Development of metrics and indices for assessing national progress on climate risk, adaptation and dissonance based on observations, perceptions, and projections.

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Abstract

The 28th Conference of the Parties (COP28) included the first Global Stocktake (GST) as part of the implementation of the Paris Agreement. GST is a five-yearly assessment of the state and advancements in global climate action and aims to help national governments keep track of their climate ambitions and implementation progress. This paper contributes to the discussion through the analysis of harmonized country level datasets of metrics and indicators relevant for loss and damage analysis, survey information about people's perceptions on climate change, projections of economic damages due to climate change. Indices are constructed to understand the association of the objective metrics of risk and vulnerability and the subjective perceptions of people in different countries. The analysis allows us to evaluate differences in vulnerability and countries where the dissonance between perceived and estimated climate change risks are larger and institutional strength and socioeconomic development are lagging. Combining the proposed indices, countries are ranked in terms of their current and future climate risk. An online tool is provided to visualize and access the results presented in this paper.

1. Introduction

The world has already warmed about 1.3ºC with respect to preindustrial times, with 2023 being the first year to temporarily exceed the 1.5ºC warming target established by the Paris Agreement for this century(1–3). This warming has already induced large changes across the climate system like more intense and frequent extreme events(4,5), changes in global atmospheric and oceanic circulation patterns(6,7), changes in storm tracks(6,8). Moreover, a world exceeding 1.5ºC warming can potentially trigger climate tipping points(9) with serious implications for natural and human systems(10–13). Deviating from the target of keeping global temperature increase below 1.5ºC-2ºC is expected to have severe socioeconomic consequences worldwide(14–16).

During the latest Conference of the Parties (COP28) the first Global Stocktake (GST) took place with mixed results(17,18). The GST is a mechanism to assess the global collective progress made to meet the goals of the Paris Agreement, and it centers on long term mitigation goals, adaptation, and means for implementation. It can also consider efforts concerning the socioeconomic consequences of response measure and address loss and damage produced by climate change(19). This type of assessment is highly dependent on the availability and quality of data, but also on how it is processed to increase its accessibility and meaningfulness for decision-makers and stakeholders.

Recent efforts have focused on generating harmonized country-level datasets that combine data from different sources and aspects, in a way that can be readily used(20). A methodological challenge for transforming data into relevant information that can be used for guiding policy is to develop appropriate methods and tools for integrating and summarizing large quantities of data into few metrics/indices that are manageable and insightful. This is particularly challenging for topics as multidimensional, interdisciplinary, and complex such as climate change and sustainability(21,22). There are several indices/metrics available in the literature that have been designed to assist decision-making regarding different aspects of climate change. Some of the most commonly used are briefly described in the next lines. The Climate Action Tracker helps rating, tracking and classifying the mitigation ambition different countries propose in their Nationally Determined Contributions (NDC)(18), providing a benchmark for countries self-assessment and cross-country comparison. This rating index considers two main categories Targets and Policies which are subdivided into: Climate finance, NDC target rated against fair share, NDC target rated against modelled pathways, and Policies and actions, also rated against fair shares and modelling pathways. The INFORM Risk Index, produced by the European Commission, focuses on supporting decision-making regarding prevention, preparedness and response to humanitarian crisis and disasters, particularly those that can overwhelm national response capacity(23,24). It is composed of four main categories of information: hazards, human exposure, societal vulnerability, and capacity to cope. The Notre Dame Global Adaptation Initiative's (ND-GAIN) index provides a country level assessment of the national current vulnerability to climate disruptions(25). ND-GAIN is composed of two aspects, namely, vulnerability and readiness and combines about 40 core indicators.

A common strategy for defining an index is to select arbitrary weights (like uniform) for the components that integrate it. This imposes a non-data driven structure to the index and part of the information contained by the data, such as the relationships between variables and countries is not considered. Here we use Rotated Principal Component/Factor Analysis to estimate from the data the appropriate weights for combining the different variables included. The relationships between countries are analyzed using hierarchical cluster analysis. The combination of these statistical multivariate methods allows us to extract further insight from the data to improve the interpretation of indices and for ranking countries accordingly. Moreover, as discussed in Scown et al.(20), evaluating the capacities, challenges and risks of countries to climate change should, ideally, be as holistic as possible and account for a wide range of contributing factors. Here we expand the common framework that includes hazard, exposure, vulnerability, and response to also include people's beliefs and attitudes towards climate change(26). Using these datasets and indices, we also propose dissonance metrics and a composite institution/social challenge index that shows the level of correspondence between institutional7adaptation capacities, climate change's perceptions and projected risks.

The remainder of this manuscript is structured as follows. Section 2 describes the methods and the data used in this paper. The multivariate statistical methods are briefly described, and it is discussed how they are connected in the analysis and how they are used to derive the metrics and indices. Section 3 presents and discusses the indices and metrics that are proposed, as well as the ranking of countries that are derived from them. This section also includes a link to the online tool that accompanies this paper which allows the reader to explore, download and visualize the data, metrics, and indices in more depth. Section 4 summarizes the main results and concludes.

2. Methods and data

Rotated principal component and cluster analysis.

Principal component analysis (PCA) is a statistical technique commonly used for dimension reduction by finding a limited number of linear combinations of the original variables that retain the maximum fraction possible of the variance contained in the original dataset (27,28). These new variables, called principal components (PC), can also provide easier interpretation of the information contained in the original dataset, as well as to give insights about the relationships between variables, and patterns across observations(29). which makes them particularly useful for constructing indices that may be related to latent variables. Rotated principal component analysis (rPCA) can help increase the interpretability of PCs. In the next paragraphs PCA and rPCA are briefly described and a thorough description of these technique can be found in authoritative textbooks (28,30).

Principal components Y_i are the linear combinations $Y_i = \sum_{j=1}^{n} a_{i,j}x_j$ where x_j are variables in the original dataset $X = \{x_1,x_2,x_3 ... x_n\}$. PCs are constructed such that the first PC $Y_1 = \sum_{j=1}^{n} a_{1,j}x_j$ maximizes the variance $var(a_1'X)$ subject to $a_1'a_1 = 1$. The maximization of quadratic forms on the unit sphere is attained when a_1 is equal to the factor loadings associated to the largest eigenvalue. By convention, these are called the first eigenvalue and eigenvector. The remaining PCs are calculated as the linear combinations $a_j'X$ such that they maximize $var(a_j'X)$ subject to $a_1'a_1 = 1$ and $cov(a_j'X, a_k'X) = 0$ for any $j \neq k$. The product of an eigenvector and the squared root the corresponding eigenvalue are the factor loadings (L), which are equal to the correlations of the PC and the original variables. The values of L determine which are the variables that contribute the most to the corresponding PC. Rotation of principal components can further help interpreting PCs(28,29,31). The rotated PCs (factors or factor scores) are calculated as $F = BZ$, where Z are the normalized values of X, $B = L(L'L)^{-1}$ is the matrix factor score coefficients(32). Although there are several rotation methods, in this paper normalized varimax rotation is used.

Hierarchical cluster analysis and the calculation of pseudo-factor loadings

Hierarchical cluster analysis is applied to the first two PCs for grouping countries in terms of the similarities expressed by these two main modes of variability. This clustering provides a space created by the two main modes of variability of the dataset to analyze the remaining factors, and to enrich their interpretation. Once the clusters are defined, the correlations between each factor and the most important variables that constitute it (i.e., those with factor loadings $L \geq 0.6$) are calculated for each cluster. These correlations constitute pseudo-factor loadings that allow to investigate the importance of the contribution of each original variable to the factor and compare them to the true factor loadings obtained for the full sample. By doing so, differences in the importance and dominance of some variables across clusters allow for a more detailed and specific interpretation of the factors.

Cluster analysis is an unsupervised learning technique that classifies similar cases or variables into groups based on the values of a data matrix X. Hierarchical clustering is the clustering method used in this paper and it consist in initially considering every observation in the dataset as an individual cluster. Then, by means of a distance measure and a linkage rule, individual observations are progressively aggregated into clusters (30). For the results presented here, Euclidean distances and Ward's method are used as distance measure and linkage rule, respectively.

Dissonance measures for current and future institutional/adaptation capacities, perceptions and risks

Social risk perceptions about climate change are highly heterogeneous among countries, and so are institutional strength, as well as social, human, and economic exposure, climate hazards and climate change impacts. The literature on impacts, adaptation and vulnerability has documented over the past decades that less developed regions are likely to suffer the most from climate change, but that if adaptation and risk reduction strategies are implemented, such damages can be severely abated. As such, we consider that the distances between both adaptation capacities and people's perceptions with respect to current and projected damages are central to understand the social and institutional challenges a country will face under current and future warming levels. Here we propose a procedure to assess the dissonance between current social and institutional scores related to climate adaptation, and the expected damages from climate change.

The procedure consists in calculating the differences in ranking for the same country in different adaptation capacity and risk/damage indices and normalizing these differences. These individual metrics can then be combined into a composite index that conveys which countries are best prepared for climate change and which are characterized by higher dissonances between their current capacities/awareness and present and future risk. The procedure is based on rank statistics, and it is implemented as follows.

The variable $Y = \{y_1, y_2, \ldots, y_n\}$ can be mapped onto $R = \{r_1, r_2, \ldots, r_n\}$ in such way that if y_i is the *i-th* largest/smallest observation r_i is its rank, if ranked in descending/ascending order. After calculating the variables ranks, the differences d between pairs of a selection of them are calculated and the results are normalized using min-max normalization d^*:

$$d = R_Y - R_X$$

$$d_i^* = \frac{d_i - d^{min}}{d^{max} - d^{min}}$$

The d_i^* measures are defined in such a way that values close to zero denote low dissonance/risk, while values close to 1 indicate high dissonance/risk. A composite index called Social and Institutional Challenge Index is defined as the average score of the individual d_i^* dissonance measures, and provides a summary measure of the present and future institutional and social challenges related to climate change, for each country.

Data description and sources

This paper uses various sets of country-level datasets that include data of observed, projected, and social perception related to different aspects of climate change. Observed data contains measurements about losses and damages, exposure to climate-related hazards, event attribution, governance and climate policies, vulnerability, and historic CO_2 emissions. Part of the data was harmonized and summarized at the country level in a recent paper (Scown et al. 2022) to provide a global overview of loss and damage in the context of the global stocktake. Projected data about economic damages from climate change comes from numerical simulations using a large dimensional intertemporal computable general equilibrium trade model that accounts for various effects of global warming (Kompas et al. 2018). This dataset contains estimates of GDP losses by country for 1°, 2°, 3° and 4° global warming scenarios. The dataset about social perceptions about different aspects of climate change was obtained from an international survey that covered public climate change knowledge, beliefs, attitudes, policy preferences, and behavior among Facebook users (Leiserowitz et al. 2022).

The data from different sources was processed to integrate all information in a single harmonized database. Field names were renamed to ensure all field names had at most 10 characters so that the integrated dataset was compatible with ESRI shapefile format for further geographical representations. ISO 3-digit code was given for each country for datasets that lacked this code to enable merging the different datasets. For the social beliefs survey (Leiserowitz et al. 2022), a summary score for each question was calculated using a weighted linear combination (see Table A1 for more details). The resulting database contains 103 countries, and 159 numerical fields plus the ISO code and the name of each country.

3. Results and discussion

Description of estimated factors

The PCA analysis was performed on a dataset that combines a selection of metrics relevant for loss and damage analysis and information about people's perceptions on climate change. Highly correlated variables were excluded to avoid numerical problems in performing PCA. The variables that were retained are shown in Table A2. The scree plot of the eigenvalues shows a relatively smooth decrease in explained variance with a possible shelf occurring between components 4 and 5, which could be used as a cut-off point for rotation (Figure A1). However, up to the first eight components the eigenvalues exceed unity and discarding PCs 6-8 could lead to ignoring potentially important information (28,33). For this reason, we decided to retain the first eight PCs as suggested by the Kaiser truncation rule (30). The retained PCs, which account for 85.27% of the variance of the original dataset (Table A2), were rotated using the varimax normalized rotation procedure (28). As discussed below, these PCs have clear and insightful interpretations regarding the vulnerability to, and the people's perceptions of, climate change.

The first PC explains 25% of the total variance of the dataset. As shown in Table A2, the loadings of the first factor (shown in parenthesis) indicate that the variables that contribute more to PC1 constitute can be divided in:

1) metrics of institutional strength, development, and societal responsibility: Rule of law (0.954), Governance effectiveness (0.947); Regulatory quality (0.941); Control of corruption (0.928); Political stability and absence of violence (0.835); Human Development Index (0.819); Voice and accountability (0.805);
2) measures of how much people are informed about climate change: how often do you hear about climate change in your daily life (0.811); Climate awareness (0.796); Climate beliefs (0.738), and;
3) how much they think their own country should reduce emissions and fossil fuels consumption in the future: Country responsibility (0.717); Fossil fuel (-0.647).

PC1 will be referred to as an institutional and societal development index (ISDI) in which positive values indicate countries that have strong institutions, high human development, and an informed and responsible society. Recent studies have shown how governance and institutions, education, development and financial/human resources are crucial for addressing sustainable development issues (34–36). This index is suggestive of the country's capacities for vulnerability reduction, the availability of resources and capabilities for implementing adaptation and risk reduction strategies, as well as people's willingness for GHG mitigation. Moreover, despite the methodological and data differences, the correlation between ISDI and the ND-GAIN Country Index[1] is 89.5% and leads to similar country rankings. The countries with higher scores in this index are mainly in northern Europe (Finland, Norway, Denmark) and in Oceania (Australia and New Zealand), while the lowest scores are from countries in Africa and the Middle East (Congo, Yemen, Libya, Iraq).

PC2 explains about 15% of the total variation of the dataset and constitutes a climate change social concern index (CCSCI). It is mainly composed of variables that represent the perceptions of population about how climate change could affect them: Climate worry (0.932); Climate change threat in the next 20 years (0.921); harm personally (0.912); government priority (0.841); Climate Importance (0.827); harm future generations (0.742); climate change happening (0.704). The CCSCI provides a comprehensive summary about the beliefs of people living in each country about the seriousness of climate change. It combines immediate and future concerns about the consequences of climate change, one's own personal and future's generation harm, and the level of priority they would like their government to assign to this threat. Latin American countries have the highest scores in the CCSCI, with Mexico being the most worried country, followed by Chile, Costa Rica, El Salvador, Brazil, Ecuador and Colombia. The ten least concerned countries are mainly from the Arab World (Yemen, Jordan, Egypt, Libya, Iraq, Lebanon, Kuwait) and a few European countries (Norway, Czech Republic and the Netherlands).

The third most important component is PC5, which explains about 11.5% of the total variance of the dataset. It is an index that associates economic losses from extreme events, historical responsibility for current climate change and GDP size (ELCCG). This PC is composed of cumulative economic losses during 1990-2019 due to extreme events (0.953), historical cumulative CO_2 emissions (0.951), GDP size in 2010 (0.942), as well as the total number of droughts, extreme temperature, flood, storm, and wildfire events during 1990-2019 (0.786). Positive values on this index indicate countries that have experienced large economic losses from frequent extreme events and that tend to show high economic development historically based on fossil fuels. The countries with highest scores in PC5 can be divided into two types. The first include those with large economies with large historical emissions such as the US, Japan, the UK, Germany, France, Italy and Australia, and the second in which developing economies, significant vulnerability to climate and weather extremes and large populations, such as Mexico, Philippines and Vietnam.

PC3 can be interpreted as an index of population size and expected exposure to extremes (PSEI) and explains 10% of the total variance of the dataset. The largest factor loadings of PC3 indicate that the variables that contribute the most to it are: population count in 2010 (0.954); expected average annual population exposed to droughts (0.924); total number of persons affected reported for droughts, extreme temperature, flood, storm, and wildfire events (0.920); expected average annual population exposed to fire events (0.786); expected average annual population exposed to floods (0.624). Positive values of PSEI denote countries with large populations and high levels of population exposed each year to extreme events. The countries with highest PSEI values are those in developing regions, particularly southeast Asia, Latin America, and Africa, such as India, Brazil, Indonesia, Nigeria, Vietnam, Thailand, Bangladesh, Mexico, Pakistan, and Iraq.

The fifth most important component (PC4) explains about 8% of the total variance and represents an expected severity index (ESI). It is composed by the average (-0.925) and maximum (-0.894) annual

[1] https://gain.nd.edu/our-work/country-index/

economic damages (as a fraction of the country's GDP), combined with the average annual deaths per capita (-0.836), all being caused by extreme events (droughts, extreme temperature, flood, storm, and wildfire). In contrast with PC5, this index contains information about the economic losses relative to the size of the economy, not the absolute expected and cumulative level of losses. Negative values of this index indicate countries where more severe weather/climate damages occur relative to the size of their GDP and population. The countries with high levels of vulnerability to extreme events have the lowest scores in this index and they are located mainly in Latin America, southeast Asia, and the Middle East. The countries with the ten highest scores are Honduras, Haiti, Bangladesh, Laos, Nicaragua, Vietnam, Cambodia, Thailand, Yemen and North Macedonia.

PC6 accounts for 7% of the dataset's total variance and it combines the maximum (0.719) and average (0.714) number of people per capita affected by extreme events (droughts, extreme temperature, flood, storm, and wildfire) during the period 1990-2019 and the people's belief about the economic impact of addressing climate change (-0.701). This PC can be interpreted as an index of how experiencing extreme weather events modifies beliefs about how costly climate action is (EECB). It suggests that in countries where more people are affected by weather events, people tend to belief actions to mitigate climate change will not have a negative economic impact and will not reduce jobs. On the contrary, people in such countries belief these actions will benefit the economy. The countries with the highest values in this index are mainly in Africa such as Malawi, Kenia, Zimbabwe, Mozambique, Burkina Faso and Ghana, as well as countries like Australia, Haiti and Philippines.

The two remaining components (PC7 and PC8) explain about 4-5% each of the total variance. The main variable in PC7 represents the people's belief about who is the most responsible entity in their country for reducing the pollution that causes climate change (0.736). Higher values on this responsibility index (RI) denote countries in which people believe the government to be the most responsible and lower values suggest progressively that business, individuals are responsible, and the lowest values indicates that nobody is responsible. Among the countries with lowest values in RI are those associated with fossil fuels' production, such as Vietnam, Kuwait, Qatar, United Arab Emirates, Oman, Saudi Arabia, and Indonesia, as well as some with large shares of fossil fuels for power generation such as Japan, Hong Kong. PC8 mainly represents the total deaths (0.780) from drought, extreme temperature, flood, storm, wildfire during the 1990-2019 period, and the expected annual number of people affected by floods. This index suggests floods are associated with a higher number of deaths than other events. The highest values in this total death and flood index (TDFI) occur in Bangladesh, Philippines, and Japan. An interactive platform that allows for visualizing the data and these indices is available at the following link: http://multidash.apps.lancis.ecologia.unam.mx/paper_cc/.

An analysis of the estimated indices to characterize countries according to risk and vulnerability.

ISDI and CCSCI jointly explain about 40% of the total variance of the original dataset. In contrast to other of the obtained indices, which represent damages associated with extreme events, ISDI and CCSCI characterize the countries institutional strength, their adaptation capacities, and the beliefs of people regarding the climate change threat. Jointly, these two indices provide a space to analyze the other principal components from a perspective of the countries' capacities to respond to climate change. In the following paragraphs we describe the space defined by ISDI and CCSCI, how countries can be clustered in it, and then we illustrate how projecting the ISDI/CCSCI space onto other indices can provide further insight on how to interpret them from the perspective of adaptation capacities and risk perception.

Figure 1 shows the biplot (scatter plot) of these two indices, divided into its four quadrants. The first quadrant (QI) contains countries with positive values in both the ISDI and CCSCI. Countries in this quadrant are expected to be less vulnerable to climate change as strong institutions are likely to act on the social concerns expressed by their citizens, and have the technical, economic, and political capacities to implement the required adaptation and risk reduction strategies. Quadrant II (QII) includes countries in which the populations express concern about climate change (positive CCSCI) but in which institutions and development are lagging in comparison with QI, which can translate into a mismatch between implemented climate policy and citizens' assessment of risk. Moreover, lower levels of development and institutional strength can imply that policies are not guided by the best available knowledge (37,38) and that support for science and technology is likely not among government priorities (39–41). The third quadrant (QIII) contains the countries in which both ISDI and CCSCI are negative, meaning that these countries' institutions and social development are weak, and people show low levels of concern (or not at all) about climate change. Countries in QIII are likely those with highest levels of vulnerability as they may fall short of institutional, economic, technical, and political resources to design and implement adaptation strategies to address climate change's challenges and their citizens are likely not to press their governments on this issue. Moreover, the low level of concern shown by populations in these countries is likely associated with lack of information about climate change science (also supported by their low scores in ISDI), and likely ignore this phenomenon's current and projected impacts. Quadrant IV (QIV) contains countries that are characterized by positive scores of institutional strength and development and low scores of climate change concern. These countries likely possess the institutional, technical, economic, and political capacities to respond to climate change. However, they risk overconfidence regarding their vulnerabilities and risks regarding this phenomenon.

A hierarchical cluster analysis was applied to group countries according to their scores in the ISDI and CCSCI indices. A linkage distance of 10 was chosen, which lead to defining six clusters of countries (Figure A2). Table A3 lists the countries that belong to each of the defined clusters. QI in Figure 1 is mainly composed of countries grouped in two clusters. The dominant cluster in QI is represented by blue circles with no fill (*Cluster1* in Figure1) and, for values of ISDI>0.5, includes European countries such as Spain, France, Hungary, Slovenia, Croatia, Poland and Cyprus, and Japan, South Korea, and Uruguay. For scores of ISDI<0.5 countries like Italy, Greece, Botswana, India, and Jamaica are included. For values of CCSCI>1 another cluster of countries is defined (Cluster3, gray filled circles) in which the level of climate change concern is high. Only three countries in this cluster show positive scores in the ISDI index (Portugal, Chile, and Costa Rica), the rest of the cluster extends over QII and is characterized by countries with considerably lower levels of ISDI and high scores of climate change concern. These are mainly Latin American countries and a few African and southeast Asian countries. The countries in this cluster with moderately low levels of ISDI (ISDI>-0.5) are Sri Lanka, Malawi, Panama, Brazil, Philippines, Peru, and Colombia. With a considerably lower level of ISDI El Salvador, México, Nicaragua and Bolivia are found. QII is dominated by Cluster5 with countries that show substantially lower scores of CCSCI and tend to have lower IDSI scores (green filled circles). The countries in this cluster are mainly in Africa (e.g., Zambia, Angola, Côte d'Ivoire, Burkina Faso, Kenya, Mozambique, Cameroon, Ghana), but also Latin America (Honduras, Guatemala. Paraguay, Dominican Republic), and Cambodia, Turkey, and Nepal. Part of this cluster continues into QIII, where lower scores of CCSCI and even more negative ISDI are found. It includes Congo, which is the country with the lowest ISDI score of all countries, Nigeria, Pakistan, Tanzania, Benin, Bangladesh, and Senegal. QIII is composed of two additional clusters. The cluster of countries that combine the lowest scores of ISDI and CCSCI (Cluster2, yellow-green filled triangles) is, apart from Haiti, exclusively composed of Arab countries. Yemen, Libya and Iraq show the most extreme combination of scores, followed by Haiti, Algeria, Egypt and Lebanon, Kuwait, and Jordan with more moderate combination of values. Cluster6 (blue unfilled squares) shows slightly lower CCSCI scores that the previous cluster but more moderate ISDI scores with countries such as (ISDI<-0.3) Indonesia, Azerbaijan, Tunisia, Armenia, Saudia Arabia, Morocco, and (ISDI>-0.3) Bosnia and Herzegovina, Laos, Albania, Serbia, and Thailand. This cluster extends to QIV and is characterized by moderate positive values of ISDI and moderate negative values of CCSCI. It includes countries such as the United Arab Emirates, the US, North Macedonia, Bulgaria, Malaysia, Qatar, Rumania, and Oman. The remainder cluster in QIV (Cluster4, gray filled rhomboids) contains the countries with the highest scores in ISDI and, with the exception of the Arab countries cluster, the lowest scores of concerns regarding climate change. Northern European countries show the most extreme combinations of scores (Norway, Netherlands, Finland, Sweden, and Denmark). This cluster also includes Australia, New Zealand, Switzerland, England, Germany, Belgium, Lithuania, Hong Kong, Israel, and the Czech Republic. Table A4 shows for each cluster its corresponding median, as well as the upper and lower quartiles.

Figure 1. Biplot of ISDI and CCSCI with hierarchical clustering. Cluster1 is denoted by blue circles with no fill, while Cluster2 is shown in yellow-green filled triangles, Cluster3 in gray filled circles, Cluster4 in gray filled rhomboids, Cluster5 in green filled circles, and Cluster6 in blue unfilled squares.

Using the clusters defined above in terms of the ISDI/CCSCI space, the other factors can be further analyzed, and new insights can be obtained for what they represent for different groups of countries.

The first grouped bars in Figure 2 (first row of Table A5) present the correlations of the ELCCG with the variables to which it is more associated (i.e., economic losses from extreme events, historical responsibility cumulative CO2 emissions and GDP in 2010, the number of attribution studies and of those that find a positive result). Note that these correlations correspond exactly to the factor loadings in Table A2 and are to be interpreted as described in the previous section. The remaining rows of the table show the same correlations calculated for each of the clusters produced using the ISDI/CCSCI space. These correlations denote, for each cluster of countries, which are the variables better represented in the index. Some new insights on how to interpret the index for the different clusters become apparent. For instance, the correlations between ELCCG with GDP and historical CO2 responsibility are less homogeneous across the clusters of countries and are only relevant for clusters that have the highest average levels of HDI, GDP and historical CO2 emissions (clusters 1, 4 and 6). In the case of clusters 2, 3 and 5 the correlations of ELCCG with these variables are considerably lower than the factor loadings (correlations) obtained for the full sample and are not statistically significant. These clusters have the lowest average values of HDI, GDP and historical CO2 emissions, with cluster 5 showing the minimum value in all of them. Moreover, cluster 5 shows almost no correlation with most of the variables that compose ELCCG. It shows only slightly higher correlations between ELCCG and the variables related to attribution studies, but these are low. Cluster 5 is not well represented by ELCCG, and this index provides limited information for such a group of countries. Clusters 2 and 3 (mainly Arab and Latin American countries, respectively) are only correlated to ELCCG through the number of recorded extreme events and their damages. In the case of clusters 2 and 3 the correlation coefficients associated with damages are smaller than those calculated for the whole sample, but in the case of cluster 3 the correlation with the number of events is considerably higher. In the case of cluster 1, which is mainly composed of central and southern European countries, the correlation coefficients in Figure 2 (see Table A5) suggest that for this cluster there is almost no effect from the number of recorded extreme events in this index. Both damages and historical CO2 responsibility are important variables but have considerably smaller effects than those of the full sample of countries, while the variable with the highest effect is their GDP size. In the case of cluster 4, ELCCG is highly correlated with all the variables included in the index, and correlations are particularly high for the attribution studies variables in comparison to the full sample estimates. This cluster has the largest average number of attribution studies and the second highest maximum value of such studies only after cluster 6. The lowest correlation occurs for the number of recorded extreme events, which indicates that this variable is the least represented by the index. Cluster 6 is characterized by having the largest correlations between ELCCG and all the variables that compose this index. These correlations are higher than those obtained for the full sample and, in most cases, close to unity. There are no clearly dominant variables in this cluster and all variables are almost equally well represented by it.

Figure 2. Correlation coefficients between ELCCG and the most important variables that compose it for different clusters of countries. +,- denote positive/negative median score values in the corresponding index,+/- denotes that the first and third quartiles include zero, while * indicates that the cluster contains the maximum or minimum score value of the index.

Table A6 contains a ranking of countries according to ELCCG and grouped using the clusters defined in the ISDI/CCSCI space, which reflects their adaptation capacities and the people's perceptions about the seriousness of the climate change threat. For the clusters characterized by low adaptation capacities (clusters 2 and 3), the ranking in this index mainly refers to their risk about the number of events and their cumulative economic losses. The five countries with higher ranking in cluster 2 are Haiti, Algeria, Yemen, Libya and Iraq, while in cluster 3 Philippines, Mexico, Brazil, Portugal and Bolivia are ranked with the highest risk levels. Despite cluster 5 is also characterized by low adaptation capacity (ISDI), it is not discussed here as ELCCG contains little information for this group of countries. For cluster 1, ELCCG is more related to GDP size, historical CO2 contribution and the size of cumulative economic losses from recorded extreme events. This cluster is characterized by high adaptation capacities and population concern for climate change. The countries with highest rank are Japan, France, Italy, Vietnam, and Spain. In the case of Cluster 4, which has the highest ISDI score values of all clusters, ELCCG dominantly represents GDP size and historical contribution to global CO2 emissions, and the size of cumulative economic losses from extreme events. The countries with highest ranking in this cluster are United Kingdom, Germany, Australia, Canada, and Netherlands. As discussed above, ELCCG in cluster 6 is very highly correlated with all the variables in the index, with no dominant contribution form any particular of them. This cluster is characterized by mixed levels of adaptation capacity, and low concern about climate change. The countries with higher ranking within this cluster are United States of America, Indonesia, Bosnia and Herzegovina, Romania, and Serbia.

Figure 3 (Table A7) shows the correlation coefficients between ESI and the annual average deaths per capita, the average and maximum annual damages as a fraction of national GDP for the full sample and each of the defined clusters. It is revealing that for all clusters in which the ISDI scores are not negative (or at least mixed as in the case of cluster 6), the correlation coefficients between ESI and the annual average deaths per capita are much lower in comparison with the full sample estimate and with those from clusters that have negative ISDI scores. This suggests that high adaptation capacities significantly reduce the number of deaths per capita, even if they may not have such a strong effect on economic damages probably because of increasing exposure associated with economic growth. Moreover, clusters 2 and 5, which have negative or near zero scores in both ISDI and CCSCI, show correlation values close to unity between ESI and the per capita death and damage variables. Cluster 1, which is the only group of countries that has positive score values in both ISDI and CCSCI, has only a weak correlation between the maximum annual damages and ESI and the second smallest correlation between ESI and the annual average damages. The highest ISDI scores correspond to Cluster 4 and this group shows the lowest correlation of all clusters between ESI and average annual damages and the second lowest correlation with maximum annual damages. It is notable that cluster 6 shows the highest correlations between ESI and annual economic damages of all clusters that correspond to more developed countries (clusters 1 and 4).

ESI for cluster 1 is related to average annual economic damage (as a fraction of national GDP), and the countries with highest levels of risk are Vietnam, Jamaica, France, Spain, and Italy (Table A8). This index for clusters 2 and 5 is strongly associated with annual per capita deaths and annual economic losses. In cluster 2, the countries with higher risk are Haiti, Yemen, Jordan, Lebanon, and Egypt, while in cluster 5 these are Honduras, Bangladesh, Cambodia, Dominican Republic, and Guatemala. Cluster 3 shows similar correlations to those obtained with the full sample with a slightly larger correlation with deaths per capita. The countries at higher risk in this cluster are Nicaragua, El Salvador, Malawi, Bolivia, and Costa Rica. Cluster 4 shows the lowest correlation between annual deaths and ESI, which can be better interpreted as an economic severity risk index for this group. Czech Republic, Australia, Belgium, Lithuania, and Netherlands are the countries in this cluster at higher risk. Similarly, cluster 6 shows a low correlation between annual deaths and ESI, but correlations close to unity for annual economic damage variables. The countries in this cluster at higher risk of economic losses (as a fraction of GDP) are Laos, Thailand, North Macedonia, Bosnia and Herzegovina, and Serbia.

Figure 3. Correlation coefficients between ESI and the most important variables that compose it for different clusters of countries. +,- denote positive/negative median score values in the corresponding index,+/- denotes that the first and third quartiles include zero, while * indicates that the cluster contains the maximum or minimum score value of the index.

The PSEI provides a measure of population size and expected exposure to extremes and, like with the other indices, separating into clusters allows further interpretation. In the case of Cluster 1, all variables in the index are highly correlated with PSEI (values close to 1; Figure 4 and Table A9). This index represents all variables almost equally well. However, this cluster shows particularly higher associations with the expected number of people exposed to flooding and fire than the estimates for the full sample. Clusters 3 and 5 have a similar pattern of correlations between PSEI and the expected number of people to drought, fire and population counts. The total number of people affected, and the expected number of people affected by floods are weakly correlated with PSEI, particularly for cluster 3. As implied by their correlation values, the PSEI for clusters 3 and 5 represents mostly the risk associated to the number of people exposed to fire (cluster 3) and to drought (cluster 5). PSEI for cluster 2 represents a risk index associated to the expected number of people exposed to fire and, to a lesser extent, flooding. In the case of cluster 4, none of the variables are strongly correlated to PSEI, with only the expected annual number of people affected by fire being statistically significant but only moderately correlated (0.52). This suggests that the high levels of adaptation capacities and risk reduction strategies that would be expected from their ISDI score, may contributed to make this index not relevant. Except for the total number of people affected by extreme events, cluster 6 shows from moderate to high correlations with the other variables that compose the index. Cluster 6 is highly correlated with the expected annual number of people affected by fire, and very highly correlated with the expected annual number of people affected by flooding. In fact, this correlation is much higher than that obtained for the full sample.

The countries in cluster 1 that show higher risk in terms of PSEI are India, Vietnam, South Africa, France, and Argentina (Table A10). PSEI in cluster 2 represents the risk related to exposure to fire and floods and Iraq, Egypt, Yemen, Algeria, and Lebanon rank the highest. Brazil, Mexico, Colombia, Malawi, and Chile rank as the countries with highest scores in PSEI, and can be interpreted as those with higher fire and drought risk in cluster 3. The countries in cluster 5 with higher drought and fire risks according to their scores in PSEI are Nigeria, Bangladesh, Pakistan, Congo, and Kenya.

Figure 4. Correlation coefficients between PSEI and the most important variables that compose it for different clusters of countries. +,- denote positive/negative median score values in the corresponding index,+/- denotes that the first and third quartiles include zero, while * indicates that the cluster contains the maximum or minimum score value of the index.

EECB hints at how experiencing extreme weather events may modify the people's beliefs about how costly climate action is, as it combines the maximum and average number of people affected per capita by extreme events and the people's belief about the economic impact of addressing climate change (Figure 5, Table A11). Across clusters, there is a strong inverse association between the correlations obtained between EECB and the maximum number of people affected per capita and those between EECB and people's beliefs about the economic impact of addressing climate change. That is, among clusters, large correlations in the maximum number of people affected per capita and EECB tends to correspond to larger (in absolute value) correlations between EECB and the perception about how costly is addressing climate change (correlation of -0.71). This suggests that extreme events with large social consequences may influence people's perception about addressing climate change. The highest correlations between the index and people's beliefs about the costs of addressing climate change occur in the clusters that are characterized by positive scores of CCSCI (clusters 1 and 3). The countries in cluster 1 that rank highest (high number of affected people, and of people that consider addressing climate change is costly) in this index are Botswana, South Africa, India, Jamaica, and Trinidad and Tobago (Table A12). In the clusters with low ISDI the countries with higher scores are: Haiti, Jordan, Lebanon, Kuwait, and Algeria (cluster 2); Malawi, Philippines, Sri Lanka, Costa Rica, and Portugal (cluster 3); Kenya, Cambodia, Zambia, Mozambique, Burkina Faso (cluster 5). The countries that rank first in cluster 4 are Australia, Hong Kong, Israel, New Zealand, and Canada, while in cluster 6 are Laos, Thailand, North Macedonia, the US, and Oman.

Figure 5. Correlation coefficients between EECB and the most important variables that compose it for different clusters of countries. +,- denote positive/negative median score values in the corresponding index,+/- denotes that the first and third quartiles include zero, while * indicates that the cluster contains the maximum or minimum score value of the index.

TDFI combines the total deaths from extreme events, and the expected annual number of people affected by floods. An inspection of Table A13 (Figure 6) shows that, across the clusters of countries, the correlation values that correspond to the total number of deaths and the expected number of people affected by floods with TDFI show a strong positive association. This suggests that the higher the expected number of people affected by floods, the higher the number of deaths would be. The coefficients in Figure 6 show that the total number of deaths show only strong correlations with TDFI in the case of the clusters of countries that are characterized by low scores in ISDI (clusters 2, 3 and 5). Moreover, the expected annual number of people affected by floods is only clearly represented in TDFI for clusters 3 and 5, suggesting that it is in these clusters of countries where flooding is of more relevance. In cluster 2 the sign of the correlation coefficients is the opposite to those that are obtained for the full sample. In this case, large values in the TDFI tend to correspond to smaller values in the total number of deaths and in the expected number of people exposed to flooding. As such, contrary to other clusters, smaller values in this index for cluster 2 represent higher risk. Clusters of countries with non-negative values of ISDI have weak associations between TDFI and the variables that compose this index, suggesting that adaptation and risk reduction measures associated with higher levels of development strongly mitigate this risk.

For clusters 5 and 3, the countries with higher ranking in this risk index are (Table A14): Bangladesh, Nepal, Ghana, Pakistan, and Tanzania (cluster 5); Philippines, Portugal, Chile, Panama, and Sri Lanka. In the case of cluster 2 the countries at higher risk are Algeria, Kuwait, Libya, Iraq, and Jordan.

Figure 6. Correlation coefficients between TDFI and the most important variables that compose it for different clusters of countries. +,- denote positive/negative median score values in the corresponding index,+/- denotes that the first and third quartiles include zero, while * indicates that the cluster contains the maximum or minimum score value of the index.

Assessing dissonances between perceptions, risk and vulnerability

As documented by the indices in the previous section, there is large heterogeneity across countries with respect to their scores in vulnerability and adaptation capacities, perceptions about the seriousness of climate change and the risk measures represented by the remaining factors. This section centers in assessing the dissonances between these indices and the economic losses that are projected for different countries for current warming (i.e., 1ºC warming in global average air surface temperature) and those projected for severe warming later in this century.

Figure 7 illustrates how institutional/adaptation capacities, as well as social concern about climate change, may not correspond to the projected damages this phenomenon can imply at the country level. The upper panel of Figure 7 shows a scatterplot of ISDI and the projected economic losses for a 4ºC warming scenario, divided into terciles for each variable. It illustrates that higher institutional/adaptation capacities tend to correspond to countries facing lower economic damages for future and current warming (Figure A3). On the contrary, those countries for which the largest damages are projected tend to be characterized by lower adaptation capacities. The lower panel of Figure 7 shows that some countries are characterized by low levels of concern and high expected impacts from climate change (dark-gray areas in Figure 7). In both cases, countries of the Middle East, Africa, South Asia, and Latin America are found in these high risk terciles, in which risk perceptions and institutional/adaptation capacities are at odds with the projected future and current damages.

Figure 7. Scatterplots of ISDI and CCSCI indices and projected damages for 1ºC warming. The upper panel shows the scatterplot between ISDI and D1, while the lower panel shows the scatterplot between CCSCI and D1. Black lines show the terciles that correspond to each variable and the darker gray fill denotes areas in which the correspondence between adaptation capacities (ISDI) or social concern (CCSCI) are considerably lower than the projected damage levels.

For assessing these dissonances, countries' rankings in ISDI and CCSCI are compared to the rankings obtained for their corresponding projected economic losses. Ideally, to minimize damages, the countries with larger expected losses would be those which would need to have the strongest adaptation and vulnerability reduction capacities. The differences in their rankings in these variables are normalized to range between 0 and 1 and are proposed as a measure of the distance or dissonance between their risks, adaptation capacities, and perceptions. The average score is called Social and Institutional Challenge Index (SICI) and provides a measure of the dissonance (distance) between the rankings of impacts of climate change and those of the institutional/adaptation capacities and of the social perception about the challenges climate change entails.

The proposed dissonance metrics are:

- g(ISDI-CCSCI): represents the extent to which adaptation and institutional capacities reflect social concern about climate change. It is calculated as the difference in ranking of each country in the ISDI and CCSCI, where negative values denote that the social concern is better ranked than the country's adaptation and institutional capacities, in comparison with other countries. Positive values denote that the country has a better ranking in adaptation and institutional capacities with respect to its social concern about climate change. As with all the measures in this section, g(ISDI-CCSCI) is normalized such that its range is [0,1], where 1 denotes maximum dissonance, i.e., the adaptation/institutional capacities are not in correspondence with the social concern about climate change. A value of 0 denotes minimal dissonance between adaptation and institutional capacities and social concern.
- g(ISDI-D1): provides a measure of dissonance between the institutional/adaptation capacities and the expected economic impacts for 1ºC warming with respect to preindustrial climate. These impacts are those that are expected for current levels of warming. The range of g(ISDI-D1) is [0,1], where 1 denotes maximum dissonance, i.e., the institutional/adaptation capacities are not in correspondence with expected economic impacts of climate change.
- g(ISDI-D4): constitutes a measure of dissonance between the institutional/adaptation capacities and the expected economic impacts for 4ºC warming with respect to preindustrial climate. These impacts are those that would be expected at the end of this century for a high global emissions scenario.
- g(CCSCI-D1): it is a measure of dissonance between social concern about climate change and the expected impacts for a 1ºC warming. The range of g(CCSCI-D1) is [0,1], where 1 denotes maximum dissonance, i.e., the social concern is not in correspondence with expected economic impacts of climate change.
- g(CCSCI-D4): provides a measure of dissonance between social concern about climate change and the expected impacts for a 4ºC warming. The range of g(CCSCI-D1) is [0,1], where 1 denotes

maximum dissonance, i.e., the social concern is not in correspondence with expected economic impacts of climate change.

- SICI: this index is computed as the average of the previously defined measures and provides a composite measure of the present and future institutional and social challenges related to climate change, for each country.

Table 1. Dissonance metrics and SICI scores for countries with highest and lowest ranking.

Rank	g(ISDI-CCSCI)	g(ISDI-D1)	g(ISDI-D4)	g(CCSCI-D1)	g(CCSCI-D4)	SICI
1	Angola (1.000)	Nigeria (1.000)	Nigeria (1.000)	Laos (1.000)	Haiti (1.000)	Nigeria (0.928)
2	Mexico (0.99)	Cote d'Ivoire (0.99)	Cote d'Ivoire (0.99)	Indonesia (0.99)	Indonesia (0.99)	Benin (0.885)
3	Ecuador (0.98)	Burkina Faso (0.98)	Haiti (0.98)	Nigeria (0.98)	Laos (0.98)	Haiti (0.869)
4	El Salvador (0.971)	Congo, DR (0.966)	Burkina Faso (0.966)	Thailand (0.971)	Nigeria (0.971)	Indonesia (0.86)
5	Nicaragua (0.956)	Benin (0.966)	Cameroon (0.966)	Haiti (0.961)	Thailand (0.961)	Cote d'Ivoire (0.857)
6	Bolivia (0.956)	Cameroon (0.951)	Congo, DR (0.951)	Egypt (0.951)	Benin (0.951)	Congo, DR (0.854)
7	Cote d'Ivoire (0.941)	Mozambique (0.941)	Benin (0.941)	Kuwait (0.941)	Egypt (0.936)	Burkina Faso (0.852)
8	Guatemala (0.931)	Nicaragua (0.926)	Indonesia (0.931)	Benin (0.922)	Yemen (0.936)	Senegal (0.834)
9	Colombia (0.922)	Indonesia (0.926)	Mozambique (0.917)	Saudi Arabia (0.922)	Malaysia (0.922)	Cameroon (0.833)
10	Nepal (0.912)	Pakistan (0.907)	Nicaragua (0.917)	Jordan (0.922)	Kuwait (0.907)	Ghana (0.819)
Rank	**g(ISDI-CCSCI)**	**g(ISDI-D1)**	**g(ISDI-D4)**	**g(CCSCI-D1)**	**g(CCSCI-D4)**	**SICI**
94	Israel (0.088)	Norway (0.088)	Austria (0.088)	France (0.093)	Peru (0.088)	Sweden (0.188)
95	New Zealand (0.078)	Austria (0.078)	Lithuania (0.078)	Brazil (0.074)	Canada (0.074)	Germany (0.186)
96	Denmark (0.069)	Germany (0.064)	United Kingdom (0.069)	Hungary (0.074)	Mexico (0.074)	Slovakia (0.186)
97	Hong Kong (0.059)	New Zealand (0.064)	Netherlands (0.059)	Croatia (0.059)	Italy (0.059)	Finland (0.185)
98	Australia (0.049)	Denmark (0.049)	Germany (0.049)	Italy (0.049)	France (0.049)	United Kingdom (0.165)
99	Czech Republic (0.039)	Netherlands (0.039)	Denmark (0.039)	Spain (0.039)	Greece (0.039)	Portugal (0.161)
100	Sweden (0.029)	Canada (0.029)	Sweden (0.025)	Mexico (0.029)	Spain (0.029)	Austria (0.156)
101	Netherlands	Sweden	Switzerland	Chile	Hungary	France

	(0.020)	(0.020)	(0.025)	(0.020)	(0.020)	(0.139)
102	Finland (0.010)	Switzerland (0.010)	Canada (0.010)	Greece (0.010)	Chile (0.010)	Switzerland (0.102)
103	Norway (0.000)	Finland (0.000)	Finland (0.000)	Portugal (0.000)	Portugal (0.000)	Canada (0.091)

Table A15 shows the scores of the dissonance metrics described above and those of the SICI index for each country, while Table 1 presents a selection of the ten countries with the highest and lowest scores. The largest dissonances between the scores of institutional/adaptation capacities and of people's concern about climate change, g(ISDI-CCSCI), occur mainly in Latin America and African countries, with Angola and Mexico at the top of the ranking. In the case of dissonance between ISDI and economic impact (D1, D4) African countries show particularly large scores, with Nigeria and Cote d'Ivoire reaching the highest values. Latin American, as well as southeast Asian countries such as Haiti, Nicaragua, Indonesia, and Pakistan show particularly large levels of dissonance between their ISDI and D1/D4 scores. The highest levels of dissonance between the projected impacts and people's concern about climate change are typically observed in southeast Asia, Arab Countries and Haiti. SICI provides an overall score for each country considering all other dissonance metrics and reveals that the countries facing greater challenges for adaptation and social awareness are Nigeria, Benin, and Haiti. In contrast, the countries with lesser adaptation and social awareness challenges are Canada, Switzerland, and France.

4. Conclusions

This paper presents an analysis of a composite of datasets aimed to characterize different aspects relevant for better understanding the capacities, challenges and risks that climate change implies for an extensive number of countries. These include economic and human development measures, institutional and adaptation capacities, recorded number of extreme events and their consequences in economic and death terms, people's beliefs about different aspects of climate change ranging from its existence, origins, consequences and responsibilities, as well as projections of the economic damages the phenomenon would generate for current and future conditions. One of the challenges for decision-making in this era is to construct methods and tools for transforming data into relevant information that can be used for guiding policy. This is particularly challenging for topics as multidimensional, interdisciplinary, and complex such as climate change and other problems related to sustainability. The analysis presented here focus on producing a limited number of indices and measures that can summarize the data contained in the composite database and that can be of help for describing advantages, risks and challenges different countries face with climate change. Moreover, an online tool is provided to visualize, explore, and analyze both the datasets and the proposed indices and measures.

By applying multivariate statistical models eight factors are defined which can be interpreted in a meaningful manner and summarize about 85% of the total variance of the dataset. ISDI and CCSCI (factors 1 and 2) represent key indices for deriving insights about the countries' capacities to address climate change and the people's perceptions of climate change. ISDI characterizes the institutional/adaptation capacities of the different countries and is in good agreement with other commonly used adaptation index

(ND-GAIN). Given that these two adaptation indices are independent, both in methodological and data source terms, they provide complementary information that can enrich adaptation assessments. CCSCI summarizes the social concern people in different countries shows and in conjunction with ISDI provides a space to explore and better understand the different countries social and institutional stance in climate change. Cluster analysis is used to define groups of countries in terms of their similarities in the ISDI-CCSCI space, which helps not only to better understand their geographical, economic, cultural, and social affinities, but also for deriving further insights from the other proposed indices related to climate change's challenges. Rankings for all the analyzed countries and for all indices are provided and cluster-specific interpretation of the proposed indices are provided. Moreover, dissonance metrics between institutional/adaptation capacities, as well as social climate concern, and projected impacts for current and possible future climate are defined, and a composite index (SICI) that represents the institutional and social challenges these dissonances suggest is defined.

This paper provides a multidimensional assessment of the readiness countries show to address climate change and of the different types of risks and challenges this phenomenon implies. Countries' scores and rankings on the proposed indices and metrics are expected to be useful for global, regional and country level assessments in the context of the first global stocktake carried out in COP28. The analysis and the online tools aim to facilitate identifying areas of opportunity for country level climate policy.

References

1. Berkeley Earth. Press Release: 2023 Was Warmest Year Since 1850 [Internet]. 2023 [cited 2024 Jan 14]. Available from: https://berkeleyearth.org/press-release-2023-was-the-warmest-year-on-recordpress-release/

2. IPCC. IPCC Special Report 1.5 - Summary for Policymakers. In: Global warming of 15°C An IPCC Special Report on the impacts of global warming of 15°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change,. 2018.

3. Hulme M. 1.5 °C and climate research after the Paris Agreement. Nat Clim Chang. 2016;

4. Estrada F, Perron P, Yamamoto Y. Anthropogenic influence on extremes and risk hotspots. Sci Rep [Internet]. 2023 Dec 1 [cited 2023 Feb 25];13(1). Available from: https://pubmed.ncbi.nlm.nih.gov/36593354/

5. Sun Q, Zhang X, Zwiers F, Westra S, Alexander L V. A Global, Continental, and Regional Analysis of Changes in Extreme Precipitation. J Clim [Internet]. 2021 Jan 1 [cited 2022 Apr 14];34(1):243–58. Available from: https://journals.ametsoc.org/view/journals/clim/34/1/jcliD190892.xml

6. Cohen J, Zhang X, Francis J, Jung T, Kwok R, Overland J, et al. Divergent consensuses on Arctic amplification influence on midlatitude severe winter weather. Nat Clim Chang [Internet]. 2020 Dec 23 [cited 2019 Dec 25];10(1):20–9. Available from: http://www.nature.com/articles/s41558-019-0662-y

7. Estrada F, Kim D, Perron P. Spatial variations in the warming trend and the transition to more severe weather in midlatitudes. Sci Rep [Internet]. 2021 Dec 8 [cited 2021 Jan 11];11(1):145. Available from: http://www.nature.com/articles/s41598-020-80701-7

8. Coumou D, Di Capua G, Vavrus S, Wang L, Wang S. The influence of Arctic amplification on mid-latitude summer circulation. Nat Commun. 2018 Dec 1;9(1):2959.

9. McKay DIA, Staal A, Abrams JF, Winkelmann R, Sakschewski B, Loriani S, et al. Exceeding 1.5°C global warming could trigger multiple climate tipping points. Science [Internet]. 2022 Sep 9 [cited 2024 Jan 14];377(6611). Available from: https://www.science.org/doi/10.1126/science.abn7950

10. Velasco JA, Estrada F, Calderón-Bustamante O, Swingedouw D, Ureta C, Gay C, et al. Synergistic impacts of global warming and thermohaline circulation collapse on amphibians. Commun Biol. 2021;4(1).

11. Defrance D, Ramstein G, Charbit S, Vrac M, Famien AM, Sultan B, et al. Consequences of rapid ice sheet melting on the Sahelian population vulnerability. Proc Natl Acad Sci U S A [Internet]. 2017 Jun 20 [cited 2019 Jul 22];114(25):6533–8. Available from: http://www.ncbi.nlm.nih.gov/pubmed/28584113

12. Anthoff D, Estrada F, Tol RSJ. Shutting down the thermohaline circulation. Am Econ Rev. 2016;106(5).

13. Warren R, Price J, VanDerWal J, Cornelius S, Sohl H. The implications of the United Nations Paris Agreement on climate change for globally significant biodiversity areas. Clim Change [Internet]. 2018 Apr 14 [cited 2019 Jul 21];147(3–4):395–409. Available from: http://link.springer.com/10.1007/s10584-018-2158-6

14. Estrada F, Botzen WJW. Economic impacts and risks of climate change under failure and success of the Paris Agreement. Ann N Y Acad Sci [Internet]. 2021 Jun 25 [cited 2021 Jul 12];1504(1):95–115. Available from: https://nyaspubs-onlinelibrary-wiley-com.vu-nl.idm.oclc.org/doi/full/10.1111/nyas.14652

15. Colón-González FJ, Harris I, Osborn TJ, Steiner São Bernardo C, Peres CA, Hunter PR, et al. Limiting global-mean temperature increase to 1.5-2 °C could reduce the incidence and spatial spread of dengue fever in Latin America. Proc Natl Acad Sci U S A [Internet]. 2018 Jun 12 [cited 2018 Dec 30];115(24):6243–8. Available from: http://www.ncbi.nlm.nih.gov/pubmed/29844166

16. Lai W, Qiu Y, Tang Q, Xi C, Zhang P. The Effects of Temperature on Labor Productivity [Internet]. Vol. 15, Annual Review of Resource Economics. Annual Reviews; 2023 [cited 2024 Jan 14]. p. 213–32. Available from: https://www.annualreviews.org/doi/abs/10.1146/annurev-resource-101222-125630

17. UNFCCC. Outcome of the first global stocktake. Draft decision CMA.5 [Internet]. 2023. Available from: https://unfccc.int/sites/default/files/resource/cma2023_L17_adv.pdf

18. Boehm S, Jeffery L, Hecke J, Schumer C, Jaeger J, Fyson C, et al. State of Climate Action 2023. World Resources Institute. Berlin and Cologne, Germany, San Francisco, CA, and Washington, DC; 2023.

19. UNFCCC. Views on the elements for the consideration of outputs component of the first global stocktake. Synthesis report on GST elements [Internet]. 2023. Available from: https://unfccc.int/sites/default/files/resource/SYR_Views on Elements for CoO.pdf

20. Scown MW, Chaffin BC, Triyanti A, Boyd E. A harmonized country-level dataset to support the global stocktake regarding loss and damage from climate change. Geosci Data J [Internet]. 2022 Nov 1 [cited 2024 Jan 14];9(2):328–40. Available from:

https://onlinelibrary.wiley.com/doi/full/10.1002/gdj3.147

21. Haro A, Mendoza-Ponce A, Calderón-Bustamante Ó, Velasco JA, Estrada F. Evaluating Risk and Possible Adaptations to Climate Change Under a Socio-Ecological System Approach. Front Clim [Internet]. 2021 Jun 10 [cited 2022 Sep 8];3:54. Available from: https://www.frontiersin.org/articles/10.3389/fclim.2021.674693/full

22. Estrada F, Velasco JA, Martinez-Arroyo A, Calderón-Bustamante O. An Analysis of Current Sustainability of Mexican Cities and Their Exposure to Climate Change. Front Environ Sci [Internet]. 2020 Mar 12 [cited 2020 Mar 24];8:25. Available from: https://www.frontiersin.org/article/10.3389/fenvs.2020.00025/full

23. Birkmann J, Welle T, Krause D, Wolfertz J, Suarez D-C, Setiadi NJ. World Risk Index: Concept and results [Internet]. World Risk Report 2011. 2011. Available from: internal-pdf://229.104.98.93/World Report 2011.pdf

24. Birkmann J, Welle T. The WorldRiskIndex 2016: Reveals the Necessity for Regional Cooperation in Vulnerability Reduction. J Extrem Events [Internet]. 2016 Jun [cited 2024 Jan 14];03(02):1650005. Available from: www.worldscientific.com

25. Chen C, Noble I, Hellman J, Coffee J, Murillo M, Chawla N. University of Notre Dame Global Adaptation Initiative Country Index. Technical report [Internet]. Indiana. US; 2023. Available from: https://gain.nd.edu/assets/522870/nd_gain_countryindextechreport_2023_01.pdf

26. Leiserowitz A, Carman J, Buttermore N, Neyens L, Rosenthal S, Marlon J, et al. International public opinion on climate change. New Haven, CT; 2023.

27. Lever J, Krzywinski M, Altman N. Points of Significance: Principal component analysis. Vol. 14, Nature Methods. Nature Publishing Group; 2017. p. 641–2.

28. Jolliffe IT. Principal Component Analysis. New York: John Wiley & Sons, Ltd.; 2002. 488 p.

29. Estrada F, Perron P. Extracting and Analyzing the Warming Trend in Global and Hemispheric Temperatures. In: Journal of Time Series Analysis. 2017. p. 711–32.

30. Johnson RA (Richard A, Wichern DW. Applied multivariate statistical analysis. Pearson Prentice Hall; 2007. 773 p.

31. Estrada F, Velasco JA, Martinez-Arroyo A, Calderón-Bustamante O. An Analysis of Current Sustainability of Mexican Cities and Their Exposure to Climate Change. Front Environ Sci. 2020 Mar 12;8.

32. Harman H. Modern factor analysis [Internet]. 3rd ed. University of Chicago Press; 1976 [cited 2017 Mar 12]. 508 p. Available from: https://books.google.com.mx/books?hl=en&lr=&id=e-vMN68C3M4C&oi=fnd&pg=PR11&dq=harman+1976+modern+factor+analysis&ots=t4PsIxjQ0y&sig=BNxhYo68T987hkXjJIbSFEvWAp4

33. O'Lenic EA, Livezey RE, O'Lenic EA, Livezey RE. Practical Considerations in the Use of Rotated Principal Component Analysis (RPCA)in Diagnostic Studies of Upper-Air Height Fields. Mon Weather Rev [Internet]. 1988 Aug [cited 2017 Mar 7];116(8):1682–9. Available from: http://journals.ametsoc.org/doi/abs/10.1175/1520-0493%281988%29116%3C1682%3APCITUO%3E2.0.CO%3B2

34. Glass L-M, Newig J. Governance for achieving the Sustainable Development Goals: How important are participation, policy coherence, reflexivity, adaptation and democratic institutions? Earth Syst Gov. 2019 Apr 1;2:100031.

35. Greenland SJ, Saleem M, Misra R, Nguyen N, Mason J. Reducing SDG complexity and informing environmental management education via an empirical six-dimensional model of sustainable development. J Environ Manage. 2023 Oct 15;344:118328.

36. Uddin I, Ahmad M, Ismailov D, Balbaa ME, Akhmedov A, Khasanov S, et al. Enhancing institutional quality to boost economic development in developing nations: New insights from CS-ARDL approach. Res Glob. 2023 Dec 1;7:100137.

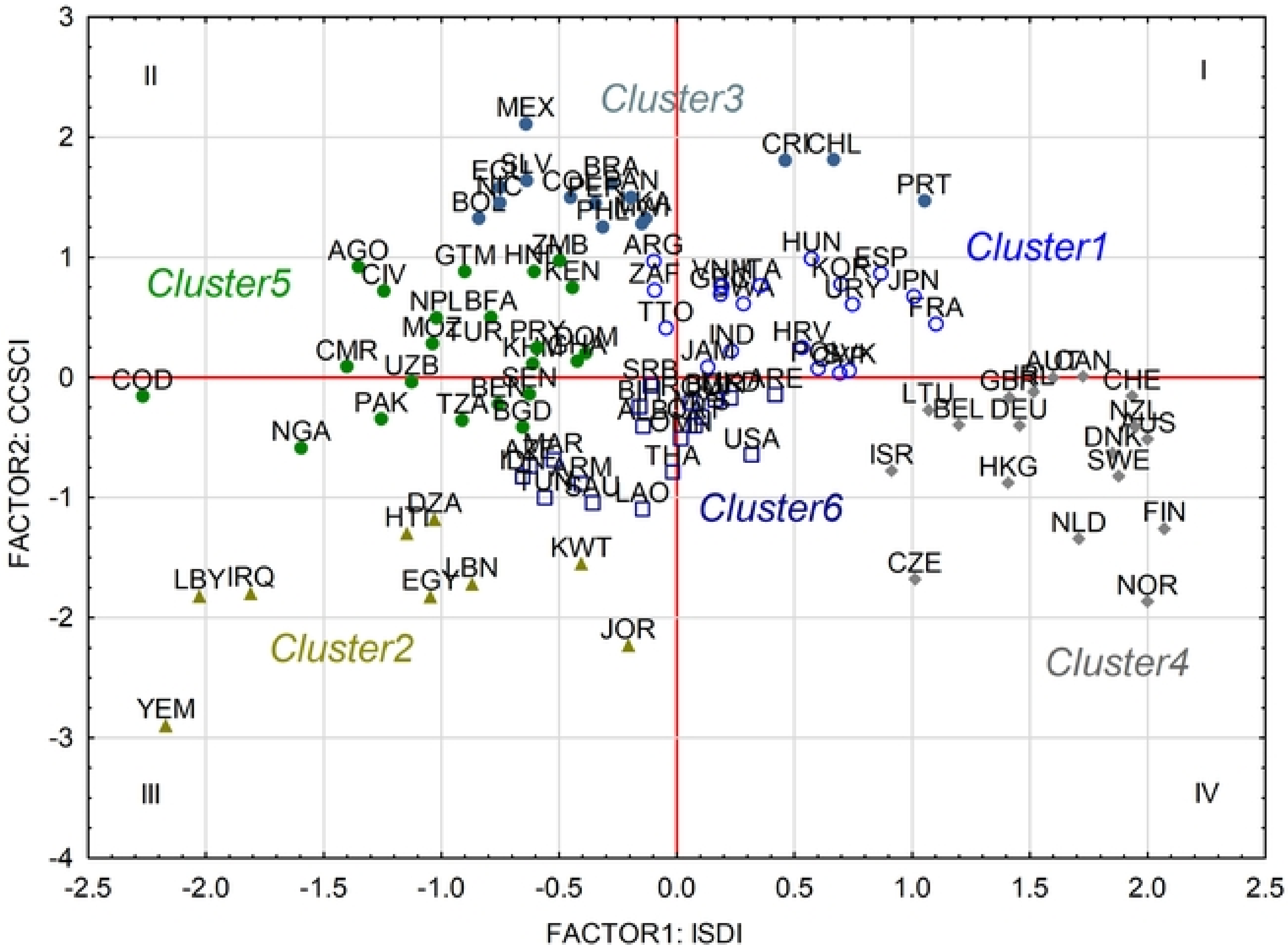
37. Estrada F, Martínez-López B, Conde C, Gay-García C. The new national climate change documents of Mexico: What do the regional climate change scenarios represent? Clim Change. 2012;110(3–4).

38. Estrada F, Papyrakis E, Tol RSJ, Gay-Garcia C. The economics of climate change in Mexico: Implications for national/regional policy. Clim Policy [Internet]. 2013;13(6):738–50. Available from: http://www.tandfonline.com/doi/abs/10.1080/14693062.2013.813806

39. Whetsell TA, Dimand AM, Jonkers K, Baas J, Wagner CS. Democracy, Complexity, and Science: Exploring Structural Sources of National Scientific Performance. Sci Public Policy [Internet]. 2021 Oct 9 [cited 2023 Dec 29];48(5):697–711. Available from: https://dx.doi.org/10.1093/scipol/scab036

40. Sachs JD, Schmidt-Traub G, Mazzucato M, Messner D, Nakicenovic N, Rockström J. Six Transformations to achieve the Sustainable Development Goals. Nat Sustain 2019 29 [Internet]. 2019 Aug 26 [cited 2023 Dec 29];2(9):805–14. Available from: https://www.nature.com/articles/s41893-019-0352-9

41. Mormina M. Science, Technology and Innovation as Social Goods for Development: Rethinking Research Capacity Building from Sen's Capabilities Approach. Sci Eng Ethics [Internet]. 2019 Jun 15 [cited 2023 Dec 29];25(3):671–92. Available from: /pmc/articles/PMC6591180/



FACTOR2: CCSCI
FACTOR1: ISDI
Cluster1
Cluster2
Cluster3
Cluster4
Cluster5
Cluster6
I
II
III
IV
MEX
CRI
CHL
PRT
BOL
AGO
CIV
GTM
ZMB
KEN
ARG
ZAF
HUN
ESP
JPN
FRA
NPL
BFA
TTO
CMR
UZB
COD
PAK
NGA
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USA
THA
LAO
ISR
HKG
LTU
BEL
DEU
CHE
NZL
DNK
SWE
NLD
FIN
CZE
NOR
DZA
KWT
LBN
EGY
LBY
IRQ
JOR
YEM

Figure1

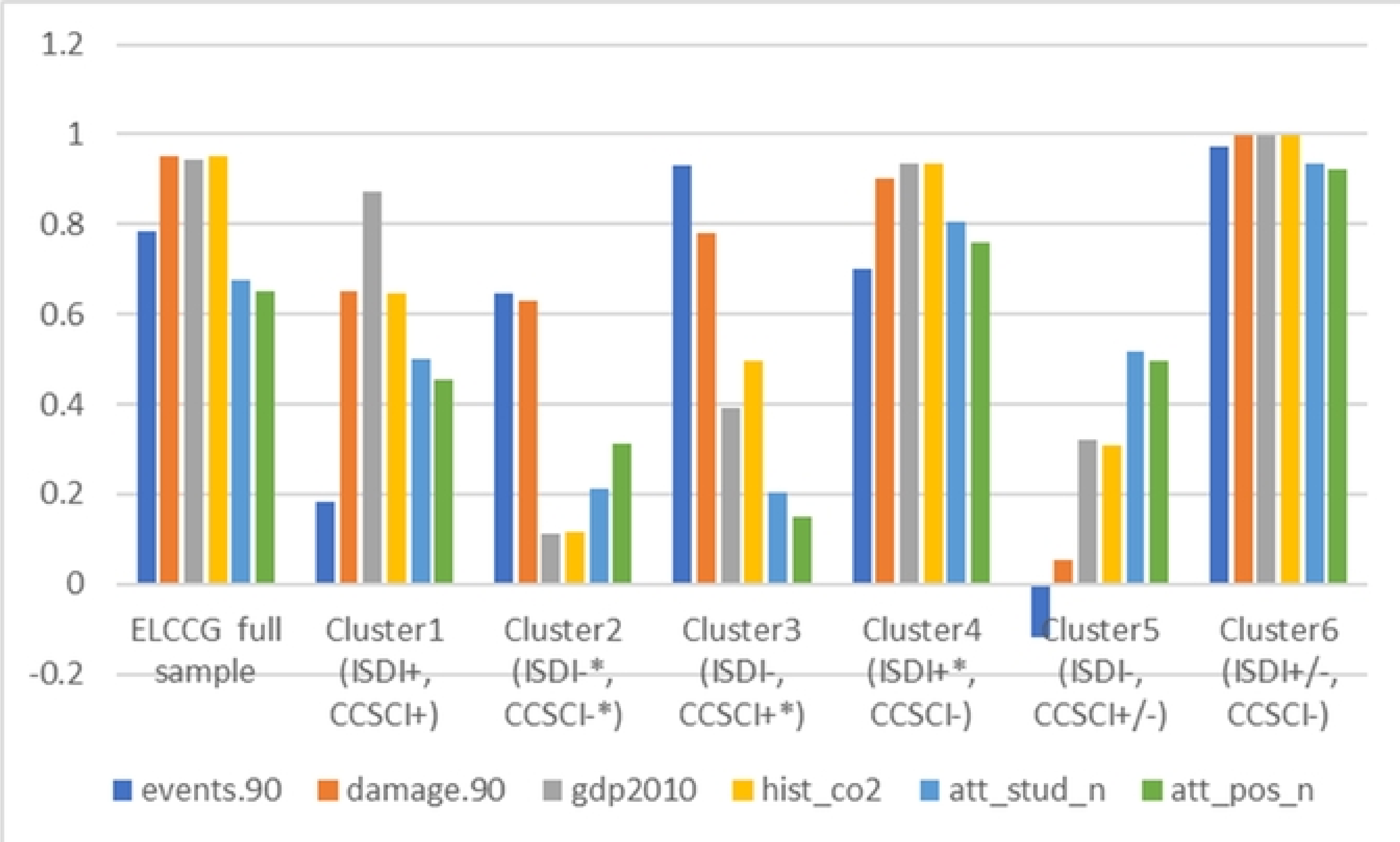

1.2
1
0.8
0.6
0.4
0.2
0
-0.2
ELCCG full sample
Cluster1 (ISDI+, CCSCI+)
Cluster2 (ISDI-*, CCSCI-*)
Cluster3 (ISDI-, CCSCI+*)
Cluster4 (ISDI+*, CCSCI-)
Cluster5 (ISDI-, CCSCI+/-)
Cluster6 (ISDI+/-, CCSCI-)
events.90
damage.90
gdp2010
hist_co2
att_stud_n
att_pos_n

Figure2

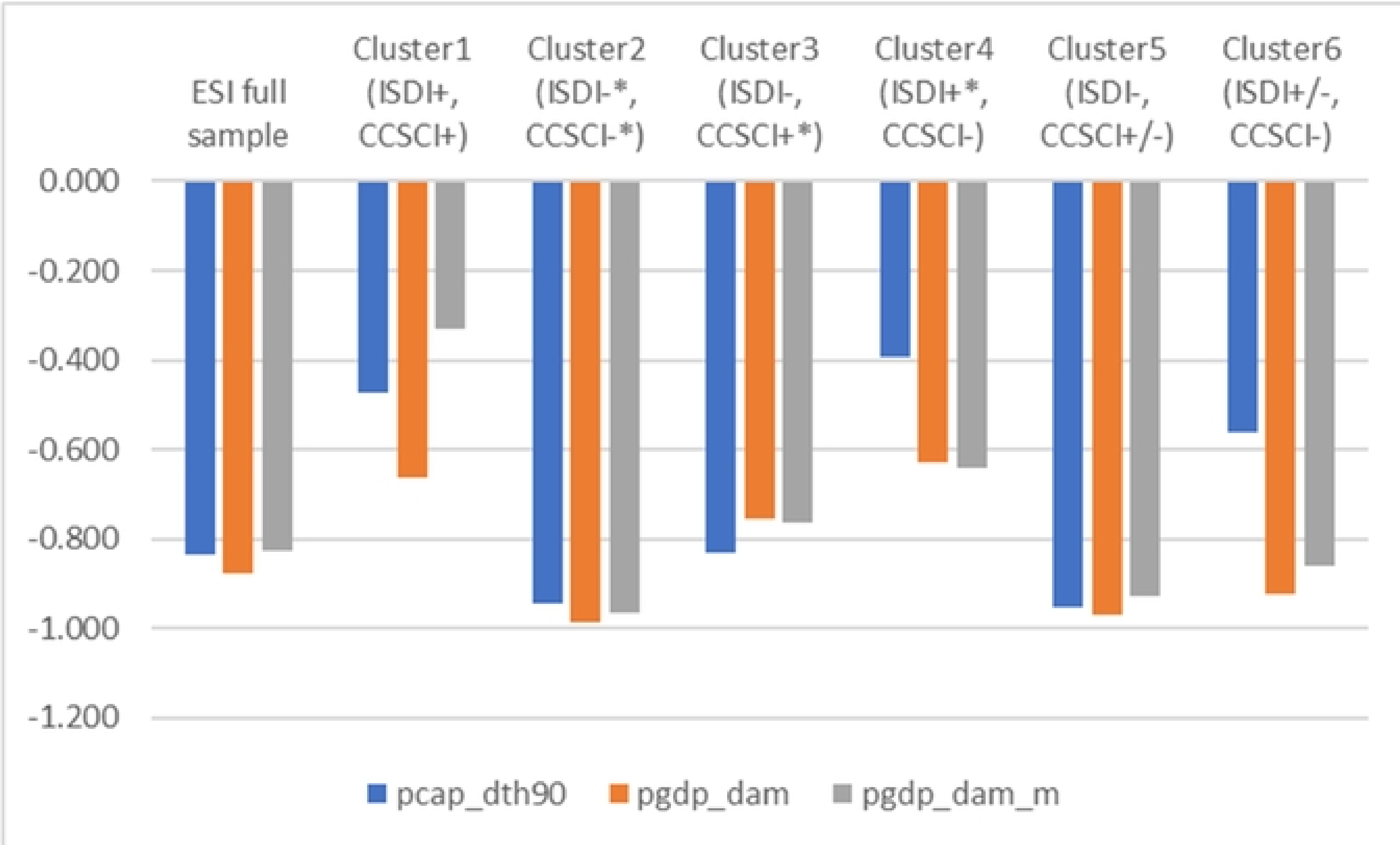

ESI full sample
Cluster1 (ISDI+, CCSCI+)
Cluster2 (ISDI-*, CCSCI-*)
Cluster3 (ISDI-, CCSCI+*)
Cluster4 (ISDI+*, CCSCI-)
Cluster5 (ISDI-, CCSCI+/-)
Cluster6 (ISDI+/-, CCSCI-)
0.000
-0.200
-0.400
-0.600
-0.800
-1.000
-1.200
pcap_dth90
pgdp_dam
pgdp_dam_m

Figure3

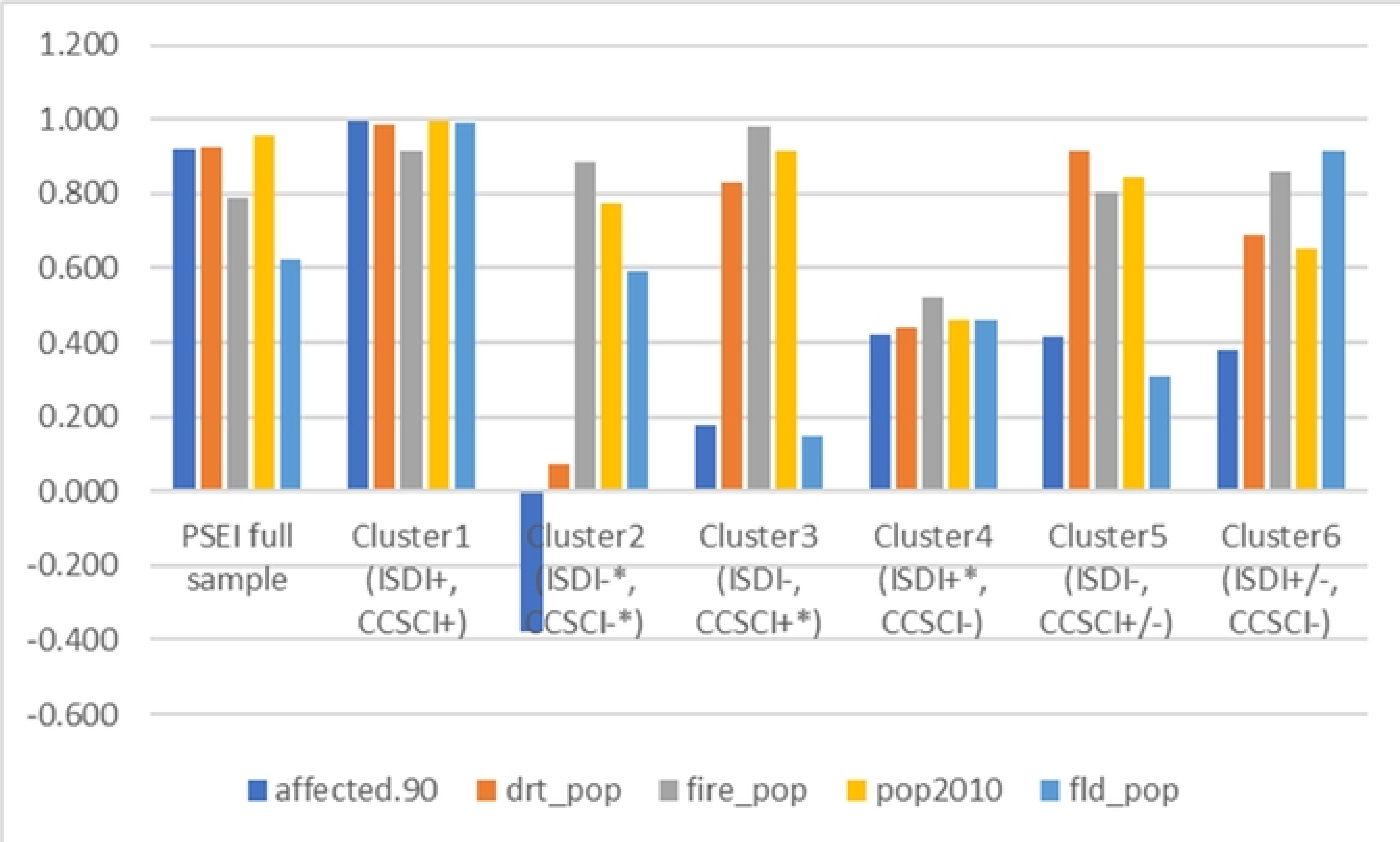

1.200
1.000
0.800
0.600
0.400
0.200
0.000
-0.200
-0.400
-0.600
PSEI full sample
Cluster1 (ISDI+, CCSCI+)
Cluster2 (ISDI-*, CCSCI-*)
Cluster3 (ISDI-, CCSCI+*)
Cluster4 (ISDI+*, CCSCI-)
Cluster5 (ISDI-, CCSCI+/-)
Cluster6 (ISDI+/-, CCSCI-)
affected.90
drt_pop
fire_pop
pop2010
fld_pop

Figure4

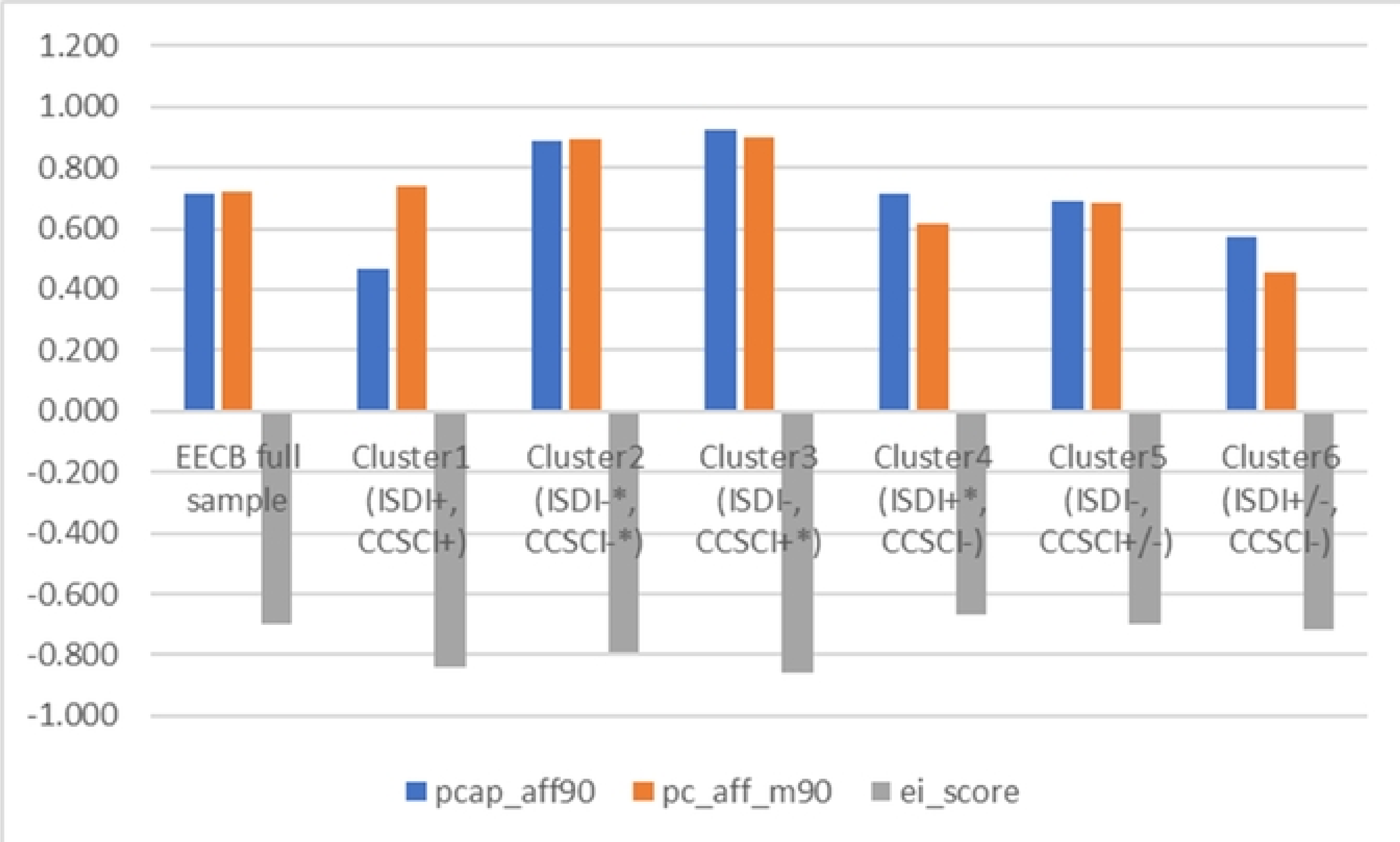

1.200
1.000
0.800
0.600
0.400
0.200
0.000
-0.200
-0.400
-0.600
-0.800
-1.000
EECB full sample
Cluster1 (ISDI+, CCSCI+)
Cluster2 (ISDI-*, CCSCI-*)
Cluster3 (ISDI-, CCSCI+*)
Cluster4 (ISDI+*, CCSCI-)
Cluster5 (ISDI-, CCSCI+/-)
Cluster6 (ISDI+/-, CCSCI-)
pcap_aff90
pc_aff_m90
ei_score

Figure5

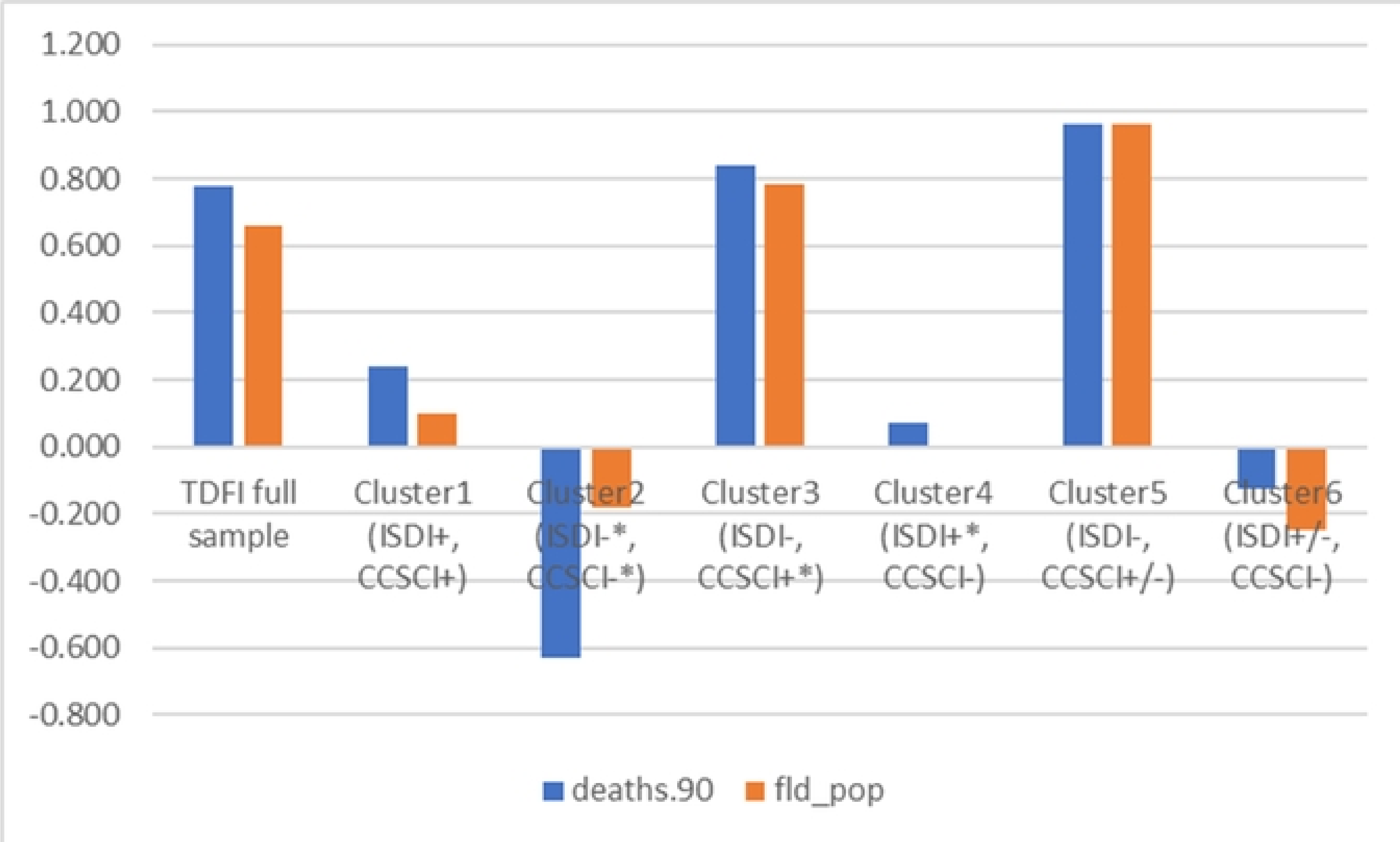
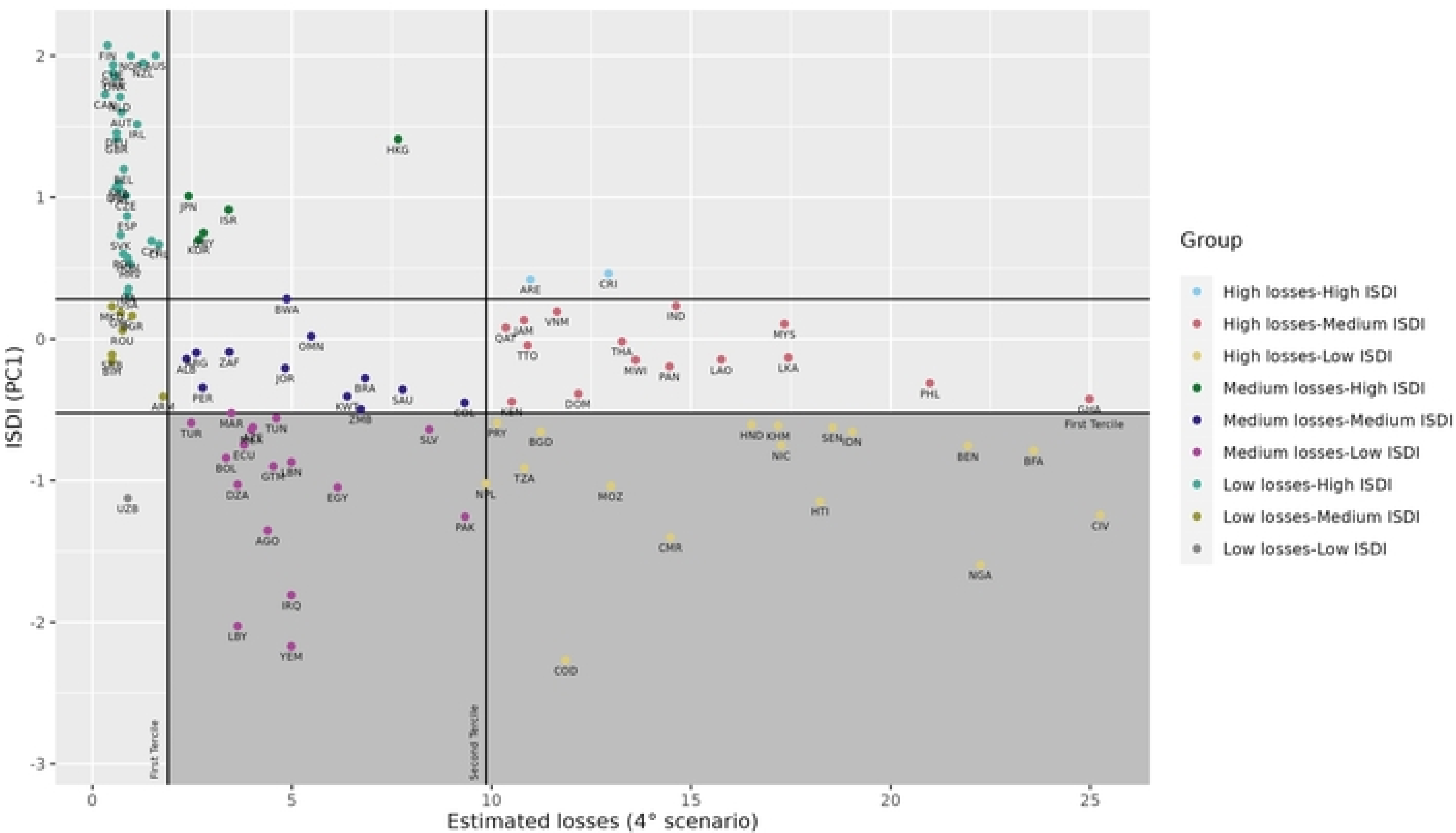
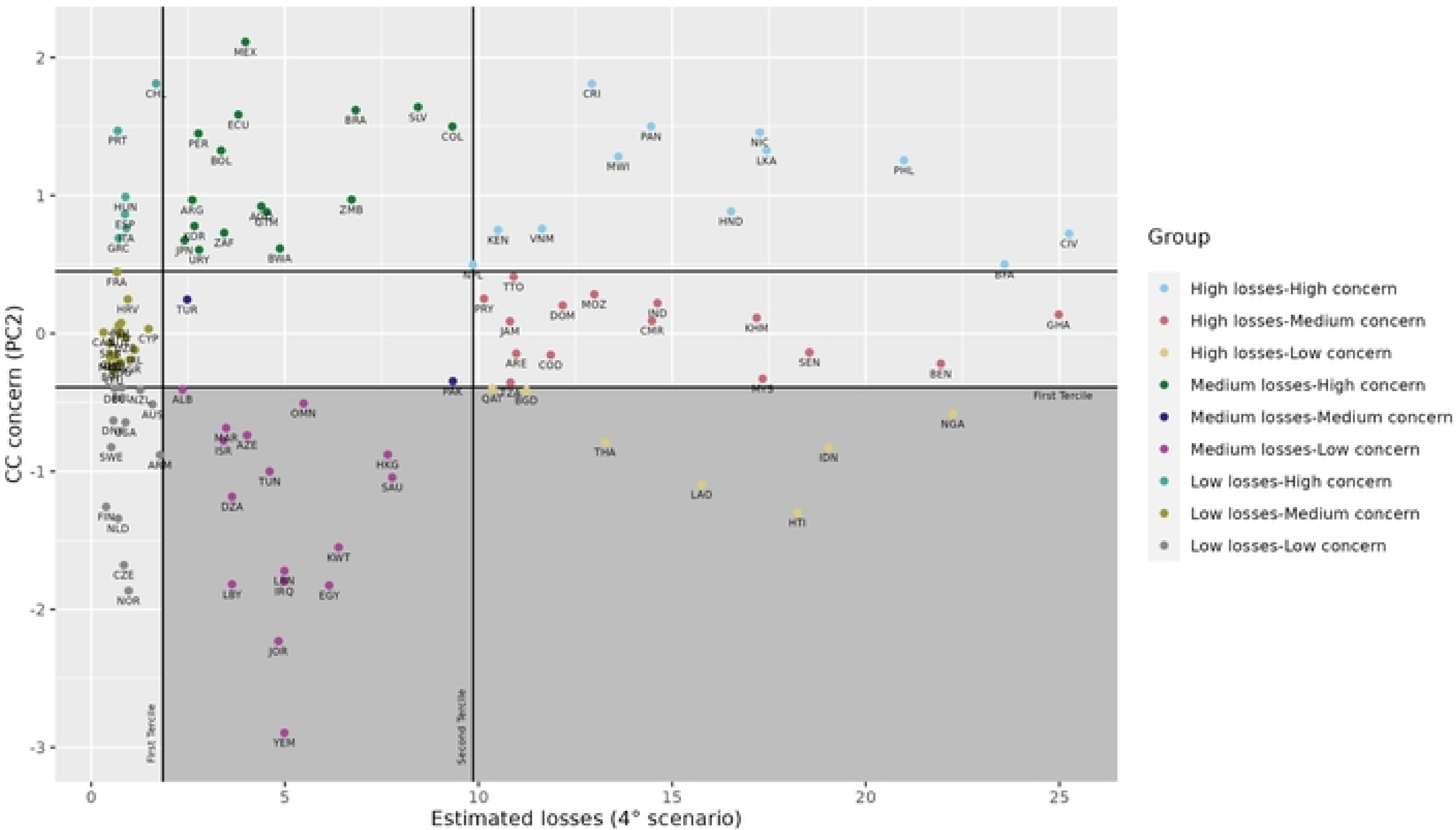

1.200
1.000
0.800
0.600
0.400
0.200
0.000
-0.200
-0.400
-0.600
-0.800
TDFI full sample
Cluster1 (ISDI+, CCSCI+)
Cluster2 (ISDI-*, CCSCI-*)
Cluster3 (ISDI-, CCSCI+*)
Cluster4 (ISDI+*, CCSCI-)
Cluster5 (ISDI-, CCSCI+/-)
Cluster6 (ISDI+/-, CCSCI-)
deaths.90
fld_pop

Figure6



ISDI (PC1)
Estimated losses (4° scenario)
First Tercile
Second Tercile
Group
High losses-High ISDI
High losses-Medium ISDI
High losses-Low ISDI
Medium losses-High ISDI
Medium losses-Medium ISDI
Medium losses-Low ISDI
Low losses-High ISDI
Low losses-Medium ISDI
Low losses-Low ISDI

Figure7



Group
High losses-High concern
High losses-Medium concern
High losses-Low concern
Medium losses-High concern
Medium losses-Medium concern
Medium losses-Low concern
Low losses-High concern
Low losses-Medium concern
Low losses-Low concern
CC concern (PC2)
Estimated losses (4° scenario)
First Tercile
Second Tercile

Figure8