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Keywords
climate risk, physical climate risk, climate risk index, composite indicator

JEL Codes
Q5, Q54

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Assessing systemic climate change risk by country. Reflections from the use of composite indicators

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Abstract

This paper proposes a transparent and replicable methodology to rank countries according to climate change risk through a composite indicator approach. We show that adherence to the IPCC definition of risk easily leads to a dominance of the exposure component in risk determination. This, on its turn, produces a country risk ranking that can differ also substantively from that of other indicators used for similar purposes, especially by rating agencies. These last indicators are, in fact, closer to the concept of vulnerability to climate change, than risk. Our major conclusion is that by accounting for all the components of risk, the dichotomy "high-climate-change-risk developing countries" vs "low-climate-change-risk developed countries" blurs substantively, while climate risk becomes relatively higher than commonly considered in the latter group.

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1. Introduction

Climate change is increasingly perceived not only as an environmental issue, but also as a much broader challenge to development and its sustainability. Its impacts affect the social, the economic and the institutional dimensions. Furthermore, these impacts are inextricably intertwined with the major challenges modern societies have to face, such as increasing human pressure on water, food, energy, biodiversity resources, inequality and poverty, which are often reciprocally hampering their negative effects ((IPCC 2022), (WEF 2022)).

Against this background, the social economic assessment of climate change impacts is a fundamental step to plan efficient, effective, and equitable response strategies. An extended literature reports challenges, methods, results, and developments of this almost 40-year-old prolific research stream (a very partial example list includes Stern (2006) the contributions of the Working Group II to the IPCC Assessment reports such as Arent et al. (2015), (IPCC 2022), many surveys like (Carleton and Hsiang 2016), Howard and Sterner (2017), Tol (2018), Bosello and Parrado (2020) and more. Within the many different impact assessment efforts and methodologies, the definition and quantification of "climate change risk" is central.

In its attempt to clarify this possibly elusive and multifaceted concept, the IPCC (Reisinger et al. 2020b) defines it as a combination of hazard, exposure and vulnerability as illustrated in Figure 1.

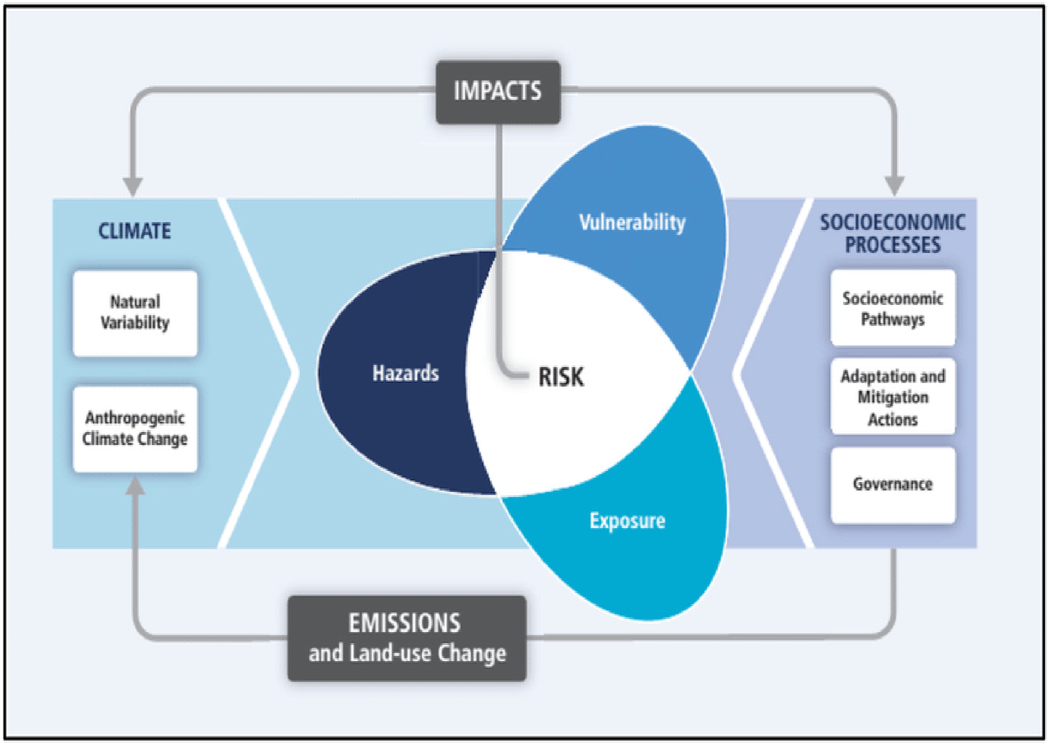

Figure 1 Climate risk definition. Source: (IPCC, 2014), *p. 3*

The vulnerability component comprises sensitivity, adaptive capacity and “other components”. This definition and the process leading to it has been debated at length (see e.g. Brooks et al. (2005), Connelly et al. (2018)). In a nutshell, the main issues concerned the adherence of these concepts to a “standard” probabilistic definition of risk and to the appropriateness of using the “risk” term itself.

An extensive discussion is beyond the scope of this work. Nonetheless, we note with Connelly et al. (2018) that the “framing” is important especially when policy action has to be designed as responses to risk are unavoidably influenced by how risk is conceptualized. Reconducting the IPCC risk framework to a probabilistic perspective consisting in an “outcome” (usually negative) times a probability is however possible. In a loose sense, exposure and vulnerability are both contributing to determining the (negative) consequences while the “hazard” component could be associated with a probability. But here the second issue emerges. In rigorous terms, “risk” presupposes the knowledge of probability distributions or, following Kaplan and Garrick (1981), of the likelihood of the hazard to happen. In fact, this is not exactly the case in most hazard assessments. A more correct wording, in this context, would be “uncertainty” rather than “risk”. This is somehow recognized by the IPCC that states: “. Hazards, exposure and vulnerability may each be subject to uncertainty in terms of magnitude and likelihood of occurrence” (Reisinger et al. 2020a).

This said, and adhering to the IPCC framework, different “types” of risks can originate from climate change. A common taxonomy lists two broad categories: physical risk and transition risk ((TCFD 2017), (Reisinger et al. 2020b)). Physical risk relates to a climate change-driven change in the hazard - exposure - vulnerability system; transitional risk is instead “policy driven” and associated with the transition to a low carbon economy. Each of these macro-categories then feature many sub-categories. Physical risk can be for instance classified into acute or chronic risk, transition risk into policy or legal risk, technology risk, reputational risk etc. The relevance of climate change physical risk as a component of country risk with implication for fiscal stability and sovereign creditworthiness, is attracting increasing attention.

In a seminal work, S&P Global Rankings (2014) identifies an inverse relation between a composite climate vulnerability index measured by the share of population living in coastal areas below five meters, the share of agriculture in national GDP and the vulnerability index provided by Notre Dame University Global Adaptation Index (ND-GAIN) and prosperity. It further shows that lower rate sovereigns are more vulnerable to climate change. Similarly, Moody’s (2016) combined the ND-GAIN vulnerability indices, with a number of indicators used in its sovereign bond methodology.

These include: the scale of the economy (as measured by nominal GDP), national income (GDP per capita), and the assessment of Fiscal Strength (defined as the "overall health of government finances and the capacity to absorb financial costs arising from economic and social disruptive events", (Moody's Investors Service 2016), p. 7). In Moody's (2016), sovereigns' ratings turned out to be quite strongly correlated with their susceptibility to climate change; moreover, in such framework countries with an overarching reliance on agriculture and countries where the quality of infrastructure is typically weaker – two important aspects of susceptibility (sensitivity using IPCC terminology) to physical climate change – tend to be lower rated.

Volz et al. (2020) estimate econometrically a positive relationship between sovereign bond yields of forty developed and emerging economies and climate risk vulnerability measured by a refined version of the ND-GAIN index developed by (Kling et al. 2021). The study also highlights that the economies that have in place measures enabling an effective contrast to the negative effects of climate change tend to have lower sovereign bond yields.

(Klusak et al. 2021) developed a machine learning application to simulate the effect of climate change on sovereign creditworthiness. They find material impacts of climate change as early as 2030, with significantly deeper downgrades across more sovereigns that, under the high climate signal RCP 8.5 scenario, could reach an average 2.48 notches, with several countries falling by five notches or more on a 20-notch scale. The additional costs to sovereigns within the analyzed sample range from US$ 22 to 33 billion under RCP 2.6, and US$ 137 to 205 billion under RCP 8.5.

The inclusion of a climate change "physical dimension" appears to be a standard practice in the country rating process of rating agencies. Moody's, Standard and Poor, Fitch explicitly recognise climate change as a sovereign risk trend. But, how this is achieved in practice is not necessarily transparent. Climate or climate-related stressors enter as part of the "environmental, social and governance" (ESG) risk. These are a set of indicators used to refine the "core" rating procedure through an external qualitative (read: analyst driven opinion) rather than a quantitative process.[1] Moreover, it is not always clear which climate change indicators are used to identify physical risk. Standard & Poor report a generic "natural conditions factors e.g., weather events" (S&P Global Ratings, 2018), Fitch, mentions "natural disasters and climate change" (Fitch Ratings 2019), p. 12,

[1] This is more evident in the Moody's and S&P methodologies, but it also applies to Fitch that corrects the results from the econometric model with the qualitative overlay.

Moody's reports: "Current and future effects of climate change" and "Exposure to heat stress, water stress, floods, hurricanes, sea level rise and wildfires" (Moody's Investors Service 2020), p.13.

Against this background, the aim of this work is to propose a country climate risk index rigorously rooted on the IPCC risk definition following a process which is transparent, replicable, and grounded on quantitative information. The country ranking obtained, is then commented in the light of the conceptual underpinnings motivating the different methodological steps followed and compared with the more common indexes used in the literature. We anticipate that the country ranking originated by climate-change risk is quite different from the country ranking that can be originated considering only "vulnerability" to climate-change. Trivial this may seem, we also show that a measure of climate vulnerability is much closer to what current indexes are proposing. But, in doing so, we claim that they also convey just partial and potentially misleading information.

In what follows: section 2 describes the structure of the climate risk index and its components; section 3 reports the computation process, while section 4 describes the data sources. Section 5 describes the results; section 6 offers a discussion and comparison with other indexes; section 7 concludes.

2. Materials and methods

Following the IPCC definition of climate risk our index evaluates the three climate risk dimensions of hazard, exposure, and vulnerability, in its turn divided into sensitivity and adaptive capacity. These four components are evaluated across five different types of climate risks arising from changes in 1) mean temperature; 2) extreme temperature; 3) water availability; 4) (coastal and river) floods 5) malaria suitability. These components have been chosen as they are often indicated by the literature as major conveyors of climate change impacts. Each risk type and dimension are measured by one or more indicators that are normalized, weighted and aggregated into a summarizing risk index measure (see section 3).

The indicators used to measure each risk type along its several dimensions were initially selected by means of expert judgment and evidence from the literature, to be then refined according to data availability and access.

The overall final index structure is reported in Table 1. The definition, motivation for the inclusion and source of each single indicator are extensively reported in Appendix 1.

Aggregate	*Individual climate-risk category*	*Risk dimension*	*(Composite) Indicator*
Aggregate Climate Risk	Mean Temperature Risk	Hazard	Changes in mean temperature
		Exposure	Total population
		Sensitivity	Biodiversity loss
			Percentage urban population
			Population growth
			Income inequality (Gini Index)
		Adaptive Capacity	Quality of institutions
			Education
			GDP per capita
			Access to basic services
	Extreme Temperature Risk	Hazard	Changes in heat waves
		Exposure	Urban population
		Sensitivity	Share of population below 14
			Share of population above 65
			Percentage urban population
			Population growth
			Income inequality (Gini Index)
		Adaptive Capacity	Quality of institutions
			Education
			GDP per capita
			Access to basic services
	Water Scarcity Risk	Hazard	Changes in number of droughts
		Exposure	Total population
			Agricultural value added
		Sensitivity	Share of population below 14
			Share of population above 65
			Percentage urban population
			Agricultural value added as % of GDP
			Population growth
			Income inequality (Gini Index)
		Adaptive Capacity	Quality of institutions
			Education
			GDP per capita
			Access to basic services
	Flood Risk	Hazard	Change in the number of floods
		Exposure	Population living in LECZ
			Population living in floodplains
		Sensitivity	Share of population living in LECZ
			Share of population living in floodplains
			Population growth
			Income inequality (Gini Index)
		Adaptive Capacity	Quality of institutions
			Education
			GDP per capita
			Access to basic services
	Health Risk	Hazard	Changes in malaria suitability
		Exposure	Total population
		Sensitivity	Percentage urban population
			Population growth
			Income inequality (Gini Index)
		Adaptive Capacity	Quality of institutions
			Education
			GDP per capita
			Access to basic services

Table 1 Structure of the composite climate risk index. Source: Own illustration.

At the “bottom level”, “Biodiversity loss”, “Quality of Institution” and “Access to Basic Services” are on their turn composite indicators whose components are shown in Table 2.

Composite Indicator	**Indicator**
Biodiversity Loss	Threatened plant species
	Threatened mammal species
	Threatened bird species
	Threatened fish species
Quality of Institutions	Government effectiveness
	Control of corruption
	Political Stability and Absence of Violence/Terrorism
	Regulatory quality
	Rule of Law
	Voice and Accountability
Access to Basic Services	Percentage population access to at least basic water services
	Percentage population access to electricity
	Percentage of population using the Internet
	Mobile cellular subscriptions per 100 people

Table 2: Composite indicators and the corresponding individual indicators. Source: Own illustration.

2.1. Computation

2.1.1. Normalisation

After indicators’ have been selected, the first necessary step is their normalisation. This allows a homogeneous comparison across variables presenting different units of measurement. The normalisation procedure used is the “simpler” rang approach described below.

- Arrange the m alternatives into an evaluation vector x in a m-dimensional column vector with a typical element $x_i, i = 1, \dots, m$:

$$(x_1 \; \dots \; x_m)$$

- Determine the minimum x_{min} and the maximum x_{max}.
- Normalize the m values in the evaluation vector x according to:

$$x_i^* = \frac{x_i - x_{min}}{x_{max} - x_{min}} \qquad (1)$$

Then the m alternatives can be homogeneously compared according to x_i^*.

2.1.2. Weighting and aggregation

After the normalisation, a key decision to be taken is determining how the different indicators composing the index are aggregated along its “nodes” or upper-level components. This process is strictly related to the weight that must be assigned to each of the components. The weighting and aggregation procedures define together the “properties” of the risk index or, put differently, reflect that specific set of preferences that will guide the evaluation by the Users.

To start from a “most standard case” we assign to the n criteria (indicators) equal weights[2].

Then, looking at the structure of the risk index from Table 1, four different aggregation steps can be identified:

The first step computes the three composite components: “Biodiversity loss”, “Quality of Institutions” and “Access to basic services”. These composite indicators have been obtained with simple averaging of the normalised component indicators.

The second step computes the “Hazard”, “Exposure”, “Sensitivity” and “Adaptive Capacity” dimensions of each of the five climate risk types. These composite components are also obtained by simple averaging.

Simple averaging has been chosen in these first two aggregation steps as we, subjectively, decided, after the application of equal weighting, to keep on using a rather neutral perspective in getting to the four components of climate risk types.

The third step computes the five climate risk dimensions (mean temperature risk, extreme temperature risk, water scarcity risk, flood risk, health risk) aggregating “Hazard”, “Exposure”, “Sensitivity” and “Adaptive Capacity”. In this case, rather than simple averaging, we use the following formula:

$$R_i = \sqrt{Hazard_i \cdot Exposure_i} \cdot \frac{1}{(1+k)} \cdot \frac{(1+k \cdot Sensitivity_i)}{(1+k \cdot Adapt.Cap_{\,i})} \tag{2}$$

This specification introduces a multiplicative relation between the Hazard, Exposure, and the joint Sensitivity and Adaptive Capacity constituents of Vulnerability.

The multiplicative relation in (2) reflects the principle that if one component of risk is null, the risk, as a whole, is null. This principle is partly loosened in the treatment of vulnerability. This component

2 This subjective choice can be easily modified.

depends positively on sensitivity and negatively on adaptive capacity. Its effect on risk is however also governed by the parameter *K*. For instance, a value of *K* equal to zero would mean that vulnerability (sensitivity and adaptive capacity) is uninfluential on risk. This parameter has been introduced given the difficulty to objectively quantify the role of vulnerability, and thus to give the possibility to the User of the index to assign a value responding to her subjective preferences/knowledge. In the current exercise, after internal scrutiny within the experts on climate change risk assessment at CMCC, a quite conservative or prudential attitude towards adaptive capacity emerged. Specifically, assuming the maximum possible normalised adaptive capacity (i.e. a value of 1) and the minimum possible normalised sensitivity (i.e. a value of 0), the idea was that roughly 60% of the combined effect of exposure and hazard still remains. This would correspond to a value of *K* of 0.25, that we used as our "reference". Anyway, sensitivity analyses for different values of *K* are performed and the results reported in the appendix (see Appendix VI). The square root is introduced to grant the "idempotency" of the aggregation.

The fourth step aggregates into the global risk index the five climate risk types (mean temperature risk, extreme temperature risk, water scarcity risk, flood risk, health risk). This is done by applying the Ordered Weighted Averaging (OWA) methodology (see Appendix II). This procedure allows treating the complex evaluation that may arise in risk assessment, with more flexibility than under simple averaging. A typical case to judge could be the following: is a "context" (that in our case is a country or region) riskier/more at risk when only one risk type materialises, as opposed to when more (say three) risk types occur, all however with lower "intensity" than the risk in the first "context"? If the answer (for whatever reason) is YES, an averaging procedure may still attach higher values to the second rather than to the first case, failing to capture, for instance, that the User of the information, say a decision maker, is more oriented towards the maximum observed value of risk regardless of all the others.

An OWA method, of which simple averaging is a special case, can accommodate different aggregation preferences or strategies by the User of the system without prejudice to the obvious rationality properties, such as monotonicity and boundary conditions[3]. Therefore, in this work we developed an algorithm capable of representing different preference structures as function of a

[3] Resolving this issue more objectively, through quantification, is possible in principle, but would require an enormous amount of data in practice such as the calculation of the percentage of the population subject to the different types of hazards considered in isolation and in combination as well as the probabilities of such events.

parameter (α). A value of zero for the parameter (α) would mean that the decision-maker attaches importance to only the highest risk and disregards the rest, while a value of one would mean the decision-maker attaches equal importance to all risks. Then we conducted appropriate sensitivity analyses to evaluate the robustness of the ranking we obtained.

2.2. Data

The index compares 145 countries depicted and listed in Appendix III. Some countries could not be taken into account due to an excess of missing data (e.g. Congo, Egypt, Somalia, Iran).

The description of the indicators, the rationales for their inclusion and the information sources are reported in Appendix I. Overall, we retrieved social economic data from: (World Bank Open Data 2022), (Worldwide Governance Indicators 2022), (World Development Indicators: Sustainable Development Goals 2022). Income inequality data were obtained from the World Income Inequality Database (WIID 2022), while those on literacy rates were sourced from Our World in Data (Our World in Data 2022).The temperature and precipitation data were sourced from the ERA5 of the ECMWF, the European Centre for Medium-Range Weather Forecasts (European Centre for Medium-Range Weather Forecasts (ECMWF) 2022). The flood data were retrieved from the Emergency Events Database (EM-DAT 2022), while the data on malaria suitability were obtained from LANCET Countdown (Lancet Countdown 2022). The population numbers in flood plains and LECZ were obtained from NASA estimates (NASA 2022).

The indicators reported are an average of the time series for the years between 2000 and 2020 to capture climate risk under "today's climate conditions". Climate is indeed characterised over long (usually 20 or 30-years) time periods. This also helped us to address the issue of individual missing values that would have been much more problematic had we used just the last known value for an indicator.

3. Results and Discussion

3.1. Aggregate climate-change risk ranking.

In the climate risk ranking (also referred to as "aggregate risk ranking") countries with large populations tend to rank high. The opposite occurs with small countries (Figure 2). Accordingly, China and India lead the climate risk ranking followed by Indonesia, Pakistan, Vietnam, Bangladesh, and the Philippines. Conversely, Vanuatu consistently ranks among the least-at-risk countries, together with small island states such as Sao Tome and Principe. Also European countries with a small population, such as Iceland and Luxembourg, tend to rank below average in terms of climate risk.

In essence, our index emphasises a dominance of the exposure component of risk over all the other components, in particular adaptive capacity which is part of vulnerability. Evidence of this dominance is provided by Figure 3 illustrating the relative contributions of Hazard, Exposure and Vulnerability to total climate risk. Exposure, in turn, is strongly driven by the population at risk that increases with the country population[4].

Eventually, in all the five different risk types, and, accordingly, also in the total climate change risk, the more populated a country is, the more exposed it is, and the riskier it gets. This is also a consequence of treating the different hazards equally. For instance, we assume that a person potentially hit by increases in average temperatures equals one hit by a flood event. This explains why, for instance, the United States or "more populated" developed countries like Italy or Germany rank rather high in risk and higher than less populated developing countries.

One could expect that by increasing k, and thus the importance of vulnerability, the picture may change. This is only partially true. Indeed, this ranking proves to be quite robust in the top and especially bottom ten positions that remain essentially the same for all values of the parameter k and also of the OWA weights (the α_s) (Figure 4).

The sensitivity, both to the different values of *ks* or the OWA weight, increases moving to the central ranking positions, featuring countries with "medium-size" populations as well. When exposure (with population) decreases, the role of other risk components, and of k, increases. Examples in this direction are given by the wider variability exhibited by the Russian Federation, Mexico, Japan and Ethiopia. Still, there is not a clear distinction across developed and developing countries that are quite mixed. For instance, the United Kingdom, France, Spain and Ukraine, Colombia and Argentina, Myanmar, Thailand, Malaysia, Saudi Arabia and Afghanistan, Uganda, Kenya, Algeria, Morocco, Haiti all get an above average climate risk score.

[4] Indeed (see Table 1) in the case of mean temperature risk, water scarcity risk, malaria risk, the exposed population coincides with the total country population. In the case of extreme temperature risk, it is the urban population, yet larger in more populated countries. In the case of flood risk, it is the total population living in low elevation areas, still larger in larger countries.

To observe small island states and more in general developing countries on the top of the aggregate risk ranking, it is necessary to consider the Hazard or the Vulnerability components alone. This especially when the OWA weight would reflect a "pessimistic" attitude of the decision maker, i.e., she cares particularly (only) about the worst possible case (Appendix VI, Figure 20 and Figure 21-24).

Figure 5 depicts the contributions of the five individual risk types to the total risk. Notwithstanding some differences across countries, and a somehow balanced role of the different components, health risk and mean temperature risk play, on average, a larger role. This trend is robust under a sensitivity analysis across the different values of *k*.

This is also reflected in the correlation of the total climate risk scores with its individual components. We find higher correlation with health, mean temperature and flood risk, and a slightly lower one with water scarcity and extreme temperature risk (Table 3).

	Individual Climate Risk Types				
	Mean	Extreme	Water	Flood	Health
Climate risk	0.74	0.62	0.65	0.72	0.78

Table 3. Correlation between total climate change risk and individual climate risk type (k = 0.25, and equal weight assigned to the different risk types). Source: Own illustration.

The individual climate risk types are, in most cases, only mildly positively correlated with each other, but, again, due to the role of exposure/population, as expected, higher correlation is identifiable across mean temperature, health and water scarcity risk (Table 4).

	Mean	Extreme	Water	Flood	Health
Mean temperature risk	1	0.33	0.40	0.26	0.69
Extreme temperature risk	0.33	1	0.26	0.37	0.25
Water scarcity risk	0.40	0.26	1	0.26	0.46
Flood risk	0.27	0.37	0.26	1	0.43
Health risk	0.69	0.25	0.46	0.43	1

Table 4. Correlation matrix for the individual climate risks types (k = 0.25). Source: Own illustration.

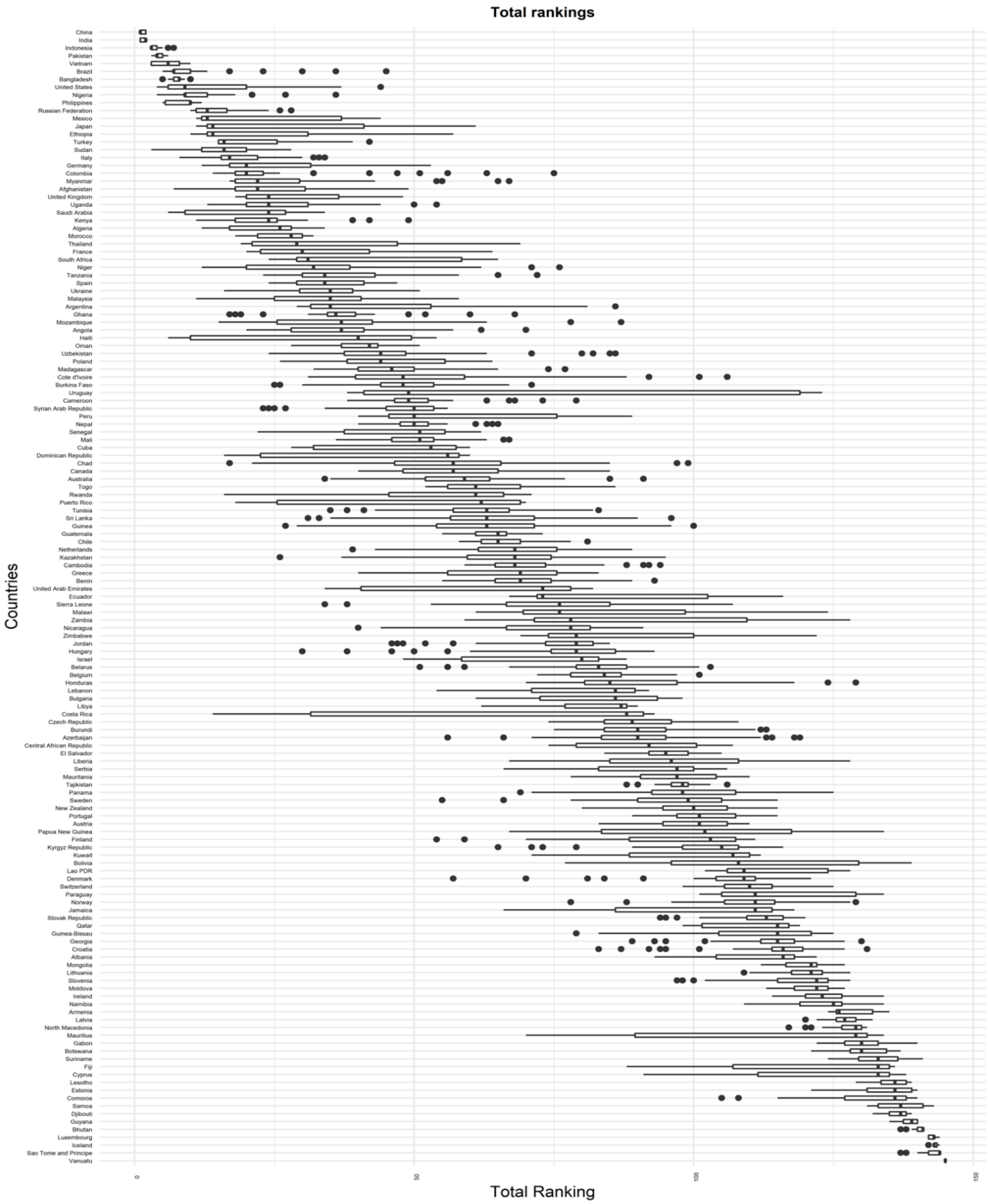

Figure 2 Country ranking according to total climate change risk. Countries are ordered by the median ranking. Variability bars arises from the different values of k and the valuation strategies of the Decision Maker expressed via the OWA weights. Source: Own illustration.

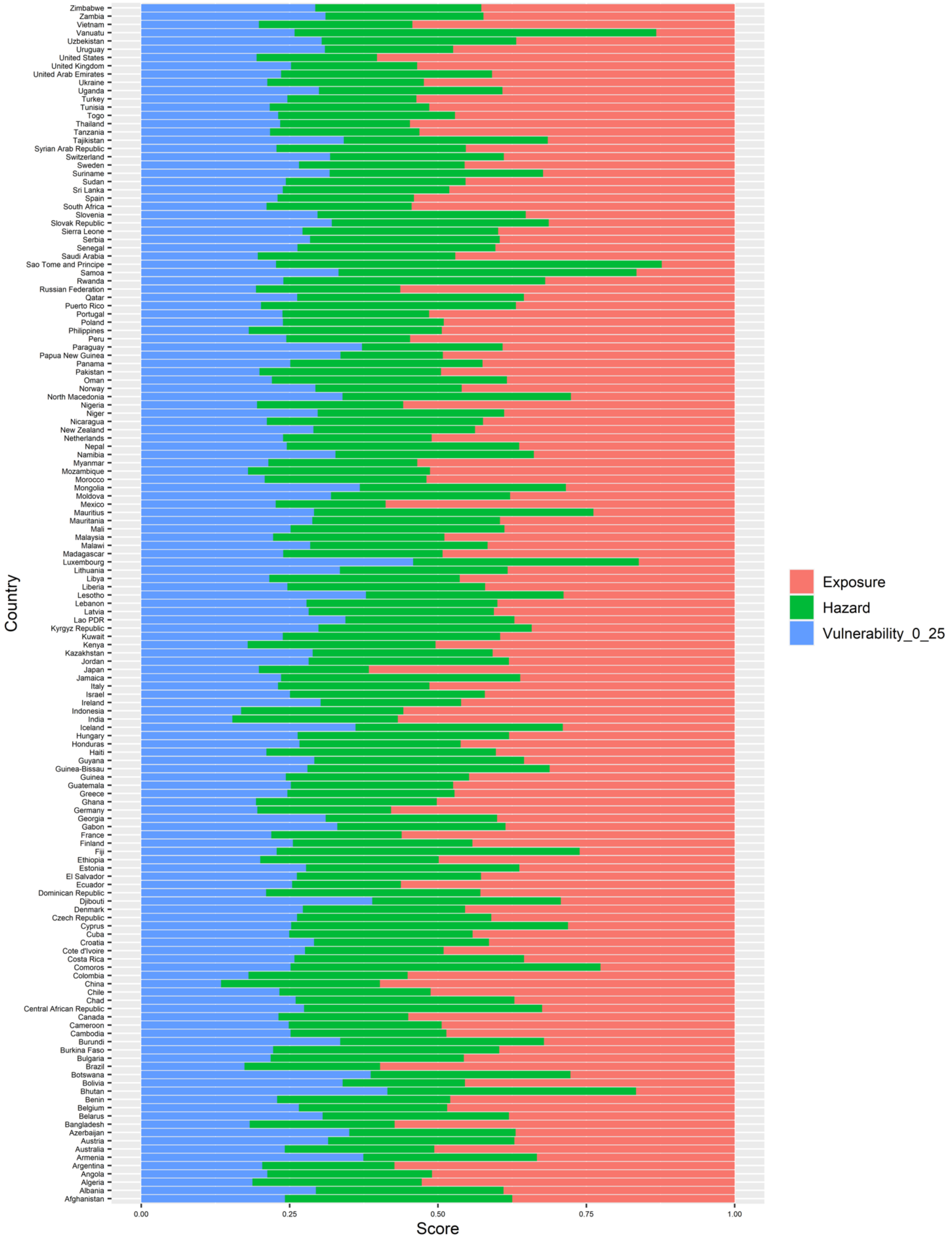

Figure 3. Contribution of Hazard, Exposure and Vulnerability to total climate change risk index (k = 0.25, α=1equal weighting of individual risk types). The relative contributions have been obtained by adding up the component scores of each individual risk type and putting them in a relation to the total sum.
Source: Own illustration.

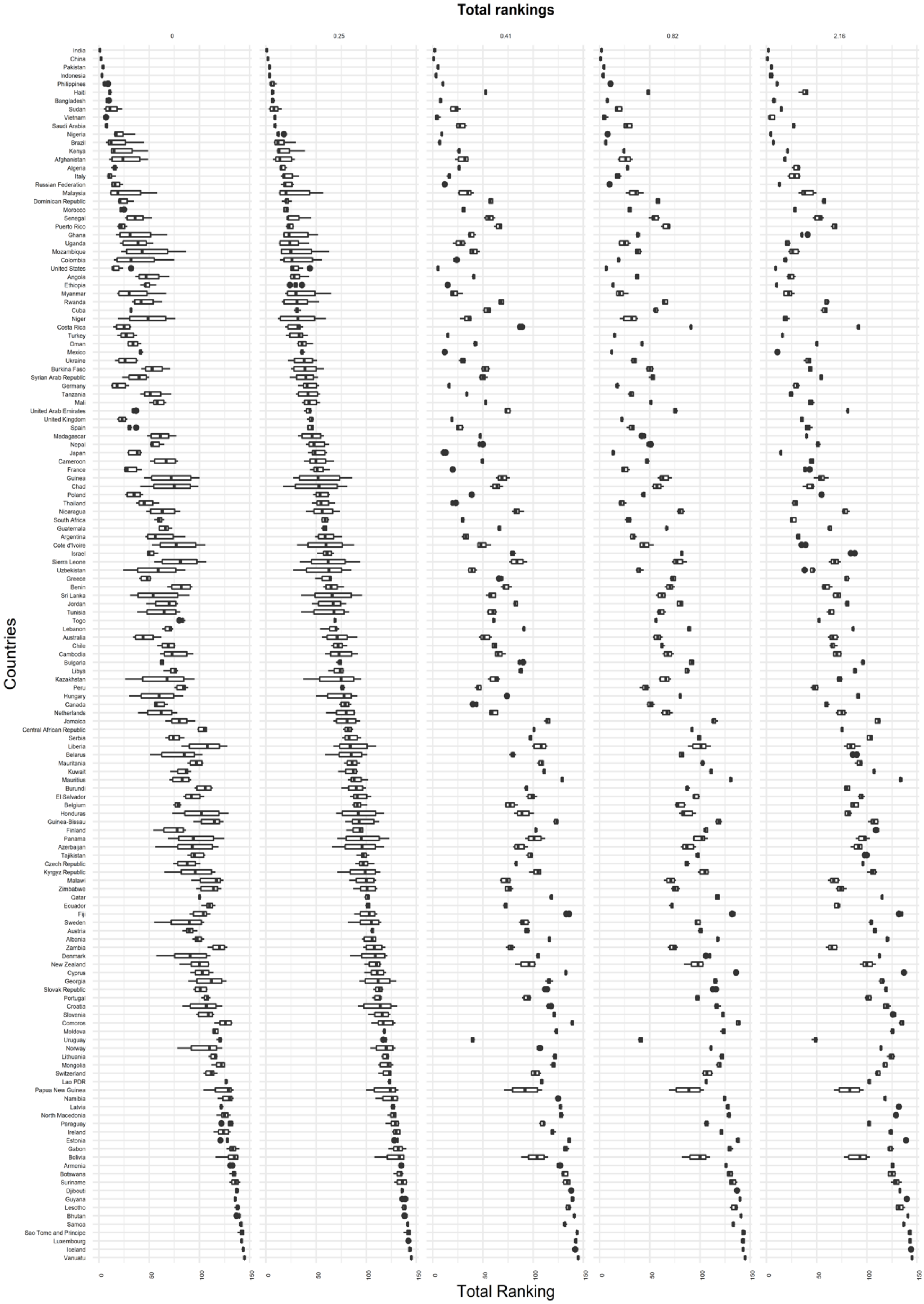

Figure 4. Total rankings for different values of the parameter k (from left to right: k = 0, k = 0.25, k = 0.41, k = 0.82, k = 2.16). The variation in the rankings arises from the valuation strategies of the Decision Maker. The countries are ordered by the median ranking of a country for k = 0.25 over all valuation strategies of the Decision Maker.
Source: Own illustration.

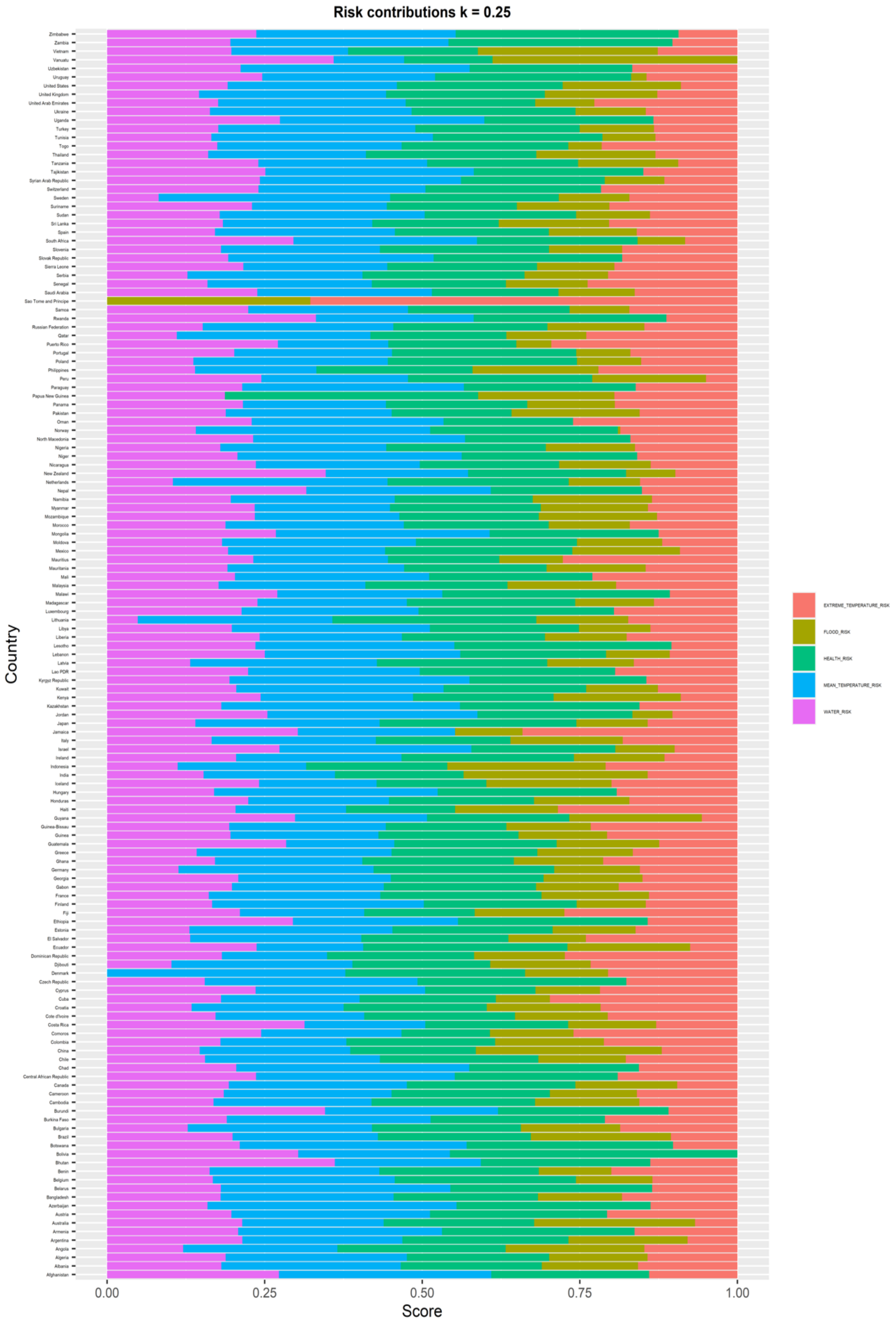

Figure 5 Contributions of individual risks to total risk under equal valuation for k = 0.25. Source: Own illustration.

3.2. Individual climate-change risk component ranking

Mean temperature risk. (Scores for different values of k are depicted in Appendix IV Figure 7). What we already noted for the total climate change risk index, is replicated here. Countries with larger population, and thus larger exposure, still tend to rank high in mean temperature risk. Accordingly, in the top positions we find "hot and populated" countries like China, Sudan, Pakistan, Afghanistan, India, and Bangladesh. African countries are also well represented among the riskier: Sudan, Niger, Uganda, Chad, Nigeria, Burkina Faso, Mali. Some traditionally considered "cold countries" like Norway, Finland, Sweden, the Russian Federation, but also UK or Germany rank anyway in a middle risk position and higher than hotter countries. Although against intuition at the first sight, (and keeping in mind the role of the exposure component), it is important to recall that the mean temperature hazard is driven by temperature deviations against own long-term mean. Accordingly, a cold country can highlight deviations comparable, or larger than, that of a warmer country. For the very same reasons, in the last positions of the mean temperature risk we find the highly expected Iceland together with less obvious small and warm island states.

Extreme temperature risk (Scores for different values of k are depicted in Appendix IV Figure 8). Extreme temperature risk also visually denotes a lower correlation with the total climate risk. The exposure dimension is also different as it is driven now by urban population and its age structure, rather than by total population. Furthermore, as for average temperature risk, the concept of "extreme" is defined as a deviation with respect to each country's "standard" characteristics. Therefore, also a cold country can exhibit a high extreme temperature hazard score if the temperature deviation is significant in relative terms although reaching "low" absolute levels. Accordingly, China is now in a rather central position. As one could expect, several hot Caribbean countries score high, but also Denmark, France, Belarus or the Russian Federation. Similarly, at the bottom of the rank, not only "cold" countries like Iceland, and Canada, can be found, but also many "hot" African countries like South Africa, Lesotho, Botswana, Zimbabwe, Zambia, Malawi, Burundi.

Water scarcity risk. (Scores for different values of k are depicted in Appendix IV, Figure 14). This risk category is also relatively less correlated with total climate risk. The top and bottom positions in the ranking follow somewhat more the intuition. Riskier are hot and dry countries in Africa especially if landlocked like Rwanda, Uganda, and Burundi, in the Middle East like Saudi Arabia, Oman, Lebanon, and the Syrian Arab Republic. Exposure is dominated by total population, and this also tends to put quite high in the rankings China, India, Pakistan or the USA. North European and less populated countries tend to score low on water risk.

Flood risk. (Scores for different values of k are depicted in Appendix IV Figure 9). We recall that this risk encompasses both riverine and sea flood hazards. Also in this case the size matters. More extended and more populated coastal zones and larger river basins increase country exposure, which in the index appears to be only partially compensated by the sensitivity and adaptive capacity components. Accordingly, large countries, especially with long coast lines like India, China, Indonesia, but also Italy or Australia, rank in the top positions, outperforming medium-small island states. Among these, the most at risk are Haiti and the Philippines. Vanuatu, Sao Tome, Fiji, Samoa, are in the middle risk position. Landlocked countries, consistently with intuition, tend to score low on flood risk.

Health risk. (Scores for different values of k are reported in Appendix IV Figure 11). The correlation between the total climate risk ranking of a country and the health climate risk scores clearly transpires from the overall monotonic appearance of the image. The highest variability in the mean temperature risk ranking is displayed by European, North American and African countries. Large countries tend to lead the ranking on health risk. India scores as the riskiest in the benchmark scenario, followed by the Philippines, Indonesia, China, Nigeria, Ethiopia, and Brazil. The USA ranks at place thirteen. Small countries are at the bottom of the ranking with Sao Tome and Principe and Jamaica sharing the last position. The least risky countries in terms of health risk are all small: Djibouti, Guyana, Bhutan, Samoa, Luxembourg, Comoros, Iceland, Vanuatu.

Given the features of our methodological underpinnings, we partly expected the climate risk index to behave rather differently from the indexes of climate change risks currently available. The reasons for the discrepancy between the rankings obtained with the climate risk index and with those of the Notre Dame-GAIN index (ND-GAIN) the ESPON climate index (ESPON) and the Standard & Poor climate risk index (S&P Global Ratings 2014) are discussed in what follows. To ensure the comparability of the scores, the discussion is framed in terms of the ranking of countries, assigning the first place to the least risky and the last one to the riskiest one, running the ranking only for the countries covered by both the climate risk index proposed here and by the index it is compared to.

We remind the reader that ours is an attempt to translate the IPCC's definition of climate risk into a viable climate risk index that can be computed based on well-established and publicly available datasets. Our index may diverge from the currently available one for the following reasons:

- The climate risk index covers a different number of countries with respect to other indexes.
- The climate risk index covers a different time span with respect to other indexes.
- The climate risk index is computed based on a different set of factors than the ones used in the computation with respect to other indexes.

These potential sources of divergence are discussed below:

- **Different number of countries.** The coverage of world countries depends ultimately on the availability of data and on the geographical focus of the study. The climate risk index has a fairly comprehensive coverage (145 countries), two countries more than ND-GAIN. S&P covers 103 countries. ESPON index covers EU27 countries at the NUTS3 sub-national (usually provincial) level, thus national averages had to be computed; since the climate risk index does not cover Malta and Romania, 25 countries in total can be compared for this index.
- **Different temporal coverage.** The climate risk index is computed for 2021, but it can be computed for previous years as well. S&P, published in 2014, was computed for 2012; ESPON yields the change in vulnerability from a reference time frame (1961-1990) compared to projections to the end of this century (2071-2100) as computed in 2011 using a specific modelling framework (COSMO-CLM (Rockel et al. 2008) for the IPCC AB1 scenario). The only index for which no temporal discrepancy is present is ND-GAIN.
- **Different "ingredients".** The choice of factors to be aggregated within the indexes and how is the major reason for their difference and similarities. The reader is referred to the methodological Section 3 for a detailed depiction of the approach. Here it suffices to recall that the approach applied here follows the definition of climate risk proposed by IPCC in AR5: it is the result of the combination of Hazards, Exposure, Sensitivity and Adaptive capacity. These factors are rarely all simultaneously present in the other indexes.

The ND-GAIN index is primarily a vulnerability-based index, although it integrates to some extent adaptive capacity of countries through indicators aimed at capturing the "readiness to improve resilience". The S&P index builds on ND-GAIN by adding two factors intended to capture exposure (namely, population living below five meters altitude in 2000 and agriculture's share of GDP in 2012). The ESPON index has a structure apparently akin to the climate risk index, in that it considers exposure, impacts and adaptability; however, it considers vulnerability as the result of the interaction of these factors (and of adaptation and mitigation measures) rather than one of the components of climate risk at the same level of others; thus, the concepts of vulnerability and risk seem to largely overlap in the ESPON framework.

In short, what seems to be more deeply integrated within our climate risk index, is the role of hazard and exposure. Exposure is by and large correlated with population, hence the world's largest countries in terms of inhabitants, such as China and India, tend to be riskier in our approach than countries with a tiny population, including little island states which are often portrayed as the likely early victims of climate change.

Indeed, looking at Figures 12, 13 and 14 in Appendix V it can be observed that the full version of the climate risk index provides very different rankings than the other indexes. However, once the components related to hazards and exposure are both switched off, the distance is strongly reduced- particularly in the case of the comparison with ND-GAIN, where the average absolute distance drops from 40 positions to only 13 (Figure 12). Lower reductions in average distance can be observed when one or the other class of factors is silenced, with stronger reductions in distance when exposure factors are silenced in the case of ND-GAIN (Figure 12) and S&P (Figure 13), while the effect is the same in the case of ESPON (Figure 14).

Thus, our preliminary conclusion is that the currently available climate risk indexes are in fact more climate vulnerability (sensitivity and adaptive capacity) index and, as such, can give quite partial support to those Users (or applications) where the full climate risk dimension is to be considered.

4. Conclusions

This work starts from the attempt to apply rigorously the definition of climate change risk by the IPCC. We believe that, albeit unavoidably subjective, our choice of the single risk types and of the indicators substantiating the hazard, exposure, sensitivity, and adaptive capacity dimensions of climate risk, are quite standard. The weighting and aggregation approaches used, which are transparent and reproducible, have been tested with sensitivity analyses without substantive changes in the final results. All in all, the study shows that a full compliance with the climate change risk definition of the IPCC may easily lead to attribute a particular importance to the exposure component and to population as one of its main drivers.

Countries with large populations such China, India, but also the US consistently obtain high risk rankings, while countries with small populations, score consistently low. This result partly contradicts the common notion that developing countries located at low latitudes, and small island states highly exposed to sea-level rise are extremely risky.

The reasons for these findings are many. Firstly, our risk index measures the hazards as experienced in the last 20 years. Therefore, the climate signal may still be relatively mild. Secondly, the hazard is represented by deviations against the country's own mean. Accordingly, a cold country can demonstrate a hazard comparable or larger than that of a hot country depending upon the relative deviations. Thirdly, we consider equally important the different hazards and exposures in the different countries. Fourthly, we assume that sensitivity and adaptive capacity have the same effect in size, although opposite in sign, in determining risk. The fact that in our "default" experiment we assume quite a pessimistic view on the ability of adaptive capacity to smooth damages plays a minor role as results are robust even when this assumption is dropped.

The climate change risk concept endorsed by other exercises like those proposed by rating agencies, or the ND-GAINS tends to depict a more intuitive picture with high income countries ranking low in risk and low-income countries ranking high. We show that also our index can reasonably replicate this pattern if we just consider its vulnerability component.

As a general conclusion, we hint that many of the currently available indexes are in fact vulnerability indexes mostly capturing sensitivity and adaptive capacity. This is fine, but this is not always clear and can induce misinterpretation as the addition of hazard and exposure can substantively change the picture. A direct consequence of this bias is to underestimate climate change risk and the potential benefits of climate policies in rich countries and consider climate change mostly an issue regarding the developing ones. Against this background, we provide a verifiable and replicable method to address climate change risk in its full determinants based on publicly available data and a transparent process.

5. References

Arent, DJ, RSJ Tol, E Faust, JP Hella, S Kumar, KM Strzepek, FL Tóth, D Yan, A Abdulla, H Kheshgi, H Xu, and J Ngeh (2015). Key economic sectors and services. In *Climate Change 2014 Impacts, Adaptation and Vulnerability: Part A: Global and Sectoral Aspects*. https://doi.org/10.1017/CBO9781107415379.015

Bordogna, G, M Boschetti, PA Brivio, P Carrara, M Pagani, and D Stroppiana (2011). Fusion Strategies Based on the OWA Operator in Environmental Applications. In *Studies in Fuzziness and Soft Computing*, J. Kacprzyk (ed.). DOI: 10.1007/978-3-642-17910-5_10.

Bosello, F, and R Parrado (2020). Macro-economic assessment of climate change impacts: Methods and findings. *Ekonomiaz*, 97(1), 45–61.

Brooks, N, WN Adger, and PM Kelly (2005). The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation. *Global Environmental Change*, 15(2), 151–163. https://doi.org/10.1016/j.gloenvcha.2004.12.006.

Carleton, TA, and SM Hsiang (2016). Social and economic impacts of climate. *Science*, 353(6304). DOI: 10.1126/science.aad9837.

Connelly, A, J Carter, J Handley, and S Hincks (2018). Enhancing the practical utility of risk assessments in climate change adaptation. *Sustainability (Switzerland)*, 10(5), 1–12. doi:10.3390/su10051399.

DATA.NASA.GOV (2022). Available at https://data.nasa.gov/. Last accessed on the 18.12.2022.

EM-DAT (2022). Available at https://www.emdat.be/. Last accessed on the 18.12.2022.

European Centre for Medium-Range Weather Forecasts (ECMWF) (2022). Available at https://www.ecmwf.int/. Last accessed on the 18.12.2022.

Fitch Ratings (2019). Introducing ESG Relevance Scores for Corporates: Marking the Intersection of Credit Risk and ESG Risks.

Gorsevski, P V., KR Donevska, CD Mitrovski, and JP Frizado (2012). Integrating multi-criteria evaluation techniques with geographic information systems for landfill site selection: A case study using ordered weighted average. *Waste Management*, 32(2), 287–296. doi:10.1016/j.wasman.2011.09.023

Howard, PH, and T Sterner (2017). Few and Not So Far Between: A Meta-analysis of Climate Damage Estimates. *Environ Resource Econ*, 68. DOI 10.1007/s10640-017-0166-z

IPCC (2014). IPCC 2014: Summary for policy makers. In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel and J.C. Minx (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

IPCC (2022). Key Risks Across Sectors and Regions. *IPCC WGII Sixth Assessment Report*, 20–22.

Kaplan, S, and BJ Garrick (1981). On The Quantitative Definition of Risk. *Risk Analysis*, 1(1), 11–27. https://doi.org/10.1111/j.1539-6924.1981.tb01350.x

Kling, G, U Volz, V Murinde, and S Ayas (2021). The impact of climate vulnerability on firms' cost of capital and access to finance. *World Development*, 137, 105131. https://doi.org/10.1016/j.worlddev.2020.105131

Klusak, P, M Agarwala, M Burke, M Kraemer, and K Mohaddes (2021). Rising temperatures, falling ratings: The effect of climate change on sovereign creditworthiness.

Lancet Countdown (2022). Available at https://www.lancetcountdown.org/. Last accessed on the 18.12.2022.

Malczewski, J, T Chapman, C Flegel, D Walters, D Shrubsole, and MA Healy (2003). GIS multicriteria evaluation with ordered weighted averaging (OWA): Case study of developing watershed management strategies. *Environment and Planning A*, 35(10), 1769–1784. DOI:10.1068/a35156

Moody's Investors Service (2016). How Moody's Assesses the Physical Effects of Climate Change on Sovereign Issuers.

Moody's Investors Service (2020). General Principles for Assessing Environmental, Social and Governance Risks Methodology.

ND-GAIN (2022). Available at https://gain-new.crc.nd.edu/. Last accessed on the 18.12.2022.

Our World in Data (2022). Available at https://ourworldindata.org/. Last accessed on the 18.12.2022.

Reisinger, A, M Howden, C Vera, M Garschagen, M Hurlbert, S Kreibiehl, KJ Mach, K Mintenbeck, B O'neill, M Pathak, R Pedace, H-O Pörtner, E Poloczanska, M Rojas Corradi, J Sillmann, M Van Aalst, D Viner, R Jones, AC Ruane, and R Ranasinghe (2020a). The concept of risk in the IPCC Sixth Assessment Report: a summary of cross-working group discussions. *Intergovernmental Panel on Climate Change, Geneva, Switzerland.*, (September), 15.

Reisinger, A, M Howden, C Vera, M Garschagen, M Hurlbert, K Mach, K Mintenbeck, BO Neill, M Pathak, R Pedace, MR Corradi, M Van Aalst, and D Viner (2020b). Use of risk concepts in IPCC assessments. (December), 1–13.

Rockel, B, A Will, and A Hense (2008). The regional climate model COSMO-CLM (CCLM). *Meteorologische Zeitschrift*, 17(4), 347–348. DOI: 10.1127/0941-2948/2008/0309

S&P Global Ratings (2014). Climate Change Is A Global Mega-Trend For Sovereign Risk.

S&P Global Ratings (2018). How Environmental, Social, and Governance Factors Help Shape the Ratings on Governments, Insurers, and Financial Institutions.

Stern, N (2006). The Economics of Climate Change: The Stern Review.

TCFD (2017). Recommendations of the Task Force on Climate-related Financial Disclosures. *Task Force on Climate-related Fiancial Disclosures*, (June), 1–74.

Tol, RSJ (2018). The Economic Impacts of Climate Change. *Review of Environmental Economics and Policy*, 12(1). https://doi.org/10.1093/reep/rex027

Torra, V (2011). The WOWA operator: A review. *Studies in Fuzziness and Soft Computing*, 265, 17–28. https://doi.org/10.1007/978-3-642-17910-5_2

Volz, U, J Beirne, NA Preudhomme, A Fenton, E Mazzacurati, N Renzhi, and J Stampe (2020). Climate Change and Sovereign Risk. *SOAS Centre for Sustainable Finance*, (October), 133. https://doi.org/10.25501/SOAS.00033524

WEF (2022). The Global Risks Report 2022. Available at wef.ch/risks22. Last accessed on the 18.12.2022.

World Bank Open Data (2022). Available at https://data.worldbank.org/. Last accessed on the 18.12.2022.

World Development Indicators: Sustainable Development Goals (2022). Available at https://unstats.un.org/sdgs. Last accessed on the 18.12.2022.

World Income Inequality Database WIID (2022). Available at https://www.wider.unu.edu/project/wiid-—-world-income-inequality-database. Last accessed on the 18.12.2022.

Worldwide Governance Indicators (2022). Available at https://info.worldbank.org/governance/wgi/. Last accessed on the 18.12.2022.

Yager, RR (1988). On Ordered Weighted Averaging Aggregation Operators in Multicriteria Decisionmaking. *IEEE Transactions on Systems, Man and Cybernetics*, 18(1), 183–190. DOI: 10.1109/21.87068

Yager, RR (1993). Families of OWA operators. *Fuzzy Sets and Systems*, 59(2), 125–148. https://doi.org/10.1016/0165-0114(93)90194-M

Yager, RR (1996). Quantifier guided aggregation using OWA operators. *International Journal of Intelligent Systems*, 11(1), 49–73. https://doi.org/10.1002/(SICI)1098-111X(199601)11:1<49::AID-INT3>3.0.CO;2-Z

Zabihi, H, M Alizadeh, PK Langat, M Karami, H Shahabi, A Ahmad, MN Said, and S Lee (2019). GIS multi-criteria analysis by ordered weighted averaging (OWA): Toward an integrated citrus management strategy. *Sustainability*, 11(4). https://doi.org/10.3390/su11041009.

Appendix I. Indicators' description

- **Change in mean temperature**

Description: Change in mean annual temperature in the 2000-2020 period compared to long-term mean in the period 1970-2021.

Climate risk: Mean temperature risk

Risk dimension: Hazard

Rationale: Deviation from the long-term mean annual temperature enables to detect possible signals of climate change. It is relevant since an increase of the mean temperature would eventually lead to a breakdown of critical ecosystem services.

Calculation: First, a long term mean $\frac{1}{52}\sum_{j=1970}^{2021} t_j$ is calculated, which covers the period since the 1970s. This long term mean is understood as the baseline. Second, the deviations from the baseline $t_i - \frac{1}{52}\sum_{j=1970}^{2021} t_j$ are calculated by subtracting the long term mean from the yearly mean temperature t_i for (i = 2000, …, 2020). Third, the average deviation from the long-term mean by averaging among the deviations $t_i - \frac{1}{52}\sum_{j=1970}^{2021} t_j$:

$$\frac{1}{21}\sum_{i=2000}^{2020} \left(t_i - \frac{1}{52}\sum_{j=1970}^{2021} t_j\right)$$

Data Source: ERA-5 by ECMWF, the European Centre for Medium-Range Weather Forecasts.

Coverage: Country-level; global

Time series: 1970 - 2021

- **Changes in extreme temperature**

Description: Average yearly change in the Warm Spell Duration Index (WSDI) in the period 2000 - 2020 compared to the long-term mean in the period 1970-2021.

Climate risk: Extreme temperature risk

Risk dimension: Hazard

Rationale: A heat wave indicator is included since heat waves pose a serious health issue, especially in urban spaces. Heat waves also exacerbate the issues related to drought and wildfires.

Calculation: First, a long term mean $\frac{1}{52}\sum_{j=1970}^{2021} WSDI_j$ is calculated, which covers the period since the 1970s. This long term mean is understood as the baseline. Second, the deviations from the baseline $WSDI_i - \frac{1}{52}\sum_{j=1970}^{2021} WSDI_j$ are calculated by subtracting the long term mean from the yearly mean temperature $WSDI_i$ for (i = 2000, …, 2020). Third, the average deviation from the long-term mean by averaging among the deviations $WSDI_i - \frac{1}{52}\sum_{j=1970}^{2021} WSDI_j$:

$$\frac{1}{21}\sum_{i=2000}^{2020} \left(WSDI_i - \frac{1}{52}\sum_{j=1970}^{2021} WSDI_j\right)$$

Data Source: ERA-5 by ECMWF, the European Centre for Medium-Range Weather Forecasts.

Coverage: Country-level; global

Time series: 1970 – 2021 in the period 1970-2021.

- **Changes in drought**

Description: Change in drought frequency compared to a long-term mean in the period 1970-2021.

Climate risk: Water risk

Risk dimension: Hazard

Rationale: The three-month Standardized Precipitation Index (SPI) is a drought indicator. Droughts are relevant since they can result in shortage of drinking water or in quality changes of the available drinking water. Droughts could also affect food security by affecting crops and livestock.

Calculation: First, a long term mean $\frac{1}{52}\sum_{j=1970}^{2021} SPI_j$ is calculated, which covers the period since the 1970s. This long term mean is understood as the baseline. Second, the deviations from the baseline $SPI_i - \frac{1}{52}\sum_{j=1970}^{2021} SPI_j$ are calculated by subtracting the long term mean from the yearly mean temperature SPI_i for (i = 2000, …, 2020). Third, the average deviation from the long-term mean by averaging among the deviations $SPI_i - \frac{1}{52}\sum_{j=1970}^{2021} SPI_j$:

$$\frac{1}{21}\sum_{i\,=\,2000}^{2020} (SPI_i - \frac{1}{52}\sum_{j=1970}^{2021} SPI_j)$$

Data Source: ERA-5 by ECMWF, the European Centre for Medium-Range Weather Forecasts.

Coverage: Country-level; global

Time series: 1970 - 2021

Notes: The three-month Standardized Precipitation Index (SPI) is based on the probability of precipitation for a three-monthly time scale and is based on the long-term precipitation mean in the period 1970-2021.

- **Changes in floods**

Description: Change in the number of riverine and coastal floods in a given year compared to a long-term mean in the period 1970-2021.

Climate risk: Flood risk

Risk dimension: Hazard

Rationale: This indicator allows us to control incidences of floods, which result in the loss of lives, property, crops, livestock, and infrastructure. Floods also tend to worsen health outcomes due to waterborne diseases.

Calculation: First, a long term mean $\frac{1}{52}\sum_{j=1970}^{2021} NumberF_j$ is calculated, which covers the period since the 1970s. This long term mean is understood as the baseline. Second, the deviations from the baseline $NumberF_i - \frac{1}{52}\sum_{j=1970}^{2021} \quad NumberF_j$ are calculated by subtracting the long term mean from the yearly mean temperature $NumberF_i$ for (i = 2000, …, 2020). Third, the average deviation from the long-term mean by averaging among the deviations $NumberF_i - \frac{1}{52}\sum_{j=1970}^{2021} \quad NumberF_j$:

$$\frac{1}{21}\sum_{i\,=\,2000}^{2020} \quad (NumberF_i - \frac{1}{52}\sum_{j=1970}^{2021} \quad NumberF_j)$$

Data Source: Emergency Events Database (EM-DAT)

Coverage: Country-level; global

Time series: 1970 - 2021

- **Changes in malaria suitability**

Description: Average change in the Lancet Countdown malaria indicator compared to a long-term mean in the period 1970-2021.

Climate risk: Health risk

Risk dimension: Hazard

Rationale: This indicator captures the suitability for malaria, a vector-borne disease responsible for many fatalities. The disease is considered one of the most important infectious diseases.

Calculation: First, a long term mean $\frac{1}{52}\sum_{j=1970}^{2021} \quad MalariaS_j$ is calculated, which covers the period since the 1970s. This long term mean is understood as the baseline. Second, the deviations from the baseline $MalariaS_i - \frac{1}{52}\sum_{j=1970}^{2021} \quad MalariaS_j$ are calculated by subtracting the long term mean from the yearly mean temperature $MalariaS_i$ for (i = 2000, …, 2020). Third, the average deviation from the long-term mean by averaging among the deviations $MalariaS_i - \frac{1}{52}\sum_{j=1970}^{2021} \quad MalariaS_j$:

$$\frac{1}{21}\sum_{i\,=\,2000}^{2020} \quad (MalariaS_i - \frac{1}{52}\sum_{j=1970}^{2021} \quad MalariaS_j)$$

Data Source: The Lancet Countdown

Coverage: Country-level; global

Time series: 1970 - 2021

Notes: The Lancet Countdown malaria indicator is a threshold-based model that tracks global changes in the climatic suitability for malaria. Climatic suitability is defined as a coincidence of precipitation accumulation above 80 mm, an average temperature of 18–32°C, and relative humidity greater than 60%.

- **Threatened mammal species**

Description: Threatened mammal species that are classified by the International Union for Conservation of Nature (IUCN) as endangered, vulnerable, rare, indeterminate, out of danger, or insufficiently known.

Climate risk: Mean temperature risk

Risk dimension: Sensitivity

Composite indicator: Biodiversity loss

Rationale: The number of threatened species is a proxy for biodiversity loss, which compromises ecosystem service provision and increases the sensitivity to climate-related risk.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: World Bank

Coverage: 217 countries and territories

Time series: Single observation (2019)

Notes: Mammal species exclude whales and porpoises.

- **Threatened fish species**

Description: Threatened fish species that are classified by the International Union for Conservation of Nature (IUCN) as endangered, vulnerable, rare, indeterminate, out of danger, or insufficiently known.

Climate risk: Mean temperature risk

Risk dimension: Sensitivity

Composite indicator: Biodiversity loss

Rationale: The number of threatened species is a proxy for biodiversity loss, which compromises ecosystem service provision and increases the sensitivity to climate-related risk.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: World Bank

Coverage: 217 countries and territories

Time series: Single observation (2019)

- **Threatened bird species**

Description: Threatened bird species that are classified by the International Union for Conservation of Nature (IUCN) as endangered, vulnerable, rare, indeterminate, out of danger, or insufficiently known.

Climate risk: Mean temperature risk

Risk dimension: Sensitivity

Composite indicator: Biodiversity loss

Rationale: The number of threatened species is a proxy for biodiversity loss, which compromises ecosystem service provision and increases the sensitivity to climate-related risk.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: World Bank

Coverage: 217 countries and territories

Time series: Single observation (2019)

Notes: Birds are listed for every country within their breeding or wintering range.

- **Threatened higher plant species**

Description: Threatened plant species that are classified by the International Union for Conservation of Nature (IUCN) as endangered, vulnerable, rare, indeterminate, out of danger, or insufficiently known.

Climate risk: Mean temperature risk

Risk dimension: Sensitivity

Composite indicator: Biodiversity loss

Rationale: The number of threatened species is a proxy for biodiversity loss, which compromises ecosystem service provision and increases the sensitivity to climate-related risk.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: World Bank

Coverage: 217 countries and territories

Time series: Single observation (2019)

Notes: The numbers refer to native vascular plant species.

- **Total population**

Description: Total population of a country.

Climate risk: Mean temperature risk, Water risk, Health risk

Risk dimension: Exposure

Rationale: Higher mean temperatures have been shown to lead to an increase in suicide rates and to negatively affect mental health. Droughts lead to shortages of drinking water and food insecurity due to crop and livestock failures. Improved suitability for malaria propagation typically leads to more cases and more fatalities. Countries with larger populations are more exposed since there are more people to potentially suffer the consequences of mean temperature, water and health risk.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: World Bank

Coverage: 218 countries and territories

Time series: 1970 - 2021

Notes: Total population numbers reflect midyear estimates of resident numbers regardless of the legal status or citizenship.

- **Percentage urban population**

Description: People living in urban areas as defined by national statistical offices as a percentage of total population.

Climate risk: Extreme temperature risk

Risk dimension: Sensitivity

Rationale: Urban areas are warmer than their rural surroundings due to the urban heat island effect. This makes a country with a larger share of urban population more sensitive to extreme temperature risk since a larger percentage of the population potentially suffers the consequences of higher temperature.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: World Bank

Coverage: 181 countries

Time series: 1990 – 2019

- **Urban population**

Description: Total population in urban areas as defined by national statistical offices.

Climate risk: Extreme temperature risk

Risk dimension: Exposure

Rationale: Urban areas are warmer than their rural surroundings due to the urban heat island effect. This makes a country with a larger urban population more exposed to extreme temperature risk since more people potentially suffer the consequences of higher temperature.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Calculated based on the percentage urban population and total population data.

Data Source: World Bank

Coverage: 181 countries

Time series: 1990 – 2019

- **Population growth**

Description: Annual population growth rate

Climate risk: Mean temperature risk, Extreme temperature risk, Water risk, Flood risk, Health risk

Risk dimension: Sensitivity

Rationale: High population growth rate implies a high strain on the natural resources and infrastructure, which leaves a country more sensitive to climate risks.

Calculation: Average across all available observations for a sovereign between 2000 and 2020. The growth rate for year *t* is the exponential population growth rate from year *t-1* to *t*, in percentage.

Data Source: World Bank

Coverage: 181

Time series: 1990 - 2019

Notes: Population numbers reflect the de facto residents regardless of legal status or citizenship.

- **Percentage population below 14**

Description: Residents 14 years of age or younger as a percentage of total population.

Climate risk: Extreme temperature risk, Water risk

Risk dimension: Sensitivity

Rationale: Children are more susceptible to heat-related conditions than the general population. This renders countries with a higher percentage of them more sensitive to climate risks.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: World Bank

Coverage: 175 countries

Time series: 1990 - 2019

Notes: Population numbers reflect the de facto residents regardless of legal status or citizenship.

- **Percentage population above 65**

Description: Residents 65 years of age or older as a percentage of total population

Climate risk: Extreme temperature risk, Water risk

Risk dimension: Sensitivity

Rationale: Elderly people are more susceptible to heat-related conditions than the general population. This renders countries with a higher percentage of them more sensitive to climate risks.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: World Bank

Coverage: 175 countries

Time series: 1990 - 2019

Notes: Population numbers reflect the number of residents regardless of legal status or citizenship.

- **Population living in LECZ**

Description: Population living in low elevation and coastal zones (LECZ)

Climate risk: Flood risk

Risk dimension: Exposure

Rationale: A larger population living in low elevation and coastal zones makes a country more exposed to flood risk, since this means more people potentially in harm's way.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: NASA

Coverage: 221 countries and territories

Time series: Single observation (2015)

- **Share of population living in LECZ**

Description: Population living in LECZ as a percentage of total population

Climate risk: Flood risk

Risk dimension: Sensitivity

Rationale: A larger share of the population living in LECZ makes a country more sensitive to flood risk. since this means a larger percentage of the population is potentially in harm's way.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: Calculated based on NASA and World bank data

Coverage: 209 countries and territories

Time series: Single observation (2015)

- **Population living in floodplains**

Description: Population living in floodplains

Climate risk: Flood risk

Risk dimension: Exposure

Rationale: A larger population living in floodplains makes a country more exposed to flood risk, since this means more people potentially in harm's way.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: NASA

Coverage: 219 countries and territories

Time series: Single observation (2015)

- **Share of population living in floodplains**

Description: Population living in floodplains as a percentage of total population

Climate risk: Flood risk

Risk dimension: Sensitivity

Rationale: A larger share of the population living in floodplains makes a country more sensitive to flood risk, since this means a larger percentage of the population is potentially in harm's way.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: Calculated based on NASA and World Bank data

Coverage: 207 countries and territories

Time series: Single observation (2015)

- **GDP per capita**

Description: Gross Domestic Product (GDP) per capita

Climate risk: Mean temperature risk, Extreme temperature risk, Water risk, Flood risk, Health risk

Risk dimension: Adaptive capacity

Rationale: GDP per capita is a proxy for wealth. The wealthier a country is, the more resources can be potentially dedicated to the adaptation to climate risks.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: World Bank

Coverage: 180 countries

Time series: 1990 - 2019

Notes: Gross Domestic Product is the sum of gross value added by all resident producers plus any product taxes, and minus any subsidies not included in the value of the products. GDP data in our index are in current US$.

- **Income inequality (Gini index).**

Description: Measurement of the income inequality

Climate risk: Mean temperature risk, Extreme temperature risk, Water risk, Flood risk, Health risk

Risk dimension: Sensitivity

Rationale: More unequal societies have a higher share of people living in relative poverty with less resources to adapt to climate risks. This makes such countries more sensitive to climate risks.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: World Income Inequality Database

Coverage: 155 countries

Time series: 1990 - 2018

- **Agriculture, forestry, and fishing, value added (% of GDP)**

Description: Net output of the agriculture, forestry, and fishing sector as a percentage of GDP.

Climate risk: Water risk

Risk dimension: Sensitivity

Rationale: Countries with a higher percentage of the agriculture, forestry and fishing value added in GDP are more sensitive to water risk, since the sectors are intricately intertwined with the water cycle. Droughts lead to failure in crops and livestock, they can exacerbate forest fires and cause water bodies to dry up.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: World Bank

Coverage: 179 countries

Time series: 1990 - 2019

Notes: "Agriculture, forestry, and fishing corresponds to ISIC divisions 1-3 and includes forestry, hunting, and fishing, as well as cultivation of crops and livestock production. Value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs. It is calculated without making deductions for depreciation of fabricated assets or depletion and degradation of natural resources. The origin of value added is determined by the International Standard Industrial Classification (ISIC), revision 4." (World Bank Open Data, 2022)

- **Agriculture, forestry, and fishing, value added**

Description: Net output of the agriculture, forestry, and fishing sector.

Climate risk: Water risk

Risk dimension: Exposure

Rationale: High value added from agriculture, forestry and fishing value makes a country more exposed to water risk, since the sectors are intricately intertwined with the water cycle. Droughts lead to failure in crops and livestock, they can exacerbate forest fires and cause water bodies to dry up.

Calculation: Average across all available observations for a sovereign between 2000 and 2020. Calculated based on data on the agriculture value added as a percentage of GDP, total population and GDP per capita.

Data Source: World Bank

Coverage: 179 countries

Time series: 1990 - 2019

Notes: In current US$.

- **Education (literacy rates)**

Description: Share of the population older than 14 years that can read and write.

Climate risk: Mean temperature risk, Extreme temperature risk, Water risk, Flood risk, Health risk

Risk dimension: Adaptive capacity

Rationale: Higher percentage of literate people allow countries to better adapt to climate risks, since the population is better equipped to understand the complex circumstances related to climate change and how it affects socio-economic systems. More people have the opportunity to access services and information that allow them to adjust.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: Our World in Data

Coverage: 156 countries

Time series: Single observation (2015)

Notes: The estimate by Our World in Data is based on several data sources.

- **Percentage population access to at least basic water services**

Description: People using at least basic water services as a percentage of the population.

Climate risk: Mean temperature risk, Extreme temperature risk, Water risk, Flood risk, Health risk

Risk dimension: Adaptive capacity

Composite indicator: Access to basic services

Rationale: Water is essential for human life. Countries with a lower share of the population with access to basic water services are less capable of adapting, since the livelihood of the people are compromised.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: World Bank

Coverage: 195 countries

Time series: 1990 - 2019

- **Percentage population access to electricity**

Description: People with access to electricity as a percentage of the total population.

Climate risk: Mean temperature risk, Extreme temperature risk, Water risk, Flood risk, Health risk

Risk dimension: Adaptive capacity

Composite indicator: Access to basic services

Rationale: A higher percentage of the population with access to electricity implies more people that can potentially use air conditioning to cool their surroundings, pumps to raise water from greater depths and create vital infrastructure in response to natural disasters and disease outbreaks.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: World Bank

Coverage: 181 countries

Time series: 1990 - 2018

- **Individuals using the Internet (% of population)**

Description: Internet users as a percentage of the total population.

Climate risk: Mean temperature risk, Extreme temperature risk, Water risk, Flood risk, Health risk

Risk dimension: Adaptive capacity

Composite indicator: Access to basic services

Rationale: A higher percentage of the population with access to the Internet implies that more people have access to information on how to effectively adapt to climate risks.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: World Bank

Coverage: 180 countries

Time series: 1990 - 2019

Notes: Internet users are people who have used the Internet in the last three months from any location and device.

- **Mobile cellular subscriptions per 100 people**

Description: Subscriptions to a public mobile telephone service per 100 people.

Climate risk: Mean temperature risk, Extreme temperature risk, Water risk, Flood risk, Health risk

Risk dimension: Adaptive capacity

Composite indicator: Access to basic services

Rationale: A higher number of mobile cellular subscriptions per 100 people implies that more people have access to information on how to effectively adapt to climate risks.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: World Bank

Coverage: 180 countries

Time series: 1990 - 2019

Notes: The data reflects subscriptions to a public mobile telephone service providing access to the PSTN using cellular technology.

- **Quality of institutions: Government effectiveness**

Description: “Government effectiveness captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies.” (Worldwide Governance Indicators, 2022)

Climate risk: Mean temperature risk, Extreme temperature risk, Water risk, Flood risk, Health risk

Risk dimension: Adaptive capacity

Composite indicator: Quality of Institutions

Rationale: Countries with higher scores in government effectiveness can adapt to climate risks more easily due to the overall credibility of the government and the commitment to mitigation and adaptation goals.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: World Governance Indicator Project of the World Bank

Coverage: 200 countries and territories

Time series: 1996, 1998, 2000, 2002 - 2019

- **Quality of institutions: Control of corruption**

Description: “Control of corruption captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests.” (Worldwide Governance Indicators, 2022)

Climate risk: Mean temperature risk, Extreme temperature risk, Water risk, Flood risk, Health risk

Risk dimension: Adaptive capacity

Composite indicator: Quality of Institutions

Rationale: Countries with a better control of corruption can adapt to climate risk more easily, since public policy more reliably serves the long-term interest of all stakeholders in this case.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: World Governance Indicator Project of the World Bank

Coverage: 200 countries and territories

Time series: 1996, 1998, 2000, 2002 - 2019

- **Political Stability and Absence of Violence/Terrorism**

Description: “Political Stability and Absence of Violence/Terrorism measures perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism.” (Worldwide Governance Indicators, 2022)

Climate risk: Mean temperature risk, Extreme temperature risk, Water risk, Flood risk, Health risk

Risk dimension: Adaptive capacity

Composite indicator: Quality of Institutions

Rationale: Countries with more political stability and absence of violence and terrorism can adapt to climate risk more easily, since political stability implies consistency of policy and the absence of violence and terrorism implies that due attention is paid to environmental issues.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: World Governance Indicator Project of the World Bank

Coverage: 200 countries and territories

Time series: 1996, 1998, 2000, 2002 – 2019

- **Quality of institutions: Regulatory quality**

Description: “Regulatory quality captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development”. (Worldwide Governance Indicators, 2022)

Climate risk: Mean temperature risk, Extreme temperature risk, Water risk, Flood risk, Health risk

Risk dimension: Adaptive capacity

Composite indicator: Quality of Institutions

Rationale: Countries with higher regulatory quality can adapt to climate risk more easily, since the regulators can more easily formulate and implement relevant and timely policies and regulations.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: World Governance Indicator Project of the World Bank

Coverage: 200 countries and territories

Time series: 1996, 1998, 2000, 2002 - 2019

- **Quality of institutions: Rule of law**

Description: “Rule of law captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.” (Worldwide Governance Indicators, 2022)

Climate risk: Mean temperature risk, Extreme temperature risk, Water risk, Flood risk, Health risk

Risk dimension: Adaptive capacity

Composite indicator: Quality of Institutions

Rationale: Countries with better rule of law can adapt to climate risk more easily, since it supports the efficient enforcement of mitigation and adaptation policies.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: World Governance Indicator Project of the World Bank

Coverage: 200 countries and territories

Time series: 1996, 1998, 2000, 2002 - 2019

- **Quality of institutions: Voice and accountability**

Description: “Voice and accountability captures perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media.” (Worldwide Governance Indicators, 2022)

Climate risk: Mean temperature risk, Extreme temperature risk, Water risk, Flood risk, Health risk

Risk dimension: Adaptive capacity

Composite indicator: Quality of Institutions

Rationale: Countries with higher scores in voice and accountability can adapt to climate risk more easily, since citizens can participate in selecting their government and thereby influence the legislation passed.

Calculation: Average across all available observations for a sovereign between 2000 and 2020.

Data Source: World Governance Indicator Project of the World Bank

Coverage: 200 countries and territories

Time series: 1996, 1998, 2000, 2002 – 2019

Appendix II: The OWA method

The OWA method represents an alternative to Weighted Averaging (WA), and is commonly used in many environmental applications, see, among other ones ((Bordogna et al. 2011), (Gorsevski et al. 2012), (Malczewski et al. 2003), (Zabihi et al. 2019)). In contrast with WA, where the weights are assigned to each criterion - the different risk type indicators in our case – in a cardinal fashion, the OWA method is a positional aggregation function. This means that the weights are assigned to the ordered criteria[5]. These operators thus combine values according to their ordering, i.e., by means of a set of ordinal weights, representing each the importance of the position of the criterion in the sampled data. For instance, once the (normalised) values of the criterion are ordered from the lowest to the highest, a system of OWA weight that assigns "one" to the first and "zero" to the others, will select the MIN operator. This means that the preference structure of the User of the information "cares" just about the lowest risk. Conversely, if all the OWA weights are null and the last equals one, the MAX of the normalised criteria will be selected. Clearly, in between these two extremes, there are infinite possibilities. For example, the simple averaging would correspond to equal OWA weights with value *1/n*, if *n* is the number of the criteria.[6]

A typical approach to define the OWA weights, is to use so-called Linguistic Quantifiers, that enable their easy interpretation in terms of the natural language concepts of "optimism/pessimism", or "conjunction/disjunction" behaviour, of the decision maker (DM) (Yager 1996).

More formally, a Linguistic Quantifier is a function that "filters" in a suitable fashion the number of criteria that satisfy a proposition of the natural language such as "most of", "few", "medium values", etc. Usually, a Linguistic Quantifier can be represented by a monotonic increasing function $Q: [0,1] \rightarrow [0,1]$, dubbed Regular Increasing Monotone function, RIM for brevity, such that the i-*th* OWA weight, *w*, can be determined as follows:

5 Even if OWA seems to be a linear operator (as the WA is), it is not, because it is linear with respect to the ordered values. This preliminary sorting operation causes the algorithm to be in fact non-linear.

6 Note that OWA cannot implement Weighted Averaging with different weights, since the weights have only a positional meaning. In order to include some cardinal weights as well, another vector representing the "importance" degree of each criterion, some methods were proposed in the specialized literature, like WOWA (Torra 2011).

$$w = Q\left(\frac{i}{n}\right) - Q\left(\frac{i-1}{n}\right)$$

with *n* the number of the criteria and *i=1,.. n.*

A commonly used RIM quantifier is given by the following function $Q(r)\colon R^{+} \rightarrow R$

$$Q(r) = r^{\alpha}$$

r is an arbitrary positive real number and $\alpha \in [0, \infty)$ is a parameter to represent the so-called *optimism* degree (Yager, 1988). In this case:

$$w_i = \left(\frac{i}{n}\right)^{\propto} - \left(\frac{i-1}{n}\right)^{\propto}$$

So that:

$$w_1 = \left(\frac{1}{n}\right)^{\propto}, w_2 = \left(\frac{2}{n}\right)^{\propto} - \left(\frac{1}{n}\right)^{\propto}, \ \dots \ , w_n = \left(\frac{n}{n}\right)^{\propto} - \left(\frac{n-1}{n}\right)^{\propto} = 1 - \left(\frac{n-1}{n}\right)^{\propto}$$

In practice, the higher the weight assigned to a given position in the OWA weights vector, the higher importance the User assigns to the corresponding criteria and the lower to all the others. This eventually defines her "optimism" degree. For instance, recalling the example above mentioned with values of the criterion ordered from the lowest to the highest, the MIN operator, is obtained when $\alpha = 0$, the MAX operator, when $\alpha \rightarrow \infty$, while the simple average when $\alpha = 1$.

The MAX operator corresponds to the case in which the User evaluates an item considering only the highest criterion; from a logical point of view, she/he is satisfied if "at least one" criterion is satisfied. This is an "optimistic" attitude reflecting what, using decision theory jargon, is a "disjunctive" behaviour or an "orness-type" DM. The other extreme, the MIN operator, corresponds to a "pessimistic" or conjunctive behaviour (aka "andness-type" DM), when the User evaluates an item considering only the worst criterion, thus he is satisfied if "all" the criteria are satisfied (Yager 1996)[7].

[7] Contextualizing to our case where higher values correspond to higher risks, the MIN case is when the (DM) is optimistic, the MAX case when the DM is optimistic.

Once the different weights have been set (or to decide which weight configuration to set), it is possible to measure the degree of optimism (or pessimism), with an "orness index" defined as follows (Yager 1988):

$$orness(w) = \frac{1}{n-1} \cdot \sum_{j=1}^{n} \quad (n-i) \cdot w_i$$

It is a function of the weights vector w and ranges between 0 (pessimistic case) and 1 (optimistic case). In the neutral case, the $orness$ index equal 0.5. Values of $orness$ in between 0 and 0.5 indicate a tendency towards pessimism, i.e., a disjunctive attitude of the User. This is the case when the User does not intend to emphasise only one (or few) criteria, but he is satisfied only if $most$ of the criteria will be satisfied.

Finally, let us remark that each weight obtained by a RIM Linguistic Quantifier represents the increase of satisfaction reaching the i-th criteria compared to the previous $(i-1)$ criteria. Thus, the User can select the optimism degree. Subsequently, the OWA aggregator computes the scores for any item, thus permitting to obtain the ranking among all the considered items. Table1 reports the set of the OWA weights for $n=5$ and for seven different values of the parameter α used in this exercise. The two extreme cases, MIN, and MAX, are the first and the last columns, corresponding to $\alpha=0$ and $\alpha=1$ respectively. As suggested above, we consider only some values of the parameter α, but in the range of the disjunctive behaviour of the User: $\alpha \in [0,1]$.

α	**0**	**0.1**	**0.3**	**0.5**	**0.7**	**0.9**	**1**
w_1	1	0.85	0.62	0.45	0.32	0.23	0.20
w_2	0	0.06	0.14	0.19	0.20	0.20	0.20
w_3	0	0.04	0.10	0.14	0.17	0.19	0.20
w_4	0	0.03	0.08	0.12	0.16	0.19	0.20
w_5	0	0.02	0.06	0.11	0.14	0.18	0.20

Table 1. OWA weight for different values of α parameters. Source: Own illustration.
Note: α=0, the decision maker "cares" just about the highest possible risk (worst outcome); α=1, the decision maker gives equal importance to the different climate risk types.

Appendix III. Countries covered by the climate risk index

Afghanistan. Albania, Algeria, Angola, Argentina, Armenia, Australia, Austria, Azerbaijan, Bangladesh, Belarus, Belgium, Benin, Bhutan, Bolivia, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon Canada, Central African Republic, Chad, Chile, China, Colombia, Comoros, Costa Rica, Cote d'Ivoire, Croatia, Cuba, Cyprus, Czech Republic, Denmark, Djibouti, Dominican Republic, Ecuador, El Salvador, Estonia, Ethiopia, Fiji, Finland, France, Gabon, Georgia, Germany, Ghana, Greece, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Kuwait, Kyrgyz Republic, Lao PDR, Latvia, Lebanon, Lesotho, Liberia, Libya, Lithuania, Luxembourg, Madagascar, Malawi, Malaysia, Mali, Mauritius, Mexico, Moldova, Mongolia, Morocco, Mozambique, Myanmar, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, North Macedonia, Norway, Oman, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Puerto Rico, Qatar, Russian Federation, Rwanda, Samoa, Sao Tome and Principe, Saudi Arabia, Senegal, Serbia, Sierra Leone, Slovak Republic, Slovenia, South Africa, Spain, Sri Lanka, Sudan, Suriname, Sweden, Switzerland, Syrian Arab Republic, Tajikistan, Tanzania, Thailand, Togo, Tunisia, Turkey, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Uzbekistan, Vanuatu, Vietnam, Zambia, Zimbabwe.

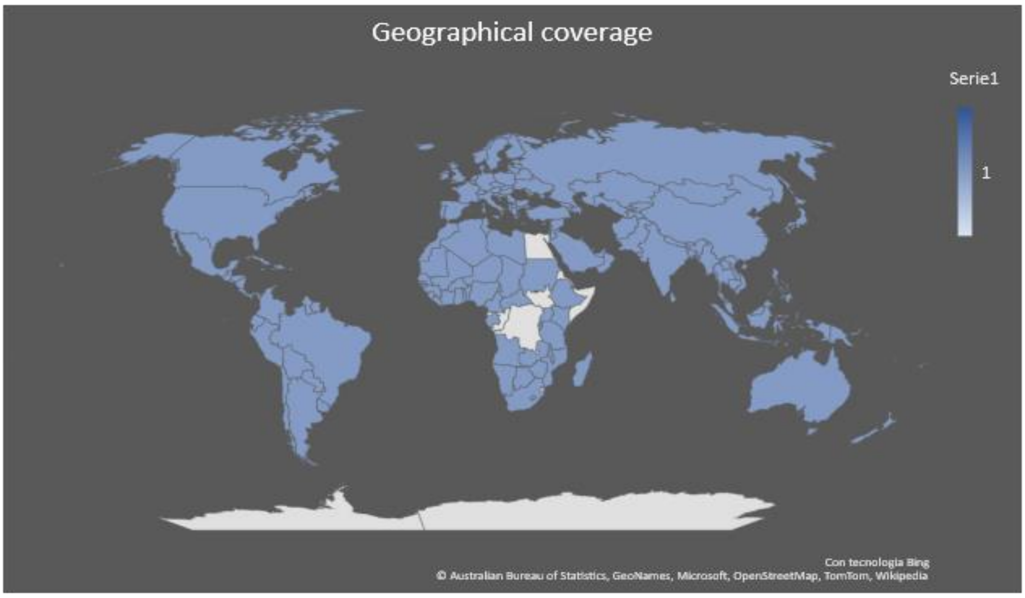

Figure 6: Geographical coverage of the index. Source: Own illustration.

Appendix IV: Country ranking per climate risk component

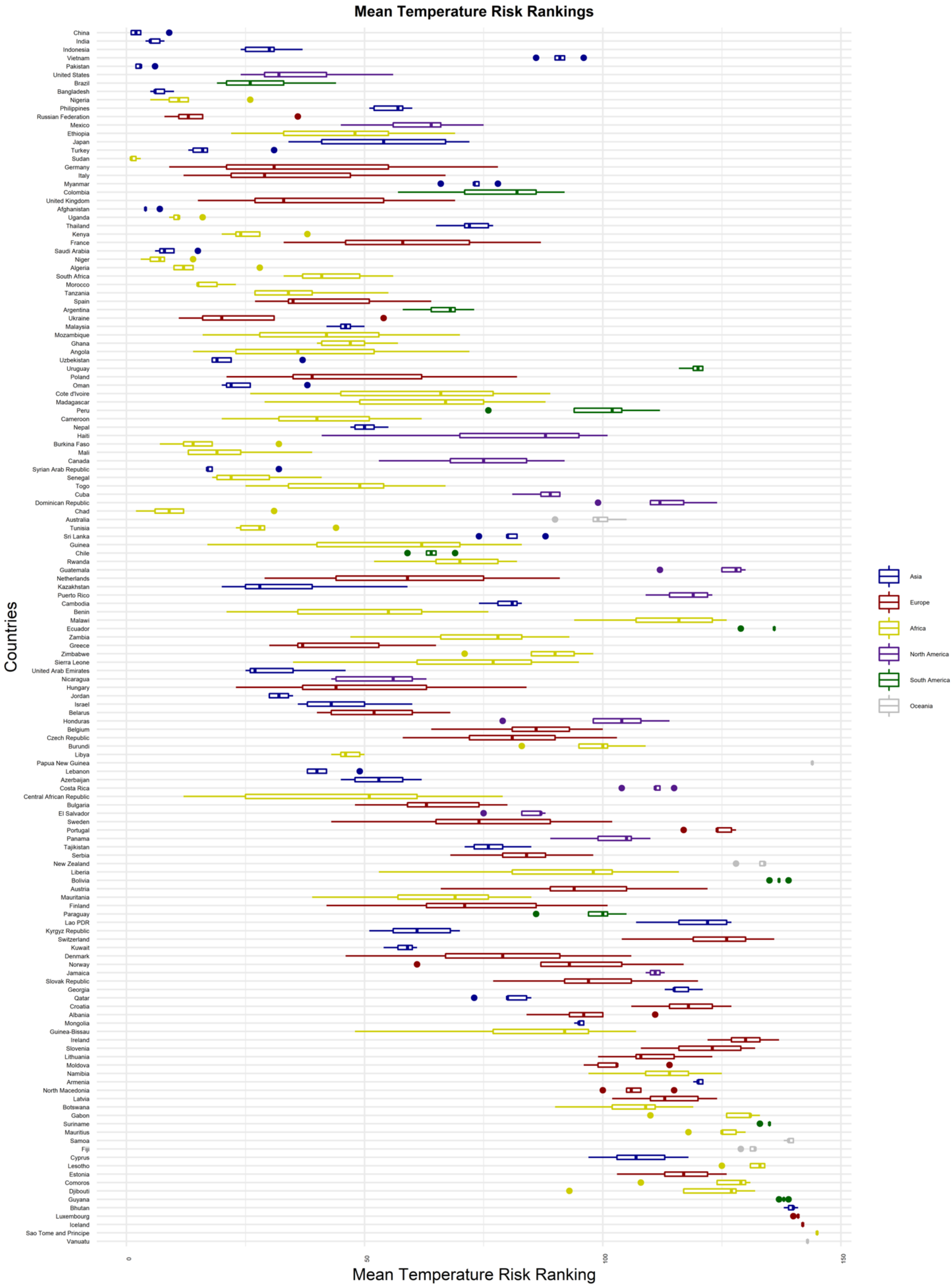

Figure 7 Mean temperature risk rankings. The variation in the rankings for a specific country arises from the different values of k. The countries are ordered by the median ranking of a country over all possible values of k.
Source: Own illustration.

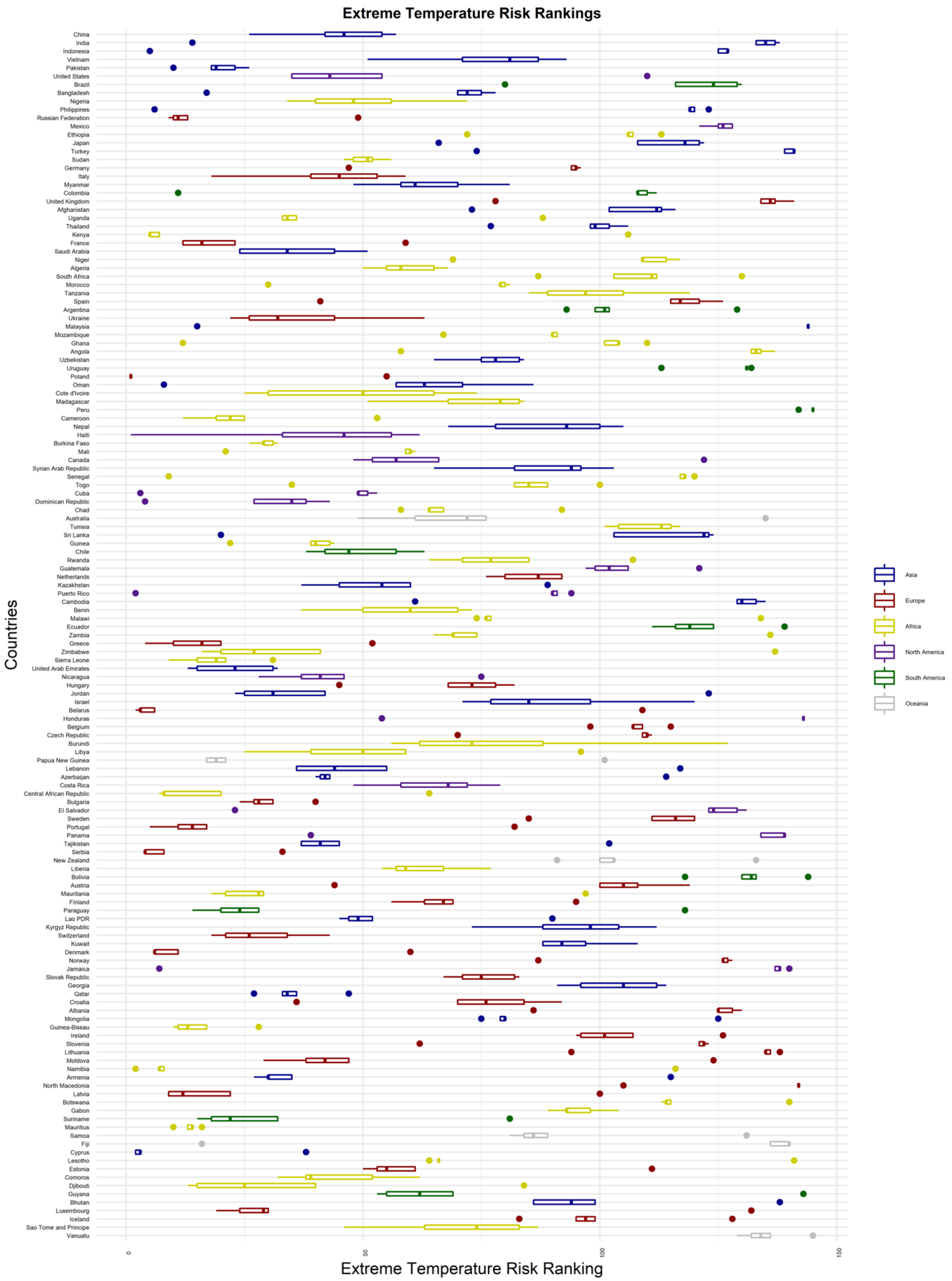

Figure 8. Extreme temperature risk rankings. The variation in the rankings for a specific country arises from the different values of k. Source: The countries are ordered by the median ranking of a country over all possible values of k. Own illustration.

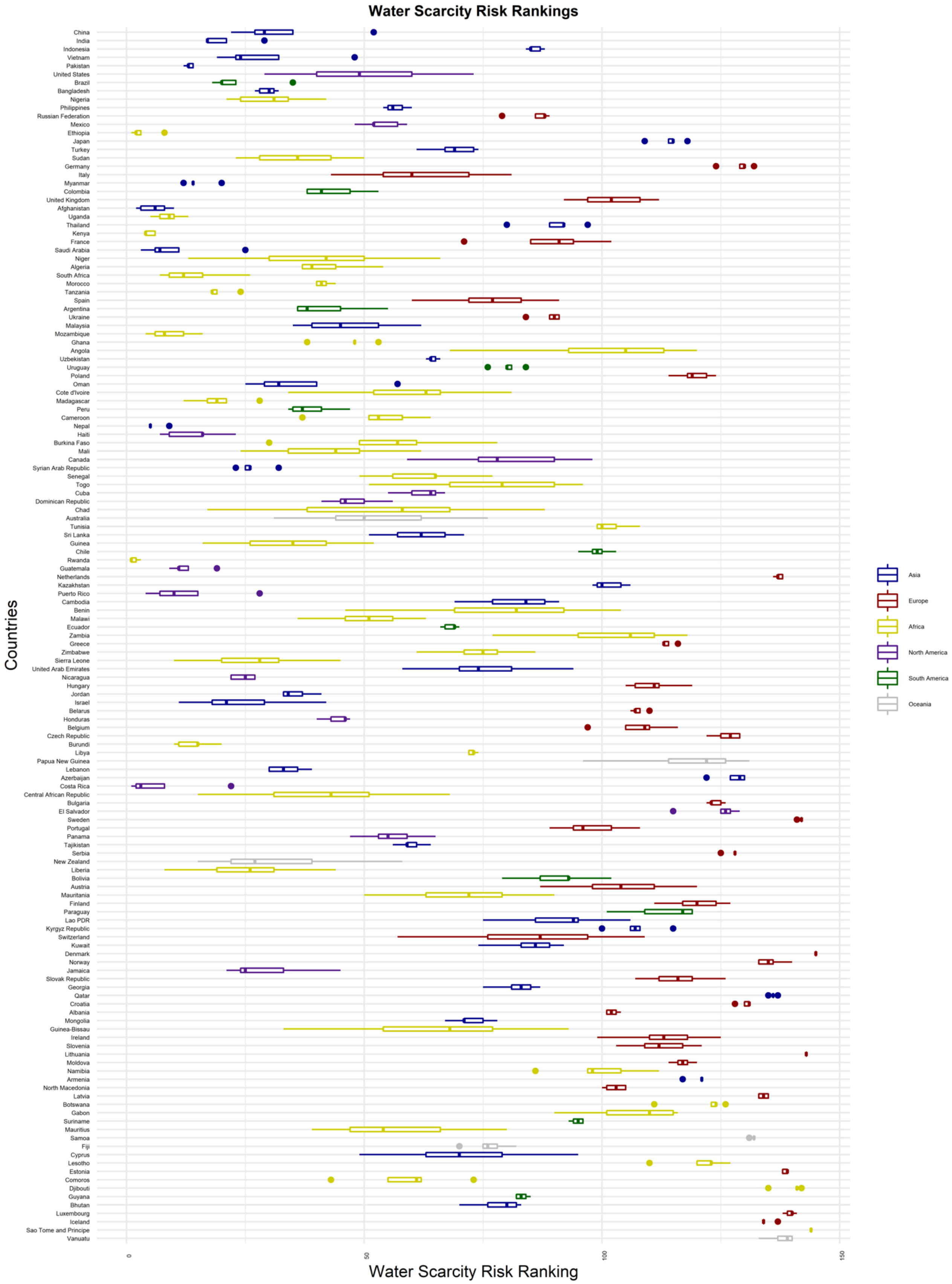

Figure 9. Water scarcity risk rankings. The variation in the rankings for a specific country arises from the different values of k. The countries are ordered by the median ranking of a country over all possible values of k.
Source: Own illustration.

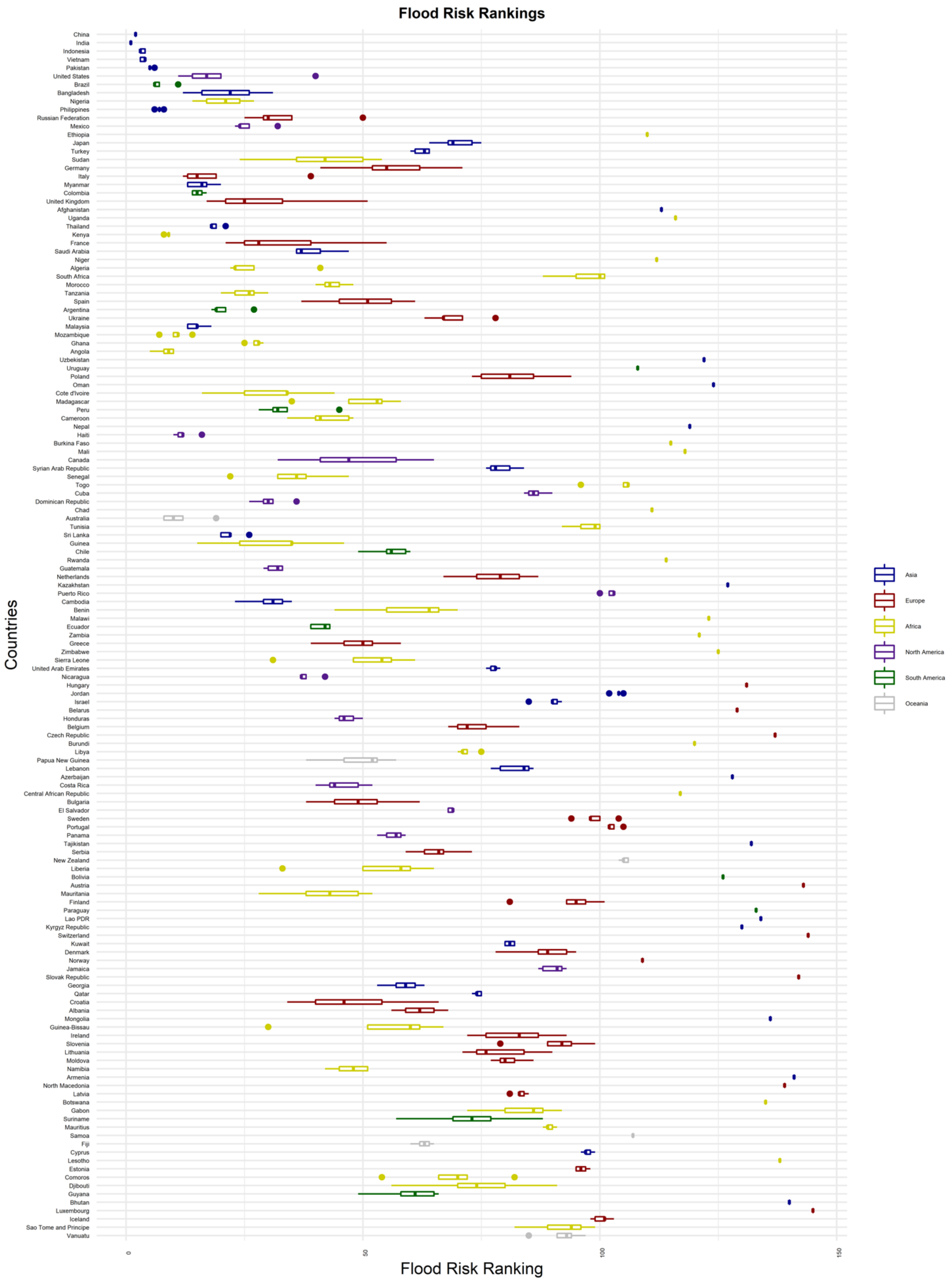

Figure 10. Flood risk rankings. The variation in the rankings for a specific country arises from the different values of k. The countries are ordered by the median ranking of a country over all possible values of k
Source: Own illustration.

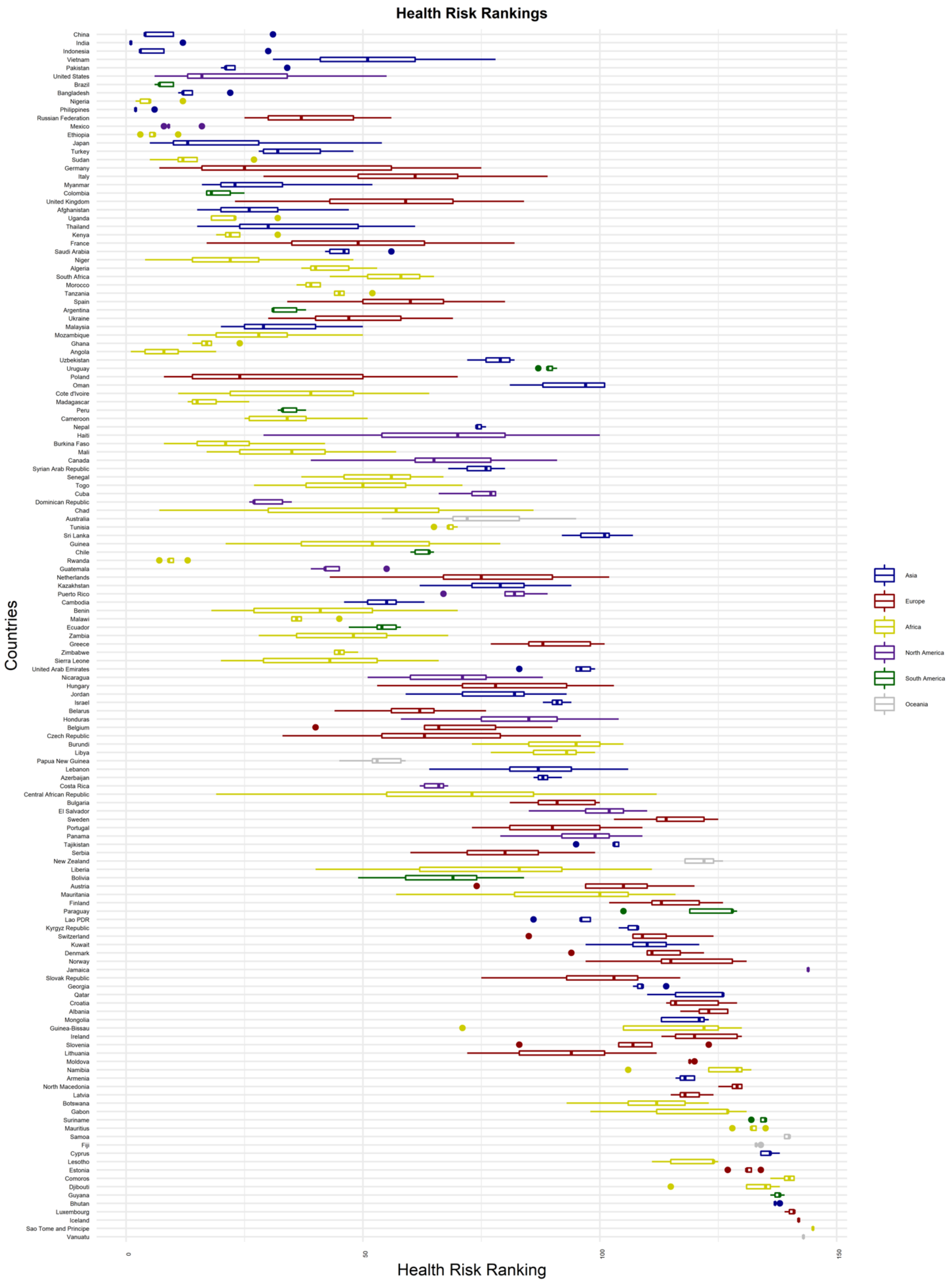

Figure 11. Health risk rankings. The variation in the rankings for a specific country arises from the different values of k. The countries are ordered by the median ranking of a country over all possible values of k
Source: Own illustration.

Appendix V: Comparison across indexes.

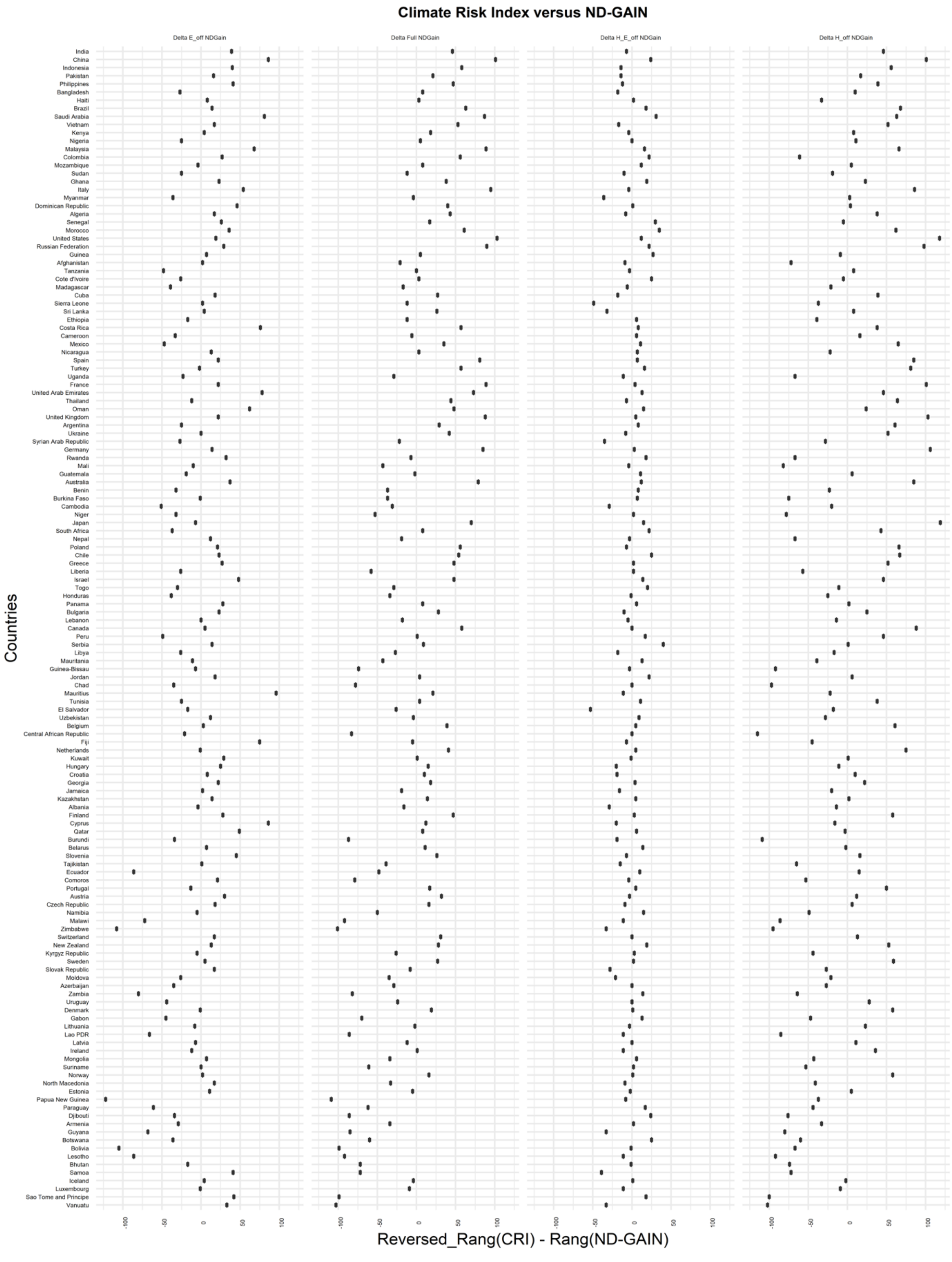

Figure 12 Absolute distance between the reversed benchmark climate risk index ranking and the ND-GAIN ranking for different versions of the climate risk index (from left to right: Climate Risk Index: Exposure off, Full Climate Risk Index, Climate Risk Index: Hazard and Exposure off, Climate Risk Index: Hazard off). The countries are ordered by the median ranking of a country for the benchmark (k=0.25, equal weights).
Source: Own illustration.

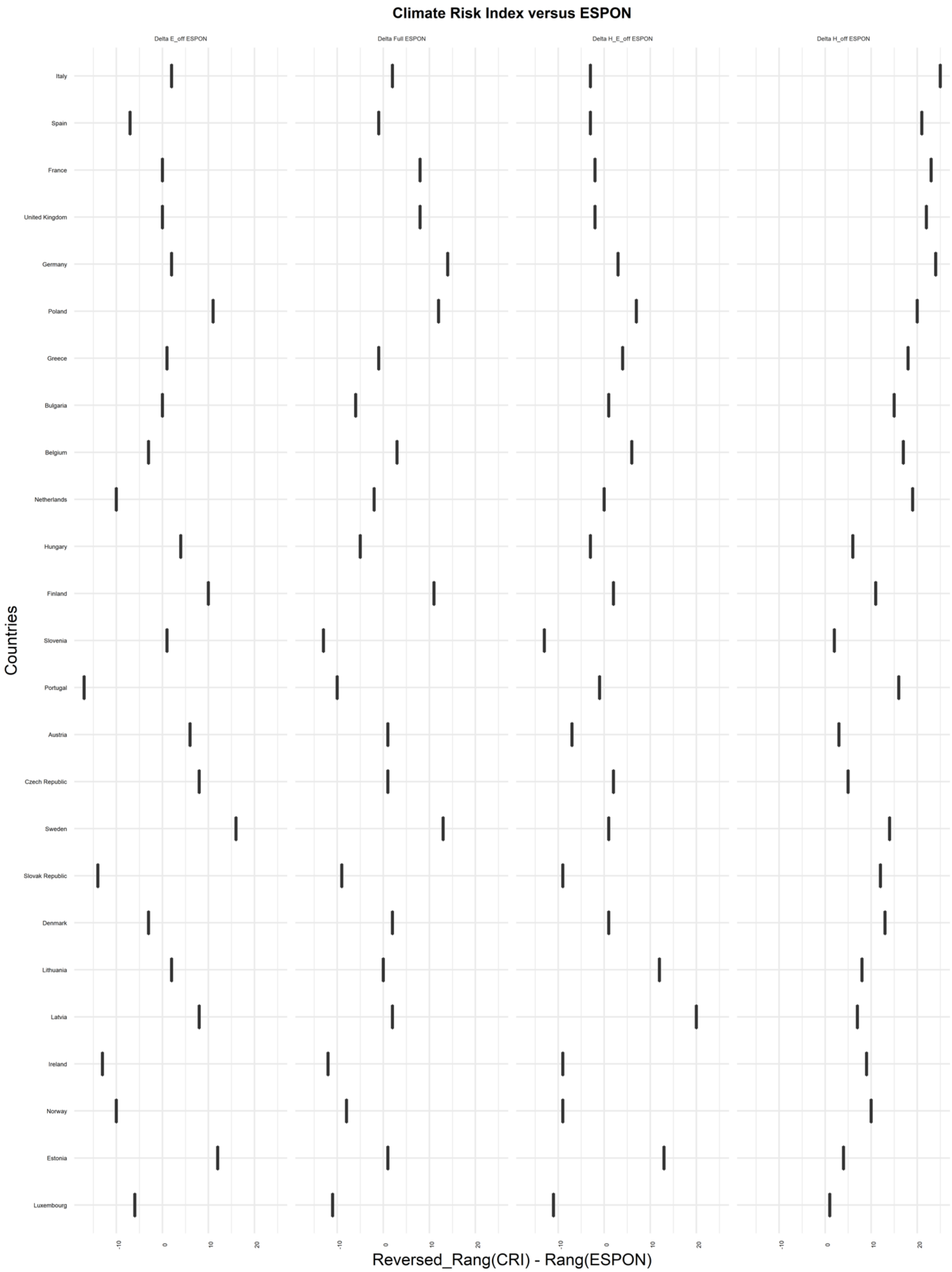

Figure 13 Absolute distance between the reversed benchmark climate risk index ranking and the ESPON ranking for different versions of the climate risk index (from left to right: Climate Risk Index: Exposure off, Full Climate Risk Index, Climate Risk Index: Hazard and Exposure off, Climate Risk Index: Hazard off). The countries are ordered by the median ranking of a country for the benchmark (k=0.25, equal weights).
Source: Own illustration.

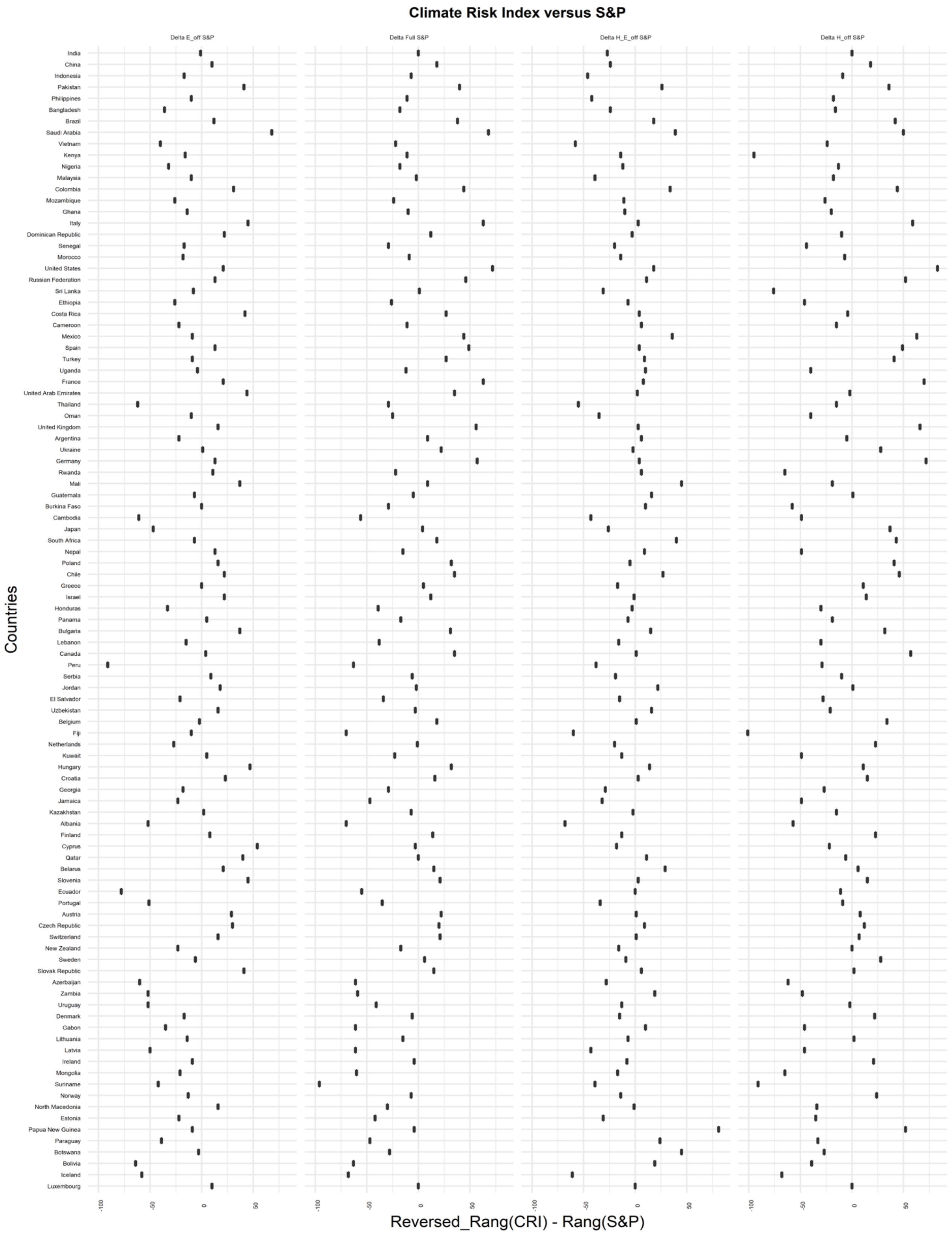

Figure 14 Absolute distance between the reversed benchmark climate risk index ranking and the S&P ranking for different versions of the climate risk index (from left to right: Climate Risk Index: Exposure off, Full Climate Risk Index, Climate Risk Index: Hazard and Exposure off, Climate Risk Index: Hazard off). The countries are ordered by the median ranking of a country for the benchmark (k=0.25, equal weights).
Source: Own illustration.

Appendix VI. Sensitivity tests

Aggregate climate risk ranking. Sensitivity to the OWA weights (αs)

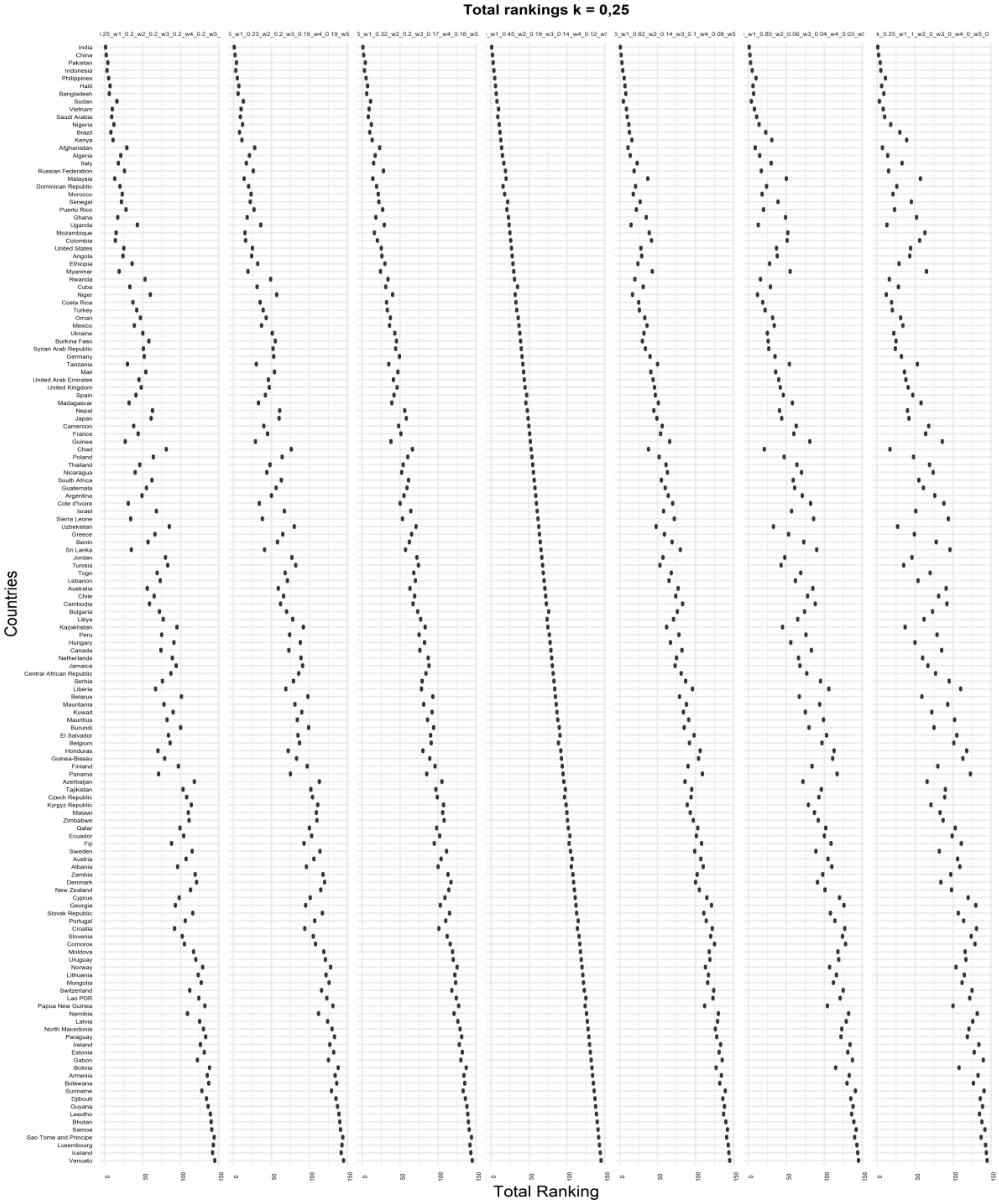

Figure 15. Sensitivity to the OWA weights of country ranking by total climate change risk. k = 0.25 (i.e. roughly 40% potential reduction in the aggregate risk when normalized adaptive capacity = 1 and normalized sensitivity = 0). OWA α = 1 (equal importance given to the different risk types) leftmost panel; OWA α = 0, (only maximum risk considered) rightmost.

Notes: For α = 0 the riskiest countries are in Asia, Africa and the Caribbean. India ranks first, Pakistan ranks fourth, Afghanistan ranks seventh and Bangladesh ranks ninth. China is scored as the second riskiest, followed by Sudan at third place. Two countries in South-East Asia enter the ten most risky countries: Indonesia in fifth position and Vietnam in eighth. The bottom of the ranking features countries with a small population. For α = 1 the riskiest countries remain in Asia. In general, the landlocked Sub-Saharan African countries tend to disappear from the top of the ranking in favour of South-East Asian and coastal African countries.

Source: Own illustration.

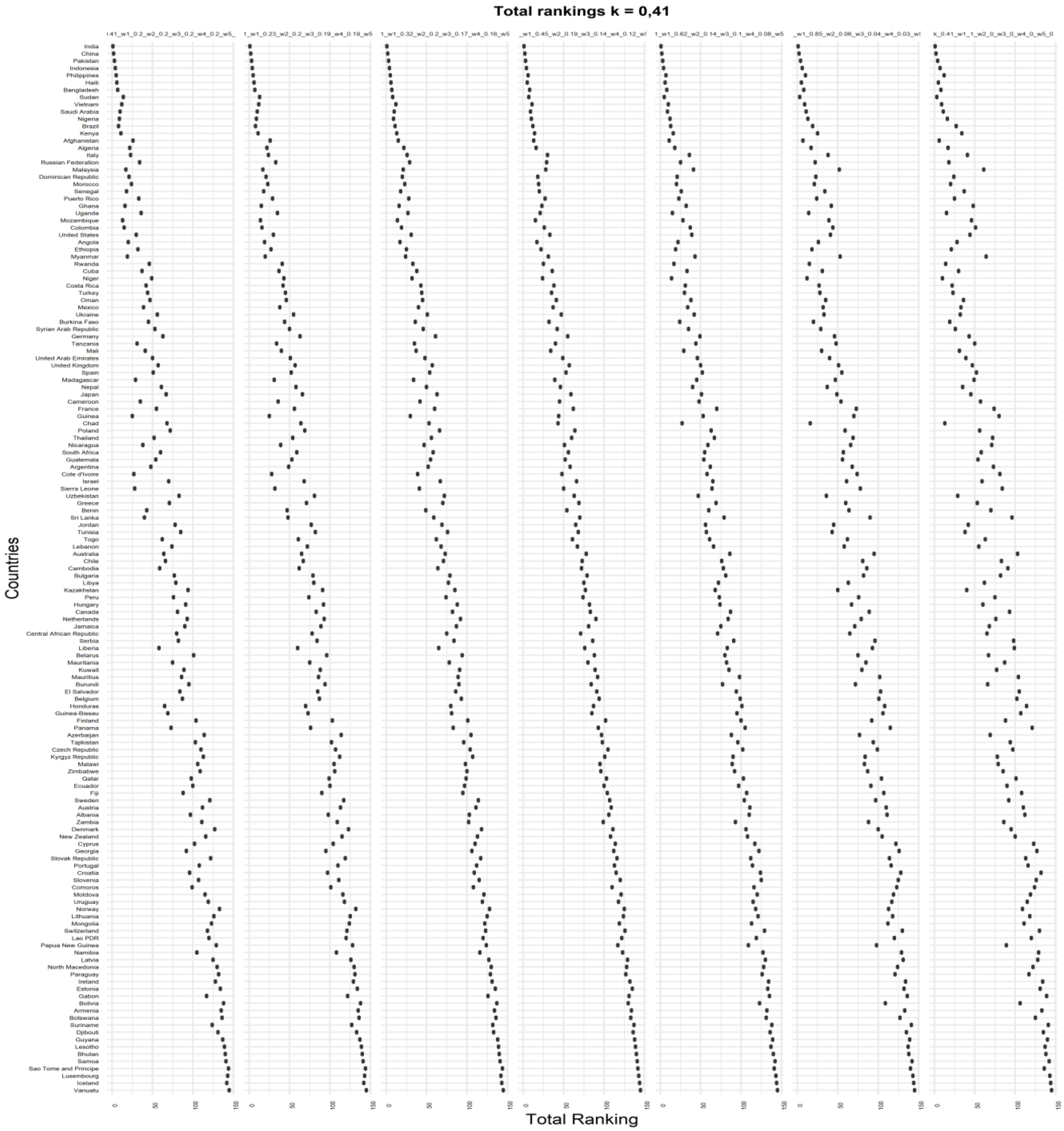

Figure 16. Sensitivity to the OWA weights of country ranking by total climate change risk. k = 0.41 (i.e. roughly 50% potential reduction in the aggregate risk when normalized adaptive capacity = 1 and normalized sensitivity = 0). OWA α = 1 (equal importance given to the different risk types) leftmost panel; OWA α = 0, (only maximum risk considered) rightmost.

Notes: For α = 0 Asian and African countries appear at the top of the ranking. India is at first place, followed by China at second. Pakistan is in forth position, Afghanistan scores sixth, Bangladesh at position eight. Haiti is at fifth position. Sudan is the riskiest African country and scores at third position. Niger is at position ten. Indonesia scores at position seven, Vietnam at position nine and the Philippines at position twelve. The bottom of the ranking is populated by small countries. For α = 1 India is scored as most risky. Pakistan is at third position, Bangladesh at position seven. China is the second most risky country. Indonesia holds forth position, Philippines is at position five, Vietnam at twelve, Coastal African countries are well represented at the top of the ranking. The bottom of the ranking is again populated with small countries.

Source: Own illustration.

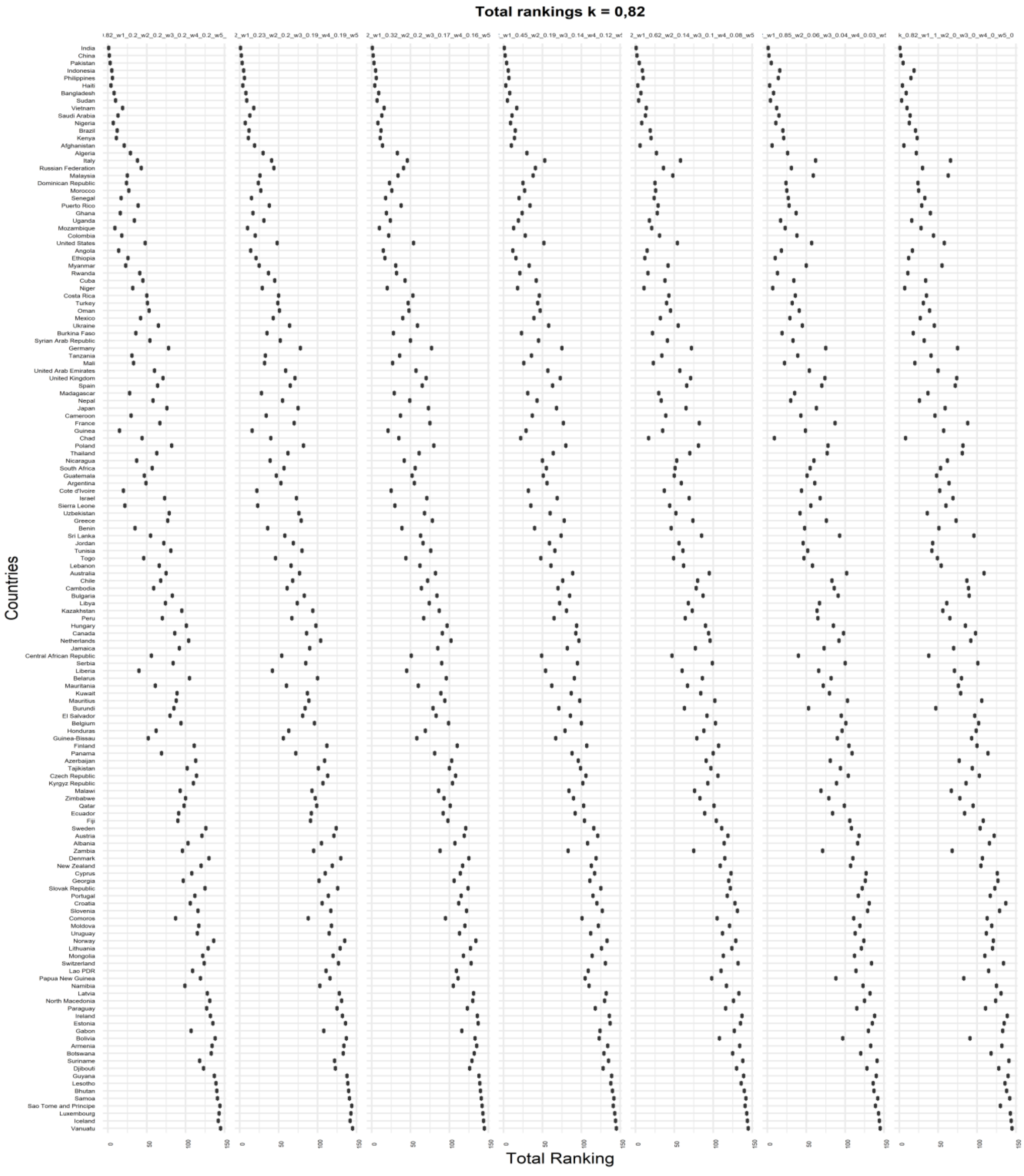

Figure 17. Sensitivity to the OWA weights of country ranking by total climate change risk. $k = 0.82$ (i.e. roughly 70% potential reduction in the aggregate risk when normalized adaptive capacity = 1 and normalized sensitivity = 0). OWA $\alpha = 1$ (equal importance given to the different risk types) leftmost panel; OWA $\alpha = 0$, (only maximum risk considered) rightmost.
Notes: For $\alpha = 0$ India ranks first followed by China, Sudan in third, and the island state of Haiti in fourth position. South Asian countries are scored among the riskier: Pakistan ranks fifth, Afghanistan ranks sixth, while Bangladesh appears in the ninth position. Niger is at position seven and Chad in position eight. Vietnam is placed at tenth position For. $\alpha = 1$ India and China are still on top followed by Pakistan and Haiti. Indonesia and the Philippines, at places five and six, rank higher than Vietnam, which comes in at place nineteen. Bangladesh scores at place eight. The landlocked African Countries disappear from the top positions in the ranking, while the coastal African countries appear among the riskiest. Small countries like Vanuatu, Iceland, Luxembourg, Samoa are among the least risky regardless of the expert preferences.
Source: Own illustration.

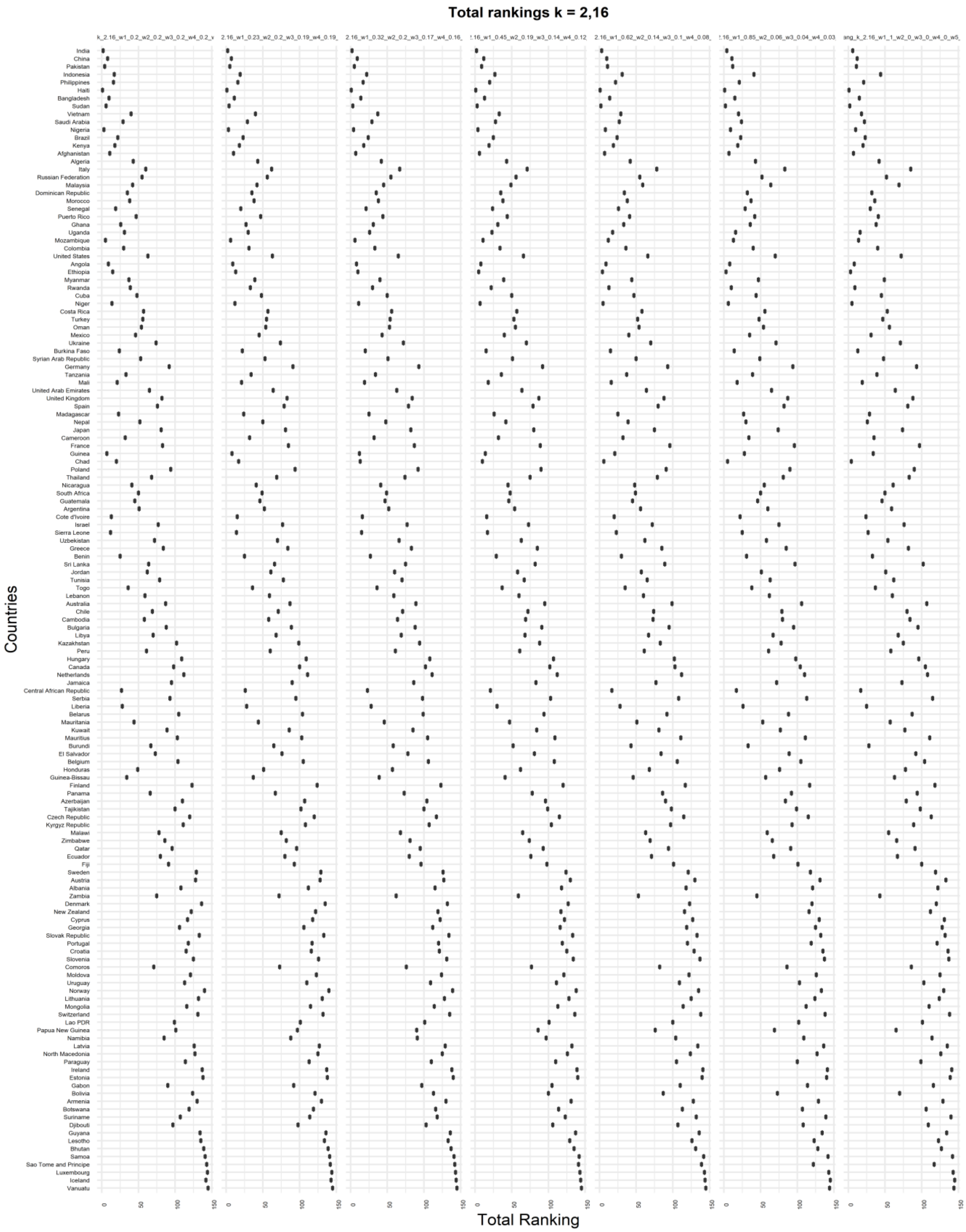

Figure 18. Sensitivity to the OWA weights of country ranking by total climate change risk. k = 2.16 (i.e. roughly 90% potential reduction in the aggregate risk when normalized adaptive capacity = 1 and normalized sensitivity = 0). OWA α = 1 (equal importance given to the different risk types) leftmost panel; OWA α = 0, (only maximum risk considered) rightmost.
Notes: For α = 0 the Caribbean Island of Haiti is ranked first due to the exposure to extreme temperature risk. Landlocked African countries are scored as less risky under an equal valuation. On the other hand, countries on the African coasts are scored as riskier.
Source: Own illustration.

Climate Hazard & Exposure ranking. Sensitivity to the OWA weights (αs)

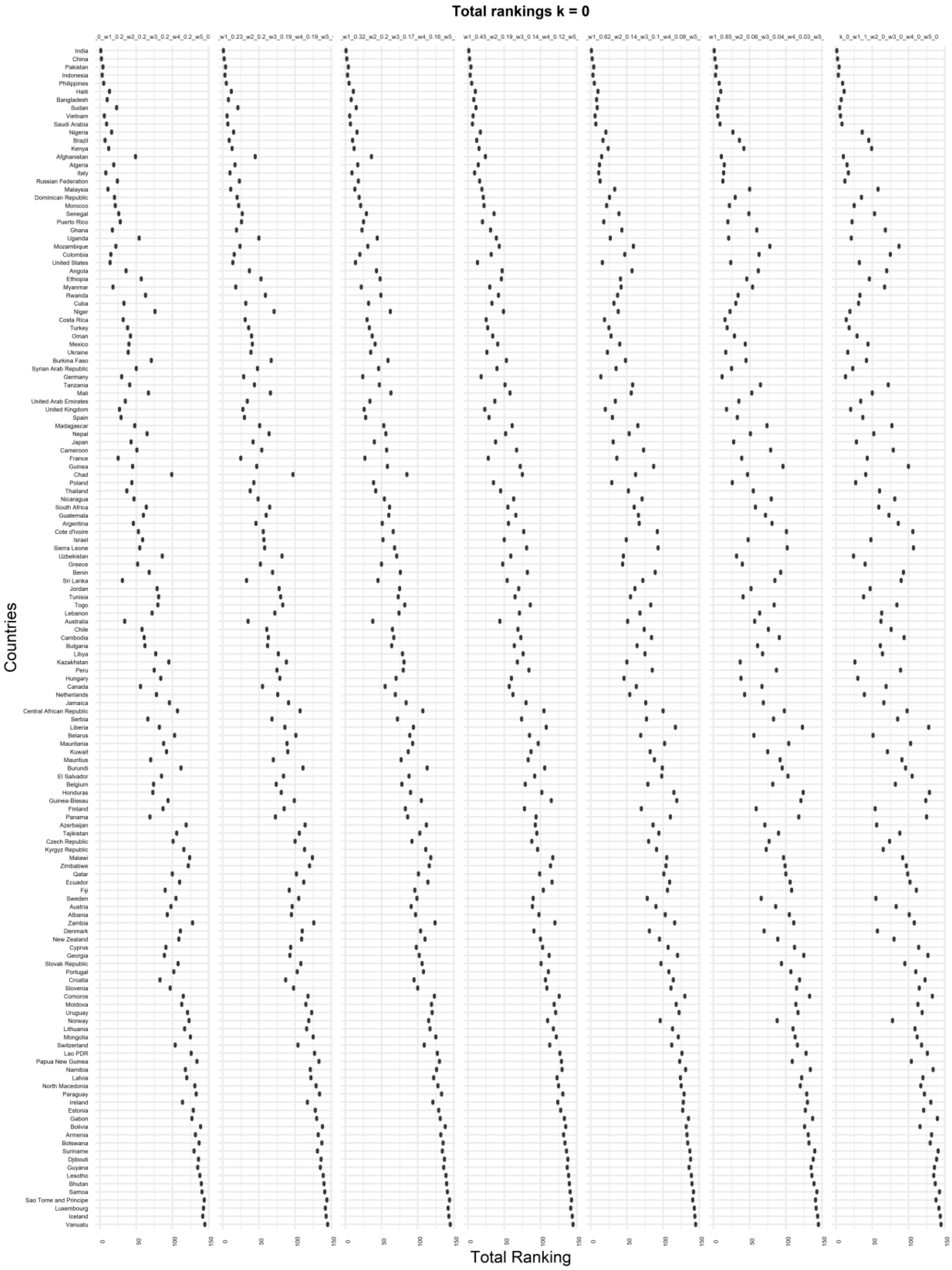

Figure 19 Country ranking according to climate change hazard and exposure ($k = 0$). When equal importance is given to the different risk types (OWA $\alpha = 1$) in the leftmost panel, only maximum risk considered (OWA $\alpha = 0$) to the rightmost. When only the largest risk is considered relevant the climate risk ranking is dominated by Asian countries with large populations. Countries with a small population tend to be ranked as less risky. Under equal risk valuation the landlocked African countries of Sudan and Niger are replaced by the coastal African counties of Kenya (twelfth place), Nigeria (sixteenth place), Ghana (seventeenth place).
Source: Own illustration.

Climate Hazard ranking. Sensitivity to the OWA weights (αs)

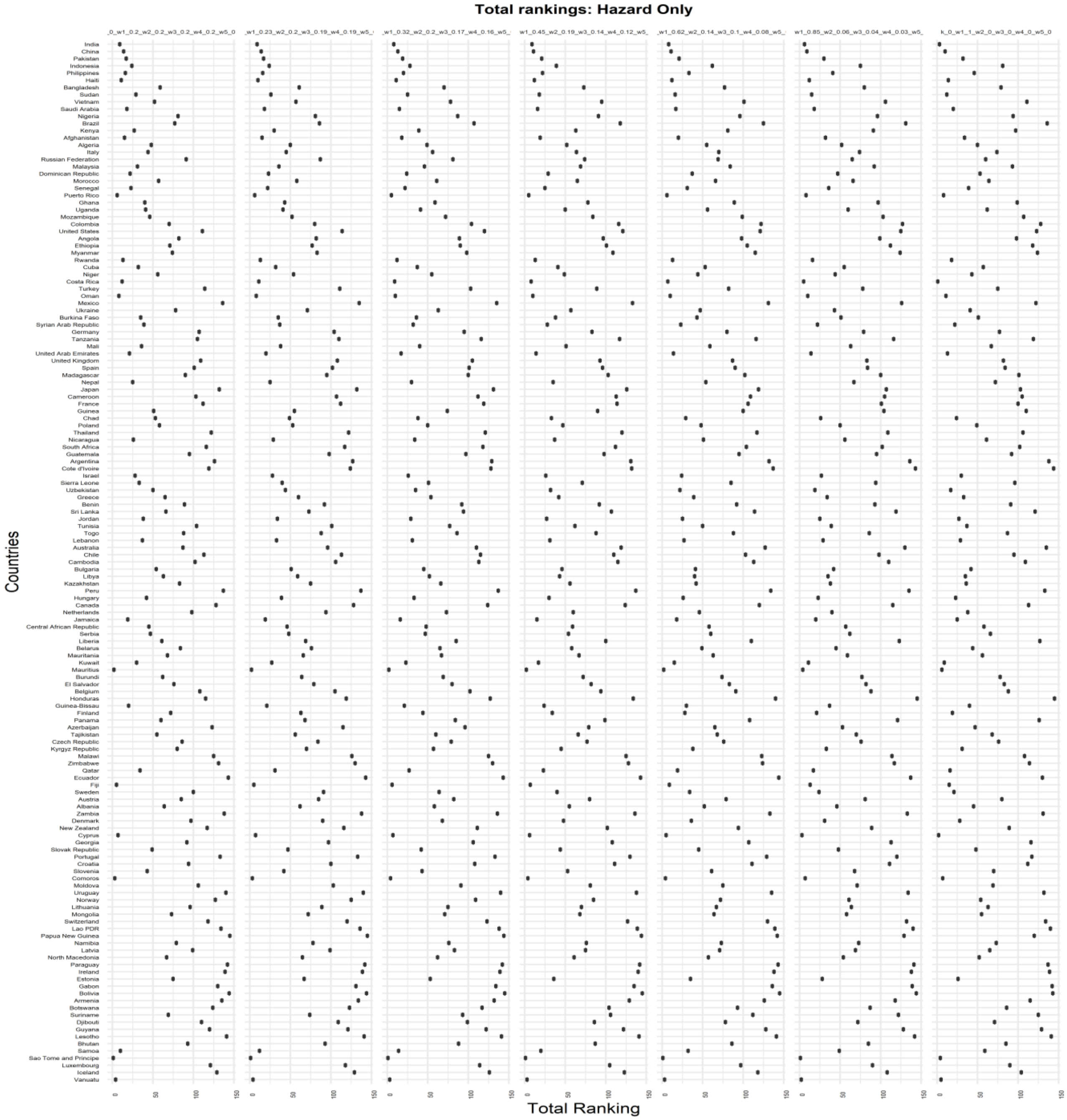

Figure 20. Country ranking according to climate change hazard (k=0, exposure = 1). Equal importance given to the different risk types (OWA α = 1) in the leftmost panel, only maximum risk considered (OWA α = 0) to the rightmost.
Source: Own illustration.
Note: for α = 0 the top positions in the rankings are generally populated by island states, countries in Africa, the Arab Peninsula, and the Middle East, but also in Northern and Central Europe and Central Asia. The USA, Mexico, Australia, and Papua New Guinea are down in the rank alongside Switzerland. Laos, Myanmar Sri Lanka also rank among the least risky alongside coastal Liberia, Cote d'Ivoire, Gabon and landlocked Lesotho and Zambia. For α = 1 still small islands score high. The Kyrgyz Republic, China and India rank high alongside Poland, the Slovak Republic, Germany, and Sweden. Landlocked African countries also obtain high scores. The USA also score high. Australia and Papua New Guinea, on the other hand, consistently place at the bottom levels regardless of the expert preferences. This is also true for the countries in South and Central America and Canada. The West-African coast is also represented among the least risky regions with countries like Guinea, Cote d'Ivoire, Togo, and Benin scoring low in the rankings. Honduras, Bolivia, and Cote d'Ivoire are ranked as the least risky countries regardless of the expert preferences.

Climate Vulnerability ranking. Sensitivity to the OWA weights (αs)

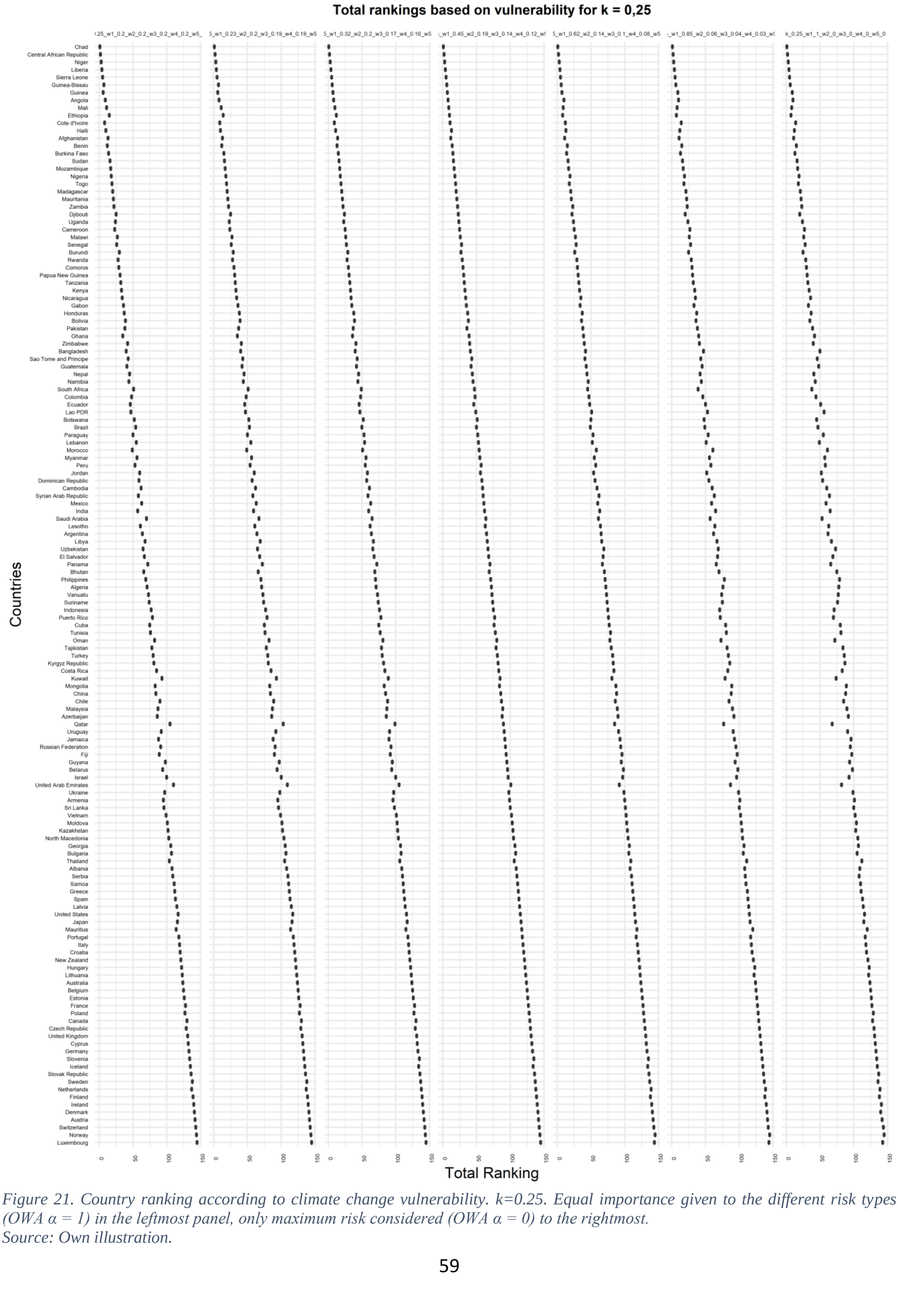

Figure 21. Country ranking according to climate change vulnerability. k=0.25. Equal importance given to the different risk types (OWA α = 1) in the leftmost panel, only maximum risk considered (OWA α = 0) to the rightmost.
Source: Own illustration.

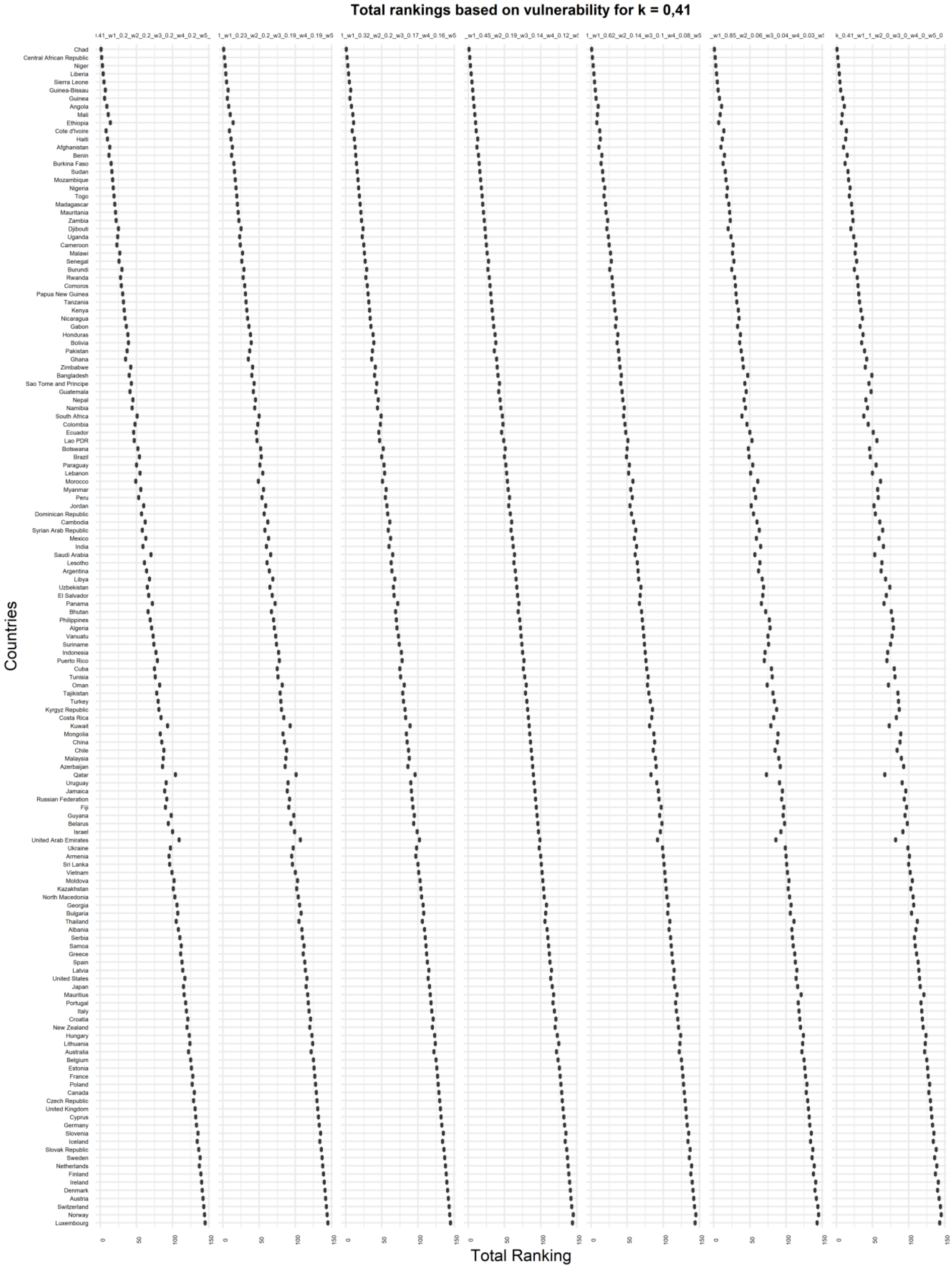

Figure 22. Country ranking according to climate change vulnerability. k = 0,41. Equal importance given to the different risk types (OWA α = 1) in the leftmost panel, only maximum risk considered (OWA α = 0) to the rightmost.
Source: Own illustration.

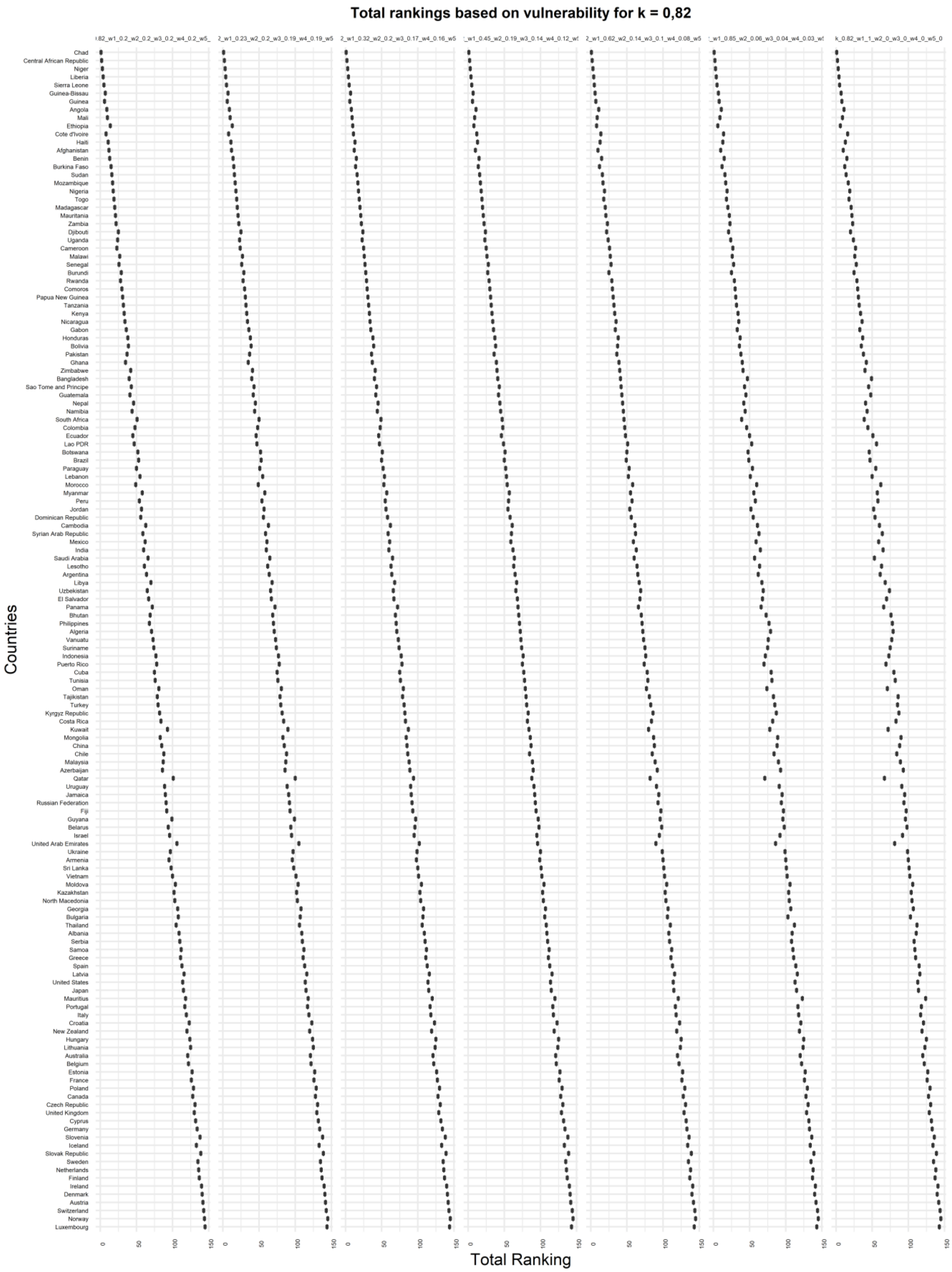

Figure 23 Country ranking according to vulnerability. k = 0,82. Equal importance given to the different risk types (OWA α = 1) in the leftmost panel, only maximum risk considered (OWA α = 0) to the rightmost.
Source: Own illustration.

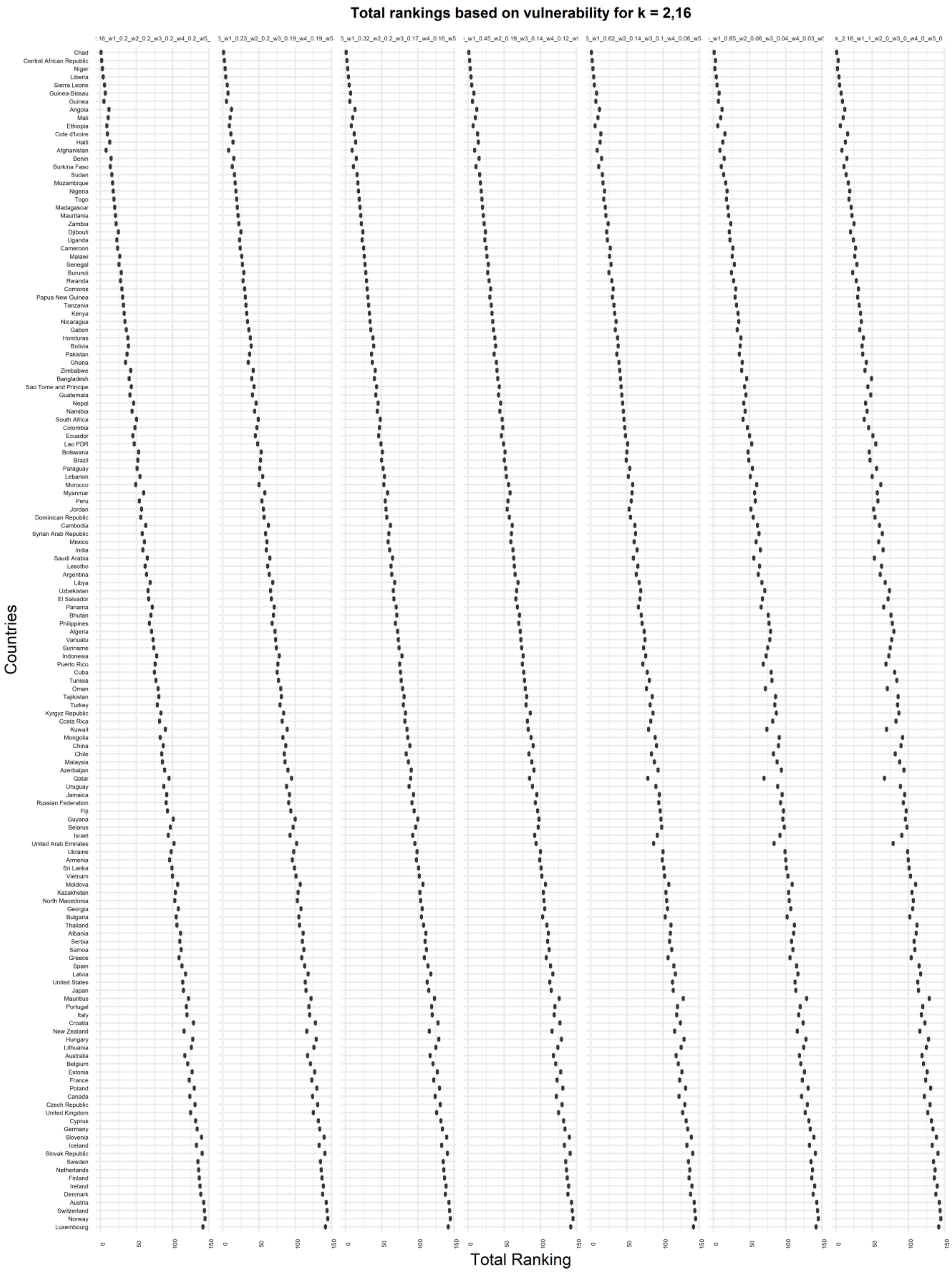

Figure 24. Country ranking according to vulnerability. k = 2,16. Equal importance given to the different risk types (OWA α = 1) in the leftmost panel, only maximum risk considered (OWA α = 0) to the rightmost.
Source: Own illustration.