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Uneven readiness: measuring climate risk and societal preparedness across OECD and key partner countries (2002–2022)

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Understanding climate risk requires an integrated perspective that links environmental hazards to societal preparedness. This study develops the Climate Risk and Societal Preparedness Index (CRISP) to measure vulnerability and readiness across 36 countries—31 OECD members and five Key Partners—between 2002 and 2022. A comprehensive and state-of-the-art literature review was conducted to identify the initial set of indicators. Correlation and network analysis methods were then applied to determine the final set of indicators, ensuring internal coherence, reducing redundancy, and strengthening the explanatory power of the index. CRISP distinguishes between climate-related risk (disasters and temperature anomalies) and societal preparedness (economic, demographic, institutional, and infrastructural factors), whereas most existing indices combine these dimensions within a single composite measure. The index enhances cross-national and longitudinal comparability. Results reveal diverse vulnerability patterns: Switzerland, Germany, and the Netherlands combine low risk with strong preparedness, while India and South Africa show persistent adaptive gaps. The United States and China face high risks but demonstrate comparatively robust preparedness. The findings suggest that cross-country differences in vulnerability are associated with socio-economic and governance conditions rather than exposure alone. CRISP thus provides a decision-support tool to identify weaknesses, prioritize interventions, and strengthen resilience in national climate strategies.

KEYWORDS
adaptation, climate change, index, mitigation, risk, vulnerability

1 Introduction

1.1 Climate change, societal preparedness, and the need for measurement

Climate change has significantly increased the frequency and severity of climate-related hazards, leading to widespread social, economic, and environmental impacts globally (Bergholt and Lujala, 2012; Wu et al., 2020; Forzieri et al., 2016; AghaKouchak et al., 2020; Raymond et al., 2022; Summers et al., 2021). As the impacts of climate change intensify and become more visible, the study of climate change vulnerability becomes increasingly significant. Such research supports efforts to build societies that are resilient to risk by identifying vulnerabilities and developing proactive strategies (IPCC, 2022).

Along with climate change, the socio-economic dynamics of climate risks have become central concerns for global sustainability and development. Climate risks such as extreme weather events, rising temperatures, droughts, and floods are no longer rare phenomena. These risks interact with socio-economic challenges and affect various segments of society and sectors, including production, infrastructure and health (UN, 2024a; UN, 2024b).

Climate change vulnerability is beyond the risks associated with climate-related events. Rather than simply recognizing climate risks, addressing and analysing vulnerability also contributes to the detailed identification and management of risks, increases awareness of these climatic events, and provides guidance for the development of policies on climate risk preparedness. In that respect, focusing on vulnerability is critical to reducing the immediate impacts of climate change and building long-term resilience that can help mitigate future risks (Jurgilevich et al., 2017).

Given this situation, a vulnerability risk and societal preparedness index becomes instrumental for assessing preparedness at a systematic, quantitative scale. Such an index also helps in formulating policy and monitoring effects over time. Stakeholders such as local governments, policymakers, citizens, and NGOs also benefit from the identification and quantification of climate change vulnerability, as they improve risk awareness and support planning to enhance resilience (Cutter, 2003; Stern et al., 2013).

A sound index is useful in measuring vulnerability and plays an important role in reducing uncertainty (Edmonds et al., 2020). The relationship between vulnerability and disaster impacts highlights the importance of preparedness and interventions (Birkmann et al., 2022). Moreover, the process of establishing a vulnerability index helps to characterize and reduce uncertainty (Edmonds et al., 2020). Such an index quantifies the risk, hence, enhances informed decisions that pertain to the prioritization of infrastructure investments, action plans for disaster preparedness, and strengthening adaptive capacity. Moreover, such an index equips governments and organizations with a tool to identify and decrease the related economic, social, and environmental risks.

Several indices are used in the earlier literature to assess climate risk and vulnerability. The ND-GAIN Index combines vulnerability and readiness into a single composite score to support cross-country benchmarking of adaptation challenges (University of Notre Dame Global Adaptation Initiative, 2024). The INFORM Risk Index focuses on humanitarian and disaster risk management. It applies a multiplicative model that integrates hazard exposure, vulnerability, and coping capacity (Marin-Ferrer et al., 2017). The IPCC framework provides a conceptual understanding of climate risk by defining risk as the interaction of hazards, exposure, and vulnerability. It does not prescribe specific indicators or aggregation rules (IPCC, 2022).

1.2 The CRISP index: motivation, research aim, and contribution

Building on this literature, this manuscript designs and computes a Climate Risk and Societal Preparedness Index (CRISP) for selected countries. The index is formulated through a comprehensive analysis of the literature concerning the socioeconomic, environmental, and institutional indicators of a country's climate risk profile and capacity to respond.

The aim of the manuscript is to provide decision support through identifying weaknesses, prioritizing interventions, and strengthening resilience in national climate strategies, hence reducing systemic vulnerabilities, and guiding prioritized adaptation and risk reduction strategies. The CRISP Index provides decision-makers with evidence for well-documented decisions on how societies can better prepare for and respond to climate hazards. The nexus draws conclusions on preparedness and timely interventions (Birkmann et al., 2022). It is also worth noting that even minor events related to the climate can escalate into major disasters when proper preparedness is lacking, especially in regions lacking infrastructure or governance systems to address the situation effectively.

Rather than replacing existing indices or introducing new theoretical foundations for vulnerability, CRISP adopts a different analytical structure regarding risk, explicitly separating climate-related risk signals from societal preparedness conditions, whereas most existing indices combine these dimensions within a single composite measure. The novelty of this approach is reflected in how it addresses a key gap in the literature by clearly distinguishing exposure-driven risk dynamics from underlying societal capacity. It enables more transparent, diagnostically oriented, and policy-relevant cross-national comparisons.

Within CRISP, preparedness is operationalized through a set of socio-economic, demographic, institutional, and infrastructural indicators that capture societies' structural capacity to anticipate and respond to climate risks. This design choice avoids over-aggregation and improves the interpretability of index results for policy analysis. Hence, CRISP does not re-theorize the exposure–vulnerability relationship. Rather, it operationalizes established concepts by allowing risk and preparedness to be examined independently and over time. The contribution of CRISP, therefore, lies in enhanced cross-national and longitudinal comparability. It helps identify the sources of persistent vulnerability and supports strategic discussion and prioritization, rather than providing operational or sector-specific policy prescriptions. Thus, CRISP complements rather than replaces ND-GAIN, INFORM Risk, and IPCC-based assessments by supporting strategic policy discussion through diagnostic benchmarking.

In this context, the main objective of this study is to develop and apply the CRISP Index in order to enable systematic cross-national and longitudinal comparisons of climate-related risk and societal preparedness. To achieve this objective, the CRISP index has been constructed for a sample consisting of 31 OECD member states and 5 OECD Key Partner countries (Brazil, China, India, Indonesia, and South Africa). The selected country set offers a scope that includes developed and emerging economies from different continents, which allows analysis across development stages (Maral, 2024; Shmelev, 2025). Moreover, these countries account for a large share of global trade and economic activity, gross domestic product and greenhouse gas emissions (Chen et al., 2018; Kang, 2021; Wang and Zhang, 2021; Bashir et al., 2023). Finally, the availability of standardized and regularly updated statistics across multiple dimensions facilitates robust cross-country comparability (OECD, 2018; Nardo et al., 2005).

In addition to the main objective, this study pursues the following objectives:

- To equip decision-makers with a robust and information-based intervention to support more responsive and long-term planning.

- To enable policymakers to make informed decisions that protect human communities from the negative repercussions of climate change.
- To reveal where improvements in institutions, healthcare, and social services are needed to enhance adaptive capacity.
- To support more efficient and strategic allocation of resources for climate risk reduction and adaptation interventions.

In summary, the CRISP index gives a clear, data-driven picture of vulnerability, empowering policymakers to make informed decisions to protect ecosystems and build more resilient communities. With continued climate change worldwide, there will be an increasing need for reliable, robust tools such as CRISP, making it a vital component of the response to the global challenge of climate change.

2 Literature review

The understanding of climate risk has evolved significantly in recent decades. Research on this domain has increasingly emphasized not only environmental hazards but also the broader socioeconomic systems that affect human societies directly. Early academic work, such as by Adger and Kelly (1999), Eakin and Luers (2006), and Füssel and Klein (2006), tended to center on the impacts of climate change while often overlooking the characteristics of the populations or systems affected by these risks. This perspective has since shifted. Scholars such as O'Brien et al. (2007), Hinkel (2010), Eakin et al. (2014), and Ford et al. (2018) have contributed to a more integrative understanding. They assess climate risk as a function of both exposure to hazards and the conditions that affect society's resilience.

Recent studies have increasingly focused on causes and motivating factors behind the impacts of climate risks on human systems. According to Cutter (2003) and Ford et al. (2018), this shift recognizes that climate risk is created by dynamic relations between a bio-physical component and non-climatic factors as emphasized by Debortoli et al. (2018). Füssel and Klein (2006) argue that the interaction between stressors and adaptive capacity plays a decisive role in shaping the outcomes of climate events. Similarly, Dilshad et al. (2018) highlight that these risks emerge as "a consequence of various socio-economic states, governance arrangements and resource accesses." Over time, the analytical focus has shifted from anticipating climate impacts to exploring the structural uncertainties and socio-political dynamics that exacerbate them (Füssel and Klein, 2006; Wang et al., 2014; McDowell et al., 2016; Räsänen et al., 2016). A comprehensive approach to climate risk is essential to developing effective, equitable, and forward-looking policy responses (Thomas and Warner, 2019).

Climate change has increased the frequency and intensity of extreme weather events and resultant disasters, such as hurricanes, floods, droughts, and heatwaves. This trend is likely to continue in the future (Morss et al., 2011; Visser et al., 2014; Stott, 2016; Ummenhofer and Meehl, 2017; Tippett, 2018). These events are primarily driven by extreme temperatures and precipitation (Stott, 2016). However, the visibility and intensity of these effects vary across regions (Morss et al., 2011). As a result, the various impacts of extreme events are unevenly distributed with some regions experiencing disproportionately severe consequences. For instance, extreme weather elements make coastal regions more frequently affected by climate risks such as sea-level rise and storm surges (Otto et al., 2023). Similarly, the effects of rising temperatures vary across regions. Particular indicators, such as the frequency of heatwaves and agricultural impacts, show wide variation mostly determined by local climate and geographic conditions. In this sense, variability indicates that particular effects can vary greatly between countries or regions even for a stipulated rise in global mean temperature (Arnell et al., 2017; Arnell et al., 2019).

Ford et al. (2018) note that both climatic and non-climatic variables must be considered to provide a more complete assessment of climate risks. Accordingly, a variety of social, economic, and political factors are prominent (Thomas et al., 2018). Among economic indicators, GDP per capita is frequently used as an indicator for economic strength and adaptive capacity. It reflects average income levels, and therefore, the general ability of a country to mobilize resources (Lo and Chow, 2015; Tudor and Sova, 2021). However, its relevance is context-dependent and has certain limitations. GDP per capita does not capture income inequality, informal economies, or the actual distribution of resources, all of which significantly affect societal preparedness and resilience. Another factor related to a country's economic and social fragility is unemployment (Catalano et al., 2019; Moore and Diaz, 2015). Recent literature shows that high unemployment rates can constrain economic resources and reduce societies' coping capacity against adverse climate risks (Benegal, 2017; Reckien et al., 2015).

Apart from unemployment, other social factors include demographic characteristics such as age dependency, urban and rural population shares, population growth, and population density. Age dependency refers to the share of dependents, people below 15 years of age (young) and above 64 years of age (old), relative to the working-age population. Young/Old Age Dependency can place strain on economic resources and depress resilience in responding effectively to climate challenges (Aruta, 2023; Andor et al., 2018). Urban areas, characterized by dense populations, infrastructure concentration, and economic activity, present a complex climate risk profile. On the one hand, cities often benefit from greater access to resources, institutional capacity, and technology, which enhance their readiness and adaptive responses (Thaler et al., 2021; Sharifi, 2020). On the other hand, they remain highly exposed to hazards such as heatwaves, flooding, and air pollution, especially when rapid urbanization outpaces infrastructure development (Kantamaneni et al., 2023; Guerreiro et al., 2018). Unplanned urban growth can increase social and spatial inequalities, strain existing systems, and limit the overall effectiveness of climate resilience strategies (Kanga et al., 2021; Chen et al., 2021).

Rural populations often face higher exposure to climate risks due to their dependency on agriculture and limited access to basic services such as clean water, sanitation, and electricity (Žurovec et al., 2017; Gutierrez et al., 2020). Climate conditions may disrupt farming, leaving rural communities with losses on their main source of income. This can lead to job losses, poverty, and long-term social and economic challenges (Madzivhandila and Niyimbanira, 2020; Asfaw et al., 2017). These impacts are especially severe in areas where public services and government support are weak. Although some demographic indicators may overlap, the share of the rural population remains important. It reflects structural differences in how countries experience and respond to climate shocks. In countries where many people live in rural areas and rely on agriculture, this indicator helps capture that unequal access to resources and the limited capacity of rural regions to recover from extreme events.

Rapid population growth increases pressure on the quality and availability of natural resources, aggravating environmental degradation and reducing the capacity of farming communities to adapt to climate change, especially in low-income countries (Maja and Ayano, 2021). When more people rely on limited land, water, and food systems, the risk of social and economic instability rises. Recent studies show that a combination of population growth and climate change will increase exposure to extreme heat events, especially during summer months. Under a business-as-usual scenario, Africa is projected to experience the largest increase in compound heat extremes, while Europe is expected to see the smallest (Ma and Yuan, 2021). Assessing population growth as an indicator helps understand the growing risks placed on adaptive systems in regions already vulnerable to climate-related shocks.

Access to electricity, as an infrastructure indicator, plays a key role in a country's ability to respond to climate-related risks. Reliable energy access supports communication systems, emergency response, and health services which are critical during climate disasters (Chen et al., 2019; Niklas et al., 2022). Life expectancy at birth, on the other hand, serves as a broad indicator of a country's public health capacity. This indicator reflects long-term investments in healthcare infrastructure. It also provides insights into how well a society can protect its population from climate-related health risks (Hahn et al., 2016; Van Aalst et al., 2008).

The political and administrative factors relevant to climate risks and preparedness relate to voice and accountability, regulatory quality, and government effectiveness. These form the last two pillars of non-climatic factors. Various factors impact the formulation and implementation of climate policies, mitigation and adaptation agendas (Lesnikowski et al., 2020; Pardoe et al., 2020). Voice and accountability, as well as the level of inclusiveness and equity of the climate action plan are determinants in this respect (Borgi et al., 2023). Regulatory quality affects the extent to which a government can enforce environmental regulations. Government effectiveness is also critical in determining how efficiently public resources are managed to respond to various climate-related challenges and disasters (Howes et al., 2014; Carvalho and Spataru, 2023).

In summary, the literature emphasizes that climate risks are not solely determined by physical hazards but are deeply influenced by a country's socio-economic conditions and institutional capacity. These interconnected factors shape countries' preparedness to climate risks. On this basis, the next section presents the research design and indicator selection process for the Climate Risk and Societal Preparedness Index (CRISP).

3 Research design and indicator selection

The state-of-the-art literature review methodology coupled with the conceptualization of climate risk and societal preparedness is utilized to identify the relevant indicators for the Climate Risk and Societal Preparedness Index (CRISP). The initial set of indicators are evaluated through correlation analysis and network diagrams, resulting in the final set of indicators, eliminating redundancy and increasing the predictive capability of the index. After identifying the final set of indicators, a two-level normalization is conducted to achieve standardization and comparability across the indicators, as well as to alleviate the issues of magnitude differences of the indicators in their contribution to the Climate Risk and Societal Preparedness Index (CRISP). After the index computation, average and comparative analyses were conducted, leading to policy implications. The methodological framework followed in this research is depicted in Figure 1.

In setting the initial query for the literature review, the following main keywords were utilized: "climate change," "vulnerability," "climate related disasters", "climate sensitivity", and "governance." The inclusion of these keywords was aimed at capturing the institutional, societal and systemic aspects of climate risk. The query was conducted using Boolean search operators combining the terms "climate change" AND "vulnerability" AND "climate-related disasters" AND "climate sensitivity" OR "governance", applied to the author keywords field. The initial query resulted in around 500 sources. Only peer-reviewed journal articles indexed in Web of Science databases were included. The bases for the selection of the most relevant sources are (1) direct relevance to the assessment of climate risk or vulnerability; (2) being recent or foundational; (3) making a conceptual and/or empirical contribution to socio-economic or governance dimensions; (4) impact factor of the manuscript, determined by a minimum of 50 citations in Web of Science.

Based on these criteria, the following 39 articles were selected. Table 1 presents the indicators identified in the cited articles and the articles that have subsequently cited them. As a result, Table 1 also provides 14 indicators cited by the 39 manuscripts.

In what follows, we present explanations for the initial set of 14 indicators, $\underline{C}_1$ through $\underline{C}_{14}$, as identified from the literature, determined by citation frequency, relevance to climate risk, and data availability for the construction of the Climate Risk and Societal Preparedness Index:

$\underline{C}_1$ *Climate-related disasters* are environmental events such as storms, floods, droughts, landslides, and wildfires that result from the increasing trend in frequency and intensity of climate phenomena driven by global change. Data are obtained from the Emergency Events Database (EM-DAT, 2024) as an annual total number of events for all countries. A higher number of disasters indicates the exposure and risk and signals that the country is experiencing higher levels of climate change impacts.

$\underline{C}_2$ *Annual temperature change:* this indicates the deviation of the average surface temperatures from year to year in degree Celsius. This is an important indicator of climate change because it shows an increasing trend in global temperatures driven by the accumulation of greenhouse gases in the atmosphere. The associated data are based on FAO (2023). Larger positive temperature changes reflect a higher risk given the change in climate.

$\underline{C}_3$ *GDP per capita:* the division of a country's Gross Domestic Product by its total population. It is an economic indicator indicating the average economic output per capita and average income levels in US dollars. Data related to these indicators have been retrieved from the World Bank (2023a). Higher values of GDP per Capita mean higher capability and societal preparedness regarding climate change.

$\underline{C}_4$ *and* $\underline{C}_5$ *Age dependency younger* ($\underline{C}_4$) *and Age dependency older* ($\underline{C}_5$)*:* this is the number of dependents - individuals below 15 years old and above 64 years of age - in relation to the working-age population, usually between the ages of 15 and 64 years. The corresponding data are obtained from the World Bank (2023b). For both measures, higher levels of age dependency imply higher risk.

$\underline{C}_6$ *Urban population:* this refers to the percentage of a country's population residing in urban areas, such as towns and cities. The data are derived from the World Bank (2023c). For a country, the higher

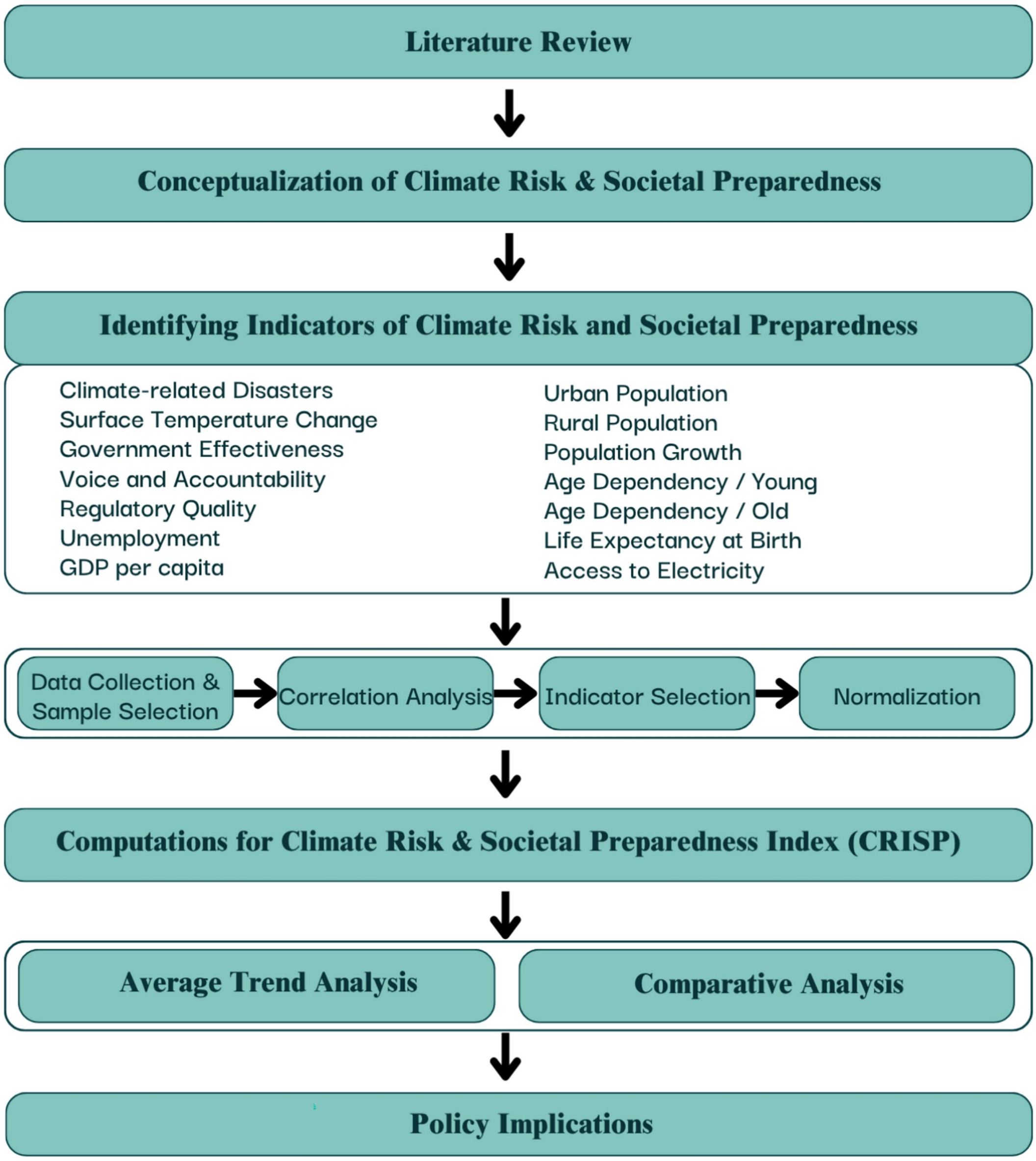

FIGURE 1
Methodological framework of the research.

the share of its population that is living in urban areas, the higher the risks are of exposure to climate change.

C_7 *Rural population:* this refers to the percentage of the total population of a country living in rural areas, usually characterized by low density, less infrastructure, and higher dependence on agriculture and natural resources. The related data are taken from the World Bank (2023d). The higher the percentage of population in rural areas, the higher the risk of exposure to climate change.

C_8 *Access to electricity* refers to the percentage of a population with reliable and consistent access to electrical power within a nation. The data are obtained from the World Bank (2023e). Higher values of this indicator correspond to lower the risks concerning climate change.

C_9 *Life expectancy at birth:* this refers to the number of years a newborn infant could expect to live, according to the demographic indicators. The data are obtained from the World Bank (2023f). The higher value of life expectancy at birth corresponds to the lower risks.

C_{10} *Population growth:* this refers to the percent change in the number of people inhabiting a country over 1 year. Available data are from the World Bank (2023g). Expressed in percent form, higher population growth rates are associated with higher risks concerning climate change and societal preparedness.

C_{11} *Unemployment* is the percentage of the labor force that is without employment but available for work. The corresponding data are from World Bank (2023h) and International Monetary Fund (IMF, 2024). Increasing unemployment levels diminish countries' preparedness to address the impacts of climate change.

C_{12} *Voice and accountability:* this is measured based on the extent to which citizens are able to participate in selecting their government, as well as the degree of free speech, freedom of association, and media freedom. The respective data are available at the World Bank (2024). Because this is an indicator of the country's adaptive capacity in regard to climate change, higher values of the Voice and Accountability imply

TABLE 1 Indicators as identified from the literature.

Article	#Cites	Climate related disasters	Annual temp.	GDP *per capita*	Age dep. - old	Age dep. - young	Urban pop.	Rural pop.	Access to electricity	Life expectancy at birth	Pop. growth	Unemployment	Voice and accountability	Regulatory quality	Government effectiveness
Lindner et al. (2009)	1,651	+	+					+					+	+	+
Fuessel (2007)	957	+	+	+									+	+	+
Hahn et al. (2016)	812	+	+		+	+	+	+		+					
O'Brien et al. (2007)	701			+								+	+	+	+
Miller et al. (2010)	629	+	+				+					+			
Van Aalst et al. (2008)	479		+	+						+		+			
Balica et al. (2012)	463	+		+	+	+	+							+	+
Serdeczny (2017)	443	+	+					+	+	+	+				
Schipper and Pelling (2006)	403	+	+	+						+		+			
Brody et al. (2007)	395	+	+	+				+							
Thomalla et al. (2006)	377	+		+			+		+	+	+	+			+
Koks et al. (2014)	371	+		+	+	+	+	+			+				+
Eriksen and Kelly (2006)	269	+	+	+			+		+	+	+		+	+	+
Engle and Lemos (2010)	268								+				+	+	+
Fuessel (2007)	225	+	+	+						+		+	+	+	+
Schilling et al. (2020)	176	+	+	+						+	+	+	+	+	+
Pandey et al. (2017)	172	+	+	+					+	+			+	+	+
Otto et al. (2023)	162	+	+	+	+	+			+	+					
Emrich and Cutter (2011)	160	+	+	+	+	+	+	+	+	+	+	+			
Spielman et al. (2020)	158			+	+	+	+	+			+	+			
Argyroudis et al. (2021)	147	+	+						+						
Weis et al. (2016)	136	+	+	+	+	+		+	+	+		+			

(Continued)

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TABLE 1 (Continued)

Article	#Cites	Climate related disasters	Annual temp.	GDP *per capita*	Age dep. - old	Age dep. - young	Urban pop.	Rural pop.	Access to electricity	Life expectancy at birth	Pop. growth	Unemployment	Voice and accountability	Regulatory quality	Government effectiveness
Tapia et al. (2017)	131	+	+	+	+	+			+	+	+	+	+	+	+
Inostroza et al. (2016)	122		+		+	+			+			+			
Simane et al. (2014)	114	+	+	+					+	+		+	+	+	+
Formetta and Feyen (2019)	108	+	+	+					+	+			+	+	+
Alam et al. (2017)	99	+	+	+				+	+	+		+	+		+
Gupta et al. (2019)	97	+	+	+	+	+		+	+		+	+	+	+	+
Wiréhn et al. (2015)	96	+	+		+	+		+	+			+			+
Birkmann et al. (2022)	94	+	+	+				+		+			+	+	+
Krishnamurthy et al. (2014)	93	+	+	+			+	+		+	+	+			+
Binita et al. (2015)	80	+	+					+			+	+	+	+	+
Campbell-Lendrum and Corvalan (2007)	76	+	+				+								
Žurovec et al. (2017)	76	+	+	+	+	+		+				+			
Omerkhil et al. (2019)	70	+	+	+								+		+	+
Edmonds et al. (2020)	61	+	+	+							+	+	+	+	+
Das et al. (2020)	56	+		+	+	+	+	+	+	+	+	+			+
Soares et al. (2012)	55	+	+								+		+	+	+
IPCC (2022)		+	+	+	+	+	+	+	+	+	+	+	+	+	+

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higher capacity and preparedness, hence lower risks with regard to climate change.

$\underline{C}_{13}$ *Regulatory* quality refers to the government's ability to formulate and implement policies and regulations that promote economic growth, public welfare, and development. The data are taken from the World Bank (2024). Higher values of Regulatory Quality for a country will imply higher preparedness with respect to climate change vulnerability.

$\underline{C}_{14}$ *Government effectiveness:* this refers to the quality of public services, quality of the civil service, quality and independence of the judiciary, and credibility of the government's commitment to such policies. Relevant data are from the World Bank (2024). Greater Government Effectiveness means greater adaptive capacity and preparedness, thereby decreasing the risks concerning climate change.

4 Data and methodology

4.1 Data sources and country selection

The construction methodology of CRISP has been employed earlier in previous studies, by Biresselioglu et al. (2019) constructed a Resource Curse Vulnerability Index for 55 countries using 9 indicators, and Cabalu (2009) proposes a Composite Gas Supply Security Index. Normalization in both studies is carried out by first mapping the range between the highest and the lowest value of an indicator to the interval [0,1], considering the direction in which the indicator affects the index. The index value, following normalization, is computed as the root mean square of the normalized indicator values for each country. The ratioed values of the indicators upon the countries over which a composite indicator is constructed by using the root mean square of the indicators.

In this manuscript, comprehensive and state of the art literature review methodology is used to select the initial set of 14 indicators. The correlation analysis and network analysis methods are then utilized to select the final set of indicators. These methods identify the redundant or overlapping variables and increase the explanatory power of the index. The final set of indicators is used to compute CRISP values for 36 countries over the period 2002 to 2022. The data relating to the indicators for the countries was extracted from appropriate, reliable sources, including datasets of EM-DAT, Food and Agriculture Organization-FAO, the World Bank, and International Monetary Fund-IMF. The selection of the final set of countries and the timeline of the CRISP was based on availability. Data on 14 indicators were available for 36 countries spanning 2002–2022.

A total of 31 OECD member states and 5 OECD Key Partner countries officially recognized by the OECD (Brazil, China, India, Indonesia, and South Africa) have full indicator coverage. The following seven OECD countries were excluded from the final analysis due to incomplete and missing data for the given timeline: Costa Rica, Estonia, Iceland, Latvia, Lithuania, Luxembourg, and Slovenia. Hence, the final selected countries for the computation of CRISP values over the timeline 2022–2022 are: Australia, Austria, Belgium, Brazil (Key Partner), Canada, Chile, China (Key Partner), Colombia, Czechia, Denmark, Finland, France, Germany, Greece, Hungary, India (Key Partner), Indonesia (Key Partner), Ireland, Israel, Italy, Japan, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, South Africa (Key Partner), South Korea, Spain, Sweden, Switzerland, Türkiye, the United Kingdom, the United States.

4.2 Final indicator selection

As with the selection of the initial set of 14 indicators, the final selection also considered citation frequency based on the comprehensive literature review, the relevance of the indicators to climate risk, and data availability for each indicator. However, at this stage, the possibility of dependence and correlation was also considered, since including highly correlated indicators poses the risk of over-emphasizing the effect in case of high positive correlation, and under-representation in case of high negative correlation. Therefore, to avoid these potential issues, preprocessing and the elimination of redundant or overlapping indicators were performed. These steps involved correlation and network analyses, resulting in a final set of 10 indicators.

Before calculating the final CRISP score, we first explored how well the initial set of selected indicators worked together. Correlation tables and visual network maps were utilized to assess how the indicators were connected and whether they made sense collectively. An important step in the construction of CRISP was the systematic assessment of relationships among the initially selected 14 indicators. To identify redundant or overlapping variables, a correlation analysis was used to assess the degree of association within the initial set of candidate indicators. Through correlation analysis, we ensured that the indicators used to compute the CRISP index contributed unique information rather than disproportionately amplifying specific dimensions of risk or societal preparedness.

Figure 2 demonstrates the correlation matrix for the 14 indicators ($\underline{C}$ i= $i=1,\ldots,14$). The results indicate several instances of strong association between indicators. For instance, Government Effectiveness was identified to have positive correlation with Voice and Accountability (r = 0.77), Regulatory Quality (r = 0.80), and Life Expectancy at Birth (r = 0.77). Accordingly, the Government Effectiveness indicator can be removed to avoid redundancy and to preserve the coherence.

Likewise, the Age Dependency (young) and Age Dependency (old) indicators demonstrated associations with the other socio-economic indicators. Rather than removing both indicators, they can be combined into a single composite indicator, allowing the index to reflect the structural economic pressures of dependent populations without disproportionately weighting this demographic dimension. On the other hand, the Urban Population and Rural Population indicators showed weaker, less interpretable correlations with the other indicators. Hence, the results of the correlation analysis suggested removing the Government Effectiveness indicator, combining the two indicators, Age Dependency (young) and Age Dependency (old) as a composite indicator in order to decouple their relationships with the other indicators, while increasing the explanatory power of the composite index, as well as eliminating the Urban Population and Rural Population indicators that have limited explanatory power.

The network map for the 14 indicators ($\underline{C}_i$, $i=1,\ldots,14$) is provided in Figure 3.

The network analysis also demonstrated that Urban Population and Rural Population indicators were positioned at the periphery of the network, with fewer and weaker connections to the other indicators. Their limited integration suggested that their contribution to the index's explanatory power would be minimal, justifying their exclusion from the final set. Hence, although theoretically relevant, Urban Population and Rural Population indicators were consequently excluded from the final set. The network diagrams also showed that indicators such as Voice and Accountability and Regulatory Quality were more central and better connected, meaning that they are more instrumental in understanding and explaining differences across countries. Hence, the network recommended eliminating the Urban Population and Rural Population indicators.

Utilizing the findings of correlation analysis and network analysis, the Government Effectiveness indicator was eliminated, Age Dependency (young) and Age Dependency (old) indicators were combined into a single indicator [Age Dependency (young)/Age Dependency (old)], and the Urban Population and Rural Population indicators were eliminated.

As a result, the analysis, which began with 14 indicators, $\underline{C}_j$'s, resulted in a refined set of 10 indicators relevant to climate risk and societal preparedness indicators that reflect governance, economy, demographics, infrastructure, and labor conditions. The removal and consolidation of indicators based on correlation and network analysis not only enhanced the statistical coherence of CRISP but also strengthened its conceptual clarity by ensuring that each dimension was represented in a balanced and non-redundant manner. By systematically identifying redundant or weakly performing indicators, this step improved the validity of the index, preserved its multidimensionality, and ensured that its outputs could serve to strengthen the evidence base for policymakers and researchers to guide their decisions.

The final list of indicators is demonstrated below:

Climate risk indicators:

C_1 –Climate-related disasters *($\underline{C}_1$)*

C_2 –Surface temperature change *($\underline{C}_2$)*

Societal preparedness indicators:

C_3 –GDP *per capita* *($\underline{C}_3$)*

C_4 –Age dependency (young and old) *($\underline{C}_4$/$\underline{C}_5$)*

C_5 –Access to electricity *($\underline{C}_8$)*

C_6 –Life expectancy at birth *($\underline{C}_9$)*

C_7 –Population growth *($\underline{C}_{10}$)*

C_8 –Unemployment *($\underline{C}_{11}$)*

C_9 –Voice and accountability *($\underline{C}_{12}$)*

C_{10} – *Regulatory quality ($\underline{C}_{13}$)*

4.3 Normalization and index computation

To ensure consistency and comparability across a diverse set of indicators in our CRISP Index framework, a two-step normalization is implemented. Indicators are measured using a variety of data types. Within the CRISP Index framework, climate risk is quantified using exposure-related hazard indicators. Specifically, risk is measured through the frequency of climate-related disasters and deviations in temperature anomalies which are commonly used in the literature (IPCC, 2022; Tippett, 2018; Ummenhofer and Meehl, 2017). These indicators show the occurrence and intensity of climate-related stresses. Also, it supports maintaining a conceptual boundary between climate risk and societal preparedness. In contrast, preparedness is measured through socio-economic, demographic, institutional, and infrastructural indicators. They are expressed in different units and scales depending on their data sources. For example, the Unemployment indicator is measured as the percentage of the labor force without jobs, while the GDP *Per Capita* is expressed in USD. To overcome such issues, ensure dimensional consistency and cross-country comparability a two-step normalization is implemented for all the indicators.

The first normalization, z-normalization, maps each indicator to a standard Normal distribution with mean $\mu = 0$ and standard deviation $\sigma = 1$. Z-normalization transforms each variable so that it has a mean of zero and a standard deviation of one, which allows for direct comparison between indicators measured in different units or scales (Carvalho et al., 2023; Cheadle et al., 2003; Colan, 2013). This method enhances interpretability, as normalized values represent standard deviations from the mean, making it easier to detect outliers and to assess how much a country deviates from global averages (Colan, 2013). Moreover, z-normalization is more robust to outliers and does not distort the original distribution of the data, which makes it preferable in real-world scenarios involving structural or geographic extremes (Jain et al., 2005; Laska and Yolanda, 2024; Rose, 1987). This is particularly important in global datasets where some countries may have extreme values for certain indicators. Finally, z-normalization supports scalability and reproducibility in cross-country studies, as new observations can be added without recalculating bounds, ensuring methodological consistency over time (Carvalho et al., 2023; Cheadle et al., 2003; Lu et al., 2025). For all these reasons, z-score normalization provides a statistically sound, robust, and interpretable foundation for building the composite index and performing related analyses.

The second normalization is performed on the z-normalized indicator values, where the values are projected within the interval [0,1]. In this step, each indicator value gets transformed into a value $N_{ji}(t)$ assuming a value between 0 and 1. That is, if higher values of a certain indicator j signal higher risks regarding climate change, the normalized indicator values are computed by considering the distance between the value of the indicator for a country in a year, and the best-performing country for the given indicator in that particular year, that is, the country with the lowest indicator value in that year. In contrast, when higher values of any given indicator j illustrate lower climate risks, normalized values of indicators are provided through comparison of distances between indicator value of a country for a year and best performing country for that indicator in that year-that is, the country with the highest indicator value for that year-and distances between performances of best- and worst-performing countries for that indicator in that year. This transformation also enhances the comparability of indicator values and mitigates the effects of scale and unit differences on the index.

In this process, the indicator value of the country with the most favorable condition according to that particular indicator for that particular year concerning the indicator is transformed to 1, and the indicator value which pertains to the country having the most unfavorable condition concerning the particular indicator assumes a value of 0. For the other countries, computation is done based on the putative distance from the worst-performing or the poorest country for the particular indicator and with respect to the particular year. By this computation, a linear scale is used. Output values of indicators provided by such conversion will show, on a scale of 0 to 1, how well the country performs with reference to it in some particular year. Values near 0 indicate high climate risks whereas values near 1 indicate low climate risks.

Hence, the z-normalization enhances interpretability of the indicator values, enhances robustness to outliers, and supports scalability, ensuring methodological consistency over time. The [0,1] normalization contributes to the comparability of the indicator values. Below,

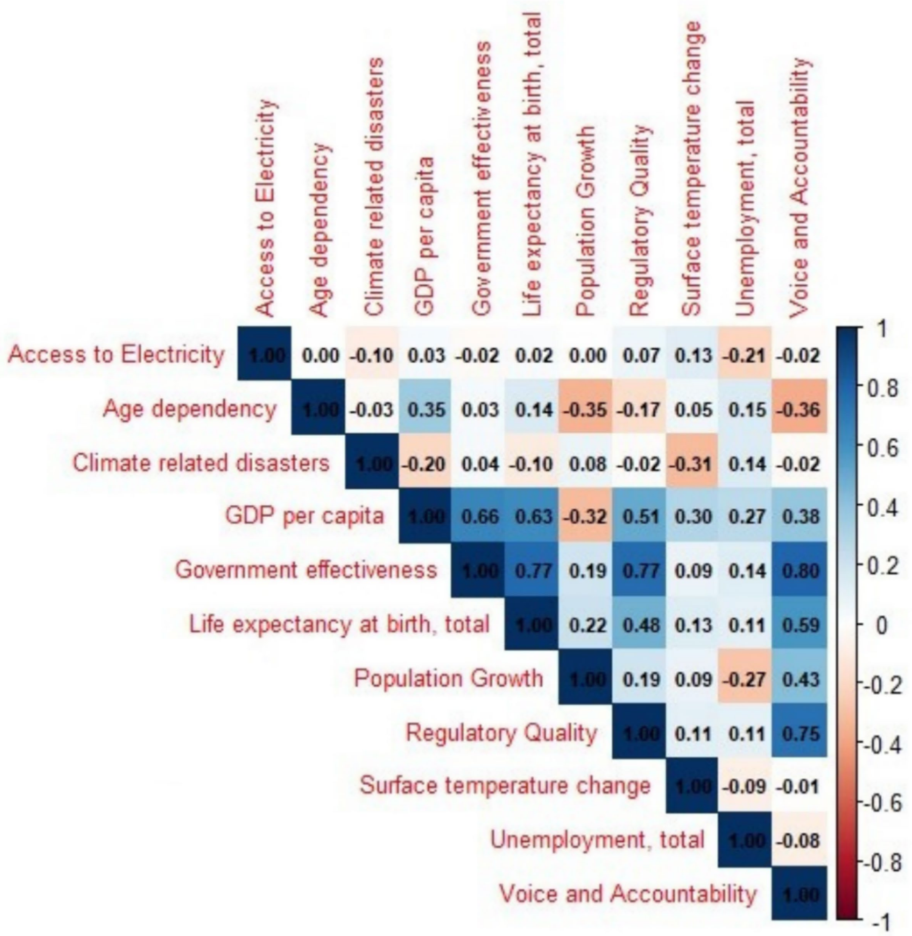

FIGURE 2
Correlation matrix for the initial set of indicators.

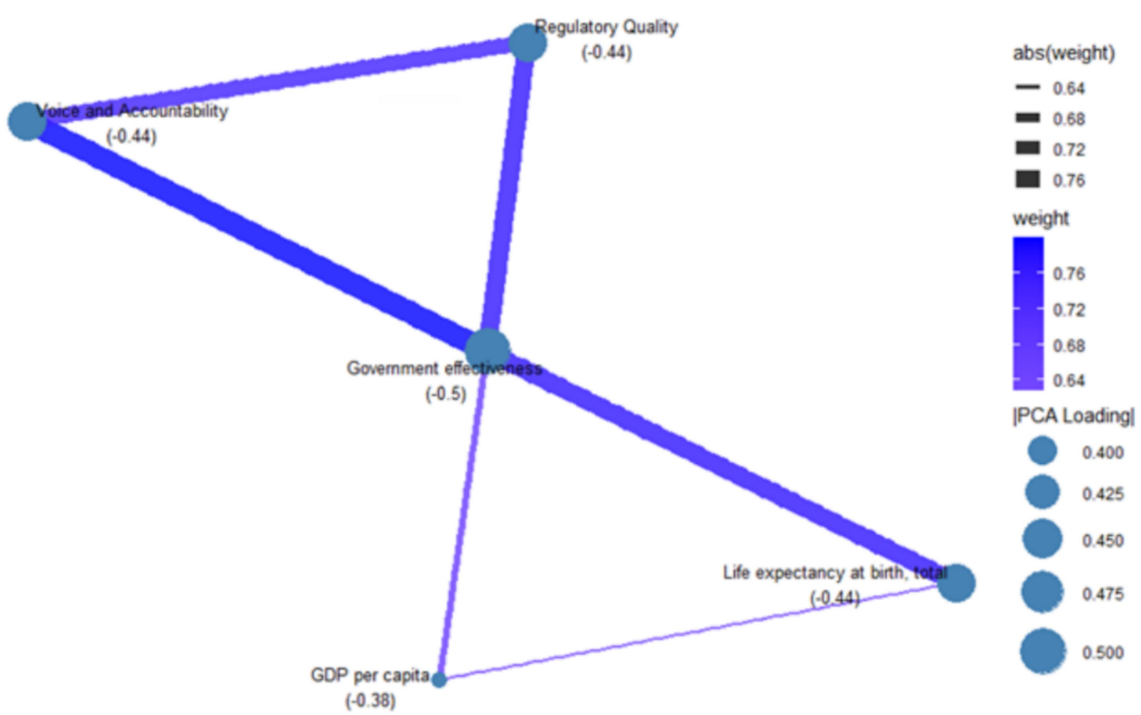

FIGURE 3
Network map for the initial set of indicators.

we explain how the normalized values have been calculated for each of the 14 indicators:

We denote by $C_{ji}(t)$ the value of indicator j for country i in year t.

m denotes the number of countries analyzed.

$\mu_j(t)$ is the mean value of indicator j in year t. That is,

$$\mu_j(t) = \frac{1}{m}\sum_{i=1}^{m} C_{ji}(t)$$

$\sigma_j(t)$ is the sample standard deviation of indicator j in year t. That is,

$$\sigma_j(t) = \sqrt{\sum_{i=1}^{m} \frac{\left(C_{ji}(t) - \mu_j(t)\right)^2}{m-1}}$$

$z_{ji}(t)$ stands for the z-normalized values of the indicators.

$MIN(z_{jt})$ and $MAX(z_{jt})$ stand for the lowest and highest values, respectively, for indicator j in year t. That is, $MIN(z_{jt}) = \min_i z_{ji}(t)$ and $MAX(z_{jt}) = \max_i z_{ji}(t)$.

$N_{ji}(t)$ denotes the [0,1]-normalized value of the indicator j for country i in year t. $N_{ji}(t) \in [0,1]$ ensuring comparability across indicators.

n stands for the total number of indicators.

The indicator $C_{ji}(t)$ is first standardized using z-normalization. That is, we define the z-normalized values of the indicators as:

$$z_{ji}(t) = \begin{cases} \dfrac{C_{ji}(t) - \mu_j(t)}{\sigma_{j(t)}} & \textit{if higher values of the indicator represent lower risk} \\ -\dfrac{C_{ji}(t) - \mu_j(t)}{\sigma_{j(t)}} & \textit{if lower values of the indicator represent lower risk} \end{cases}$$

After obtaining the z-scores, min-max rescaling is applied to map all values into the interval $[0,1]$. The rescaled indicator values, $N_{ji}(t)$, are computed as:

$$N_{ji}(t) = \frac{z_{ji}(t) - MIN(z_{jt})}{MAX(z_{jt}) - MIN(z_{jt})}$$

Finally, the CRISP score for country i in year t is calculated as the arithmetic average of the rescaled indicator values.

$$CRISP(i,t) = \frac{1}{n}\sum_{i=1}^{n} N_{ji}(t)$$

That is, to demonstrate the effects of each indicator equally, the CRISP score assumes equally weighted indicators. Although the index can be easily modified to incorporate different weights for the indicators, for instance, by expert opinion, any process to determine weights introduces subjectivity and bias, which need to be further discussed and managed.

The climate risk scores and social preparedness scores for the countries are calculated in the same fashion, using the associated indicators in the computation (i.e., Climate-related Disasters and Surface Temperature Change for the climate risk score, and GDP *Per Capita*, Age Dependency (Young and Old), Access to Electricity, Life Expectancy at Birth, Population Growth, Unemployment, Voice and Accountability, and Regulatory Quality for the societal preparedness score.

Using the above-derived data and formulae, the values for the $CRISP(i,t)$ in 36 countries for the timeline between 2002 and 2022 are computed. Based on the $CRISP(i,t)$ values, the average values of $CRISP_{AVG}(i)$, for the countries over 2002–2022 are computed as:

$$CRISP_{AVG}(i) = \frac{\sum_{t=2002}^{2022} CRISP(i,t)}{21}$$

Although CRISP is based on the yearly values of the indicators, for the sake of analytical and discussion conciseness, the initial results and the visualizations are mainly reported from the perspective of average values, whereas the comparative analysis tracks the yearly progress.

5 Results and analysis

5.1 Average trend analysis

Figure 4 presents the cross-country distribution of average climate risk and social preparedness CRISP scores ($CRISP_{AVG}$). The x-axis shows the Climate Risk Score (higher values indicate higher risk), while the y-axis represents the Societal Preparedness Score (higher values indicate better preparedness). The colour of each circle represents the $CRISP_{AVG}$ score, colours closer to red indicating higher vulnerability.

As observed by their positions in the quadrants of Figure 4, countries in the top-left quadrant such as Switzerland, the Netherlands, Germany, Finland, and Denmark, have low CRISP scores, translating into low climate risk and strong preparedness. In this context, strong preparedness refers to consistently high performance across CRISP's societal preparedness indicators. These countries usually have strong institutions, good infrastructure, effective governments, and strong economies. All these characteristics help them respond to climate challenges.

Similarly, observing that countries in the bottom-right, such as India and South Africa (Key Partners), exhibit persistent adaptive gaps, characterized by high climate risk combined with comparatively weak societal preparedness. In this context, adaptive gaps indicate that a country is exposed to climate risks without having sufficient socio-economic, institutional, or infrastructural capacity to cope with them. This makes them more vulnerable. For example, India is exposed to extreme weather and water shortages, and South Africa struggles with infrastructure and economic inequality. These problematic dynamics make it harder for them to deal with climate impacts.

Countries such as Brazil, Indonesia, Mexico, and Türkiye are positioned towards the center of the figure, hence, medium levels of risk and preparedness. Their CRISP scores are relatively higher because they face risks such as deforestation, urban flooding or weak climate planning systems. Especially, Brazil and Indonesia are affected by land-use change and forest loss, while also struggling with climate governance.

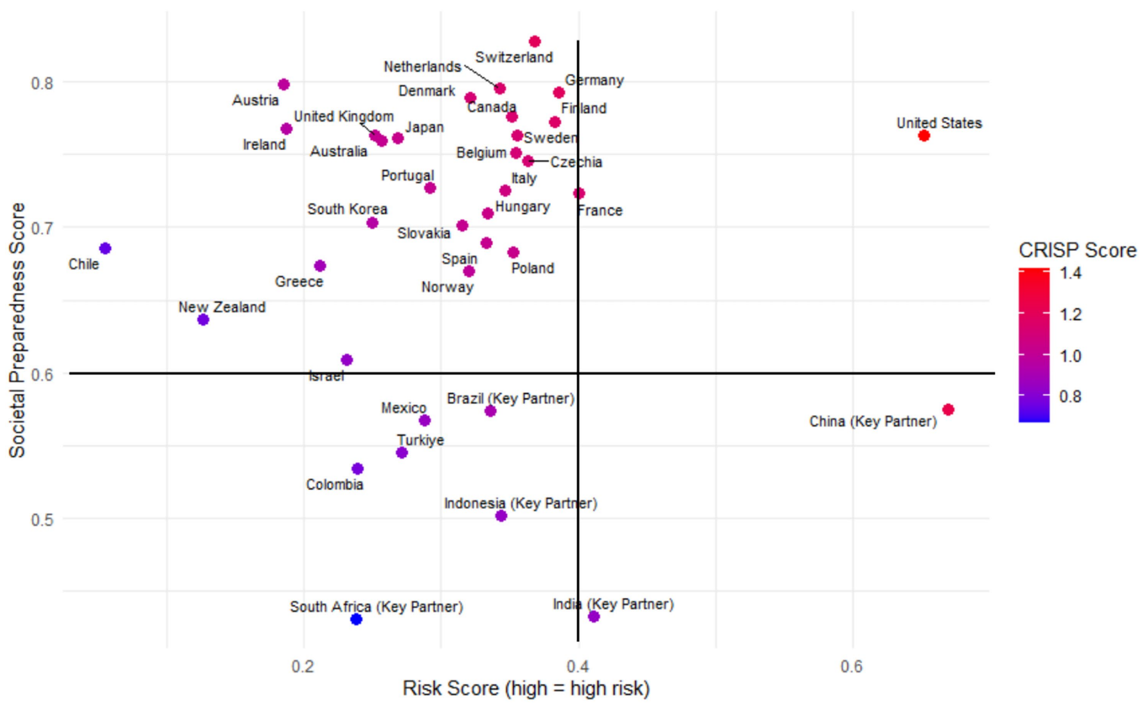

FIGURE 4
Distribution of $CRISP_{AVG}$ scores for selected countries over 2002–2022.

China is a special case. It has one of the highest climate risk scores, but also a decent level of preparedness. This puts the country in a unique situation regarding the CRISP analysis. It faces threats but has invested in and pursued policies to address them.

The United States is another stimulating case. It faces significant risks from wildfires, storms, and sea-level rise. But it also scores very high in preparedness thanks to developed emergency systems, infrastructure, and technology. As a result, the United States' CRISP score remains moderate.

Although the observations regarding China and the United States suggest that the country-specific results may be further analysed in the subnational context, the current sample and data for the CRISP are at the national scale; hence, the current analysis does not capture subnational disparities. However, given data availability, implementing CRISP at the subnational scale may pinpoint subnational aspects.

Positioned at the lower end of the graph, countries such as Chile, Ireland, Austria, and New Zealand have lower risk levels. However, their preparedness levels vary. For instance, Chile and New Zealand have lower preparedness even though they face less risk, leaving them still exposed to climate challenges.

This average analysis shows how climate risk and societal preparedness interact differently across countries. It shows patterns such as low risk and high readiness, high risk and low readiness, and more balanced situations. These insights can guide global policy to support resilience-building and reduce climate risks.

5.2 Comparative analysis

5.2.1 OECD—Western Europe

Figure 5 presents the annual CRISP scores of nine Western European OECD countries from 2002 to 2022: Switzerland, Germany, the Netherlands, Belgium, the United Kingdom, Ireland, France, Portugal, and Spain. In this analysis, a higher CRISP score indicates stronger societal preparedness and lower vulnerability to climate risks, while lower CRISP scores indicate weaker readiness and greater vulnerability.

Switzerland, Germany, and the Netherlands consistently maintain high CRISP scores. Their preparedness remains strong over time thanks to solid institutional systems, high adaptive capacity, and proactive climate policies. Even with fluctuations, these countries show a clear trend of overall resilience in the face of evolving climate risks.

Belgium and the United Kingdom follow a similar pattern with slightly lower CRISP values. These countries perform well on average, but their preparedness seems to fluctuate more from year to year. This could reflect changing political priorities or varying levels of investment in adaptation over time.

Ireland and France demonstrate moderate CRISP scores. While both countries have improved gradually over the years, they still lag behind the region's top-performing countries. For example, France has faced recurring heatwaves and institutional challenges, while Ireland has shown consistent but slower progress in building adaptive systems.

In contrast, Portugal and Spain have the lowest CRISP scores in the region. This suggests that their level of preparedness remains relatively limited. Both countries face serious climate-related threats, including droughts and water scarcity. Moreover, slower or inconsistent adaptation progress may contribute to their lower resilience.

5.2.2 OECD—Central and Eastern Europe

Figure 6 shows the yearly CRISP scores from 2002 to 2022 for nine Central and Eastern European OECD countries: Czechia,

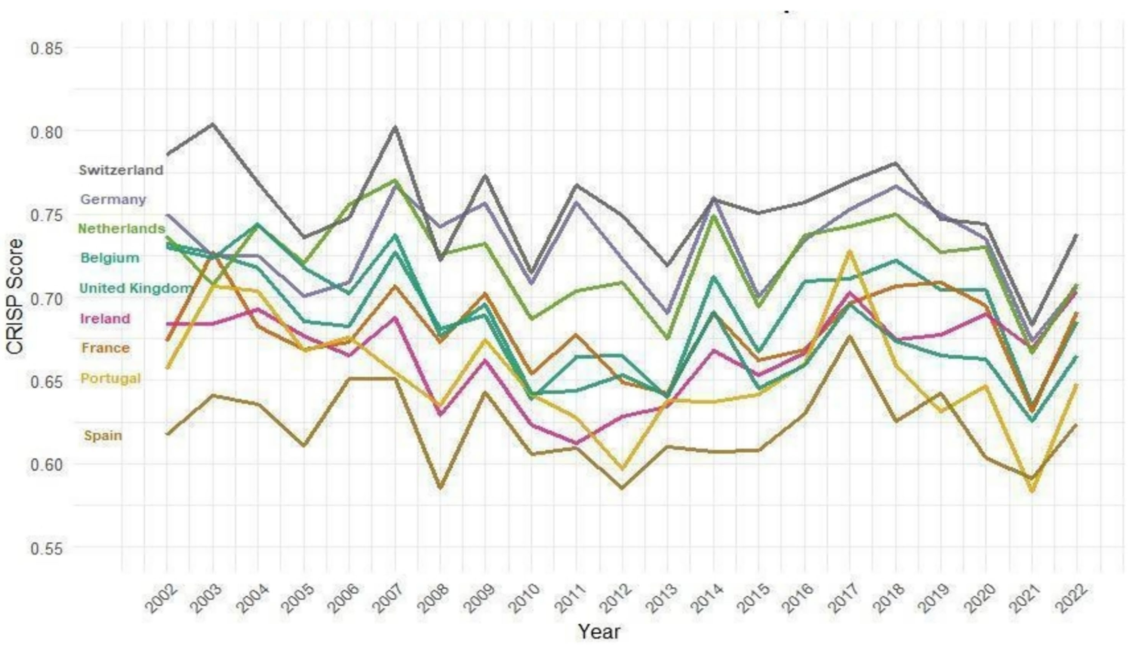

FIGURE 5
CRISP score trend - OECD - Western Europe.

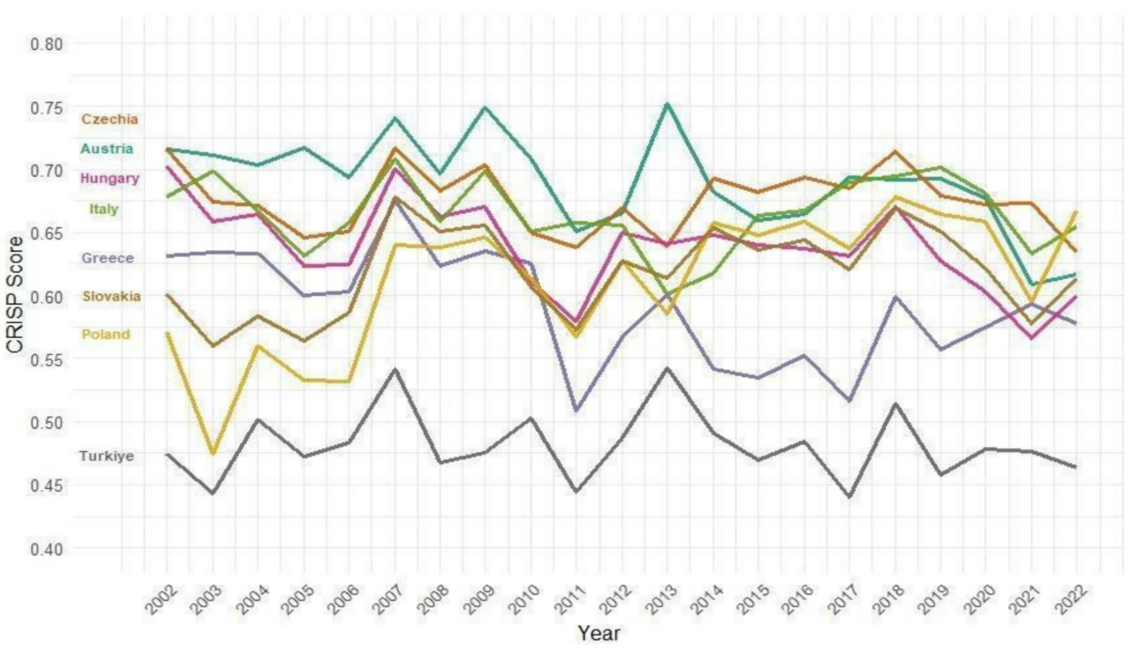

FIGURE 6
CRISP score trend - OECD - Central and Eastern Europe.

Austria, Hungary, Italy, Greece, Slovakia, Poland, and Türkiye. Among these countries, Austria and Italy have the highest CRISP scores. This means they are better prepared to handle climate-related challenges. They have strong institutions, reliable infrastructure, and have invested in long-term strategies. Italy's line is more fluctuating, which could be due to its climate risks and political changes over time.

Czechia and Hungary seem to have steady, mid- to high scores. This shows that their climate preparedness is generally good, even though their scores dropped around 2011 and 2016. These drops might be related to policy changes or economic slowdowns.

Poland and Slovakia show a positive trend. Especially after 2010, Poland's CRISP score increased, which suggests improvements in the country's management of climate risk. Slovakia's scores are a bit lower but still follow a similar upward path. These upward trends may be associated with closer alignment with the EU climate frameworks and increased access to adaptation funding.

Greece has a more unstable trend. Its CRISP scores declined between 2010 and 2015, likely due to the economic crisis during that period.

Financial struggles can decrease a country's ability to invest in climate resilience. After 2015, Greece's scores started to rise again, but the country still shows signs of vulnerability to climate risk. Also, Türkiye's scores stay between 0.45 and 0.55 throughout most of the 20-year period. This indicates a high climate risk and limited preparedness. In this process, the country may face challenges such as regional inequality, coordination among institutions, and slow progress in climate adaptation.

5.2.3 OECD—Northern Europe

Figure 7 shows CRISP scores from 2002 to 2022 for four Northern European countries: Denmark, Sweden, Finland, and Norway. Denmark, Sweden, and Finland consistently show high levels of preparedness. Their CRISP scores stay mostly above 0.70. It could be related to strong institutions, effective climate strategies, and investments in adaptation. Despite some fluctuations around 2010, their overall trend remains stable and resilient.

Norway has lower CRISP scores, mostly ranging from 0.60 to 0.66. This suggests relatively weaker performance in climate preparedness compared to its Nordic neighbors. It could be due to sectoral vulnerabilities or slower adaptation progress. Northern Europe generally shows strong climate readiness, but Norway's lower scores highlight how even high-income countries may differ in their preparedness levels.

5.2.4 OECD—Americas

Figure 8 displays the CRISP score trends for five American nations—the United States, Canada, Mexico, Chile, and Colombia—from 2002 to 2022. Among the countries, the United States has the highest and most consistent CRISP scores. Its ratings remain mostly above 0.75, indicating it is adequately prepared to withstand environmental hazards. Strong institutions, modern infrastructure, and consistent expenditures in emergency response and adaptation systems most certainly help to explain this.

Though its scores fell between 2009 and 2012, Canada also shows great preparedness. Still, Canada turned around once more following 2012. Based on its scores, Canada seems to have been working on resilience strategies and climate plans nonstop.

In the region, Mexico, Chile, and Colombia have lower CRISP ratings. Their marks remain mostly between 0.45 and 0.60. They are more susceptible to the effects of climate change, likely due to infrastructure gaps, limited fiscal capacity, or long-term planning issues. Colombia also ranks lowest among these nations, which could reflect challenges such as weak infrastructure, limited financial resources, or less competent planning.

5.2.5 OECD—Asia-Pacific

Figure 9 shows the CRISP score trends from 2002 to 2022 for four countries in the Asia-Pacific region: Australia, Japan, South Korea, and New Zealand. Japan and Australia lead the group with relatively high and stable scores over the two decades. Japan shows some early fluctuation but stabilizes after 2010. Australia shows a similar pattern with slight declines in later years. These trends suggest consistent climate strategies and institutional capacity, despite occasional pressures.

South Korea shows a mid-range performance. While its scores remain mostly above 0.60, the line is less even. It indicates some variability in climate planning or adaptation delivery over time. New Zealand has the lowest score in this group. The country remains in the 0.50–0.60 range for most of the period. New Zealand's performance suggests a limited change in preparedness capacity.

5.2.6 OECD key partners

Figure 10 presents the annual CRISP scores for five OECD Key Partner countries—Brazil, China, India, Indonesia, and South Africa. China has the highest and most consistent CRISP ratings among the Key Partner nations over the two decades. Though there has been a slight

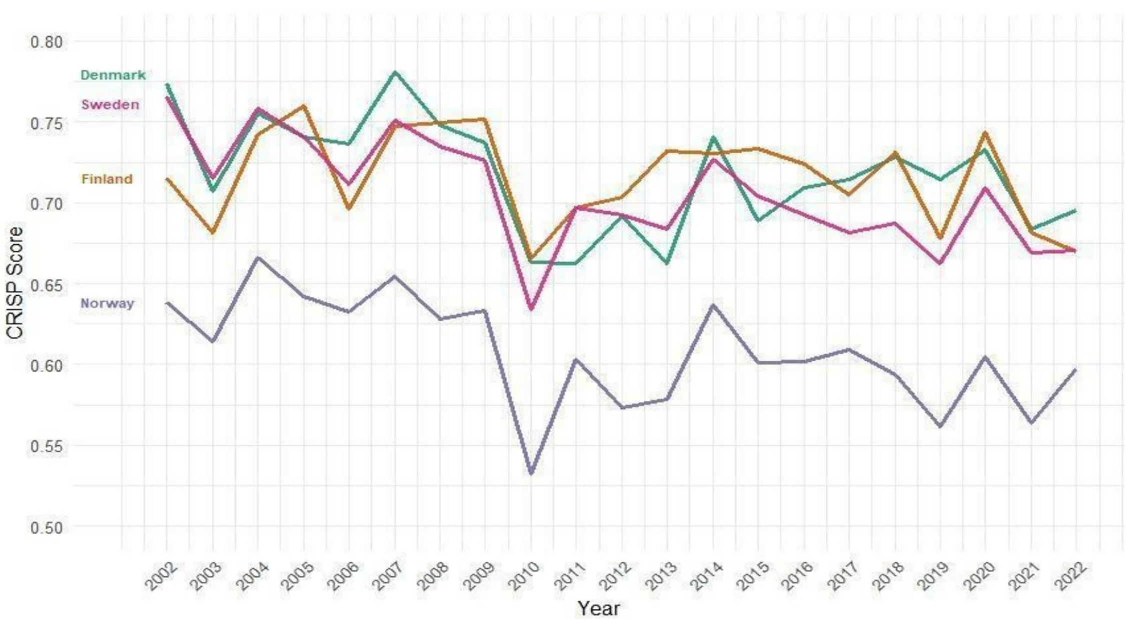

FIGURE 7
CRISP score trend - OECD - Northern Europe.

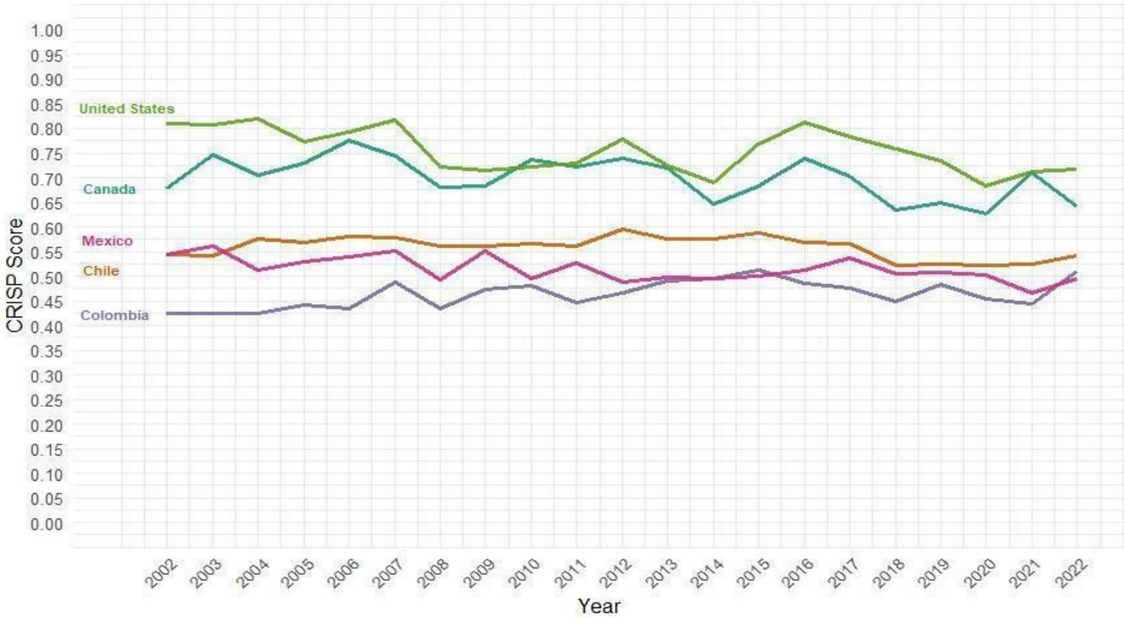

FIGURE 8
CRISP score trend - OECD - Americas.

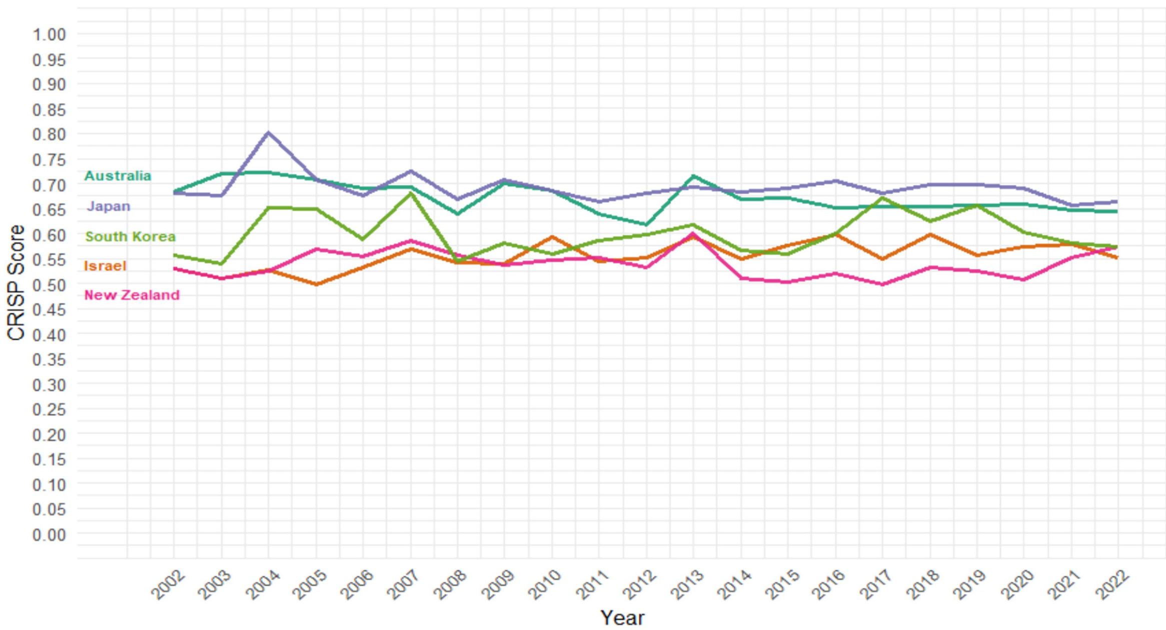

FIGURE 9
CRISP score trend - OECD - Asia-Pacific.

decline recently, it is still far ahead of the others, most likely reflecting long-term investments in infrastructure, planning, and coordination.

Brazil follows with consistent mid-high marks. Its performance has not changed much, suggesting a consistent yet slow pace toward climate readiness. India and Indonesia exhibit more dynamic tendencies. Both began with lower marks but improved over time. India rises slowly, surpassing South Africa midway and almost matching Brazil at the end—probably in line with developments in government and economy.

Sharp increases in Indonesia between 2015 and 2019 point to either internal or outside support for reform. Though its ratings are more volatile, generally the direction is positive. South Africa stays at the bottom with flat or declining ratings. Often reversed, any temporary increases point to continuous difficulties with policy and capacity.

6 Conclusion and policy implications

This study has developed and applied the Climate Risk and Societal Preparedness Index (CRISP) as a comprehensive framework

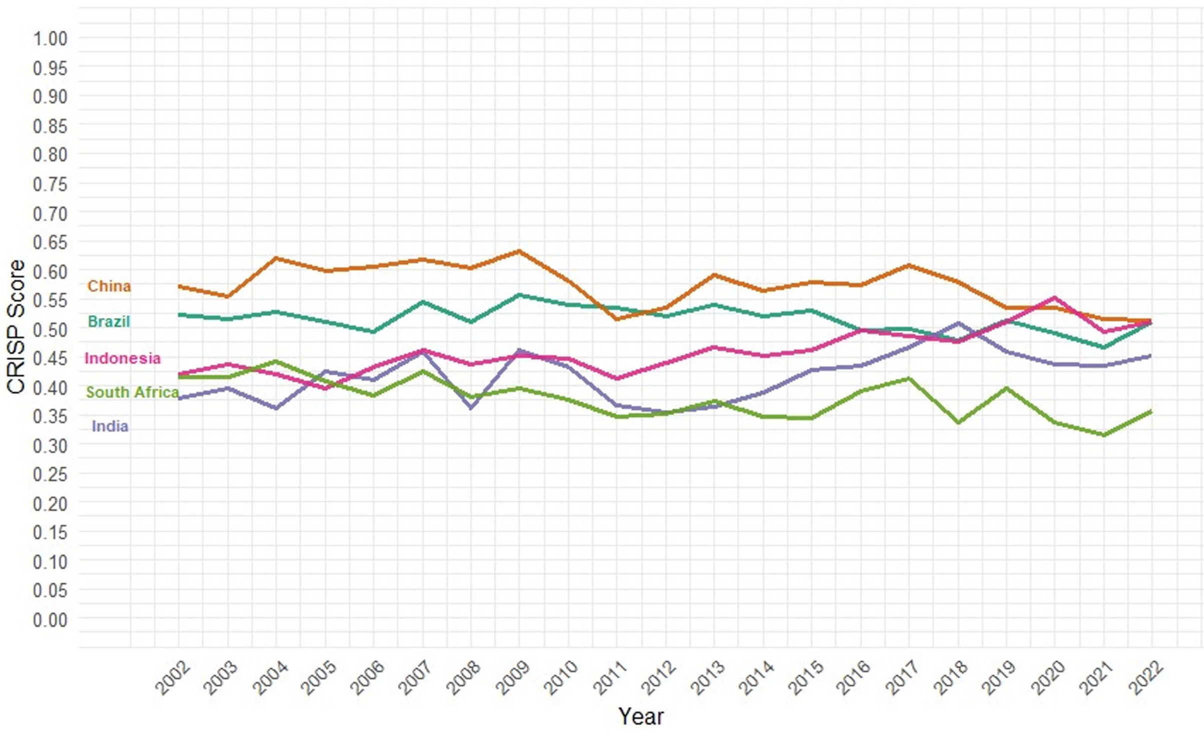

FIGURE 10
CRISP score trend - OECD - key partners.

to evaluate the evolving climate vulnerability of 36 OECD and Key Partner countries over the period 2002–2022. The CRISP framework underscores that climate risk cannot be understood in isolation from the socio-economic, demographic, and governance systems that shape societies' resilience and adaptive capacity. By integrating climate-related hazards such as disasters and temperature anomalies with indicators of institutional quality, economic strength, demographic pressures, and infrastructure provision, the CRISP framework demonstrates the complex and uneven patterns of vulnerability that emerge across different national contexts.

Countries that invest in institutional strength, inclusive development, and resilient infrastructure are better able to cope with the accelerating impacts of climate change, while those constrained by inequality, weak governance, and limited resources remain trapped in high-vulnerability pathways. Policymakers may therefore use CRISP not only as a comparative tool but also as a practical guide for identifying structural weaknesses, prioritizing interventions, and fostering more resilient and equitable societies in the face of escalating climate pressures.

The findings reveal important regional contrasts. Northern and Western European countries, such as Switzerland, Germany, the Netherlands, Denmark, and Finland, consistently score high on preparedness while facing relatively moderate climate risks. Their capacity to combine robust institutions with effective adaptation strategies has allowed them to maintain resilience even as climate pressures intensify. In contrast, Southern European countries such as Spain, Portugal, and Greece are in more fragile positions, reflecting how economic crises, limited investment in adaptation, and recurring climate extremes, such as droughts and heatwaves, can undermine resilience. Central and Eastern European countries, including Poland, Hungary, and Czechia, have made progress over time but remain marked by uneven performance, underscoring the importance of sustained, consistent policy attention.

The results for the Key Partner countries underscore the central role of development pathways and governance structures in shaping vulnerability. India and South Africa represent cases where high climate risk converges with limited preparedness, revealing the challenges of addressing vulnerability in contexts of socio-economic inequality, unemployment, and infrastructural deficits. Brazil and Indonesia are at intermediate positions, with significant improvements in preparedness in recent years, yet they remain constrained by deforestation, land-use change, and weak climate governance structures. China stands out as a unique case, combining high levels of climate risk with relatively strong preparedness due to sustained investment in infrastructure and institutional capacity, while nevertheless remaining vulnerable to systemic shocks and regional disparities. These findings suggest that the trajectories of vulnerability are deeply contingent on the interplay among economic growth, governance reforms, and states' capacity to implement effective adaptation strategies.

Even among advanced economies, the analysis shows that wealth does not guarantee immunity from climate risks. The United States combines high levels of preparedness with very high levels of climate risk, particularly from wildfires, hurricanes, and sea-level rise, underscoring the limits of technological and institutional capacity when structural exposure is acute. Japan and Australia similarly face high climate risks but maintain relatively strong adaptive capacities. New Zealand and Chile illustrate cases where moderate risks interact with comparatively lower preparedness, suggesting that smaller or mid-sized economies can face disproportionate vulnerability if long-term adaptation strategies are not sufficiently embedded in governance and planning frameworks.

From a policy perspective, several cross-cutting implications emerge from the CRISP analysis. First, the results confirm that governance quality and institutional strength are critical determinants of resilience. Countries with high values for indicators such as voice and accountability, regulatory quality, and government effectiveness consistently perform better in terms of preparedness. This highlights the importance of strengthening democratic institutions, enhancing transparency, and ensuring that climate policies are embedded within broader governance reforms. Weak institutional capacity not only reduces the efficiency of adaptation measures but also exacerbates existing inequalities, making societies less able to cope with climate shocks. The CRISP evidence thus suggests that climate adaptation should be seen not merely as a technical challenge but as a broader reform agenda for governance and state capacity.

Second, the results highlight the socio-economic underpinnings of climate vulnerability. High unemployment, rapid demographic growth, and heavy dependence on agriculture and natural resources are repeatedly associated with lower preparedness and higher overall vulnerability. Countries with high age dependency ratios or with large rural populations reliant on agriculture face compounded risks, as these demographic and economic structures limit their adaptive capacity. Addressing vulnerability in such contexts requires integrated development policies that go beyond climate-specific measures, including investments in education, health, labor markets, and rural infrastructure. The CRISP framework illustrates how economic and social fragilities intersect with environmental pressures, creating compound risks that cannot be addressed through narrowly defined adaptation policies.

Third, urbanization emerges as a double-faceted factor in climate preparedness. While urban populations often benefit from better access to resources, institutions, and services, rapid and unplanned urbanization amplifies exposure to climate hazards such as flooding, heatwaves, and air pollution. Countries with high urban growth rates but weak planning frameworks, such as India and Indonesia, face particular risks in this regard. The CRISP results highlight the need for sustainable urban planning, investment in resilient infrastructure, and inclusive policies that address social and spatial inequalities within cities. At the same time, rural vulnerability remains a challenge in countries where agriculture and natural resource dependence dominate livelihoods, as seen in Brazil and South Africa. These dynamics suggest that climate adaptation strategies must simultaneously target rural and urban vulnerabilities, while recognizing their interconnections.

Finally, the global inequalities revealed by CRISP call for renewed emphasis on international cooperation. OECD members and Key Partner countries demonstrate disparities in preparedness levels, with many emerging economies unable to mobilize the institutional and financial resources required for large-scale adaptation. This underlines the importance of climate finance, technology transfer, and capacity-building initiatives to support vulnerable states. Beyond the provision of external resources, the CRISP evidence points to the need for mechanisms that ensure long-term sustainability of adaptation investments, including monitoring systems, accountability frameworks, and the institutionalization of preparedness metrics within national planning systems.

Findings from the comparative analysis emphasize the need for different policy responses in different contexts. For instance, in high climate risk - low preparedness contexts, policies focusing on reliable infrastructure, institutional capacity building, and rapid integration of climate adaptation into the agendas can be prioritized. On the other hand, in high climate risk-high preparedness contexts, policy efforts should focus on reducing physical exposure to risks through better land use and long-term risk-reduction strategies. Low climate risk - high preparedness contexts are well positioned to develop innovative governance mechanisms, support international cooperation, and maintain stability in their existing societal structures. Lastly, countries with medium risk and preparedness should focus on consolidating institutional adaptation policies and addressing land-use management and regional inequalities.

The study has several limitations. To begin with, like any index, CRISP is sensitive to the choice of indicators and weights. Such indices also lack mechanisms to address data gaps or temporal inconsistencies. These limitations emphasize the significance of a pre-assessment of the data prior to computing the index values. On the one hand, these limitations need to be considered when interpreting results from CRISP implementation and drawing conclusions from it. On the other hand, they can be considered in the future for designing and improving similar indices.

Data availability statement

Publicly available datasets were analyzed in this study. The data relating to the indicators for the countries was extracted from appropriate, reliable sources, including datasets of EM-DAT, https://www.emdat.be/; Food and Agriculture Organization (FAO), https://openknowledge.fao.org/items/3ad69d37-395b-4485-9c4d-5067c283409a; the World Bank, https://data.worldbank.org; and International Monetary Fund (IMF), https://climatedata.imf.org/datasets/b13b69ee0dde43a99c811f592af4e821/explore. All are available publicly.

Author contributions

MB: Conceptualization, Formal analysis, Supervision, Writing – original draft, Methodology. MD: Writing – original draft, Software, Data curation, Validation, Investigation. BO: Investigation, Formal analysis, Software, Writing – original draft, Visualization, Data curation. MA: Software, Writing – original draft, Data curation, Visualization, Investigation.

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