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Research Article

The Canonical Discriminant Model of the Environmental Security Threats

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The existence of modern humanity directly depends on environmental security. Human society, biodiversity, ecosystems, and climate safety are interdependent. The anthropogenic influence that causes irreversible climate change threatens both the ecosystem's existence and humans' survival. To maintain a balance between human well-being and a safe environment, it is important to have a diverse knowledge of the interrelations between the technological impact on the natural environment and climate change and an understanding of action strategies to mitigate climate change and ensure sustainable development. Applying a scientific approach, data analytics, and data science tools can effectively support climate change mitigation and prevent a climate disaster. Based on the components of the climate change performance index (CCPI) 2023 for 59 countries and the EU, a canonical discriminant model was built to identify the significant factors that influence the assessment of the effectiveness of climate protection in a particular country or region and the assessment of climate risks. It can be used to assess the level of climate protection effectiveness of countries that have not defined the CCPI 2023. Based on empirical data, we have determined the real weights of the relevant CCPI components in relation to the effectiveness of actions aimed at reducing global warming. We have established that there are additional factors important for assessing climate protection, but the CCPI rating does not consider them. We conducted a comparative analysis of the CCPI index and the sustainable development goals (SDG) index. The study establishes that the differences in environmental protection among the world's countries do not determine the assessment of the level of sustainable development of the world's countries. The obtained results can provide information to support decision-making in developing effective strategies and urgent actions to ensure climate protection.

1. Introduction

Global climate change and environmental disasters are among the greatest threats to modern civilization. We need appropriate knowledge and a qualitative study of the problem to prevent these threats. The World Economic Forum in the Global Risks Report 2023 defined the environmental risks as 5 out of 10, the most important over the 5 years, and 6 out of 10 over the 10-year term [1]. The failure to mitigate climate change was ranked as the first global risk by severity. Failure of climate change adaptation in the second place in this rating, natural disasters and extreme weather events, biodiversity loss and ecosystem collapse, natural resource crises, and large-scale environmental damage incidents are ranked 3rd, 4th, 6th, and 10th position over the long term.

Climate risks are multifaceted, with diverse short-, medium-, and long-term effects of climate change at the local and global levels. This is the impact of natural disasters and natural catastrophes. Global warming is exacerbating the growing dynamics of extreme weather events that cause significant casualties, destruction, and economic losses [2, 3]. Often, these disasters are caused by anthropogenic activities. In addition, climate experts and military analysts are also increasingly concerned about the possible testing and use of climate weapons by certain influential states [4, 5]. None of the world's governments has recognized the existence or use of seismic weapons, but they can become a significant tool for economic and political pressure on other states. Radical climate change on a global scale today is a complex interdisciplinary problem that can no longer be perceived as exclusively scientific. This problem covers economic, social, and political aspects and affects all regions of the world and all population segments.

Climate change has already caused widespread negative impacts on ecosystems and human systems. Land resources, agriculture, food security, forestry, and energy have proven to be the most vulnerable to climate change, although the fuel and energy sector are traditionally considered to be the sector with the most significant impact on climate change as the main source of greenhouse gases [6, 7]. We are particularly concerned about the high rate of oil and natural gas consumption, which results in adverse environmental impacts [8]. The war in Ukraine has worsened this problem [9, 10]. Global warming has led to sea level rise, caused damage to ground, soil, river, and ocean ecosystems worldwide [11, 12]. This has caused changes and migration of animals and birds, marine biodiversity, and disrupted water balance, quality, and availability [13, 14]. The consequences of climate change affect all sectors of the economy, causing a shortage of resources [15]. Climate change, combined with the negative effects of urbanization, directly threatens environmental, economic, and social security and provokes serious risks: flooding, heat waves, and natural disasters [16]. A large part of biological systems with limited adaptive capacity is particularly sensitive to climate change. This significantly increases the threat of biodiversity loss. Climate change also has a negative effect on public health [17]. It causes thousands of human deaths worldwide every year, mainly driven by the effects of extremely high temperatures on the body, lack of water, malnutrition, and infections. Climate change is forcing thousands of people to migrate in search of a habitable environment [18].

The influence of climate change on safety indicators is the most tangible and indicative [19]. In the global dimension, extreme weather events are related to climate change, claim thousands of lives annually, and cause enormous damage worldwide [3]. Climate change can cause complex risks, posing an increased danger to the stability of states and societies and the emergence of conflicts [20]. These include competition for local resources, danger to livelihoods and migration, natural disasters and catastrophes, food price volatility, instability of cross-border water use, sea level rise and coastal destruction, and unpredictable results of policies aimed at climate change adaptation and mitigation. The environmental security dilemma is that while environmental preservation is a global issue, each state individually strives to address climate change while protecting its own interests [21–23]. Environmental security is one of the prerequisites for sustainable development of the world, which moves international relations to a new plane [24–26]. Climate change poses a global security threat [27, 28]. Today, the real extent of the damage caused by climate change to humanity remains unknown. However, it is the feeling of insecurity against natural disasters that undermines the sense of security [29]. The negative influence of natural and anthropogenic climate change will continue to grow. Today, a deep understanding and qualitative analysis of all factors and the scale of the influence of various factors are needed to successfully prevent catastrophic climate change and develop coordinated strategies to identify, assess, and mitigate climate-related security risks.

2. Related Work

Scientists and practitioners have long confirmed the impact of climate change on global sustainable development. The IPCC Synthesis Report presents a generalized assessment of climate change knowledge, dangerous influences, risks, and possible strategies for preventing climate change [30]. Papadopoulos and Balta analyzed the benefits of using big data and analytics to study the impact of climate change on businesses, operations, and supply chains [31]. Bhardwaj and Peter studied the possibilities of tools developed for visual climatic analysis [32]. Rolnick et al. gave recommendations for using machine learning as a powerful tool for reducing greenhouse gas emissions and adapting society to climate change [33]. Maganathan et al. investigated the influence of innovations in machine learning and data analytics of innovations on various aspects of environmental science [34]. Zennaro et al. explored machine learning potential for climate change risk assessment [35]. Haq et al. applied a deep neural network model for time series forecasting of environmental variables [36]. Ho computes mutual fund covariance with a market-wide climate change news index [37]. Ali and colleagues examine the environmental performance of South and East Asian countries and their association with trade and other economic variables [38]. Agnieszka and coauthors created a model to assess climate change competitiveness at a regional level. This facilitated the analysis of the region's indicators concerning climate change, enabling the identification of vulnerabilities in climate change adaptation [39]. Puertas and Marti used cluster analysis and contingency tables based on the 2001 Climate Change Performance Index to study countries' efficiency profiles in combating climate change. The authors provided statistical evidence of the relationship between climate change policies, the use of renewable energy in electricity supply, and the reduction of harmful gas emissions [40]. However, studies of this kind are insufficient to fully understand the interconnections and dynamics of climatic safety. Diverse research and high-quality results are needed to inform decision-makers. The development of new methodological approaches and tools can facilitate the management of current and future climate change risks and improve policies toward a more sustainable future. Despite the unanimity of the world's governments on many climate change mitigation issues, significant regional differences still exist. Our research aims to identify variations in the effectiveness of climate policies across different countries and determine the key factors influencing climate risk assessment. This article presents a canonical model for evaluating the effectiveness of climate policies in specific regions, identifying the most impactful factors on climate protection rates in individual countries, and assessing climate risks.

In comparison to previous studies, the main advantages and originality of the research presented here are as follows:

(1) We employ canonical discriminant analysis to construct a system of linear equations that optimally allocate countries to groups (high, medium, low, and very low) based on the Climate Change Performance Index (CCPI) components

(2) We establish the weights of the relationship between the relevant CCPI components and the effectiveness of measures aimed at reducing global warming

(3) The constructed model empowers us to categorize new observations and evaluate the effectiveness of environmental security policies for countries not covered in the CCPI rating

(4) When we classify the analyzed countries into groups (high, medium, low, and very low) according to the CCPI level, we find that the energy use indicator holds the greatest weight, followed by renewable energy, climate policy, and global greenhouse gas (GHG) emissions

(5) There are additional factors crucial for assessing climate protection but not considered in the CCPI rating

(6) Our findings indicate that the differences in the environmental policy strategies of the world's countries do not support the hypothesis of the reliability of the CCPI in the context of sustainable development

3. Climate Protection and International Security

3.1. Concepts of International Security. International security ensures mutual survival and safety among countries worldwide. It includes national security (the country's ability to detect, prevent, and neutralize threats to its interests) and state security (the protection of state authority, sovereignty, territorial integrity, defense capability, people's well-being, social harmony, environment, and national and religious equality) on a global level [41]. The theoretical approaches defining security are evolving, formulating, and refining principles. In the contemporary understanding, international security consolidates numerous global issues vital to humanity's survival, such as war, peace, and interstate conflicts based on economic, ideological, ethnic, territorial, religious, trade, energy supplies, technological, and cultural disputes. Significant threats to humanity's existence include personal security, infectious diseases, terrorism, energy-related, cyber threats, environmental pollution, and global climate change, which can lead to interstate military conflicts over territories, water resources, and access to food [42–48]. As of now, there are no universally recognized methodological foundations for defining security and its key indicators [49]. Various countries have developed metrics for national security [50–53]. Table 1 presents common indicators used to measure a country's national security level.

National security is a complex problem that consists of several interrelated components. Also, each of these components is significantly influenced by modern climate change and global warming. The biggest problem is the escalation of emergencies related to climate change, which in recent years has been defined by most scientists as "global change." These changes, in particular, pose serious risks to the life and health of citizens [54], affect the global economy (production, supply, trade, and pricing) [55], change approaches to energy use and agricultural production [6], cause large-scale migration processes of all living beings in search of habitat [56], pose a serious threat to biodiversity conservation and food security [2], and provoke armed conflicts over territories and resources [43]. Today, there is no universally accepted scientific explanation for the causes of global climate change. Each country develops its own climate protection strategy. That is why diverse research on the selection and improvement of sets of indicators that can measure the level of national security, in particular in the climate and energy dimension, is relevant today.

3.2. Climate Change Performance Index as a Measure of Climate Protection. Countries' efforts to mitigate global warming have proven inadequate as the planet continues to experience rising temperatures. Urgent and effective solutions, bolstered by international collaboration, are imperative to confront the catastrophic consequences of climate change. In this sense, reliable climate protection monitoring tools are extremely relevant. Such tools should reliably identify which countries are doing the most to protect the climate and which countries need to take immediate action to increase the effectiveness of their climate policies. One of the most reliable independent tools for monitoring and evaluating the effectiveness of climate protection is the Climate Change Performance Index (CCPI) [57]. Because the CCPI calculates scores for merely 59 countries responsible for 92% of global greenhouse gases, we suggested employing the canonical discriminant model to assess the CCPI score for countries absent from this ranking yet influencing global climate change. We devised this model using the values of key CCPI components: GHG emissions, renewable energy, energy consumption, and climate policy. These components condense estimates of all 14 CCPI subcomponents and embody most input data for our intended analysis. This indicator enhances understanding and measurement of countries' climate policies on the international level, facilitating the development of joint and

Table 1: The major safety indicators.

Dimension	Indicator
Economic	GDP per capita Inflation Employment Poverty National external debt National internal debt Illegal financial flows Illegal trade
Health	Disease Unsafe food Malnutrition Access to healthcare Deaths due to disease/epidemics Environmental degradation
Climate and energy	Resource depletion Natural disasters Pollution Energy use Renewable energy Global greenhouse gas emissions Climate policy Environmental Regulations Violations of fuel and energy supplies
Personal	Life expectancy Physical violence Crime Domestic violence Terrorist attacks Child labor
Food	Hunger Famine Water resources
Community	Interethnic Religious Identity tensions Political repression Human rights abuses Uncontrolled immigrants Social unrest acts
Political	Internal conflicts over the partition of territories Military conflicts Modern weapons, military, and special equipment National nuclear forces International military conflicts

effective strategies for climate protection. Financial entities often use this index to evaluate sovereign bonds. The CCPI provides important information on the effectiveness of climate change mitigation actions taken by governments [57]. This information aids in creating environmental, social, and governmental ratings, informing decisions on investment redistribution. Financial actors are increasingly investing heavily in zero- and low-greenhouse gas emissions infrastructure and solutions and renewable energy technologies. They use the CCPI as a tool to monitor and evaluate the feasibility of making such investments in specific countries. For example, countries with a top CCPI rating are more attractive to investors. Investing in countries with a bottom CCPI rating is questionable.

This paper presents the results of building a canonical discriminant model of the CCPI, enabling the categorization of countries based on their level of risk to global climate security. We are looking for an answer to the question: what is the weight of each of the indicators included in the model in measuring climate protection and testing the hypothesis of the reliability of using the CCPI to assess the effectiveness of climate policies of the world's states in the context of the concept of sustainability. The findings can help inform decision-making on actions aimed at improving climate security at the national level and strengthening control over the implementation of joint climate security agreements at the international level. Climate change significantly amplifies existing global security threats. It worsens natural disasters, increasing the chances of habitat destruction, biodiversity loss, state instability, human migration, interethnic conflicts over natural resource access, and widespread mortality. The consequences of climate change increasingly imperil national security across the globe [58, 59]. The canonical model we have created can help governments better understand the steps they need to take to address climate change effectively. For instance, it aids in revising strategies and opportunities to guarantee targeted emissions, renewable energy utilization, energy efficiency, and climate policy values for achieving higher CCPI scores.

The Climate Change Performance Index has been calculated annually since 2005 for 59 countries (Algeria, Argentina, Australia, Austria, Belarus, Belgium, Brazil, Bulgaria, Canada, Chile, China, Chinese Taipei, Colombia, Croatia, Cyprus, Czech Republic, Denmark, Egypt, Estonia, Finland, France, Germany, Greece, Hungary, India, Indonesia, Iran, Ireland, Italy, Japan, Kazakhstan, Korea, Latvia, Lithuania, Luxembourg, Malaysia, Malta, Mexico, Morocco, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Romania, Russian Federation, Saudi Arabia, Slovak Republic, Slovenia, South Africa, Spain, Sweden, Switzerland, Thailand, Turkey, United Kingdom, United States, Vietnam) and EU. Ukraine was not rated this year because of the Russian invasion. These 59 countries produce 92% of global greenhouse gas. The CCPI is used to ensure the transparency and effectiveness of international climate policy and to compare the effectiveness of climate protection strategies chosen by individual countries. The effectiveness of actions aimed at climate protection is assessed by the following criteria: GHG emissions, renewable energy, energy use, and climate policy. CCPI can provide significant information on climate change and the environmental situation in the country for the authorities and social management (Table 2, Figure 1) [57].

None of the countries assessed by the CCPI demonstrated sufficient results in ensuring climate protection. Their CCPI scores ranged from 18.7 to 79.61. Therefore, the top 3 (rating very high) remain vacant. Denmark, Sweden, and Chile lead the ranking of countries by CCPI, while Iran, Saudi Arabia, and Kazakhstan received the lowest scores. The researchers of the NewClimate Institute and Climate Action Network divided all countries into 4 groups

Table 2: Climate Change Performance Index 2023—ranking table.

Country	CCPI	GHG emissions	Renewable energy	Energy use	Climate policy
Algeria	42.26	24.46	1.65	13.53	2.61
Argentina	41.19	17.9	4	15.43	3.87
Australia	36.26	18.39	2.94	7.43	7.51
Austria	51.58	20.07	9.42	10.99	11.08
Belarus	43.69	23.77	2.98	14.01	2.93
Belgium	48.38	21.44	6.71	11.22	9.01
Brazil	48.39	20.63	11.46	14.66	1.65
Bulgaria	49.15	21.78	9.07	12.34	5.96
Canada	26.47	10.45	3.3	4.45	8.26
Chile	69.54	34.5	10.25	11.05	13.74
China	38.8	11.58	9.59	5.95	11.7
Chinese Taipei	28.35	9.98	2.65	8.38	7.33
Colombia	54.5	22.67	4.52	17.71	9.6
Croatia	52.04	20.06	11.49	12.63	7.85
Cyprus	49.39	19.92	7.55	13.65	8.27
Czech Republic	44.16	21.4	5.16	11.27	6.33
Denmark	79.61	31.42	14.76	13.43	20
Egypt	59.37	29.88	2.98	16.8	9.7
Estonia	65.14	30.55	11.91	14.88	7.8
European Union	59.98	24.94	7.69	13.3	14.03
Finland	61.24	29.23	12.89	5.75	13.38
France	52.97	26.52	4.97	13.15	8.33
Germany	61.11	27.36	6.82	13.76	13.17
Greece	57.52	25.3	7.57	15.71	8.93
Hungary	38.51	20.54	5.69	10.87	1.41
India	67.35	29.69	7.77	16.03	13.85
Indonesia	54.59	20.97	11.09	13.16	9.37
Iran	18.77	5.16	1.46	7.14	5.02
Ireland	48.47	19.22	8.49	13.29	7.46
Italy	52.9	22.81	6.87	13.93	9.29
Japan	40.85	19.92	4.62	12.98	3.33
Kazakhstan	24.61	9.23	5.43	5.55	4.4
Korea	24.91	10.51	3.49	5.93	4.98
Latvia	56.51	21.56	13.07	12.24	9.95
Lithuania	59.21	25.57	9.56	12.86	11.21
Luxembourg	60.76	26.76	10.88	11.68	11.44
Malaysia	33.51	13.47	6.34	10	3.7
Malta	60.42	28.67	8.82	15.31	7.62
Mexico	51.77	26.52	2.38	15.97	6.9
Morocco	67.44	29.04	7.2	16.11	15.09
Netherlands	62.24	24.6	9.69	13.07	14.87
New Zealand	50.55	19.15	12.09	11.41	7.9
Norway	64.47	26.42	19.35	8.98	9.72
Philippines	62.75	31.45	7.6	16.75	6.95
Poland	37.94	18.33	5.78	10.88	2.95
Portugal	61.55	26.14	8.91	13.73	12.77
Romania	47.09	24.87	4.86	14.31	3.05
Russian Federation	25.28	15.17	1.27	8.85	0
Saudi Arabia	22.41	6.43	5.81	6.01	4.17
Slovak Republic	50.12	25.31	4.86	12.21	7.75
Slovenia	48.16	22.29	7.17	11.36	7.33
South Africa	45.69	20.09	3.17	15.16	7.27
Spain	58.59	25.97	7.39	13.84	11.38
Sweden	73.28	34.48	15.96	9.97	12.89
Switzerland	58.61	26.6	7.73	13.99	10.28
Thailand	47.23	21.89	4.85	13.11	7.38
Turkey	43.32	21.89	10.25	10.7	0.48
United Kingdom	63.07	30.38	6.44	16.37	9.88
United States	38.53	14.24	2.65	8	13.64
Vietnam	48.31	20.87	6.2	11.46	9.78

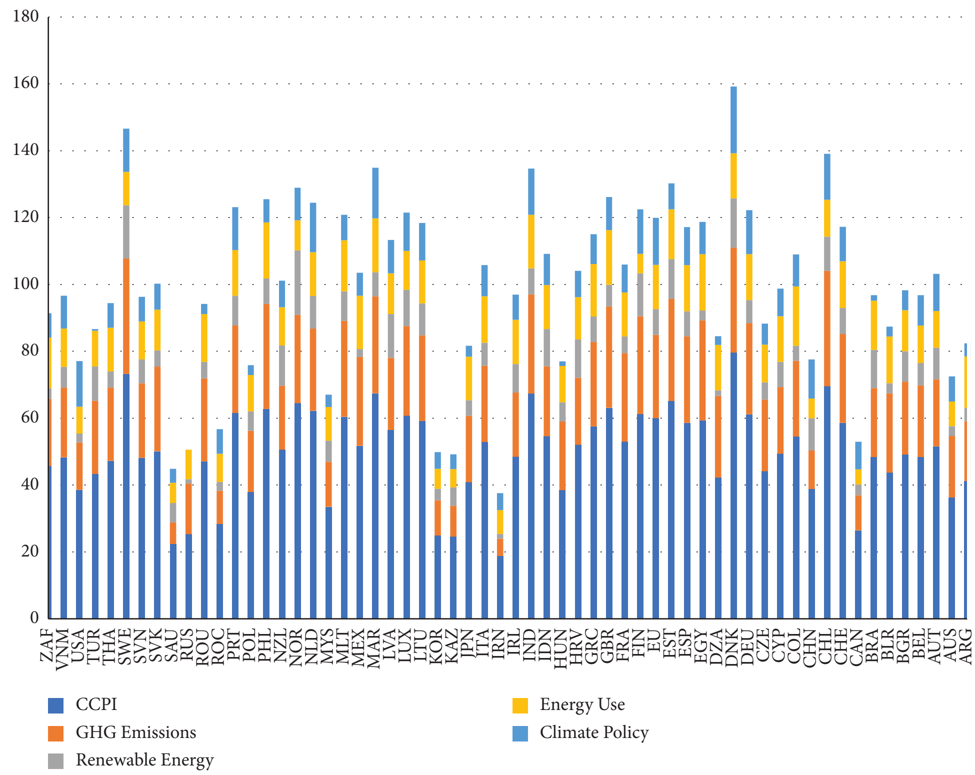

FIGURE 1: Global development of key indicators 2023.

according to the CCPI rating: high: more than 60; medium: more than 50, less than 60; low: more than 40, less than 50; very low: less than 40 points [57].

The researchers of the NewClimate Institute and Climate Action Network divided all countries into 4 groups according to the CCPI rating:

(i) High: more than 60 points

(ii) Medium: more than 50, but less than 60 points

(iii) Low: more than 40, but less than 50 points

(iv) Very low: less than 40 points [57]

Table 3 represents the components of the CCPI countries.

The most significant measure of the CCPI level is the indicator of global greenhouse gas [57]. The share of fossil fuels is more than 75% of all global greenhouse gases produced by humanity. Reducing its production is an essential component of global energy security. However, countries that receive excessive profits from the sale of fossil fuels do not plan to reduce their production. The CCPI identifies countries responsible for increasing global greenhouse gas (GHG) emissions, encourages their compliance with international agreements, and urges other countries to reduce investment in this area.

The countries' efforts in this area were rated from 5.16 to 34.5 points. Countries worldwide must at least halve their GHG emissions this decade to prevent dangerous climate change. Denmark, Sweden, and Chile lead the ranking of countries by CCPI, while Iran, Saudi Arabia, and Kazakhstan received the lowest scores. All analyzed countries were divided into 5 groups

TABLE 3: Components of the CCPI countries.

Measure	% of the overall score
GHG emissions	40
Renewable energy	20
Energy use	20
Climate policy	20

according to the GHG emissions rating: very high: more than 32; high: more than 27 and less than 32; medium: more than 22.5 and less than 27; low: more than 22.5 and less than 19.5; very low: less than 19.5 points. Only two countries (Chile and Sweden) received very high scores in the GHG emissions ranking. Therefore, the top position remains vacant.

The following indicators are taken into account in equal proportions when assessing the GHG emissions of an individual country:

(i) GHG per capita-current level (including land use, land-use change, and forestry)

(ii) GHG per capita-current trend (excluding land use, land-use change, and forestry)

(iii) GHG per capita-compared to a well-below-2°C benchmark

(iv) GHG 2030 target-compared to a well-below-2°C benchmark

Fossil fuels account for 75% of all anthropogenic greenhouse gas emissions. Most countries in the world are heavily dependent on fossil fuels.

The second assessment in the CCPI calculation is renewable energy. The use of renewable energy continues to grow quickly around the world. However, the global energy system is still heavily dependent on fossil fuels [60], even though wind and solar energy generation is a much cheaper source of power generation [61]. The scores of the analyzed countries ranged from 1.27 to 19.35 points. The top country in this ranking is Norway, and the last place was taken by the Russian Federation [57]. All analyzed countries were divided into 5 groups according to the GHG emissions rating: very high: more than 16; high: more than 9.4 low than 16; medium: more than 6 low than 9.4; low: more than 4 less than 6; very low: less than 4 points. Only Norway received a very high score in the renewable energy ranking. Therefore, the top 2 positions remain vacant.

Indicators are taken into account in equal proportions when determining the renewable energy potential of an individual country:

(i) Energy use (total primary energy supply)-current level (including hydro)
(ii) RE current trend (excluding hydro)
(iii) Share of RE in energy use (total primary energy supply) (including hydro)-compared to a well-below-2°C benchmark
(iv) RE 2030 target (including hydro)-compared to a well-below-2°C benchmark

The third component of the CCPI is energy use, which depends on economic activity. This indicator for the analyzed countries ranged from 4.45 to 17.71 points [57]. The top 3 (rating very high) remain vacant again. Colombia, Egypt, and the Philippines received the highest scores. Canada, Kazakhstan, and Finland are at the bottom. All the analyzed countries were divided into 4 groups according to their energy consumption rating: high: more than 12.95; medium: more than 12.9, less than 14.1; low: more than 10.1, less than 12.9; very low: less than 10.1 points.

The economic activity of an individual country was assessed by the following indicators (in equal proportions):

(i) Energy use (total primary energy supply) per capita-current level
(ii) Energy use (total primary energy supply) per capita-current trend
(iii) Energy use (total primary energy supply) per capita-compared to a well-below-2°C benchmark
(iv) Energy use 2030 target-compared to a well-below-2°C benchmark

The fourth dimension of the CCPI is climate policy. Due to the energy crisis caused by Russia's military aggression against Ukraine in 2022, climate policy was not a priority for countries worldwide. The Russian Federation received 0 points in this rating [57]. It is at the bottom. Denmark is at the top (20 points). Countries were divided into 4 groups according to their political policy rating: high: more than 14.0; medium: more than 7.9 low than 14.0; low: more than 4.0 low than 7.9; very low: less than 7.9 points.

The overall assessment of each country's climate policy was carried out in equal proportions according to the following criteria:

(i) National climate policy performance
(ii) International climate policy performance

Denmark, Sweden, and Chile top the overall ranking of the leading CCPI countries. Overall, Denmark received the highest score among all the countries analyzed. However, this did not allow it to enter the top three, which remained vacant. Denmark takes high in terms of GHG emissions, renewable energy, and climate policy, but it is only 26th (medium rank) in the energy consumption ranking. Sweden is 2nd in the overall CCPI ranking. It received very high assessments in GHG emissions, high rank in renewable energy, however medium in climate policy, and very low in energy use. Chile takes 3rd in the GHG ranking among the countries analyzed. It receives a very high rating in the GHG emissions, a high rating in renewable energy, a medium rating in climate policy, and a low rating in the energy use measures.

The Islamic Republic of Iran takes the last position in the overall ranking of countries in terms of CCPI. It received very low assessments in the GHG emissions, renewable energy, and energy use measure, and a low rank in climate policy. South Korea took the penultimate place in the overall ranking for the countries in the CCPI, receiving very low ratings across all main measures.

We developed the model to identify the significant dimensions that affect the distribution of 59 countries and the EU as analyzed by Climate Change Performance Index levels (high, medium, low, and very low). Based on this model, we assessed the climate protection levels of countries that are not included in the CCPI rating. The resulting analytical dependencies can make it possible to determine the CCPI rating for any country not included in this rating based on the numerical values of the four CCPI components taken into account in the model. The Climate Change Performance Index calculates the index for 59 countries, accounting for 92% of global greenhouse gases. However, countries not included in this ranking also contribute to climate change.

Developing nations require up-to-date information to understand crucial factors and formulate effective climate protection strategies. We can assess the GHG emissions, renewable energy, energy use, and climate policy of these countries. The CCPI calculates the index for only 59 countries. A rule needs formulation for assigning the analyzed countries to one of the selected groups (high, medium, low, and very low). Using this rule, we can determine the CCPI level corresponding to each country not included in the ranking with the highest probability.

We conducted a canonical discriminant analysis to create a classification model that enables us to assess the level of climate protection in countries not included in the CCPI rating and identify significant dimensions that influence the distribution of the 59 countries and the EU analyzed by the Climate Change Performance Index levels (high, medium, low, and very low). Unfortunately, there are no quantitative estimates of all CCPI indicators in the public domain. Therefore, our canonical discriminant model utilizes only 4 main CCPI components. They are the consolidated scores of all subcomponents, so they retain the bulk of the input information sufficient to conduct an adequate analysis. In this section, we discuss multivariate statistical analysis methods that classify observations based on the principle of maximum similarity with training samples. Unlike cluster analysis, these methods do not create new clusters but, instead, formulate a rule to assign objects to existing (training) subsets (classes) by comparing the value of the discriminant function of the object with a specific discrimination constant. For instance, if a new object with the same features as those under study emerges in the system, we can use discriminant analysis to improve the classification results from cluster analysis. Machine learning tools, including generalized linear model, deep learning, decision tree, random forest, gradient-boosted trees, and support vector machine, can predict the class to which the analyzed object belongs to a certain probability and assess the significance of each analyzed variable.

Discriminant analysis is widely used in various fields, including economics, psychology, sociology, politics, and other sciences to study multivariate data, regression models, and time series analysis. Chen et al. used discriminant analysis by quantile regression to identify interesting features of climate change and to test changes in each quantile of the innovation distribution. The results show that the probability of misclassification of discriminant statistics decreases with increasing sample size [62]. Zhang et al. applied Fisher discriminant analysis to detect drought in an alpine meadow ecosystem depending on various factors of soil water deficit and atmospheric water deficit [63]. Paeth et al. utilized discriminant analysis to examine the distinctions between past and future climates based on state-of-the-art climate model simulations. They analyzed several well-known climate indices [64].

This study introduces a new approach that utilizes discriminant analysis to improve the differentiation between levels of overall CCPI ranking by considering the multivariate fingerprints identified within the space of several climate indicators. The constructed discriminant model can efficiently and accurately consider all the analyzed key indicator factors comprehensively.

4. Methods and Data

4.1. Discriminant Analysis Classification. Discriminant analysis is used to predict which group new observations will belong to if there are already a certain number of previous observations with known group memberships. In fact, it is a task of classifying into predefined groups [65].

Discriminant analysis is a branch of multidimensional statistical analysis that includes methods of classifying multidimensional observations based on the principle of maximum similarity in the presence of training samples. The discriminant analysis procedure consists of formulating a rule for assigning the studied objects to one of the training known subsets (classes). Objects are assigned to these classes by comparing the value of the discriminant function of the classification object with the discrimination constant. For new cases, it is necessary to determine which class it is most likely to belong to. In general, the discriminant function is written as the following linear combination of the analyzed attributes:

$$F_i = a_1 x_{i1} + a_2 x_{i2} + \cdots a_p x_{\mathrm{ip}}, \tag{1}$$

where $x_{ij}\,(i = \overline{1, n}, j = \overline{1, p})$: discriminant attributes, $a_1, a_2, \ldots, a_p$: discriminant factors, n: number of attributes, and p: number of cases.

The coefficients that determine the linear combination (1) are calculated from the condition of the largest differences in the function between the known classes.

To compare samples by several features, use the coefficient of determination (canonical R) and feature λ (eigenvalue).

The following formula calculates the coefficient of determination:

$$\eta^2 = \frac{\mathrm{SS}_u}{\mathrm{SS}_x}, \tag{2}$$

where SS_u: sum of squares of deviations of group averages from the value of the overall average (variability between groups) and SS_x: the sum of the squares of deviations of the values of individual cases from the average value for all cases (overall variability).

The closer the value of η^2 is to one, the better the discriminative ability of the attribute $x (0 \leq \eta^2 \leq 1)$.

Eigenvalue is calculated by the following formula:

$$\lambda = \frac{\mathrm{SS}_u}{\mathrm{SS}_e}, \tag{3}$$

where SS_e: the sum of squares of deviations of individual cases from the group averages (variability within groups).

The higher the value λ, the better the discriminant function is selected. The quality assessment of the classification is F-test or Wilks' lambda. The following formula calculates the F-test value:

$$F = \lambda \frac{n - q}{q - 1}, \tag{4}$$

where p: number of attributes and q: number of known classes or estimate by the significant level α (the probability that differences between groups are random).

To verify the significant discriminant function, use the chi-squared test. The discriminant function is significant if $\alpha < 0.01$. Wilks' lambda is calculated by the following formula:

$$\Lambda = \prod_{i=1}^{q} \frac{1}{1 + \lambda_i}. \tag{5}$$

Wilks' lambda is a measure of model uncertainty. Therefore, its value should be as small as possible.

4.2. Data. In this study, the data of the Climate Change Performance Index 2023 and their components (global greenhouse gas emissions, renewable energy, energy use, and climate policy) for 59 countries of the world are obtained from [57].

5. Results and Discussion

For applied research, we used Statistica software. The main assumption for the discriminant analysis is that the normal probability is included in the model-independent attributes: GHG emissions, renewable energy, energy use, and climate policy.

The graphical analysis confirmed that all the predictor variables met the normal probability test. Thus, one of the prerequisites for reasonable use of discriminant analysis is met (Figure 2).

Table 4 shows the estimates of the discriminant function and the independent variables on the basis of which the classification function was built. The Wilks' lambda value is $0.088 \in [0;\ 1]$ and is close to 0. This means that the discrimination is good. $F_{0.01}$ (12, 140) = 17.58 (Table 3), which is greater than the table value of the F-distribution: $F_{0.01}$ (12, ∞) = 3.36. Hypothesis H0: "observations belong to the same class" is rejected. The discriminant analysis is reasonable, and the classification is correct. All independent variables included in the model have high statistical significance ($p < 0.01$). The GHG emission variable has the highest weight for discrimination, as the Wilks' lambda (0.15) of this variable is the largest.

Table 5 presents the classification matrix, and the correctness checks of the training samples are constructed.

From the resulting classification matrix, it can be concluded that 2 out of 59 countries (Cyprus and Japan) are incorrectly assigned to the selected CCPI groups. However, the squared Mahalanobis distances of the object "Cyprus" to the "low" group to which it was assigned (1.92) are smaller than those to the centers of other groups (17.25, 1.96, and 13.05). The value of the squared Mahalanobis distances from the object "Japan" to the center of gravity of the "very low" group, to which it is assigned (1.32), is also the smallest compared to the distances to other groups (8.13, 8.96, 25.29) (Table 6). We conclude that the classification of Cyprus and Japan into the previously identified Climate Change Performance Index groups is correct, and there is no reason to exclude these countries from the analyzed sample.

Table 7 presents the estimates of the discriminant function. The Wilks' lambda value (0.06) indicates that there is a difference between the groups. The value of the canonical correlation coefficient is R (0.93). The value of the chi-squared test $\chi^2(12) = 133.4$ for $p < 0.01$ is higher than the table value $\chi^2(12) = 26.2$. Thus, there is a close connection between the discriminant function and the selected CCPI groups.

We conducted the classification based on classification functions. As a result of the analysis of discriminant functions, we obtained the classification function coefficients for each class (Table 8).

The analytical record of the canonical discriminant model is presented as follows:

(i) High = −90.57 + 2.42·GHGE + 2.83·RE + 3.81·EU + 2.23·CP

(ii) Medium = −68.44 + 1.82·GHGE + 2.47·RE + 3.88·EU + 1.90·CP

(iii) Low = −51.59 + 1.58·GHGE + 2.15·RE + 3.48·EU + 1.37·CP

(iv) Very low = −23.20 + 0.96·GHGE + 1.42·RE + 2.30·EU + 1.11·CP

where GHGE: GHG emissions, RE: renewable energy, EU: energy use, and CP: climate policy.

The resulting discriminant model is a system of linear equations (linear combinations of independent variables) that will optimally distribute countries into the selected CCPI groups (high, medium, low, and very low). These functions can be used to classify new observations. They are assigned to those classes whose classification values are maximized.

Figure 3 shows a scatter plot of the canonical values. It visualizes the contribution of each of the discriminant functions to the distribution of countries by CCPI groups.

The built discriminant model shows that the energy use indicator has the greatest weight when assigning the analyzed countries to groups (high, medium, low, and very low) according to the CCPI level. The second most important is renewable energy. The lowest weight in determining whether a country belongs to the medium and very low CCPI groups is given to the global greenhouse gas emissions indicator and the climate policy indicator to the high and low CCPI groups. However, these indicators are also important for the CCPI rating. The intercept value is large in each of the four linear classification functions. This means that there are still important factors for assessing climate protection that is not taken into account when assessing the CCPI level of the countries under study.

To test the hypothesis that the CCPI is reliable for assessing the effectiveness of climate policies in the context of the concept of sustainability, we conducted a comparative analysis of the CCPI rating 2022 and the sustainable development goals (SDG) 2022. The Index serves countries ranked by global and regional progress [66], encompassing 57 countries in both ratings. The results of the comparative analysis show that the CCPI index does not correlate with the overall score measures the overall progress (Figure 4). The results on the differences in environmental policy strategies of the world's countries do not support the hypothesis that the CCPI is reliable in the context of sustainable development. Today, the world's countries are not making enough efforts to prevent global climate change, focusing on economic development.

Our model uses empirical data to assess the effectiveness of environmental policies for countries not in the CCPI ranking, enabling comparisons with previous studies on the subject. This is important, as climate security is a global issue and requires coordinated action by all countries of the world.

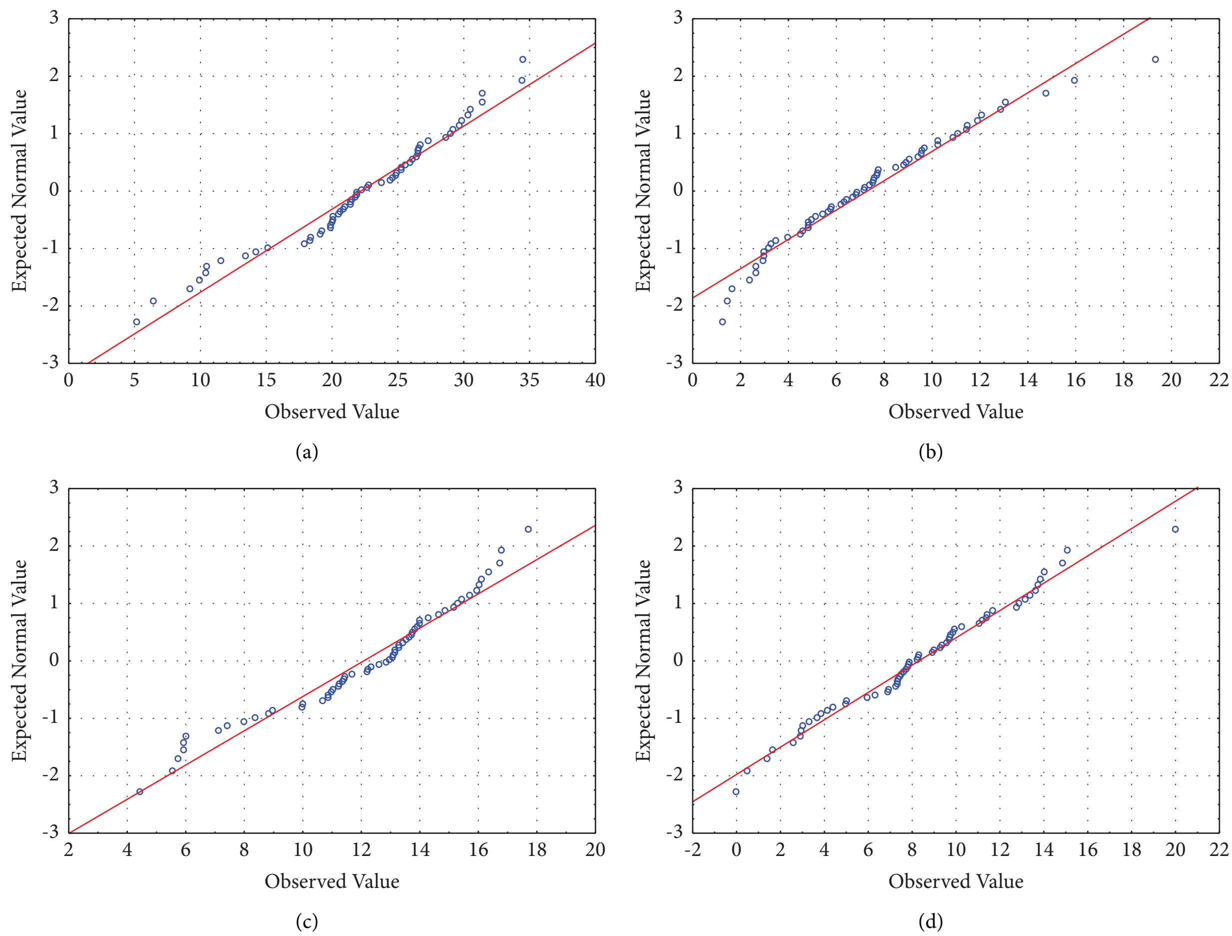

FIGURE 2: The normal probability of independent variables. (a) Normal probability plot of GHG emissions. (b) Normal probability plot of renewable energy. (c) Normal probability plot of energy use. (d) Normal probability plot of climate policy.

TABLE 4: Discriminant function analysis summary.

Group	No. of variables in the model: 4; grouping: CCPI rank (4 groups) Wilks' lambda: 0.08842 approx. $F(12.140) = 17.579$ $p < 0.00$					
	Wilks' lambda	Partial lambda	F-remove (3.53)	p value	Toler	1–toler. (R–sgr.)
GHG emissions	0.16	0.61	11.45	0.00	0.87	0.13
Renewable energy	0.12	0.73	6.38	0.00	0.75	0.25
Energy use	0.13	0.68	8.43	0.00	0.64	0.36
Climate policy	0.13	0.69	7.56	0.00	0.92	0.08

Multiple correlation (R-square) for each variable with all other variables that are included in the model.

TABLE 5: Classification matrix.

Group	Rows: observed classifications columns: predicted classifications				
	Percent correct	Very low $p = 0.23$	Low $p = 0.25$	Medium $p = 0.27$	High $p = 0.25$
Very low	92.86	13	1	0	0
Low	93.33	0	15	1	0
Medium	100.00	0	0	16	0
High	100.00	0	0	0	14
Total	96.55	13	16	17	14

Table 6: Squared Mahalanobis distances from group centroids (fragment).

Case	Observed classification	Very low $p = 0.23$	Low $p = 0.25$	Medium $p = 0.27$	High $p = 0.25$
AUS	Very low	4.16	12.59	21.99	37.95
*CYP	Low	17.26	1.92	1.96	13.05
DNK	High	94.72	48.93	26.77	11.09
EU	Medium	34.57	10.63	2.37	3.53
FIN	High	46.50	27.82	21.03	12.57
FRA	Medium	22.25	3.75	2.61	7.52
DEU	High	37.41	11.15	2.83	2.33
ITA	Medium	21.56	2.48	0.27	7.75
*JPN	Very low	8.13	1.32	8.96	25.29
LUX	High	35.69	10.03	2.97	1.04
NOR	High	55.41	24.97	16.81	9.80
RUS	Very low	4.84	20.32	39.12	65.23

Incorrect classifications are marked with*.

Table 7: Chi-square tests with successive roots removed.

Roots removed	Eigenvalue	Canonical R	Wilks' lambda	Chi-sgr.	df	p value
0	6.61	0.93	0.059	133.41	12	0.00
1	0.37	0.52	0.52	21.78	6	0.00
2	0.08	0.28	0.28	4.35	2	0.11

Chi-squared test of discriminant functions.

Table 8: Classification functions; grouping: CCPI rank.

Variable	Very low $p = 0.23$	Low $p = 0.25$	Medium $p = 0.27$	High $p = 0.27$
GHG emissions	0.96	1.58	1.82	2.42
Renewable energy	1.42	2.15	2.47	2.83
Energy use	2.30	3.48	3.88	3.81
Climate policy	1.11	1.37	1.90	2.23
Constant	−23.20	−51.59	−68.43	−90.57

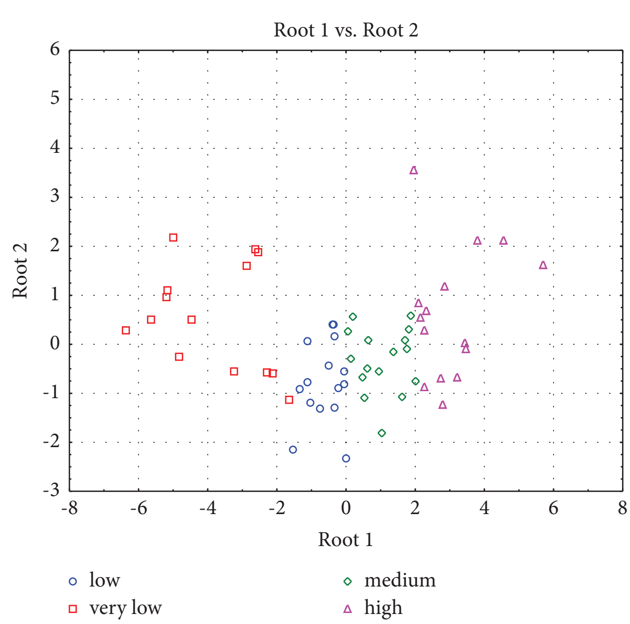

Figure 3: Scatterplot of canonical score.

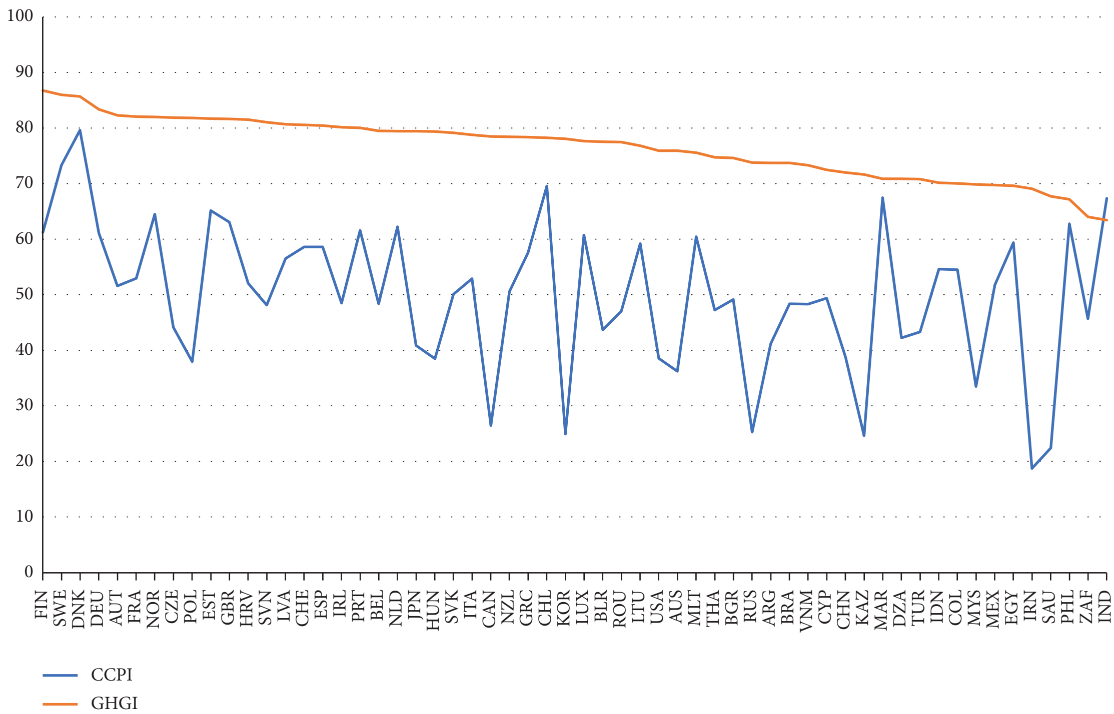

FIGURE 4: Chart of the CCPI and SDGI comparison.

The results show that the CCPI rating does not take into account certain factors that are important for assessing climate protection. Climate security is an important component of the overall concept of sustainable development, internal security of countries, and global security, so improving the methodological framework for developing its indicators is an important strategic task.

6. Conclusion

Humanity is already experiencing the consequences of its excessive, unsustainable exploitation of biological diversity, exacerbated by human-induced climate change. We live off other species (animals, plants, fungi, and microorganisms) and their habitats. The threat of extinction of other species is a direct threat to the survival of humanity. Environmental security can reduce complex risks to the stability of states and societies and reduce the number of conflicts over natural resources. Only a deep scientific understanding of the interrelationships and main risks of climate security and the formulation of key conclusions can provide useful information support for the development of an effective environmental security policy at the national and global levels. This paper introduces the discriminant analysis results of the components of the Climate Change Performance Index 2023 for 59 countries and the EU. The canonical discriminant model is built to identify the significant factors that influence the assessment of climate risks and the effectiveness of climate protection in a particular country or region. This system of linear equations classifies countries (high, medium, low, and very low) according to their level on the Climate Change Performance Index, which is determined based on its components. It can be used to assess the level of climate protection effectiveness of countries for which the CCPI 2023 has not been defined. We have determined the weights of the relevant CCPI components in relation to the effectiveness of actions aimed at reducing global warming. It was found that in assessing the level of climate security, the main focus is on energy use and renewable energy. Global greenhouse gas emissions and climate policy have the least weight. However, these indicators also hold significance for the built model. We have established that there are additional factors important for assessing climate protection, but the CCPI rating does not consider them. The constructed classification model takes into account the real coefficients obtained from empirical data and does not require the definition of subindicators. This will make it possible to determine the CCPI score for countries that are not included in the ranking and may use other methodologies in calculating the indicators that are the main components of the CCPI. We conduct a comparative analysis of CCPI and SDGI and find that the differences in the environmental policy strategies of the world's countries do not decisively impact the assessment of their level of sustainable development. The CCPI measures the effectiveness of the government's actions to mitigate climate change and informs investment redistribution decisions. Investments create the preconditions for economic security. Experience shows that actions aimed at mitigating climate change are not effective.

The relationship between climate change and sustainable development is very complex, as it touches on all components of sustainable development goals. National, food, or water security, migration processes depend on the effects of global warming. Therefore, the effectiveness of the state's climate policy also affects its overall security. Renewable energy and energy use indicators have an impact on energy security. The level of GHG emissions can pose a threat to health security. Abnormal temperatures have led to a decrease in food production as agriculture is not adapted. Additionally, climate change impacts environmental safety, biodiversity, and human migration and can cause political disputes and military conflicts over access to habitable areas and water resources. The problem of environmental security is global and requires global solutions for the use and equitable distribution of natural resources and the fulfillment of commitments by each country to mitigate climate change. Environmental security is a prerequisite for sustainable development and global security. We recommend that decision-makers and climate protection policymakers take decisive and serious actions to mitigate climate change and preserve an environmentally friendly environment.

The world's countries need to rethink the key aspects of measuring climate protection, identify other significant factors, and outline new trajectories for shaping strategies to ensure environmental protection and speed up the transition to a sustainable future.

Data Availability

The aggregated results and overall performance for the countries the CCPI evaluated are available at https://ccpi.org/. The additional data are available from the corresponding author upon request.

Disclosure

The funders had no role in the design of the study; in the collection, analyses or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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