.274×10^6	1.824	0.033
STJA	−512.012	−5.333	−274.135	87.483	4.709	21.614	−34.513	-1.274×10^6	1.688×10^9	9.109	5.227
SLRI	364.583	0.569	2.681	−9.415	0.881	−0.660	40.078	1.824	9.109.037	16.784	0.980
VA	−3.969	−0.687	0.698	5.012	0.808	0.510	0.840	0.033	5.227.804	0.980	1.015

Table A5. Correlation Matrix between Climate Stress (HI35) and Governance Indicators.

	HI35	GDPG	PS	RFTM	RQ	RDE	RL	SEPS	STJA	SLRI	VA
HI35	1.000	−0.044	0.652	−0.301	0.151	−0.070	0.500	0.796	−0.025	0.235	−0.253
GDPG	−0.044	1.000	−0.067	0.014	−0.082	−0.174	−0.064	−0.067	−0.023	0.048	−0.124
PS	0.652	−0.067	1.000	−0.266	0.322	0.065	0.688	0.694	−0.003	0.371	0.689
RFTM	−0.301	0.014	−0.266	1.000	−0.231	0.429	−0.555	−0.246	0.086	−0.097	0.251
RQ	0.151	−0.082	0.322	−0.231	1.000	−0.066	0.549	0.101	0.022	0.297	0.805
RDE	−0.070	−0.174	0.065	0.429	−0.066	1.000	−0.258	0.041	0.388	−0.139	0.555
RL	0.500	−0.064	0.688	−0.555	0.549	−0.258	1.000	0.377	−0.038	0.493	0.834
SEPS	0.796	−0.067	0.694	−0.246	0.101	0.041	0.377	1.000	−0.024	0.353	0.390
STJA	−0.025	−0.023	−0.003	0.086	0.022	0.388	−0.038	−0.024	1.000	0.046	0.119
SLRI	0.235	0.048	0.371	−0.097	0.297	−0.139	0.493	0.353	0.046	1.000	0.331
VA	−0.253	−0.124	0.689	0.251	0.805	0.555	0.834	0.390	0.119	0.331	1.000

Appendix D. Long-Term Trends in National Heat Exposure (HI35), 2000–2022

Appendix D provides descriptive temporal evidence on the evolution of national HI35 values between 2000 and 2022. These time series are reported to contextualize the long-run HI35 averages used in the main clustering analysis. They are not used as direct inputs in the clustering algorithms, which rely on temporally averaged country-level indicators, nor are they used for temporal inference, trend estimation, or causal analysis. Their purpose is to show the historical variability and persistence of heat exposure across countries and to support the interpretation of HI35 as a long-run climatic exposure indicator.

Table A6. Country-Level Heat Exposure (HI35) Across 78 Countries, 2000–2022.

Countries	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Afghanistan	0.41	1.27	1.12	2.52	0.65	1.96	3.87	1.43	4.19	1.99	1.77	1.61
United Arab Emirates	83.69	86.74	95.64	96.85	81.72	101.45	107.61	112.91	92.32	103.76	114.52	110.83
Argentina	0.61	2.19	1.85	1.55	0.51	1.05	1.66	1.21	0.74	2.71	2.98	0.65

Table A6. *Cont.*

Countries	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Australia	2.27	4.92	4.68	4.37	6.46	5.73	6.03	5.01	5.62	4.33	4.77	4.95
Azerbaijan	0.32	0.02	0.11	0.01	0	0.14	1.13	0.3	0.22	0	1.03	1.13
Benin	12.56	9.78	13.61	10.24	14.21	19.23	11.56	16.12	5.47	15.47	35.61	14.88
Burkina Faso	25.67	24.07	29.38	26.19	27.53	31.18	21.54	32.6	16.08	33.99	53.16	33.45
Bangladesh	45.64	50.58	45.47	62.47	56.82	71.71	66.63	68.43	58.2	84.19	102.99	64.67
Bahrain	120.96	119.06	144.76	132.35	122.43	126.94	140.15	142.5	116.94	126.39	139.49	130.7
Belize	0.15	0.26	1.57	8.07	4	15.13	4.08	3.15	5.23	11.06	21.78	8.29
Bolivia	0.22	0.35	1.52	0.75	1.04	1.2	0.99	0.64	1.33	2.59	3.71	0.67
Brazil	0.17	0.34	0.71	0.36	0.41	0.63	0.57	0.32	0.14	0.74	1	0.18
Brunei Darussalam	0.12	0.37	0.39	0.51	0.05	0.65	0.17	0.63	0	1.04	1.07	0.13
Bhutan	0.01	0.04	0	0.08	0	0.05	0.15	0.09	0.02	0.12	0.01	0.04
Central African Republic	0.05	0.66	0.43	0.27	0.68	0.63	0.2	0.47	0	0.22	1.99	0.45
China	2.56	2.75	2.52	4.04	2.41	2.63	3.41	2.77	1.86	2.78	3.9	2.3
Cote d'Ivoire	0.03	0.04	0.26	0.08	0.23	1.88	0.08	0.35	0.08	0.23	4.71	0.54
Cameroon	0.8	1.88	2.28	1.64	2.08	2.67	1.7	2.18	0.88	2.23	4.93	3.08
Colombia	0.14	0.43	2.03	1.42	1.48	2.44	1.44	1.41	0.55	3.17	5.77	1.53
Djibouti	23.24	27.24	32.14	29.18	30.18	42.76	28.87	31.06	24.45	32.58	41.88	21.56
Algeria	4.62	11.2	17.92	11.88	8.11	14.76	13.77	11.48	12.42	12.62	20.14	13.05
Egypt	1.19	1	2.71	0.79	0.37	1.25	0.95	0.72	0.55	0.32	5.47	1.08
Eritrea	28.83	32.93	27.51	32.25	29.42	32.55	28.72	28.29	25.3	28.23	35.05	25
Ethiopia	2.65	3.12	2.88	2.96	3.05	3.44	2.72	2.85	2.31	2.91	3.82	2.45
Ghana	11.25	11.09	16.04	10.82	12.31	23.15	12.19	16.18	8.09	20.75	36.07	16.17
Guinea	0.44	0.5	1.06	1.24	1.6	1.86	1.37	1.57	0.76	1.35	4.76	1.87
Gambia	6.55	11.98	20.7	17.81	15.78	46.82	36.29	15.71	14.45	26.07	34.09	32.47
Guinea-Bissau	2.14	2.8	3.62	7.97	2.49	24.52	9.16	8.02	6.92	7.63	27.07	10.06
Guatemala	0.16	0.29	0.32	3.52	0.45	5	1.06	1.2	1.74	2.24	9.06	4.59
Indonesia	0.14	0.08	0.24	0.26	0.42	0.2	0.1	0.18	0.02	0.28	1.43	0.21
India	34.74	34.3	44.58	39.59	38.22	40.51	40.2	42.43	28.7	45.88	53.66	39.17
Iran	9.41	11.5	11.31	13.05	9.7	12.76	13.5	13.01	13.76	13.23	13.74	14.2
Iraq	35.25	30.51	25.55	25.34	23.77	25.85	37.31	33.37	33.67	22.45	46.18	31.65
Israel	0.55	0.23	0.75	0.01	0.01	0.04	0.04	0.33	0.23	0	3.48	0.08
Jordan	0.56	0.13	0.15	0.01	0	0.03	0.04	0.21	0.12	0	1.07	0.22
Japan	0.12	0.63	0.27	0.17	0.25	0.12	0.36	0.5	0.5	0.25	1.06	0.24
Kazakhstan	0.03	0.01	0.13	0.02	0	0.16	0.01	0.03	0.1	0	0.04	0.11
Kenya	0.02	0.03	0.64	0.33	0.18	0.77	0.11	0.32	0.08	0.21	1.17	0.23
Cambodia	9.35	26.74	33.71	38.56	36.24	33.21	19.21	28.26	14.28	21.6	65.09	17.83
Kuwait	61.8	52.34	52.03	54.62	52.51	55.09	79.95	62.7	66.43	52.8	80.64	57.14
Lao PDR	0.34	2.74	0.77	3.25	1.31	1.77	1.44	2.63	0.84	1.24	7.46	0.99
Libya	0.02	0.13	0.97	0.1	0.06	0.21	0.18	0.07	0.16	0.18	1.33	0.32
Sri Lanka	4.19	6.53	5.9	10.52	6.84	15.28	9.01	11.71	5.47	13.96	21.54	7.18
Morocco	0.52	1.2	0.4	1.39	0.81	0.98	1.05	1.18	1.21	1.33	2.62	1.46
Madagascar	0.03	0.03	0.05	0.07	0.25	0.22	0.32	0.04	0.02	0.15	0.21	0.15
Mexico	3.57	4.38	3.12	5.31	3.93	6.59	5.73	4.64	4.93	8.29	8.45	8.73
Mali	13.42	18.71	35.84	29.82	21.1	33.13	24.1	28.51	20.64	35.49	58.95	41.94

Table A6. *Cont.*

Countries	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Myanmar	4.99	6.51	5.47	11.01	8.61	16.45	8.94	11.05	6.84	15.16	22.62	8.28
Mozambique	0.1	0.19	0.07	1.15	0.3	1.14	1.76	0.87	0.52	1.4	1.36	0.25
Mauritania	15.01	25.07	24.6	27.9	17.77	31.44	29.94	21.5	26.36	35.59	48.03	34.55
Malawi	0.02	0.05	0.02	0.1	0	0.08	0.08	0.03	0.08	0.13	0.25	0.03
Malaysia	0.14	0.09	0.38	0.37	0.78	0.58	0.19	0.16	0.01	0.46	1.68	0.42
Niger	4.82	6.89	10.39	7.36	8.53	7.79	6.21	7.53	4.75	10.33	20.86	12.57
Nigeria	6.33	7.44	9.85	7.96	10.9	14.86	11.33	10.69	3.75	11.06	27.04	13.02
Nepal	4.16	6.06	5.55	6.16	5.99	8.18	7.7	7.01	4.31	8.32	7.67	5.16
Oman	38.26	42.36	46.83	54.99	38.51	49.46	50.12	62.14	43.76	58.15	65.3	58.94
Pakistan	55.23	54.93	53.93	53.51	53.22	50.29	58.79	61.13	56.81	59.35	57.55	59.7
Philippines	0.84	1.79	2.88	2.84	2.32	4.51	2.91	5.02	0.93	2.46	9.78	2.02
Paraguay	5.49	8.1	19.4	8.67	4.5	5.4	12.85	7.52	4.47	18.29	19.22	2.17
West Bank and Gaza	0.89	0.42	1.39	0	0.02	0.07	0.3	0.7	0.4	0	4.82	0.33
Qatar	93.67	97.44	116.13	112.84	94.59	98.96	121.15	131.67	108.87	118.38	127.5	119.78
Saudi Arabia	20.04	22.29	17.28	22.45	16.43	23.69	27.61	26.71	24.59	22.87	42.59	29.37
Sudan	4.8	6.1	6.52	7.2	3.79	8.04	5.2	5.44	4.31	6.8	11.9	4.95
Senegal	18.4	26.33	34.94	35.17	30.18	53.39	52.19	30.61	29.58	43.09	51.92	52.87
Sierra Leone	0.04	0.02	0.03	0.01	0.15	0.12	0.03	0.17	0.01	0	0.4	0.02
Somalia	1.52	2	2.36	2.65	2.06	2.86	2.62	2.84	1.75	2.29	4.38	2.14
South Sudan	0.35	2.31	3.22	2.23	1.25	2.9	1.32	2.05	0.05	2.64	6.19	0.73
Syrian Arab Republic	3.86	3.45	1.63	1.77	0.74	1.45	0.71	2.44	0.97	0.12	4.73	1.47
Chad	2.04	5.2	5.46	6.57	7.45	8.33	6.22	6.48	2.17	5.23	17.44	9.5
Togo	8.33	7.26	9.58	6.1	8.51	14.95	9.02	10.6	4.33	12.13	28.07	12.28
Thailand	8.7	18.21	18.2	26.68	19.96	30.31	21.09	23.86	10.95	17.51	45.66	11.2
Turkmenistan	1.66	1.11	5.92	2.41	1.13	4.05	2.24	0.92	3.61	1.44	4.42	6.44
Tunisia	0.67	3.88	3.96	8.67	2.35	5.9	3.95	1.91	4.25	3.95	4.26	3.16
United States	0.47	0.6	0.3	0.49	0.31	0.66	0.64	0.62	0.35	0.94	2.24	2.43
Uzbekistan	0.38	0.08	2.14	0.62	0	2.08	0.08	0.27	1.42	0.01	0.77	2.2
Venezuela, RB	0.09	0.28	0.39	0.68	1.68	3.28	1.46	1.26	0.7	2.79	6.9	1.44
Viet Nam	8.28	12.28	13.78	16.69	11.86	12.9	9.8	13.78	7.54	13.36	25.55	9.81
Yemen	14.56	16.67	12.42	14.33	14.41	23.43	17.52	19.1	17.87	16.88	25.83	23.11
Countries	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**% Var 2000–2022**
Afghanistan	0.87	3.36	1.11	2.09	1.71	1.97	2.38	2.56	1.46	3.84	3.76	817.1
United Arab Emirates	105.72	87.6	102.6	113.29	105.53	114.55	109.98	123.08	108.75	129.78	105.13	25.6
Argentina	2.62	2.06	2.44	1.51	2.89	2.03	1.47	2.92	1.93	0.47	3.23	429.5
Australia	3.08	7.76	6.53	6.07	7.45	7	8.53	12.85	8.6	5.32	6.12	169.6
Azerbaijan	0.04	0	0.39	0.28	0.18	0.15	0.94	0.05	0.05	0.79	0.02	−93.8
Benin	12.81	21.12	13.5	14.27	38.21	16.68	18.38	30.65	28.73	24.01	16.25	29.4
Burkina Faso	24.26	38.06	34.59	35.86	48.19	35.2	37.71	47.23	47.55	41.28	32.8	27.8
Bangladesh	91.74	76.63	91.94	81.21	102.7	99.08	87.94	108.78	103.79	101.66	106.76	133.9
Bahrain	137.54	108.77	149.22	146.33	126.44	145.19	145.21	157	139.89	149.92	131.35	8.6
Belize	3.2	4.92	5.18	12	22.02	20.88	2.29	29.19	26.65	13.54	6.36	4140.0

Table A6. *Cont.*

Countries	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Bolivia	1.74	1.33	1.32	5.49	4.36	1.53	1.25	2.73	4.52	2.9	1.9	763.6
Brazil	0.4	0.25	0.32	1.44	1.18	0.54	0.77	0.76	0.36	0.32	0.16	−5.9
Brunei Darussalam	0.26	2.07	3.09	3.52	6.77	2.61	5.31	9.49	8.52	4.87	2.13	1675.0
Bhutan	0.15	0.07	0.05	0.07	0.22	0.26	0.3	0.55	0.29	0.13	0.61	6000.0
Central African Republic	0.02	0.08	0.01	0.09	1.81	0.42	0.25	2.17	0.89	0.24	0.18	260.0
China	2.65	4.4	2.57	2.42	4.71	4.63	4.69	4.13	4.02	3.97	6.24	143.8
Cote d'Ivoire	0.31	0.72	0.42	0.26	6.38	1.01	0.1	0.81	4.29	0.46	0.66	2100.0
Cameroon	2.21	2.46	2.56	2.69	4.73	3.29	3.71	4.28	4.97	2.82	2.92	265.0
Colombia	2.89	4.11	6.32	10.45	9.69	4.59	3.52	7.68	5.32	1.43	1.3	828.6
Djibouti	23.44	25.77	28.53	49.78	55.74	70.09	35.21	49.15	37.64	38.61	28.61	23.1
Algeria	14.37	13	19.89	14.83	16.94	18.13	20.85	20.73	17.88	23.59	15.4	233.3
Egypt	1.86	1.11	1.52	6.56	1.26	2.54	3.66	3.99	2.89	2.12	1.83	53.8
Eritrea	29.37	31.27	29.67	33.5	38.06	39.83	33.43	36.23	28.57	31.31	28.11	−2.5
Ethiopia	2.86	3.08	3.05	4	5.07	5.15	3.55	4.37	3.37	3.29	3.01	13.6
Ghana	11.27	20.06	16.74	20.34	37.16	27.76	23.5	34.57	37.24	31.36	21.13	87.8
Guinea	1.56	0.98	0.94	2.18	3.43	3.28	1.11	2.43	4.73	1.95	1.5	240.9
Gambia	28.85	26.26	31.89	23.95	29.53	50.88	20.27	24.67	39.31	42.95	26.29	301.4
Guinea-Bissau	9.64	10.39	8.18	11.83	8.8	24.39	6.12	12.41	22.15	14.27	10.79	404.2
Guatemala	1.31	3.21	2.23	4.54	10.18	5.74	1.75	10.08	9.51	4.94	3.77	2256.3
Indonesia	0.21	0.73	0.57	0.7	2.38	0.88	0.81	1.31	2.27	0.78	0.93	564.3
India	42.48	41.74	46.16	51.12	60.12	57.96	52.24	60.91	57.43	47.54	57.18	64.6
Iran	10.38	12.7	12.68	13.45	13.47	13.69	15.29	16.87	16.02	17.12	16.1	71.1
Iraq	35.23	20.17	34.62	44.55	47.13	50.62	32.42	39.78	39.52	44.64	39.35	11.6
Israel	0.85	0.01	0.06	3.17	0.08	0.37	0.02	0.03	2.72	0.23	0.64	16.4
Jordan	0.32	0.01	0.05	1.02	0.1	0.38	0.02	0.03	2.12	0.11	0.7	25.0
Japan	0.28	2.07	0.53	0.66	1.1	2.1	2.6	1.88	2.52	0.54	2.55	2025.0
Kazakhstan	0.01	0.01	0.01	0.2	0.01	0.12	0.17	0.14	0.01	0.23	0.11	266.7
Kenya	0.03	1.44	0.71	1.32	7.3	0.74	0.03	4.1	5.23	0.55	1.09	5350.0
Cambodia	31.03	50.28	49.17	57.62	69.7	47.71	25.53	63.76	64.83	45.38	33.16	254.7
Kuwait	63.81	47.75	76.33	87.15	82.21	91.91	91.17	90.44	80.33	89.63	90.54	46.5
Lao PDR	2.26	3.63	5.46	7.67	8.12	4.57	2.1	10.15	10.75	8.56	3.8	1017.6
Libya	0.04	0.07	0.27	0.3	0.14	0.04	1.04	0.44	0.17	0.56	0.16	700.0
Sri Lanka	8.9	13.01	13.67	13.74	26.46	22.13	4.1	25.13	19.04	6.46	9.34	122.9
Morocco	2.67	0.76	0.83	0.82	1.64	1.31	1.19	0.85	2.33	1.57	1.8	246.2
Madagascar	0.01	0.13	0.07	0.07	0.74	0.2	0.15	0.49	0.39	0.77	0.11	266.7
Mexico	5.25	5.09	6.25	7.76	9.07	7.18	6.26	11.41	10.3	6.41	5.47	53.2
Mali	24.82	25.72	36.64	38.14	50.77	50.88	40.63	48.48	43.4	46.48	28.91	115.4
Myanmar	15.89	13.92	21.61	17.39	19.32	16.62	11.78	27.17	25.61	25.02	20.94	319.6
Mozambique	0.41	0.35	0.33	0.92	4.17	0.28	1.2	3.08	2.91	2.71	0.2	100.0
Mauritania	27.39	30.14	31.74	37.03	40.87	41.6	28.09	32.96	48.06	36.29	29.24	94.8
Malawi	0	0.03	0.05	0.19	0.72	0.02	0.23	0.34	0.49	0.37	0.01	−50.0
Malaysia	0.24	1.46	1.73	1.58	6.09	1.58	1.86	3.52	4.39	1.38	1.17	735.7
Niger	7.31	9.05	13.99	16.3	20.19	15.87	15.4	21.05	16.87	11.11	9.45	96.1
Nigeria	9.45	16.1	12.44	12.33	25.49	13.79	13.47	19.07	20.42	11.69	12.24	93.4

https://doi.org/10.3390/cli14070138

Table A6. *Cont.*

Countries	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Nepal	8.68	7.55	9.07	9.73	9.21	11.2	10.55	12.19	8.4	8.42	12.99	212.3
Oman	57.43	46.29	51.87	66.79	56.44	68.56	61.1	70.03	73.83	60.43	53.3	39.3
Pakistan	54.03	61.39	56.7	53.61	68.89	64.2	60.84	64.93	66.89	66.44	59.12	7.0
Philippines	2.5	5.25	7.57	5.33	11.39	6.53	5.29	9.8	12.39	7.95	3.62	331.0
Paraguay	11.14	11.38	7.61	16.15	19.11	14.98	10.68	22.93	16.49	6.13	15.46	181.6
West Bank and Gaza	1.61	0	0.12	4.69	0.31	0.85	0.02	0.05	4.08	0.41	1.39	56.2
Qatar	114.34	83.54	115.71	130.02	109.07	128.6	135.49	141.22	129.78	128.76	118.79	26.8
Saudi Arabia	30.4	19.27	21.3	31.85	34.79	43.57	33.8	35.22	35.74	39.35	36.52	82.2
Sudan	6.32	4.75	4.66	8.01	7.8	8.65	7.27	10.27	4.22	6.08	4.65	−3.1
Senegal	42.58	45.24	54.22	48.24	51.74	56.56	32.76	50.04	62.99	58.58	45.87	149.3
Sierra Leone	0	0	0.01	0.02	0.6	1.11	0	0.19	3.81	0.24	0.32	700.0
Somalia	1.92	3.03	2.86	3.7	7.07	3.35	1.89	5.79	6.7	2.34	3.11	104.6
South Sudan	0.21	0.64	0.06	0.28	10.62	1.55	1.36	5.94	1.94	0.23	0.65	85.7
Syrian Arab Republic	3.29	0.11	2.44	3.25	5.3	4.17	0.57	2.52	3.12	2.47	1.09	−71.8
Chad	6.68	5.4	9.64	11.78	15.98	13.75	13.34	14.49	9.77	6.23	8.73	327.9
Togo	7.27	15.19	10.99	11.48	26.82	15.21	16.39	26.05	22.54	20.2	11.06	32.8
Thailand	17.99	24.63	32	39.22	47.9	28.59	17.79	45.79	48.59	37.83	24.51	181.7
Turkmenistan	1.83	2.05	3.78	8.73	2.66	4.81	11.37	8.59	2.59	9.22	6.04	263.9
Tunisia	6.72	1.18	3.45	3.36	2.37	3.76	4.82	5.55	2.9	13.5	9.04	1249.3
United States	0.83	0.51	0.37	0.99	1.36	0.91	0.95	1.65	1.35	0.97	1.62	244.7
Uzbekistan	0.17	0.2	0.3	2.47	0.05	1.65	2.43	2.26	0.23	3.08	1.97	418.4
Venezuela, RB	2.23	4.15	4.18	7.28	8.04	1.14	1.17	1.96	3.75	0.33	0.62	588.9
Viet Nam	13.55	18.22	22.07	27.54	28.29	20.5	16.47	33.28	32.34	24.35	17.68	113.5
Yemen	20.77	17.66	17.72	18.5	19.17	22.09	17.72	21.39	19.81	16.38	16.14	10.9

References

1. Alam, A.; Banna, H.; Alam, A.; Bhuiyan, M.; Mokhtar, N. Climate change and geopolitical conflicts: The role of ESG readiness. *J. Environ. Manag.* **2024**, *353*, 120284. [CrossRef]
2. Yu, B.; Huang, G.; Zhou, X.; Wang, S.; Li, Y.; Wu, Y.; Ren, J. A stepwise-clustered heat stress downscaling approach to analyze future variations of heat stress in East China. *Theor. Appl. Climatol.* **2025**, *156*, 112. [CrossRef]
3. Liu, H.; Zhang, Q.; Xia, X.; Yang, X.; Yi, Z.; Yue, L.; Huang, L. ESG performance and organizational resilience—Based on an "extreme heat event. *Borsa Istanb. Rev.* **2024**, *24*, 304–313.
4. Liang, Y.; Tan, Q.; Pang, J. Bless or curse, how does extreme temperature shape heavy pollution companies' ESG performance? Evidence from China. *Energy Econ.* **2024**, *131*, 107378. [CrossRef]
5. Orlandi, L. Environmental Policies and Firms' Financial Performance and Risks: Is the Environmental Score of European Firms a Tool for Financial Risk Mitigation and Financial Performance Improvement After the Heatwaves of August 2022? Masters's Thesis, HEC-Ecole de Gestion de l'Université de Liège, Liège, Belgium, 2023.
6. Li, C.; Tang, W.; Liang, F.; Wang, Z. The impact of climate change on corporate ESG performance: The role of resource misallocation in enterprises. *J. Clean. Prod.* **2024**, *445*, 141263. [CrossRef]
7. Rossi, C.; Byrne, J.; Christiaen, C. Breaking the ESG rating divergence: An open geospatial framework for environmental scores. *J. Environ. Manag.* **2024**, *349*, 119477.
8. Murari, K. *Heat Resilience as a Key Element of City-Level Climate Action Plans. Confronting the Climate Crisis: Pathways to Urban Resilience in India*; Observer Research Foundation: Delhi, India, 2023; Volume 4, p. 34.
9. Jiang, Y.; Tang, Q. Mandatory carbon reporting, voluntary carbon disclosure and ESG performance. *Pac. Account. Rev.* **2023**, *35*, 534–561. [CrossRef]
10. Marotta, A.; Porras-Amores, C.; Rodríguez Sánchez, A. Are green buildings an indicator of sustainable development? *Appl. Sci.* **2023**, *13*, 3005. [CrossRef]

11. Barotov, T. Climate Change Risk Premium, Stock Returns and Volatility Analysis in Relation to ESG Score. Master's Thesis, Faculty of Social Sciences, Institute of Economic Studies, Charles University, Prague, Czech Republic, 2022.
12. Iqbal, N.; Bouri, E.; Shahzad, S.; Alsagr, N. Asymmetric impacts of Chinese climate policy uncertainty on Chinese asset prices. *Energy Econ.* **2024**, *133*, 107518. [CrossRef]
13. Capriotti, A.; Muzzioli, S. *Climate Risk Measures and Main Data Providers*; DEMB Working Paper Series; Dipartimento di Economia Marco Biagi: Modena, Italy, 2024.
14. Zhu, Y.; Carrasco, L. Where is biodiversity in ESG? Environmental, social and governance (ESG) assessments largely overlook biodiversity. *Resour. Conserv. Recycl.* **2025**, *217*, 108187. [CrossRef]
15. Lupu, I.; Hurduzeu, G.; Lupu, R. How is the ESG reflected in European financial stability? *Sustainability* **2022**, *14*, 10287. [CrossRef]
16. Feng, X.; von Mettenheim, H.; Sermpinis, G.; Stasinakis, C. Sustainable Portfolio Construction via Machine Learning: ESG, SDG and Sentiment. In *European Financial Management*; John Wiley & Sons Ltd.: Hoboken, NJ, USA, 2024.
17. Bebchuk, L.; Tallarita, R. The perils and questionable promise of ESG-based compensation. *J. Corp. Law.* **2022**, *48*, 37–75.
18. Pompella, M.; Costantino, L. ESG disclosure and sustainability transition: A new metric and emerging trends in responsible investments. *TalTech J. Eur. Stud.* **2023**, *13*, 8–39. [CrossRef]
19. Jiang, P.; Feng, G.; Wang, H.; Chang, C. CSR from different perspectives: The global ESG indexes updated. *Corp. Soc. Responsib. Environ. Manag.* **2024**, *31*, 4694–4714. [CrossRef]
20. Wang, L.; Ji, Y.; Ni, Z. Spillover of stock price crash risk: Do environmental, social and governance (ESG) matter? *Int. Rev. Financ. Anal.* **2023**, *89*, 102768. [CrossRef]
21. Luo, L.; Tang, Q. The real effects of ESG reporting and GRI standards on carbon mitigation: International evidence. *Bus. Strategy Environ.* **2023**, *32*, 2985–3000.
22. Oliver Yébenes, M. Climate change, ESG criteria and recent regulation: Challenges and opportunities. *Eurasian Econ. Rev.* **2024**, *14*, 87–120. [CrossRef]
23. Jinga, P. Governance (ESG) Investing in Combating Climate Change. In *Environmental Management: Pollution, Habitat, Ecology, and Sustainability*; Intechopen: London, UK, 2022; Volume 279.
24. Oza, P.; Singhal, P. *A Study of Factors Influencing Environmental, Social and Governance (ESG) Investing Among Retail Investors in India*; Faculty of Management Studies and Commerce University of Sri Jayewardenepura: Nugegoda, Sri Lanka, 2024.
25. Yu, L.; Keilani, A.; Tran, N.N.; Escribà-Gelonch, M.; Goodsite, M.; Sandhu, S.; Hessel, V. ESG assessment methodology for emerging technologies: Plasma versus conventional technology for ammonia production. *Rsc Sustain.* **2025**, *3*, 1102–1113. [PubMed]
26. Xu, X.; Zhao, H. An Empirical Study on ESG Evaluation of Chinese Energy Enterprises Based on High-Quality Development Goals—A Case Study of Listed Company Data. *Sustainability* **2024**, *16*, 6602. [CrossRef]
27. Ren, M.; Zhou, J.; Si, J.; Wang, G.; Guo, C. The impact of ESG performance on green innovation among traditional energy en-terprises—Evidence from listed companies in China. *Sustainability* **2024**, *16*, 3542. [CrossRef]
28. Treepongkaruna, S.; Au Yong, H.; Thomsen, S.; Kyaw, K. Greenwashing, carbon emission, and ESG. *Bus. Strategy Env.* **2024**, *33*, 8526–8539. [CrossRef]
29. Rasool, N.; Arunachalam, M.; Wellalage, N.; Kumar, V. Unveiling the relationship between ESG and growth of unlisted firms: Empirical insights from Eastern Europe and Central Asia. *Bus. Strategy Environ.* **2025**, *34*, 5669–5686. [CrossRef]
30. Trinh, H.H. Corporate ESG Profile, Innovation Investment, and Cost of Debt Financing: Global Evidence from Uncertainty Episodes. *Strateg. Bus. Res.* **2026**, *2*, 100079. [CrossRef]
31. Trinh, H.H. Global Economic Policy Uncertainty, Corporate ESG Ratings, and Default Probability Risk in the Era of Climate Change. SSRN. Available online: https://ssrn.com/abstract=4697422 (accessed on 17 January 2024).
32. De Giovanni, P. Why Nobody Measures the Scope 4 (Avoided) Emissions? Let's Get It Started! *Sustainability* **2025**, *17*, 8317. [CrossRef]
33. Hu, C.; Guo, R. Research on risk contagion in ESG industries: An information entropy-based network approach. *Entropy* **2024**, *26*, 206. [CrossRef] [PubMed]
34. Verma, R.; Mohnot, R. Relative impact of the US energy market sentiments on stocks and ESG index returns: Evidence from GCC countries. *Int. J. Energy Econ. Policy* **2023**, *13*, 290–300. [CrossRef]
35. Yu, Y.; Meng, X.; Ren, C. The Impact of Extreme Temperature on Enterprise ESG: An Empirical Analysis of China. *Green. Low.-Carbon Econ.* **2026**, *4*, 9–20.
36. Liu, K.; Fu, Z.; Chai, Y. Efficiency Calculation and Analysis of Green Economy Based on Improved Fixed Effects Model. *IEEE Access* **2024**, *12*, 162714–162728. [CrossRef]
37. Sugiarto, A.; Puspani, N.; Fathia, F. ESG leverage towards stock performance in Indonesia stock exchange. *Int. J. Energy Econ. Policy* **2023**, *13*, 593–606. [CrossRef]
38. Muddasir, M.; Ramon-Llorens, M. Impact of Macroeconomic Factors on S&P Europe 350 ESG Index During the Rus-so-Ukrainian War. *Sci. Ann. Econ. Bus.* **2025**, *72*, 145–164.

39. Tan, J.; Zou, X.; Zhang, X.; Chang, C. Does national ESG performance move together with climate warming? *Econ. Anal. Policy* **2025**, *86*, 19–29. [CrossRef]
40. Lee, E.; Kim, G. Analysis of domestic and international green infrastructure research trends from the ESG perspective in South Korea. *Int. J. Environ. Res. Public Health* **2022**, *19*, 7099. [CrossRef] [PubMed]
41. Semet, R.; Roncalli, T.; Stagnol, L. ESG and sovereign risk: What is priced in by the bond market and credit rating agencies? 2021. Available online: https://ssrn.com/abstract=3940945 (accessed on 28 December 2025).
42. He, J.; Wu, F. *Sovereigns and ESG: Taking a Stance in a Complicated World*; JP Morgan Asset Management: Mumbai, India, 2022.
43. Enriquez, R.; Hillbom, E.; Palacio, A. Can Sovereign ESG Help Guide Nation-States' Transformative Change? *J. Sustain. Dev.* **2025**, *18*, 56–76.
44. Chen, X.; Huang, R.; Zhang, X.; Zhang, Y.; Yu, Y.; Otaki, T.; Shaw, R. Synergies and Gaps in ESG, Climate Disasters, and Social Inequality: A Literature Review. *Climate* **2025**, *13*, 241. [CrossRef]
45. Manjengwa, E.; Dunga, S.; Mncayi-Makhanya, P.; Makhalima, J. ESG performance and economic growth in BRICS countries: A dynamic ARDL panel approach. *Sustainability* **2025**, *17*, 6334. [CrossRef]
46. Mouti, K.; Kilincarslan, E.; Li, J. Environmental credit risk, climate change and bank performance: Evidence from a global panel of banks. *Bus. Strategy Environ.* **2026**, *35*, 1646–1666.
47. Wang, H.; Zhou, L.; Xu, J.; Shan, J. Can National ESG Inhibit the Impact of Extreme Climate on Global Financial Risks? In *International Studies of Economics*; John Wiley & Sons: Hoboken, NJ, USA, 2025.
48. Lanzante, J. A new heat stress index for climate change assessment. *Bull. Am. Meteorol. Soc.* **2024**, *105*, E2482–E2495. [CrossRef]
49. Alvarez, I.; Diaz-Poso, A.; Lorenzo, M.; Roye, D. Heat index historical trends and projections due to climate change in the Mediterranean basin based on CMIP6. *Atmos. Res.* **2024**, *308*, 107512. [CrossRef]
50. Zitouni, D.; Berkouk, D.; Matallah, M.; Ben Ratmia, M.; Attia, S. Advancing Heat Health Risk Assessment: Hotspot Identification of Heat Stress and Risk Across Municipalities in Algiers, Algeria. *Atmosphere* **2025**, *16*, 484. [CrossRef]
51. Chander, S.; Vijaya, P. Unsupervised learning methods for data clustering. *Artif. Intell. Data Min.* **2021**, *3*, 41–64. [CrossRef]
52. Mishra, B.; Pandey, O.; Dehuri, S.; Cho, S. Unsupervised functional link artificial neural networks for cluster analysis. *IEEE Access* **2020**, *8*, 169215–169228. [CrossRef]
53. Sinaga, K.; Yang, M. Unsupervised K-means clustering algorithm. *IEEE Access* **2020**, *8*, 80716–80727. [CrossRef]
54. Saxena, A.; Prasad, M.; Gupta, A.; Bharill, N.; Patel, O.; Tiwari, A.; Er, M.; Ding, W.; Lin, C.-T. A review of clustering tech-niques and developments. *Neurocomputing* **2017**, *267*, 664–681.
55. Hancer, E.; Xue, B.; Zhang, M. A survey on feature selection approaches for clustering. *Artif. Intell. Rev.* **2020**, *53*, 4519–4545. [CrossRef]
56. Hennig, C. Cluster-wise assessment of cluster stability. *Comput. Stat. Data Anal.* **2007**, *52*, 258–271. [CrossRef]
57. De Amorim, R.; Hennig, C. Recovering the number of clusters in data sets with noise features using feature rescaling factors. *Inf. Sci.* **2015**, *324*, 126–145. [CrossRef]
58. Charrad, M.; Ghazzali, N.; Boiteau, V.; Niknafs, A. NbClust: An R package for determining the relevant number of clusters in a data set. *J. Stat. Softw.* **2014**, *61*, 1–36. [CrossRef]
59. Wattanatorn, W. Climate change exposure, circular economy and default probability: Global evidence. *Cogent Econ. Financ.* **2025**, *13*, 2544175. [CrossRef]
60. Jiang, W.; Hu, Y.; Nistor, S.; Xu, Y. Bank profitability under environmental and climate pressures: The case of European banks. *J. Appl. Econ.* **2025**, *28*, 2491397. [CrossRef]
61. Karkowska, R.; Samaniego-Medina, R.; Giráldez-Puig, P.; Korzeb, Z. Boards and ESG performance: The contingent influence of climate vulnerability on global banks. *Bus. Strategy Environ.* **2026**, *35*, 2842–2863.
62. Katta, V.; Shrivastava, G.; Kushwah, V. Hierarchical K-means clustering of earthquake data for in-depth spatial and magnitude analysis in Gujarat India. *Multidiscip. Sci. J.* **2024**, *7*, 2025325.
63. Sterzel, T.; Lüdeke, M.; Walther, C.; Kok, M.; Sietz, D.; Lucas, P. Typology of coastal urban vulnerability under rapid urbanization. *PLoS ONE* **2020**, *15*, e0220936. [CrossRef] [PubMed]
64. D'Orazio, P. Mapping the emergence and diffusion of climate-related financial policies: Evidence from a cluster analysis on G20 countries. *Int. Econ.* **2022**, *169*, 135–147. [CrossRef]
65. Kocur-Bera, K.; Czyża, S. Socio-economic vulnerability to climate change in rural areas in the context of green energy development—A study of the great Masurian Lakes Mesoregion. *Int. J. Environ. Res. Public Health* **2023**, *20*, 2689. [PubMed]
66. Pathiranage, H. Navigating the trade-offs between economic growth and environmental sustainability: A global analysis of long-term trends and strategic policies. *Sustain. Environ.* **2024**, *10*, 2419161. [CrossRef]
67. Matviychuk, A.; Zhytkevych, O.; Osadcha, N. Modeling carbon dioxide emissions reduction. *Energy Rep.* **2024**, *12*, 1876–1887. [CrossRef]
68. Baloch, M.; Khan, S.; Ulucak, Z.; Ahmad, A. Analyzing the relationship between poverty, income inequality, and CO2 emission in Sub-Saharan African countries. *Sci. Total Environ.* **2020**, *740*, 139867. [CrossRef] [PubMed]

69. Khan, I.; Hou, F.; Le, H.; Ali, S. Do natural resources, urbanization, and value-adding manufacturing affect environmental quality? Evidence from the top ten manufacturing countries. *Resour. Policy* **2021**, *72*, 102109. [CrossRef]
70. Acheampong, A.; Boateng, E.; Amponsah, M.; Dzator, J. Revisiting the economic growth–energy consumption nexus: Does globalization matter? *Energy Econ.* **2021**, *102*, 105472. [CrossRef]
71. Shahzad, U.; Radulescu, M.; Rahim, S.; Isik, C.; Yousaf, Z.; Ionescu, S. Do environment-related policy instruments and technologies facilitate renewable energy generation? Exploring the contextual evidence from developed economies. *Energies* **2021**, *14*, 690.
72. Zhao, X.; Mahendru, M.; Ma, X.; Rao, A.; Shang, Y. Impacts of environmental regulations on green economic growth in China: New guidelines regarding renewable energy and energy efficiency. *Renew. Energy* **2022**, *187*, 728–742.
73. Sharif, A.; Aloui, C.; Yarovaya, L. COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *Int. Rev. Financ. Anal.* **2020**, *70*, 101496. [CrossRef] [PubMed]
74. Romanello, M.; di Napoli, C.; Green, C.; Kennard, H.; Lampard, P.; Scamman, D.; Walawender, M.; Ali, Z.; Ameli, N.; Ayeb-Karlsson, S.; et al. The 2023 report of the Lancet Countdown on health and climate change: The imperative for a health-centred response in a world facing irreversible harms. *The Lancet* **2023**, *402*, 2346–2394. [CrossRef]
75. Béné, C.; Fanzo, J.; Prager, S.; Achicanoy, H.; Mapes, B.; Alvarez Toro, P.; Bonilla Cedrez, C. Global drivers of food system (un) sustainability: A multi-country correlation analysis. *PLoS ONE* **2020**, *15*, e0231071. [PubMed]
76. Vicedo-Cabrera, A.; Scovronick, N.; Sera, F.; Royé, D.; Schneider, R.; Tobias, A.; Gasparrini, A. The burden of heat-related mortality attributable to recent human-induced climate change. *Nat. Clim. Change* **2021**, *11*, 492–500. [CrossRef]
77. Hasegawa, T.; Fujimori, S.; Takahashi, K.; Yokohata, T.; Masui, T. Economic implications of climate change impacts on human health through undernourishment. *Clim. Change* **2016**, *136*, 189–202. [CrossRef]
78. Murphy, D. Theorizing climate change, (im)mobility and socio-ecological systems resilience in low-elevation coastal zones. *Clim. Dev.* **2015**, *7*, 380–397.
79. Fränti, P.; Sieranoja, S. How much can k-means be improved by using better initialization and repeats? *Pattern Recognit.* **2019**, *93*, 95–112. [CrossRef]
80. Rodriguez, M.; Comin, C.; Casanova, D.; Bruno, O.; Amancio, D.; Costa, L.; Rodrigues, F. Clustering algo-rithms: A comparative approach. *PLoS ONE* **2019**, *14*, e0210236. [CrossRef] [PubMed]
81. Xu, D.; Tian, Y. A comprehensive survey of clustering algorithms. *Ann. Data Sci.* **2015**, *2*, 165–193. [CrossRef]
82. Bayliss, A. Validating Classical Multivariate Models in Archaeology: English Medieval Bellfounding as a Case Study. Doctoral Dissertation, University of London, London, UK, 2006.
83. Jain, A. Data clustering: 50 years beyond K-means. *Pattern Recognit. Lett.* **2010**, *31*, 651–666. [CrossRef]
84. Mukherjee, S.; Mishra, A.; Trenberth, K. Climate change and drought: A perspective on drought indices. *Curr. Clim. Change Rep.* **2018**, *4*, 145–163. [CrossRef]
85. Wutich, A.; Ragsdale, K. Water insecurity and emotional distress: Coping with supply, access, and seasonal variability of water in a Bolivian squatter settlement. *Soc. Sci. Med.* **2008**, *67*, 2116–2125. [PubMed]
86. Diffenbaugh, N.; Burke, M. Global warming has increased global economic inequality. *Proc. Natl. Acad. Sci. USA* **2019**, *116*, 9808–9813. [CrossRef] [PubMed]
87. Stoler, J.; Brewis, A.; Kangmennang, J.; Keough, S.; Pearson, A.; Rosinger, A.; Stauber, C.; Stevenson, E. Connecting the dots between climate change, household water insecurity, and migration. *Curr. Opin. Environ. Sustain.* **2021**, *51*, 36–41. [CrossRef]
88. Gagolewski, M.; Bartoszuk, M.; Cena, A. Are cluster validity measures (in) valid? *Inf. Sci.* **2021**, *581*, 620–636. [CrossRef]
89. Da Silva, L.; Melton, N.; Wunsch, D. Incremental cluster validity indices for online learning of hard partitions: Exten-sions and comparative study. *IEEE Access* **2020**, *8*, 22025–22047.
90. Blasilli, G.; Kerrigan, D.; Bertini, E.; Santucci, G. Towards a visual perception-based analysis of clustering quality metrics. In *2024 IEEE Visualization in Data Science (VDS)*; IEEE: St. Pete Beach, FL, USA, 2024; pp. 15–24.
91. Sarmas, E.; Fragkiadaki, A.; Marinakis, V. Explainable AI-based ensemble clustering for load profiling and demand response. *Energies* **2024**, *17*, 5559. [CrossRef]
92. La Marca, K.; Bedle, H.; Stright, L.; Marfurt, K. Uncertainty assessment in unsupervised machine-learning methods for deep-water channel seismic facies using outcrop-derived 3D models and synthetic seismic data. *Interpretation* **2024**, *12*, T303–T319.
93. Duan, Y.; Lu, Z.; Wang, R.; Li, X.; Nie, F. Toward balance deep semisupervised clustering. In *IEEE Transactions on Neural Net-works and Learning Systems*; IEEE: Piscataway, NJ, USA, 2024.
94. Vo Duy, A.; Che, Q.; Nguyen, V. Adaptive Scheme of Clustering-Based Unsupervised Learning for Person Re-identification. In *Asian Conference on Intelligent Information and Database Systems*; Springer: Singapore, 2024; pp. 193–205.
95. Rosti, A.; Rota, M.; Penna, A. An empirical seismic vulnerability model. *Bull. Earthq. Eng.* **2022**, *20*, 4147–4173. [CrossRef]
96. Kaufmann, D.; Kraay, A.; Mastruzzi, M. The worldwide governance indicators: Methodology and analytical issues. *Hague J. Rule Law.* **2011**, *3*, 220–246.

97. Ouragini, I.; Ben Hassine Louzir, A. University social responsibility and sustainable development: Illustration of adapted prac-tices by two Tunisian Universities. *Soc. Responsib. J.* **2024**, *20*, 1177–1192.
98. Mechkova, V.; Lührmann, A.; Lindberg, S. How much democratic backsliding? *J. Democr.* **2017**, *28*, 162–169.
99. Joshi, D. Good governance, state capacity, and the millennium development goals. *Perspect. Glob. Dev. Technol.* **2011**, *10*, 339–360. [CrossRef]
100. Hallegatte, S.; Rentschler, J.; Rozenberg, J. *Adaptation Principles: A Guide for Designing Strategies for Climate Change Adaptation and Resilience*; World Bank: Washington, DC, USA, 2020.
101. Besley, T.; Persson, T. Democratic values and institutions. *Am. Econ. Rev. Insights* **2019**, *1*, 59–76. [CrossRef]
102. Sachs, J.; Kroll, C.; Lafortune, G.; Fuller, G.; Woelm, F. *Sustainable Development Report 2022*; Cambridge University Press: Cambridge, UK, 2022.
103. Dzigbede, K.; Gehl, S.; Willoughby, K. Disaster resiliency of US local governments: Insights to strengthen local response and recovery from the COVID-19 pandemic. *Public Adm. Rev.* **2020**, *80*, 634–643. [PubMed]
104. Andrews, M.; Pritchett, L.; Woolcock, M. *Building State Capability: Evidence, Analysis, Action*; Oxford University Press: Oxford, UK, 2017.
105. Li, P.; Chiou, J. Functional clustering and missing value imputation of traffic flow trajectories. *Transp. B Transp. Dyn.* **2021**, *9*, 1–21. [CrossRef]
106. Călin, A.; Coroiu, A.; Mureşan, H. Analysis of preprocessing techniques for missing data in the prediction of sunflower yield in response to the effects of climate change. *Appl. Sci.* **2023**, *13*, 7415. [CrossRef]
107. Si, Y.; Heeringa, S.; Johnson, D.; Little, R.; Liu, W.; Pfeffer, F.; Raghunathan, T. Multiple imputation with massive data: An ap-plication to the panel study of income dynamics. *J. Surv. Stat. Methodol.* **2023**, *11*, 260–283. [PubMed]
108. Alejo-Sanchez, L.; Márquez-Grajales, A.; Salas-Martínez, F.; Franco-Arcega, A.; López-Morales, V.; Acevedo-Sandoval, O.; González-Ramírez, C.; Villegas-Vega, R. Missing data imputation of climate time series: A review. *MethodsX* **2025**, *15*, 103455. [CrossRef] [PubMed]
109. Nugroho, H.; Surendro, K. A comprehensive bibliometric analysis of missing value imputation. *IEEE Access* **2024**, *12*, 14819–14846. [CrossRef]
110. Dorabiala, O.; Aravkin, A.; Kutz, J. Ensemble principal component analysis. *IEEE Access* **2024**, *1221*, 6663–6671. [CrossRef]
111. Mohammed, M.; Akawee, M.; Saleh, Z.; Hasan, R.; Ali, A.; Sutikno, T. The effectiveness of big data classification control based on principal component analysis. *Bull. Electr. Eng. Inform.* **2023**, *12*, 427–434. [CrossRef]
112. Chen, F.; Rohe, K. A new basis for sparse principal component analysis. *J. Comput. Graph. Stat.* **2024**, *33*, 421–434.
113. Barba, E.; Casamichana, D.; Figueiredo, P.; Nakamura, F.; Castellano, J. The Use of Principal Component Analysis for Reduction in Sleep Quality and Quantity Data in Female Professional Soccer. *Sensors* **2024**, *25*, 148. [PubMed]
114. Eriksen, S.; Schipper, E.; Scoville-Simonds, M.; Vincent, K.; Adam, H.; Brooks, N.; Harding, B.; Khatri, D.; Lenaerts, L.; Liverman, D.; et al. Adaptation interventions and their effect on vulnerability in developing countries: Help, hindrance or irrelevance? *World Dev.* **2021**, *141*, 105383. [CrossRef]
115. Thomas, K.; Hardy, R.; Lazrus, H.; Mendez, M.; Orlove, B.; Rivera-Collazo, I.; Roberts, J.; Rockman, M.; Warner, B.; Winthrop, R. Explaining differential vulnerability to climate change: A social science review. *Wiley Interdiscip. Rev. Clim. Change* **2019**, *10*, e565. [PubMed]
116. Seneviratne, S.; Zhang, X.; Adnan, M.; Badi, W.; Dereczynski, C.; Luca, A.; Ghosh, S.; Iskandar, I.; Kossin, J.; Lewis, S.; et al. Weather and climate extreme events in a changing climate. In *Climate Change 2021: The Physical Science Basis: Working Group I contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*; Cambridge University Press: Cambridge, UK, 2021; pp. 1513–1766.
117. Carleton, T.; Jina, A.; Delgado, M.; Greenstone, M.; Houser, T.; Hsiang, S.; Hultgren, A.; E Kopp, R.; E McCusker, K.; Nath, I.; et al. Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. *Q. J. Econ.* **2022**, *137*, 2037–2105. [CrossRef]
118. Cinner, J.; Adger, W.; Allison, E.; Barnes, M.; Brown, K.; Cohen, P.; Gelcich, S.; Hicks, C.; Hughes, T.; Lau, J.; et al. Building adaptive capacity to climate change in tropical coastal communities. *Nat. Clim. Change* **2018**, *8*, 117–123. [CrossRef]
119. Newell, P.; Srivastava, S.; Naess, L.; Torres Contreras, G.; Price, R. Toward transformative climate justice: An emerging research agenda. *Wiley Interdiscip. Rev. Clim. Change* **2021**, *12*, e733. [CrossRef]
120. Macnee, R.; Tokai, A. Heat wave vulnerability and exposure mapping for Osaka City, Japan. *Environ. Syst. Decis.* **2016**, *36*, 368–376. [CrossRef]
121. Koman, P.; Romo, F.; Swinton, P.; Mentz, G.; de Majo, R.; Sampson, N.; Battaglia, M.; Hill-Knott, K.; Williams, G.; O'Neill, M.; et al. MI-Environment: Geospatial patterns and inequality of relative heat stress vulnerability in Michigan. *Health Place* **2019**, *60*, 102228. [CrossRef] [PubMed]
122. Carrasco, C.; Hernandez-del-Valle, A. Energy intensity, economic structure, and capital goods imports in upper-middle income countries: Insights from HDBSCAN clustering. *J. Environ. Manag.* **2023**, *339*, 117840.

123. Wijayanti, P.; Latifah, L.; Purwoko, S.; Riyanto, S.; Yunitawati, D.; Setyaji, T. Spatial Analysis of Drought Vulnerability Related to Climate Change and Under Five Children's Nutritional Status. In *BIO Web of Conferences*; EDP Sciences: Les Ulis, France, 2024; Volume 133, p. 00019.
124. Bista, R. Assessment of climate change induced household vulnerability in Nepal: Application of index method. *ARRUS J. Soc. Sci. Humanit.* **2023**, *3*, 9–20. [CrossRef]
125. Albahouth, A.; Tahir, M. Institutional Quality and Climate Vulnerability: Empirical Evidence from GCC Economies. *Sustainability* **2025**, *17*, 2047. [CrossRef]
126. Macharia, C.; Kiage, L. Conceptualizing heat vulnerability: Equity-centered approaches for comprehensive resilience in a changing climate. *Nat. Hazards* **2024**, *120*, 6923–6941. [CrossRef]
127. Ofori, E.; Onifade, S.; Ali, E.; Alola, A.; Zhang, J. Achieving carbon neutrality in post COP26 in BRICS, MINT, and G7 economies: The role of financial development and governance indicators. *J. Clean. Prod.* **2023**, *387*, 135853. [CrossRef]
128. Robertson, S.; Walker, G.; Horne, R. Tracing the ruptures and rhythms of summer heat, energy vulnerability and home. *Geoforum* **2024**, *155*, 104095. [CrossRef]