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JRC Statistical Audit of the INFORM Risk index

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Contents

Abstract

The main aim of INFORM Risk is to provide information on the risk of countries to humanitarian crises caused by hazards and people's exposure to them including all main type of natural and human hazards, vulnerability and resources available to help people cope. The Competence Centre on Composite Indicators and Scoreboards (COIN) of the Joint Research Centre (JRC) was invited by the developers to audit the index. The aim of the audit is to help ensure the transparency of the methodology and the reliability of its results by focusing on data quality, the statistical soundness of the multi-level structure, and the impact of key modelling assumptions.

The INFORM risk index provides information on the risks of humanitarian crises and disasters on country level across the globe. This year, the 2024 version of the index is composed by 74 indicators and covers 191 countries across the world. JRC-COIN concludes the INFORM Risk index is an adequate representation of most of the underlying data by examining the structural coherence of correlations and Principle Component Analysis. The JRC-COIN team has identified some areas for further improvement that the developers could consider such as the statistical coherence of certain aggregates in the index. The JRC-COIN team suggests some small changes which developers could test to improve the statistical coherence. Lastly, the analysis shows that the scores and risk categories reliably reflect a wide range of scenarios and are robust to certain methodological alterations, including the imputation method, aggregation formulas and weighting.

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1 Introduction

This technical report presents a statistical audit of the INFORM Risk Index. The INFORM Risk Index is an essential tool for risk management and policy planning, providing crucial insights into risk exposures and vulnerabilities in various regions and countries. The main aim of INFORM Risk is to provide information on the risk of countries to humanitarian crises caused by hazards and people's exposure to them including all main type of natural and human hazards, vulnerability and resources available to help people cope.

The INFORM Risk index is one of products of the INFORM suite of tools which have developed in response to an increasing need to proactively manage risk natural disasters and humanitarian crises. This need is evident from communications between EU bodies and adopted regulation, which aim to make Europe a more resilient to the risks of humanitarian crises posed by disasters and their increasing intensity due to climate change (Marin-Ferrer, Vernaccini and Poljansek 2017). The INFORM Risk index is able to support global policy process such as the Sustainable Development Goals, The 2016 World Humanitarian Summit and the 2015 Sendai Framework for Disaster Risk reduction, among others.

Currently, INFORM is a joint initiative of the European Commission (EC) and the Inter-Agency Standing Committee Task Team (IASC) for Preparedness and Resilience which includes UN and humanitarian partners. As such, it is an outstanding example of composite indicator which engages stakeholders and users in development and dissemination to create the greatest potential for impact. Regular revisions of the INFORM Risk since its first launch in 2014 continue to develop and reflect state-of-the-art methodologies in disaster and risk management including semi-annual data updates and an annual methodological review. INFORM Risk currently covers 191 countries that are given a risk class based on their index score. The index includes three sub-indices: hazard and exposure, vulnerability and lack of coping capacity. These sub-indices include several levels of aggregation and 74 indicators.

In this report, we examine the statistical soundness of the calculations and assumptions used to arrive at the final index scores and rankings (OECD/JRC 2008). The overall aim is to assess to what extent information contained in the indicators is reflected in and taken up in the final index scores and the reliability of its rankings. However, statistical soundness should be regarded as a necessary but not sufficient condition for a sound index, as correlations need not "necessarily represent the real influence of the individual indicators on the phenomenon being measured" (OECD/JRC, 2008: 26). Consequently, a dynamic, iterative dialogue between the theoretical understanding of the phenomenon under consideration as well as the statistical properties of the index including its data and methodology informs the development of any index. Accordingly, the INFORM Risk developers have continually updated the framework over the last ten years to reflect the latest scientific understand on measuring risk and continue monitoring the availability of data to ensure they use the best available.

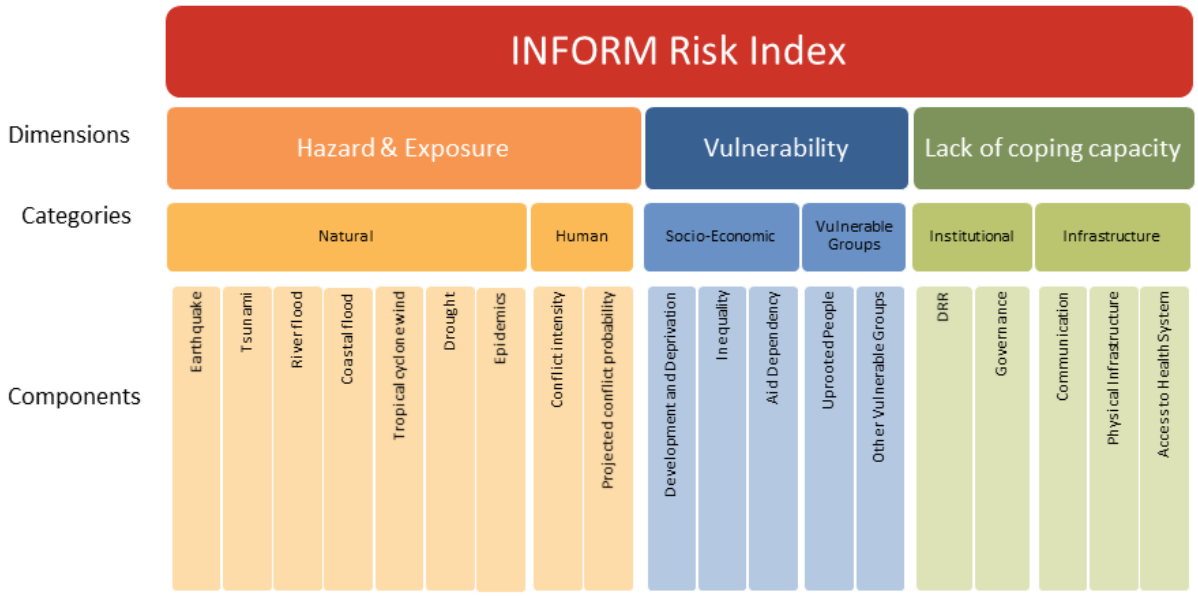
The Competence Centre for Composite Indicators and Scoreboards (CC-COIN) of the JRC, developed a set of tools, guidelines and methodology for assessing the statistical soundness of composite indicators. It includes examining the distributions of indicators and their aggregates, their correlations and assessing the robustness of the chosen methodology to viable alternatives by conducting uncertainty and sensitivity analysis.

2 Conceptual Framework

The INFORM Risk Index includes three dimensions which each contain categories, components and lastly indicators. The three dimensions of the index present the three main concepts involved in gauging disaster risk. For more information about the definitions of individual indicators and their data sources please see INFORM (2023). These include:

- Hazards & Exposure: the probability of physical (population) exposure associated with specific hazards, including natural disasters and human conflict.
- Vulnerability: represents socio-economic characteristics of the community and vulnerable groups that can make communities more susceptible.
- Lack of coping capacity: measures the ability of a country to cope with disasters in terms of formal, organised activities and the effort of the country's government as well as the existing infrastructure, which contribute to the reduction of disaster risk.

Figure 1. The structure of the INFORM Risk Index



Source: INFORM 2024

Raw indicators are first normalised to a 0 to 10 score where higher scores indicate more hazard, exposure, vulnerability or lack of coping capacity. Indicators are aggregated with sums, geometric or arithmetic mean, depending on a set of criteria (De Groeve et al., 2014), through several levels of aggregation. During geometric aggregation indicators are reversed so that lower numbers reflect more risk. This choice was a smart use of the mathematical properties of geometric aggregation, which returns averages that tend toward the lower values being aggregated compared to arithmetic averages. The developers chose to reverse scores to more closely represent their concept. Namely, the developers want to emphasize the higher risk present in the data. Once the geometric aggregation is complete, the aggregate score is reversed again to provide a consistent interpretation to users, where higher scores represent more risk.

The indicator weights, numbers of levels of aggregation and aggregation formulas vary from component to component, especially within the hazard and exposure dimension. These choices reflect scientific and methodological knowledge on measuring risk with hazards, exposure,vulnerability and coping capacity information.

The three dimensions are aggregated using the geometric mean with equal weights as recommended by CC-COIN and further justified by the developers in the methodological report (De Groeve et al;, 2014). Geometric aggregation is common and valid choice in composite indicators. A geometric mean implies that the dimensions are non-substitutable and favours countries with a balanced set of scores over countries with an unbalanced set of scores. The aggregation method reflects the developers' concept of risk and is therefore appropriate. As the index reflects risk, higher scores of the index refer to worse conditions and higher risk of humanitarian disaster.

The INFORM team publishes annual reports with clear and concise descriptions of their model and interpretations of the results. Thus, the complexity of the index is clearly communicated to users facilitated by the deep involvement of stakeholders in the INFORM Risk Index.

3 Data quality, preparation and aggregation

In this section, the CC-COIN team will revise the data and data preparation prior to its aggregation. This includes an assessment of data quality in terms of the coverage across countries and missing data of indicators, data timeliness as well as any data imputation strategies employed to counter missing data. Data preparation includes the treatment of outliers, denomination and normalisation of indicators.

The INFORM team has thoroughly documented the data availability, timeliness and imputation strategies as well as the treatment of outliers, denomination and normalisation. In fact, the INFORM team has gone an extra step to construct a data reliability index for each country. According to the 2017 methodology and concept report (Marin-Ferrer, Vernaccini and Poljansek 2017), the index takes into account missing data, out-of-date data, and conflict status of the country to inform users when the INFORM Risk index may not reflect the actual state of affairs.

3.1 Data quality

The INFORM team includes documentation on the timeliness, missing data percentages and imputation methods for each country, indicator and data-point. This information fully complies with the trust and confidence building strategies of transparent and open communication. In this section we will examine the data at the lowest level reported by the INFORM documentation. The provided data is several levels of aggregation lower than indicators, i.e. the data used to denominate or construct indicators. Therefore, in this section we will use the terms data, data-points and variables.

3.1.1 Unique values

A composite indicator is often used to rank countries. In these cases, it is desirable to have many unique values on indicator to be able to discriminate differences between countries. In the case of the INFORM Risk index, the aim is to assess the level of risk and therefore non-unique values simply reflect an absolute level of risk present in the country. Therefore, non-unique values are not a problem, as long as the values on the indicators adequately reflect the concepts being measured. The fraction of unique values in the indicators of the index is below 50% for all but two of the 46 indicators. It is an exceptionally high proportion and implies that many countries are scored very similarly in the index. In most cases, this is undesirable as an indicator's primary purpose is to distinguish differences between countries. However, as noted previously, these non-unique values simply reflect the fact that many countries are not at risk. Therefore, it is appropriate and meaningful to have a high proportion of non-unique values on indicators and similar ranking countries.

3.1.2 Timeliness

Composite indicators are used to make decisions in politics and policy. Therefore, the timeliness of data is important to reflect the most up-to-date state of affairs. Overall, the INFORM risk index of 2024 is based on recent data. Over half of the data included in the index refers to the last 3 years and 83% of data refers to the last four years. General guidelines are to include data collected up to five years before and to replace any data that was collected ten or more years ago. However, these guidelines should also be interpreted within the context of the nature of the phenomenon under study and the data availability.

Less than two percent of the data was collected before 2014, which is distributed across seven variables (“Household Size”, "Multidimensional Poverty Index”, “U5 Underweight”, “Income GINI coefficient”, “HFA scores”, “Adult Literacy Rates” and “Physicians Density”), for some variables collection year also depends on the country. Only the HFA scores and household size variables have a high percentage of date that was collected ten or more years ago. Lastly, the majority of data collected more than five years ago refers to 2015 (8% of the data)[1]. The COIN team recommends to keep on monitoring available data for alternatives, as the INFORM Risk team does every year.

3.1.3 Missing data

The INFORM Risk 2024 index includes 89.75% of observed data-points. Data coverage is therefore excellent across the 75 variables of which 56 include at least 90% of observed data. Missing data is clustered on specific variables. Five variables includes less than 50% of observed data points. In these cases, the data is missing because populations are not at risk (returned refugees, living in slums, Ebola, Lassa Fever, Marburg Virus) and can therefore be safely assumed to be 0. Indeed, the INFORM Risk developers do impute 0 when data is missing on these variables. Therefore, the high percentage of missing data on these indicators does not pose a problem.

An additional ten variables include more than 70% observed data and four indicators have between 50% and 70% observed data. In these cases, too, data is often missing because countries have such high coverage or negligible risk that they do not report on these variables, for example, adult literacy rate is missing for several EU27 countries. In these cases, the INFORM team has committed to find the best available data and deals with these on an indicator by indicator basis.

3.1.4 Variable measurement

One common issue in composite indicators is the presence of non-continuous indicators (dichotomous, categorical and ordinal). These types of indicators have some undesirable properties that make them unsuitable for common statistical methods related to correlation, outliers and imputation. The INFORM Risk 2024 index includes a two ordinal indicators, “Current Subnational Conflict Intensity” and “Current National Power Conflict Intensity” that belong to the “Human Hazard” dimension. Nevertheless, aggregation loses its statistical meaning with these indicators unless the developers have a good justification that the values of the indicators represent equal distant quantities in the underlying phenomenon. To circumvent this issue, the INFORM Risk team has created a mapping algorithm which assigns scores on the aggregated based on certain combinations of scores on these indicators. In effect, the INFORM Risk team has made an expert judgement to map the ordinal indicators to another scale. The CC-COIN team notes these limitations to make the developers and users aware, noting, however, that the INFORM team continually monitors available data to ensure they include the best indicators available. Indeed these ordinal indicators will be replaced in the next edition with continuous indicators.

[1] These includes all data points for the variables: Population exposed to EVD (zoonoses), Population exposed to Lassa Fever (zoonoses), Population exposed to MVD (zoonoses), Population exposed to Zika (vector borne), Population at Risk to Aedes (vector borne), Population exposed to Dengue (vector borne) and 60% of data points on the variable HFA scores.

Another type of indicator that may require additional attention are composite indicators. The use of other composite indicators is generally discouraged due to the lack of control which developers have over the methodology, structure and contents of the composite indicator used as data. Furthermore, there is a risk of redundancy, as some of the individual indicators incorporated by the developers may overlap with those included within the composite indicator being developed, leading to duplication of information. The INFORM Risk 2024 index contains the following composite indicators: "Gender Inequality Index", "Human Development Index", "Corruption Perception Index" and "Multidimensional Poverty Index". The CC-COIN team notes these limitations to make the developers and users aware, noting, however, that the INFORM team continually monitors the content of these composite indicators to avoid the pitfalls mentioned above and monitors available data to ensure they include the best indicators available.

3.2 Imputation

Data is imputed for 19 data points on the variable "Average Dietary Energy Supply Adequacy" and 40 data points on the variable "Prevalence of Undernourishment" using regional averages. The "Human Development Index" is also imputed once using the GDP. The conditional mean imputation strategy is valid as long as there is a substantive link between the regional and (missing) national values. This judgement is up to the developers of the index and outside of the expertise of CC-COIN. The INFORM Risk developers have tried many alternative imputation methods (Poljansek et al. 2020) and found that using a variety of common strategies such as last-value-carried-forward, interpolation, linear regression and imputing values based on substantive knowledge (e.g. zeros on International humanitarian aid by the Financial Tracking Service) tailored to the specific indicators is able to reduce missing values from 50% to 11%. The individualised approach to missing data practiced by INFORM Risk follows best practices in data imputation, namely using the most pertinent statistical information and substantive knowledge to build an imputation function for each indicator.

The aggregation formulas also create implicit imputations. In the INFORM Risk index, any missing values are excluded in the aggregation formulas (arithmetic and geometric) for components, categories and dimensions. For example, in the "Communication" component of the "Infrastructure" dimension, averages are based on the number of available indicators: adult literacy rate, access to electricity, internet users, and mobile cellular subscriptions. In this category, the adult literacy rate indicator is often missing which results in the Communication score being based on three – not four – indicators for those countries with missing values. Given that the developers can make reasonable estimates on the literacy rates of those countries with missing values, it could be reasonable to impute them. The current procedure is equivalent to imputing the row-mean of the remaining indicators in the place of the missing value. For example, Luxembourg is missing only adult literacy rate. The arithmetic average of the remaining indicators is 1.1, which is the value implicitly imputed and corresponds to the adult literacy rate of Malaysia – 95%. A small improvement could be made using k-NN or imputing likely values based on expert knowledge. The CC-COIN team recommends the developers assess whether the implicit row-mean imputation impacts the aggregate scores. Nevertheless, the 'non-imputation' approach is valid as long as it is clearly communicated and the implications are acknowledged by the developers to maintain transparency in the computation of the index.

3.3 Treatment of outliers

The presence of outliers that could potentially bias the effect of the indicators on the aggregates. Outliers may cause indicators to have very few unique values after normalisation, which then reduced the ability of the indicator to discriminate between units. CC-COIN recommends an approach for outlier identification based on the values of skewness and kurtosis, i.e., when the variables simultaneously have an absolute skewness higher than 2.0 and a kurtosis higher than 3.5. The INFORM Risk team uses these CC-COIN criteria to spot outliers as well as a second method. The second method is based on the interquartile range (IQR), where outliers are identified by exceeding 1.5 IQR from the lower or higher quartile.

The INFORM Risk developers calculate these statistics based on ten years of data to be able to create index scores and ranks that can be compared across time. Outliers are treated using the minimum and maximum observed values that meet the conditions to be considered non-outliers. Therefore, the treatment of outliers is incorporated into the normalisation procedure, see **section 3.5**. The procedure is equivalent to winsorising any outlier values. The CC-COIN team would like to note that this is a valid strategy but can also cause a compression of the distribution in case there are many values which are identified as outliers. In such cases where the distribution of variables is skewed, the log base ten or natural log can be applied to normalise the distribution before applying the min-max normalisation. This is indeed the strategy the INFORM Risk team applies.

The CC-COIN team would like to note four indicators that have outlying values after the treatment. These include “Current National Power Conflict Intensity”, “Current Subnational Conflict Intensity”, “Maternal Mortality ratio” and “Physical exposure to tropical cyclone wind (relative)”. The first two indicators are categorical indicators based on qualitative data. Therefore, the outlier statistics are not meaningful. The second two indicators, however, do meet the criteria for outlier treatment[2]. The CC-COIN recommends that the INFORM team plots the scores of these indicators and their aggregates to assess whether the outliers have an undesirable impact. If so, the distribution can be treated using the logarithmic transformation.

3.4 Denomination

Denominating indicators is essential to compare scores and ranks of countries in a fair manner. The denomination of a variable allows a fair comparison by relativizing the country’s “performance” on a certain variable relative to inputs. In composite indicators on social issues, these are often the population or the GDP. However, the INFORM Risk index, calculates the risk of humanitarian crises by relating a country’s level of hazards and exposures, and its vulnerabilities to its coping capacity. As such, the INFORM Risk team has decided to take into account both denominated and non-denominated indicators to have the best understanding of the risk facing a country. For example, the natural hazard component includes both the absolute and percentage of population exposed to better capture the severity of risk in both large countries and small island nations. The

[2] Maternal Mortality ratio is not treated but it has a skew just over the threshold of 2.01 and a kurtosis of 3.9. Physical exposure to tropical cyclone wind (relative) is computed using the geometric mean of two other variables that are not treated. The resulting indicator has a skew of 2.64 and kurtosis of 5.59.

measurement approach was decided through stakeholder consultation. In the majority of cases, indicators are denominated by a relevant statistic.

3.5 Normalisation

The normalisation of indicators is achieved through the min-max normalisation that transforms all indicators to a scale of 0 to 10. The minimum and maximum values are those identified in the last ten years of data that fall within the boundaries of the outlier criteria. In many cases, the normalised values are also rounded to the first decimal point. This could be considered a loss of precision, however, the developers judged that including more decimal points is misleading in terms of the accuracy of the results. Therefore, rounding the scores to the first decimal place is scientifically more appropriate than to report "precise" estimates.

3.6 Aggregation

The INFORM risk team uses both types of aggregation that are commonly used in composite indicators, the geometric and arithmetic mean. These two aggregation methods have different computational implications which the INFORM Risk team has used to reflect the concepts measured. The geometric mean is the nth root of the product of its n elements. The formula penalises to some extent series of data that are unbalanced and creates higher values when the series are of similar values. Conceptually this indicates that the elements of the aggregate cannot substitute for each other. The second type of aggregation is the arithmetic mean, which is the product of n elements divided by n. In this case, perfect substitution is possible: a higher score on one element can completely make up for a lower score on another.

During the computation of geometric averages, the developers reverse the scoring of indicators. The decision avoids zero values, which is necessary to compute geometric averages. Additionally, the developers are able to take advantage of the properties of geometric mean which tend to lower values. However, transforming indicators in geometric averages does not simply shift the average as it would in arithmetic averages. More specifically, the transformation adds a constant (new minimum) which compresses the range of the aggregate distribution at the lower end. Additionally, adding a large value (in this case 10% of the total range) has a bigger impact. Thus, the reverse scoring could reduce the ability of the aggregate to distinguish between countries most at risk. The CC-COIN team recommends the developers to assess the extent to which this effect is a conceptual or methodological issue. The CC-COIN team suggests to minimize the constant being added as much as possible, for example to 1% of the total range (0.1) so that the reverse scores go from 0.1 to 10. In Section 5, the JRC-COIN team assesses the impact of this alternative methodological choice, concluding it has a minimal impact on the scores and ranks. Moreover, this decision will mainly affect countries from "low" and "very low" categories which are not important in terms of policy relevance.

3.7 Ranking

The INFORM Risk index is primarily communicated through its five tiers of 'risk class'. However, the publicly available excel file also include the ranking of countries. Therefore, the CC-COIN team will also comment on the rankings. The INFORM index uses a minimum ranking algorithm where k units which have the same scores are given the same ranking, upon which the next available rank skips k positions. As a result of this choice the number of unique ranks in the INFORM Risk index is

substantially lower than the 191 units, namely 61 unique ranks. Although an uncommon choice, the ranking strategy is perfectly valid and, in this case, conceptually motivated. The INFORM Risk rankings are meant to show how many countries are more at risk than another country, thus the ties are calculated using the lowest rank possible.

4 Statistical coherence

The assessment of statistical coherence presented in this step consists of a multi-level analysis of the correlations of its indicators, components, categories, dimensions and index scores and a principal components analysis of the relation between the index and its constituent dimensions ([3]).

4.1. Correlation analysis

The statistical coherence of an index should be considered a necessary but not a sufficient condition for a sound index. Given that the statistical analysis is mostly based on correlations, the correspondence of every index to a real-world phenomenon needs to be critically addressed by developers and experts, because 'correlations do not necessarily represent the real influence of the individual indicators on the phenomenon being measured' (OECD and JRC, 2008). This influence relies on the interplay between both conceptual and statistical soundness. The degree of coherence between the conceptual framework and the statistical structure of the data is an important factor for the reliability of an index.

The correlation analysis is used to assess the extent to which the observed indicator data support the defined conceptual framework. Ideally, correlations among factors (indicators or aggregates) within every level of the index should be positive, statistically significant, and, as suggested by JRC-COIN, ideally lie between 0.30 and 0.95. This condition effectively ensures that the overall index scores adequately reflect the underlying indicator values, i.e., that an adequate level of information is passed on from the indicators to the aggregates and finally to the overall composite index.

The logic of correlation coherence is based on the idea that aggregates should summarise the values of the underlying indicators because indicators are all different aspects of the same phenomenon. Thus, it follows that all aspects of the phenomenon (indicators) increase or decrease in quantity together, systematically. Statistically, this can be assessed by the correlation between indicators and between indicators and their aggregates, which shows that, on average a higher score on one indicator is reflected in the aggregate score. If there is no correlation between aggregate and indicator, it shows that indicator scores are not systematically connected with scores on the aggregate. It is also important that indicators of the same aggregate are correlated, otherwise an aggregate score may hide widely differing scores on the indicators (e.g. an arithmetic average of two low indicators is biased by a high score on a third indicator if all their correlations are low). Following the same logic, the correlations between indicators of the same aggregate should be higher than their correlations with other indicators and aggregates. A well separated correlation structure indicates each aggregate is indeed a separate phenomenon that is measured by appropriate indicators.

However, in other situations, some indicators are meant to include specific information on a very few units. In these cases, correlations are expected to be low, but the indicator may still be valid to include if it can be shown to meaningfully contribute to aggregate scores for those few units for which it is included. These cases should be assessed by developers by plotting the indicator scores

[3] The INFORM Risk Index contains an unbalanced number of aggregation levels across its sub-pillars. Due to the technical difficulties this implies, the CC-COIN team decided to keep 5 levels (index, dimensions, categories, components, indicators) for the purposes of this audit

and their aggregates. In the INFORM Risk index the conflict indicators are an example. However, such judgements are left to developers who have substantive knowledge on the issue.

Lastly, correlations can highlight whether the index framework includes redundancy among its indicators and aggregates, which can be identified by very high correlations greater than 0.95. If two indicators or aggregates are collinear, this may amount to double counting (and therefore over-weighting) of the aspect that they measure.

4.1.1 Correlation analysis between indicators and aggregates

Due to the large number of indicators, the correlations between indicators are not shown, instead we summarise their correlation structure. Taking into account the criteria described above, looking at the correlation structure of the index 36 out of 41 (88%) unique pairs of indicators within the same aggregate meet the quality standards to achieve statistical coherence. The following are the set of indicators which have correlations with their sibling indicator that do not meet the criteria:

- The two indicators in the Drought component “Probability of agricultural drought” and “Drought impact” have a correlation of -0.02. Their aggregate may therefore not accurately summarise information from both indicators.
- The two indicators within the “Current Highly Violent Conflict Intensity Score” aggregate. Given that the aggregate is not computed by any aggregation formula and takes into account categorical variables, the previously mentioned criteria do not apply.
- There is a strong correlation between two of three indicators in the “Other Vulnerable groups” of 0.65, however, the correlation between the “Recent Shocks” with the other indicators ranges from 0.25 to 0.33. The information from this indicator may be covered up by the strong correlations between other indicators in this version of the index and have a negligible impact on the aggregate. However, this issue is unlikely to be structural to the index as the “Recent Shocks” indicator changes considerably over time.
- The correlation (0.17) between the indicators “Volume of Remittances” and “Net ODA received (% of GNI)” in the “Economic Dependency Index” component. The low correlation indicates that it is likely that, on average, information from these two indicators will not be represented in an aggregate.
- The indicators “Physical exposure to zoonoses” and “Person-to-person” with a correlation value of 0.28, although is close to the thresholds of 0.30.

However, the correlation between the indicators described and the next levels of aggregation are adequate, suggesting that the information that they capture is transmitted to the index. Overall, the correlation structure at the indicator level is adequate in the other dimensions which have more than one indicator. Thus, the correlation structure is quite satisfactory. In this version of the INFORM Risk, the indicators with low correlations with other indicators also show adequate correlations with their aggregates, indicating there are no serious issues at the first level of aggregation. However, these results can change from year to year. Therefore, the CC-COIN team recommends that INFORM Risk developers keep an eye on these indicators and their correlations to be aware of any potential issues with the information transfer from indicator to aggregate.

The next step is to examine the correlations between indicators and their aggregates. The correlations between indicators and components are quite high, in most cases above 0.7. The high correlation between indicator and aggregate is evidence that the information from indicators is

reflected in the aggregate scores. Even in the two dimensions where indicators have low correlations with each other, they do have adequate values with their aggregate. The CC-COIN team would like to flag there are several indicators whose correlation with their immediate aggregate exceeds the 0.95 threshold[4]. In these cases, the INFORM team could consider dropping one of the indicators in their respective aggregates without much loss of information. Dropping or keeping these indicators is unlikely to have any impact as most are aggregated together in the INFORM risk index. High correlations are an issue when three or more indicators are aggregated where two have a high correlation. In these cases the two highly correlated indicators will supress variation of the other indicators to be reflected in the aggregate.

Building on this analysis, the separation in indicator correlations is also notably good. Most indicators correlate with their own indicators and aggregates more strongly than with others. However there are a set of indicators that are more correlated with other components.

- "Children under five" is more correlated with the components "Development & Deprivation", "Physical Connectivity", "Communication" and "Access to Health Care Index" than with its assigned category, suggesting that it may be more suitable in one of the other components.
- The indicators "P2P" and "Waterborne - Foodborne", are more correlated with the components "Communication, "Physical Connectivity", "Access to health care Index", and "Development & Deprivation".

CC-COIN recommends to review the indicators in the list above the respective aggregates to determine whether there is a valid conceptual reason for reassigning these indicators to a different component. As shown in **Table 1**, correlations between the indicators and their second level aggregates (categories) are less uniform than with their first level aggregates (components).

- The "Natural Hazards" category has a weak correlation with three indicators (cyclone (relative), P2P, waterborne-foodborne) and a negligible correlation with "Agricultural Droughts probability".
- The "Vulnerable Groups" category has a weak correlation with its indicators "Health Conditions" and "Food Security".
- However, these cases are the exception and the remaining four category aggregates have good or acceptable correlations with all their indicators.

Correlations between indicators and their third level aggregates (dimensions) are overall adequate. The "Lack of coping capacity" dimension includes only moderate to strong correlations with its indicators. The "Vulnerability" dimension includes only one weak correlation out of 13 indicators, namely "Volume of Remittances". Lastly, the "Hazard & Exposure" dimension includes thirteen adequate correlations and six weak correlations. The weak correlations indicate there may be some lack of information transfer from indicators to aggregates.

[4] These indicators include: Human Development Index, Multidimensional Poverty Index, Government Effectiveness, Corruption Perception Index, Physical Exposure to Coastal Flood (absolute), Annual Expected Exposed People to River Floods, Physical exposure to river flood (relative), Annual Expected Exposed People to Cyclone's Wind (absolute), Physical exposure to tsunami (relative), GCRI Highly Violent Internal Conflict probability, Total Uprooted people (percentage of the total population) and Uprooted people (total population)

A similar pattern emerges when indicators are correlated with the INFORM Risk index, the indicators in the “Coping Capacity” and “Vulnerability” dimensions have good correlations with the index. However, the indicators in the “Hazards & exposure” dimension have weak or in some cases negligible correlations.

Overall, the correlations structure in terms of the strength of correlations and separation between aggregates is good. The correlations between indicators with each other show that an adequate and in many cases good correlation structure, with only a few minor cases where correlations or separation is outside the recommended bounds. These are minor issues that are unlikely to have an impact on the index. The correlation structure between indicators and second or third level aggregates shows some weak correlations. For all the indicators in the “Coping Capacity” and “Vulnerability” dimensions these correlations do not pose a potential issue as their correlation with the index is still adequate. However, when it comes to the indicators of the natural hazard dimension, there are more weak or negligible correlations with the dimension and index in comparison to the other two dimensions. This indicates information from these indicators is not well reflected in the overall index scores.

Table 1. Correlations between indicators and aggregates in the INFORM Risk index of 2024

Dimension	Category	Component	Variable	Compo-nent	Cate-gory	Dimen-sion	INFORM
Hazard & Exposure	Human Hazard	GCRI Highly Violent Internal Conflict probability	GCRI Highly Violent Internal Conflict probability*	1.00	0.94	0.62	0.62
		Current Highly Violent Conflict Intensity Score	Current National Power Conflict Intensity*	0.61	0.34	0.31	0.26
			Current Subnational Conflict Intensity*	0.72	0.39	0.36	0.38
	Natural Hazard	Drought	Agriculture Droughts probability	0.67	-0.10	-0.03	-0.06
			People affected by droughts and Frequency of events	0.76	0.36	0.50	0.59
		Coastal flood	Physical exposure to coastal flood absolute	0.96	0.63	0.33	0.07
			Physical exposure to coastal flood relative	0.93	0.41	0.03	0.14
		Earthquake	Physical exposure to earthquake absolute	0.92	0.72	0.49	0.26
			Physical exposure to earthquake relative	0.93	0.47	0.16	0.05
		Tsunami	Annual Expected Exposed People to Tsunamis	0.94	0.76	0.37	0.15
			Physical exposure to tsunami relative	0.97	0.52	0.13	0.02

Dimension	Category	Component	Variable	Compo-nent	Cate-gory	Dimen-sion	INFORM
		Epidemic	P2P	0.72	0.01	0.38	0.66
			Physical exposure to vector borne	0.82	0.42	0.50	0.61
			Physical exposure to zoonoses	0.74	0.38	0.47	0.48
			Waterborne Foodborne	0.75	0.03	0.38	0.70
		River Flood	Annual Expected Exposed People to River Floods	0.97	0.54	0.58	0.42
			Physical exposure to river flood relative	0.97	0.36	0.37	0.27
		Tropical Cyclone	Annual Expected Exposed People to Cyclone's Wind absolute	0.96	0.61	0.27	0.10
			Physical exposure to tropical cyclone wind relative	0.82	0.18	-0.04	0.13
Vulnerability	Socio-Economic Vulnerability	Development & Deprivation	Human Development Index	0.98	0.97	0.80	0.80
			Multidimensional Poverty Index	0.98	0.91	0.71	0.64
		Economic Dependency Index	Net ODA received % of GNI	0.85	0.62	0.39	0.17
			Public Aid per capita US	0.92	0.55	0.41	0.28
			Volume of remittances	0.62	0.32	0.18	0.11
		Inequality	Gender Inequality Index	0.90	0.92	0.77	0.78
			Gini Index	0.80	0.48	0.40	0.35
	Vulnerable Groups	Other Vulnerable Groups	Children Under 5	0.74	0.37	0.74	0.76
			Food Security	0.77	0.23	0.59	0.55
			Health Conditions	0.73	0.19	0.55	0.48
			Recent Shocks	0.74	0.46	0.53	0.47
		Uprooted people	Total Uprooted people percentage of the total population	0.95	0.84	0.48	0.36
			Uprooted people total population	0.97	0.85	0.50	0.48
Lack of Coping Capacity	Institutional	Access to health care Index	Immunization coverage	0.73	0.66	0.65	0.61
			Maternal Mortality ratio	0.80	0.84	0.77	0.67
			Per capita public and private expenditure on health care	0.90	0.83	0.85	0.71

Dimension	Category	Component	Variable	Compo-nent	Cate-gory	Dimen-sion	INFORM
			Physicians Density	0.92	0.85	0.80	0.64
		Communication	Access to electricity	0.90	0.85	0.75	0.64
			Adult literacy rate	0.88	0.85	0.76	0.68
			Internet users	0.91	0.89	0.87	0.78
			Mobile cellular subscriptions	0.73	0.61	0.59	0.51
		Physical Connectivity	Drinking water	0.90	0.91	0.81	0.71
			Road density	0.81	0.71	0.67	0.63
			Sanitation	0.91	0.91	0.82	0.68
	Infrastructure	DRR	HFA Scores	1.00	0.88	0.69	0.36
		Governance	Corruption Perception Index	0.98	0.87	0.83	0.74
			Government Effectiveness	0.98	0.91	0.90	0.76

Note: Correlations between 0.30 to 0.95 are desirable. Correlations lower than 0.30 indicate a lack of information transfer between indicator and aggregate. Correlations higher than 0.95 indicate redundancy. Highlighted in grey and italic coefficients that are negligible (values below 0.3). For cases marked with '*' the Kendall Tau correlation coefficient is reported due to the presence of categorical data.

Source: European Commission's Joint Research Centre, 2024.

4.1.2 Correlation analysis between aggregation levels

To further understand the statistical coherence of the aggregates, this section we will analyse if the information of all components, categories and dimensions are equally represented in their aggregates and whether components and categories are grouped under the best fitting aggregate from a statistical point of view.

The correlations between components of each dimension show a similar pattern as those between indicators and higher aggregates. That is, overall the correlations look adequate or strong however components within the "Hazard & exposure" dimension correlations are weak or negligible. It is likely because of the diverse types of natural and human hazards included do not co-occur. However, it does pose a potential issue as, on average, information from indicators in these dimensions is not aggregated to the index, as shown by the correlations flagged in the previous section.

The correlations between component and their assigned category are shown with a black border in **Table 2**. These correlations should be higher than others in the same row to indicate the component fits best under that category. The separation of components between aggregates indicates that the aggregates capture separate phenomenon and that the components are attributed to the appropriate phenomenon. Additionally, correlations of components that share the same aggregate should be similar so that each has a similar contribution of the information to the

aggregate. If one element is much more strongly correlated with an aggregate, it implies that those scores have a greater impact on the scores of the aggregate than other elements.

Correlations between components and their assigned category are overall well within the recommended bounds. This solid correlation structure of dozens of indicators is a testament to the continual effort of the INFORM team. The “Human Hazard”, “Infrastructure”, “Institutional” and “Socio Economic Vulnerability” categories, show a compact range of correlations with values above 0.8 in most of the cases. This ensures that the information is properly transmitted to the next level of aggregation and that there is a similar contribution of each component.

The correlation structure between the different components and categories provided in **Table 2** shows that the “Natural Hazard” and “Vulnerable Groups” categories have unbalanced correlations between components, or their categories have a higher correlation with another component. The results suggest that the component “Other Vulnerable Groups” is more suitable in the “Infrastructure” (0.79) or “Socio Economic Vulnerability” (0.81) categories, from a statistical point of view. The INFORM Risk team could consider moving the component there to better enable the information contained to contribute to the index. Another potential issue can be observed in the “Natural Hazard” category, where the indicator “Physical Exposure to Coastal Flood” and “Droughts probability and historical impact”. Such a correlation structure makes it more difficult for these indicators to have a meaningful impact on the index. A more detail analysis of this particular category is provided in **section 4.2**.

Regarding the range of values, CC-COIN notes that in the “Vulnerable Groups” category there is a large imbalance between the information transmitted to the aggregate by “Uprooted people” and “Other Vulnerable Groups“, suggesting that the value of the aggregate is mainly driven by the former. This can also be observed in the “Socio Economic Vulnerability” category, where the “Economic Dependency Index” is not as highly correlated as the other two components. However, the imbalance in the “Socio Economic Vulnerability” reflects the developers’ weighting of these components and is therefore conceptually motivated.

Table 2. Correlations between components and categories in the INFORM Risk index of 2024

	Human Hazard	Natural Hazard	Infrastructure	Institutional	Socio Economic Vulnerability	Vulnerable Groups
Current Highly Violent Conflict Intensity Score*	0.55	0.19	0.34	0.26	0.31	0.38
Projected conflict intensity*	0.94	0.33	0.37	0.30	0.31	0.44
Physical exposure to coastal flood	0.01	0.57	-0.17	-0.20	-0.26	-0.02
Physical exposure to epidemics	0.56	0.38	0.78	0.58	0.74	0.32
Droughts probability and historical impact	0.36	0.25	0.35	0.30	0.35	0.26
Physical exposure to tropical cyclone	-0.01	0.52	-0.04	-0.06	0.04	-0.23
Physical exposure to tsunami	0.01	0.65	-0.08	-0.05	-0.05	-0.05
Physical exposure to river flood	0.40	0.46	0.14	0.06	-0.01	0.38
Physical exposure to earthquake	0.14	0.64	-0.14	-0.03	-0.08	0.12
Access to health care Index	0.48	0.20	0.94	0.71	0.92	0.26
Communication	0.51	0.09	0.93	0.61	0.85	0.40
Physical Connectivity	0.53	0.16	0.96	0.61	0.83	0.36
DRR	0.12	-0.10	0.43	0.88	0.52	0.08
Governance	0.52	0.26	0.74	0.91	0.77	0.35

	Human Hazard	Natural Hazard	Infrastructure	Institutional	Socio Economic Vulnerability	Vulnerable Groups
Development & Deprivation	0.49	0.16	0.96	0.69	0.96	0.33
Economic Dependency Index	0.07	-0.05	0.42	0.48	0.66	0.12
Inequality	0.45	0.19	0.76	0.58	0.81	0.31
Other Vulnerable Groups	0.42	0.09	0.79	0.59	0.81	0.43
Uprooted people	0.51	0.20	0.04	0.00	-0.04	0.88

Source: European Commission's Joint Research Centre, 2024.

Note: The table includes Pearson correlations except for cases marked with '*' where the Kendall Tau correlation coefficient is reported dueue to the presence of categorical data.

The correlation structure shown in **Table 3** between categories and the dimensions is overall well balanced and separated. Only the "Socio Economic Vulnerability" seems to be more suitably aggregated to the "Lack of Coping Capacity" dimension with a strong correlation coefficient of 0.9, however the difference is small and not a great concern. Additionally, the "Hazard & Exposure" dimension includes some imbalance between the information transmitted by the "Human Hazard" category and the "Natural Hazard". The imbalance is clearly shown by the coefficient of determination (R^2) which is a measure of the amount of variation in the indicator that is captured by the aggregate. In this case the aggregate reflects most of the variation in the "Human Hazard" category (86%) but less than half of the variation of the "Natural Hazard" category (45%). This indicates that the "Hazard & Exposure" category is mainly based on human hazards. As mentioned before, the presence of categorical variables, low correlations between indicators and adding a constant to elements during geometric aggregation may have a role in producing these results. These potential issues could be ameliorated by assigning higher weights to indicators, components or categories which have a low correlation to boost their signal and transmit more information to the index. Alternatively, the categories with low correlations with their aggregates could be moved to another aggregate where they have a higher correlation (e.g. move "Physical exposure to epidemics" to "Socio Economic Vulnerability"). In the case that the developers believe the imbalance between the contribution of natural and human hazards accurately reflect the concepts they aim to measure, the JRC-COIN suggest to clearly communicate this decision to the users.

Table 3. Correlations between categories and dimensions in the INFORM Risk index of 2024

	Hazard & Exposure	Lack of Coping Capacity	Vulnerability	INFORM
Human Hazard	0.93	0.53	0.64	0.85
Natural Hazard	0.67	0.15	0.20	0.45
Infrastructure	0.50	0.93	0.78	0.81
Institutional	0.37	0.90	0.61	0.67
Socio Economic Vulnerability	0.41	0.90	0.81	0.77
Vulnerable Groups	0.58	0.36	0.81	0.69
Hazard & Exposure	-	0.48	0.59	0.86
Lack of Coping Capacity	0.48	-	0.77	0.82
Vulnerability	0.59	0.77	-	0.89

Source: European Commission's Joint Research Centre, 2024.

Regarding the correlations between dimensions, it seems that there is a strong association between the "Vulnerability" and "Lack of Coping Capacity", but not with the "Hazard & Exposure". This correlation structure creates a possibility that the index mostly reflects the first two dimensions and to a much lesser extent the "Hazard & Exposure" dimension. Despite that, the information transmitted to the index among these components is strong and balanced, as shown by the correlation between the index and dimensions.

Overall, the INFORM risk index is computed in a way that ensures equilibrium across four out of six categories and two of three dimensions. The majority of correlations at each level of aggregation, from indicators to dimensions, show a good strength and separation. CC-COIN has identified imbalances within "Hazard & Exposure" and the "Vulnerable Groups" dimension which lead to an suboptimal flow of information from the elements to the aggregates. The clearest example is the "Hazard & Exposure" dimension, which is mainly driven by "Human Hazard". As a result, the indicators on coastal floods, earthquakes and cyclones have a negligible relationship with the index. For this reason, CC-COIN recommends exploring the relationships between the indicators creating these aggregates to understand if indicators can be aggregated in a different manner. A more coherent correlation structure could be achieved, from a statistical point of view, through weighting or moving indicators to another aggregate or moving categories to another component. However, such changes are always difficult to make given other relevant considerations such as conceptual framework, data constraints and stakeholder engagement. In case the correlation structure cannot be improved, the CC-COIN recommends to visually check cases (countries) that may be most impacted by plotting the risk-class or dimension scores against indicators with a low correlation

with the index. Through such visual inspection the INFORM Risk team can make an expert judgement whether these cases require addition attention in their publications.

4.2 Principle Component Analysis

As a further step in the analysis of statistical coherence principal components analysis (PCA) is used to confirm the presence of one single statistical dimension among the components, categories and dimensions that form the index. PCA is a data reduction technique to capture common trends among variables. The conceptual interpretation is that PCA assess to what extent variables can be effectively summarised by an arithmetic aggregate. Technically, the expectation is that there is one eigenvalue above one capturing at least 65%-70% of the variance. The achievement of these thresholds suggests the presence of a common, unidimensional phenomenon underlying the aggregate.

Overall, 23 out of the 29 aggregates satisfy this standard, enhancing the statistical coherence of the INFORM index and proving the existence of an underlying unidimensional phenomenon, particularly within the "Lack of Coping Capacity" sub-index. **Table 4** lists the six aggregates that fall short of meeting this requirement and that require special attention. In these cases there is more than one dimension, CC-COIN would like to note that aggregating the underlying indicators may not accurately represent the multidimensional nature of the phenomenon in question and cause information to be lost through aggregation. In particular, the Natural Hazard category could be the focus of some reflection, as it is an important category with many diverse indicators which at the moment includes three principal components.

Table 4. Principle Component Analysis results of the elements of components, categories, dimension and index of the INFORM Risk index of 2024

Sub-Index	Aggregate	Level	Numbers of Indicators	Explained Variance	Number of Dimensions
Hazard & Exposure	Current Highly Violent Conflict Intensity Score*	Component	2	54%	1
	Droughts probability and historical impact	Component	2	51%	2
	Natural Hazard	Category	7	30%	3
Vulnerability	Economic Dependency Index	Component	3	60%	1
	Other Vulnerable Groups	Component	4	61%	1
	Vulnerable Groups	Category	2	52%	2

Note: Explained Variance refers to the variance captured by the first principle component. Aggregates marked with '*' are based on categorical variables.

Source: European Commission's Joint Research Centre, 2024.

A closer look at the correlation matrix for the "Natural Hazard" category is provided in **Table 5**, where five out of 21 correlations presented in the "Natural Hazard" category are adequate. Statistically speaking, the transmission of information from the component to the next level of aggregation is lost due to this lack of coherence. An indicative statistic is that only nine countries score higher than 7 on "Natural Hazards". The highest scoring country is Japan with an 8.3, however four of seven indicators are above nine. It is up to the developers to assess whether these dynamics under estimate the hazards and pose a potential issue for the index within the context of its use and target audience. Following up on the suggestions in the previous section could help improve the results of the PCA. From a statistical viewpoint, a solution could be to add another layer of aggregation to group of natural hazards, for example aggregating tropical cyclones, tsunami, and coastal flood and earthquake hazards on the one hand and epidemics, river floods and droughts on the other hand before aggregating to the natural hazard component. However, such aggregation may be difficult to justify from a conceptual viewpoint. Another suggestion is to add up only the top three highest hazards per country to capture the most important information. The INFORM Risk team could experiment with such changes, if they are feasible within the conceptual framework.

Table 5. Correlations between Natural Hazard components.

	Droughts	Coastal flood	Earthquake	Epidemics	River flood	Tropical cyclone	Tsunami
Droughts	-	-0.11	0.03	0.27	0.18	-0.16	-0.07
Coastal flood	-0.11	-	0.14	-0.08	0.20	0.33	0.51
Earthquake	0.03	0.14	-	0.09	0.14	0.33	0.39
Epidemics	0.27	-0.08	0.09	-	0.23	0.08	0.02
River flood	0.18	0.20	0.14	0.23	-	-0.12	-0.04
Tropical cyclone	-0.16	0.33	0.33	0.08	-0.12	-	0.40
Tsunami	-0.07	0.51	0.39	0.02	-0.04	0.40	-

Source: European Commission's Joint Research Centre, 2024.

Overall the coherence of the correlation structure in the INFORM Risk index meets criteria established by CC-COIN, most aggregates can accurately capture the information embedded in their sub-components. The only potential issue is the low coherence in the correlation structure of the "Natural Hazards" category, which reflects the empirical co-occurrence of indicators. For example, landlocked countries have zero values on the coastal flood indicator. Many countries do not lie on fault lines and do not have earthquakes. The correlations indicate countries are unlikely to be exposed to both tropical cyclones and droughts. Thus, it is to be expected that these different hazard indicators do not have high correlations. Unfortunately, it is a common reality in composite indicators that coherent human-made concepts, such as our concept of "natural disasters", contain

events that do not empirically co-occur. The challenge for developers is to retain as much information from indicators representing such concepts, balancing statistical and conceptual coherence. In cases where statistical coherence cannot be achieved, the developers can always enrich the index by highlighting specific indicators and countries for the full picture to emerge.

5 Uncertainty and Sensitivity Analysis

A fundamental step in the statistical analysis of a composite indicator is to assess the effect of different modelling assumptions on the country scores and risk class. Despite the efforts in the development process, there is an unavoidable subjectivity (or uncertainty) in the resulting choices. This subjectivity can be explored by comparing the results obtained under different – alternative – assumptions.

The literature on this topic (Saisana *et al.*, 2005; 2011) suggests assessing the robustness of the index by means of a Monte Carlo simulation and by applying a multi-modelling approach. This also assumes 'error-free' data as possible errors have already been corrected in the preliminary stage of the index construction before the audit.

The INFORM Risk index, like most composite indicators, is the outcome of several choices. Among other things, these choices include: (i) the underlying theoretical framework; (ii) the indicators selected; (iii) the imputation of missing values; (iv) the weighting scheme; (v) the normalisation method; and (vi) the aggregation method. Some of these choices may be based on expert opinion or other consideration driven by statistical analysis or the need to ease communication or draw attention to specific issues.

This section aims to test the impact of varying some of these assumptions within a range of plausible alternatives in an uncertainty analysis. The objective is therefore to try to quantify the uncertainty in the scores and risk class assigned to countries.

The modelling issues considered in the robustness assessment of the index are the (i) data imputation, (ii) the aggregation formula and, (iii) the applied set of weights. The following paragraphs describes each of them.

Imputation. The developers of the INFORM index imputed the value by taking the mean of all available values within the same aggregate. JRC-COIN team contrasted this approach with a different set of imputation methods: k-Nearest Neighbours (KNN) and Expectation–Maximization (EM).

Aggregation formula. The developers of the INFORM index opted for the geometric averaging of the three dimensions, which implies a limited compensability, penalising all countries with unbalanced performances. This approach can reward an "all-around performer", that is, a country with average results on all dimensions outperforms countries with outstanding achievements in one pillar accompanied by under-performing values in the others. However, to avoid zero values, the developers add one to each element during aggregation. This may have unintended consequences by compressing the bottom of the score distribution. To assess the impact of this choice, the JRC-COIN team included a comparison with geometric average that adds a smaller value, namely 0.1.

Weights. JRC-COIN team generated a set of 1,000 different weights for the index and the three dimensions. The weights are the result of a random extraction based on uniform continuous distributions centred in the reference values plus or minus 25% of these values.

Models were tested combining different imputations and aggregation methods simultaneously, which resulted in 5,000 runs of simulations in which a random set of weights is chosen. A summary of the alternative methodological choices considered is given in **Table 6**.

Table 6. Alternative assumptions considered in the robustness analysis.

		Reference	Alternative
I. Imputation		No imputation[(1)]	Nearest-neighbour, Expectation Maximization,
II. Uncertainty in the aggregation		geometric average	geometric average[(2)]
III. Uncertainty in the weights			
INFORM	Hazard & Exposure	0.33	U[0.25, 0.41]
	Vulnerability	0.33	U[0.25, 0.41]
	Lack of Coping Capacity	0.33	U[0.25, 0.41]
Hazard & Exposure	Human Hazard	0.50	U[0.38, 0.63]
	Natural Hazard	0.50	U[0.38, 0.63]
Vulnerability	Socio-Economic Vulnerability	0.50	U[0.38, 0.63]
	Vulnerable Groups	0.50	U[0.38, 0.63]
Lack of Coping Capacity	Infrastructure	0.50	U[0.38, 0.63]
	Institutional	0.50	U[0.38, 0.63]

Source: European Commission's Joint Research Centre, 2024.

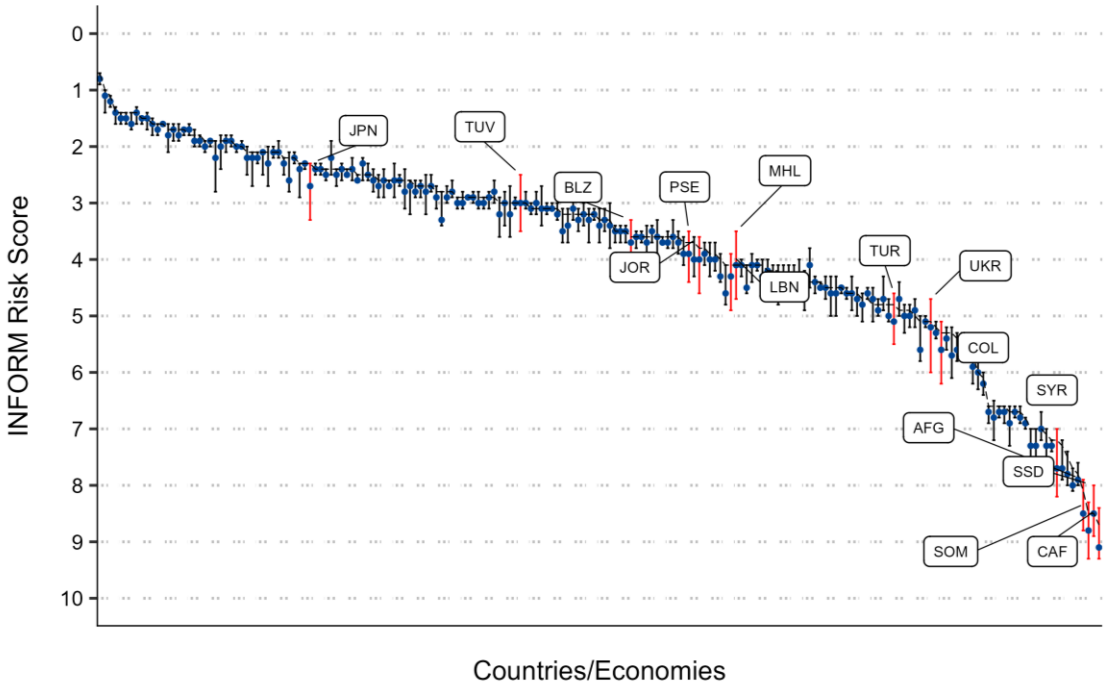
Note: [(1)] INFORM Risk does impute values for two indicators Prevalence of Undernourishment and Average Dietary Energy Supply Adequacy using conditional mean imputation, namely the regional average. Additionally, it uses last-carry forward imputation if data is missing on the latest years for some countries. The Human Development Index is imputed for Korea DPR with the GDP/capita. We take these values as given in the sensitivity analysis and instead impute any other missing data. [(2)] The current geometric average adds a constant to all elements to avoid zero values, namely 10% of the range, whereas the alternative one only uses 1%.

Score

Regarding the scores, results are displayed in

Table 9 and graphically in **Figure 2** where each blue dot represents the median rank among the iterations for each country, and error bars represent the 95% interval across all simulations, i.e. from the fifth to the 95th percentile. Notice that some intervals are flagged in red and the country code is provided, this indicates countries with the top 5% largest intervals.

Figure 2. Robustness analysis on scores, INFORM Risk score vs median score and 90% intervals.



Note: Flagged countries show an interval range within the 95% quantile.

Source: European Commission's Joint Research Centre, 2024.

INFORM Risk scores are shown to be consistent across the 5,000 iterations; there are only 9 countries[5] with a confidence interval that exceed one point (more than 10% of the range). This a very low number, given that there are 191 countries and only 10% of the range is considered, showing INFORM Risk is robust to methodological changes. Although there is more uncertainty in the dimensions, there results are still robust with only one country exceeding 20% of the range for the "Lack of Coping Capacity" category, six for "Hazard & Exposure" and 10 for "Vulnerability".

When analysing the deviation between the actual score and median, the results are very consistent. There are only 15 cases where the variation between the nominal score and median score is above 1, all of them in the "Vulnerability" category except for one case in "Lack of Coping Capacity".

Risk category

The developers of the INFORM Risk index defined five different risk categories depending on the total value of the score. The methodology applied by the developers has been assessed relative to

[5] These countries include: Ukraine, Marshall Islands, Syria, Colombia, Lebanon, Somalia, Tuvalu, Japan and Jordan.

alternatives by JRC-COIN by optimising the eta squared of an ANOVA using data for the last 10 years at the index and dimension levels. The thresholds computed following this methodology are very similar to the ones used in the INFORM Risk index and do not entail large differences. **Table 7** shows the number of countries that are categorised in a different exposure level using the most frequent category among the 5,000 simulations using the thresholds provided by the developers.

Table 7. Number of discrepancies in risk level categorisation.

Aggregate	Very Low	Low	Medium	High	Very High	Total
INFORM	5	4	4	4	0	17
Hazard & Exposure	3	5	2	2	0	12
Vulnerability	1	5	7	6	0	19
Lack of Coping Capacity	0	3	5	2	1	11
Total	9	17	18	24	1	59

Source: European Commission's Joint Research Centre, 2024.

Only 17 of the 191 countries would have a different risk category from the INFORM Risk index. This amounts to just 9% of countries and is an excellent result. Most discrepancies occur between the low, medium and high risk categories. **Table 8** summaries countries that present a different risk class in the index and categories after the 5,000 simulations.

Table 8. Countries that are classified in a different median risk class over 5,000 simulations compared to the nominal INFORM risk class.

	INFORM Risk Class				Robustness Analysis Risk Class			
Country / Region	INFORM	Hazard & Exposure	Vulnera-bility	Lack of Coping Capacity	INFORM	Hazard & Exposure	Vulnera-bility	Lack of Coping Capacity
AUT	Very Low	Very Low	Low	Very Low	Very Low	Very Low	Medium	Very Low
AZE	Medium	High	High	Medium	Medium	High	High	Low
BEL	Very Low	Low	Low	Very Low	Low	Low	Low	Very Low
BHS	Very Low	Very Low	Very Low	Low	Low	Low	Very Low	Low

	INFORM Risk Class				Robustness Analysis Risk Class			
Country / Region	INFORM	Hazard & Exposure	Vulnera-bility	Lack of Coping Capacity	INFORM	Hazard & Exposure	Vulnera-bility	Lack of Coping Capacity
BIH	Low	Very Low	Medium	Medium	Low	Very Low	Medium	Low
BLR	Very Low	Very Low	Low	Low	Very Low	Very Low	Very Low	Low
BLZ	Medium	Low	Medium	Medium	Medium	Low	High	Medium
CHN	Low	High	Very Low	Low	Medium	High	Very Low	Low
COG	High	Medium	High	Very High	High	Medium	High	High
COL	High	Very High	High	Low	High	Very High	Very High	Low
CUB	Low	Low	Low	Low	Medium	Low	Medium	Low
CYP	Low	Very Low	Medium	Low	Low	Very Low	Medium	Very Low
DJI	High	Medium	High	High	Medium	Low	High	High
DOM	Medium	Medium	Medium	Low	Medium	High	Medium	Medium
EGY	High	High	Medium	Medium	High	Very High	Medium	Medium
FSM	Medium	Very Low	Medium	Medium	Low	Very Low	Medium	Medium
GAB	Medium	Very Low	Medium	High	Medium	Low	Medium	High
GBR	Very Low	Low	Low	Very Low	Low	Low	Low	Very Low
GTM	High	Medium	High	Medium	High	Medium	Very High	Medium
HND	Medium	Medium	High	Medium	High	Medium	High	Medium
IRN	High	Very High	Medium	Medium	High	Very High	High	Medium
IRQ	High	Very High	High	High	Very High	Very High	High	High
ITA	Low	Low	Low	Very Low	Low	Medium	Low	Very Low

	INFORM Risk Class				Robustness Analysis Risk Class			
Country / Region	INFORM	Hazard & Exposure	Vulnera-bility	Lack of Coping Capacity	INFORM	Hazard & Exposure	Vulnera-bility	Lack of Coping Capacity
JAM	Low	Low	Low	Low	Low	Medium	Low	Low
JOR	Medium	Low	High	Low	Medium	Low	Very High	Medium
KEN	High	Very High	High	High	Very High	Very High	High	High
KNA	Very Low	Very Low	Very Low	Low	Low	Very Low	Low	Low
MDA	Low	Low	Medium	Medium	Medium	Low	Medium	Medium
MHL	Medium	Low	Medium	High	Medium	Low	Medium	Medium
MNE	Low	Very Low	Medium	Low	Low	Low	Medium	Low
MWI	Medium	Low	High	High	Medium	Low	Very High	High
NLD	Very Low	Low	Low	Very Low	Low	High	Low	Very Low
PAN	Medium	Low	Medium	Low	Medium	Medium	Medium	Low
PER	Medium	High	High	Medium	High	High	High	Medium
PHL	High	Very High	Medium	Low	High	Very High	High	Low
PLW	Low	Very Low	Medium	Low	Low	Very Low	High	Low
PNG	High	Very High	High	Very High	Very High	Very High	High	Very High
PSE	Medium	Low	High	Low	Medium	Low	Very High	Low
RUS	Medium	High	Medium	Medium	Medium	High	Medium	Low
SUR	Low	Low	Low	Medium	Medium	Low	Low	Medium
SWE	Very Low	Very Low	Low	Very Low	Very Low	Very Low	Medium	Very Low
TKM	Low	Low	Very Low	High	Low	Low	Very Low	Medium
TON	Medium	Low	Medium	Low	Medium	Low	High	Low

	INFORM Risk Class				Robustness Analysis Risk Class			
Country / Region	INFORM	Hazard & Exposure	Vulnera-bility	Lack of Coping Capacity	INFORM	Hazard & Exposure	Vulnera-bility	Lack of Coping Capacity
TUR	Medium	High	High	Low	High	High	High	Low
TUV	Low	Very Low	Medium	Medium	Low	Very Low	High	Low
UKR	High	High	High	Medium	High	High	Very High	Low
USA	Medium	High	Low	Very Low	Medium	High	Medium	Very Low
VUT	Medium	Low	Medium	Medium	Medium	Medium	High	Medium
YEM	Very High	High	Very High	Very High	Very High	Very High	Very High	Very High

Source: European Commission's Joint Research Centre, 2024.

Table 9. The INFORM Risk nominal scores and the median, 5th and 95th percentile in the uncertainty analysis.

Country	Score	Median	Range	Category	Dominant
CAF	8.7	9.1	[8.4, 9.3]	Very High	Very High
SOM	8.5	8.8	[8.3, 9.3]	Very High	Very High
SSD	8.5	8.5	[8, 8.9]	Very High	Very High
AFG	8.1	8.5	[7.9, 8.8]	Very High	Very High
TCD	7.8	7.9	[7.6, 8]	Very High	Very High
COD	7.7	8	[7.7, 8.1]	Very High	Very High
YEM	7.5	7.8	[7.4, 8]	Very High	Very High
SDN	7.3	7.7	[7.2, 7.9]	Very High	Very High
HTI	7.2	7.3	[7.2, 7.4]	Very High	Very High
SYR	7.2	7.7	[7, 8.2]	Very High	Very High
MMR	7.1	7.3	[7, 7.6]	Very High	Very High
BFA	7	7.3	[7, 7.5]	Very High	Very High
ETH	7	7.3	[7, 7.5]	Very High	Very High
UGA	7	7	[6.7, 7.2]	Very High	Very High
MLI	6.8	6.9	[6.8, 7]	Very High	Very High
MOZ	6.7	6.7	[6.6, 6.8]	High	High
IRQ	6.7	6.9	[6.6, 7.3]	High	Very High
PNG	6.7	6.8	[6.6, 6.9]	High	Very High
CMR	6.6	6.7	[6.6, 6.9]	High	High
NER	6.6	6.7	[6.6, 6.8]	High	High
NGA	6.6	6.7	[6.6, 6.9]	High	High
KEN	6.6	6.8	[6.5, 7.2]	High	Very High
PAK	6.1	6.2	[6, 6.4]	High	High
ERI	6	6	[5.5, 6.3]	High	High
BGD	5.7	5.9	[5.6, 6.2]	High	High

Country	Score	Median	Range	Category	Dominant
TON	3.3	3.4	[3, 3.8]	Medium	Medium
FSM	3.2	3.1	[2.7, 3.3]	Medium	Low
CHL	3.2	3.5	[3.1, 3.7]	Medium	Medium
CRI	3.2	3.4	[3.1, 3.7]	Medium	Medium
GAB	3.2	3.3	[3.1, 3.5]	Medium	Medium
KAZ	3.2	3.2	[3, 3.4]	Medium	Medium
USA	3.2	3.3	[3.1, 3.7]	Medium	Medium
UZB	3.2	3.2	[3.1, 3.3]	Medium	Medium
ALB	3.1	3.1	[3, 3.2]	Low	Low
BIH	3.1	3	[2.8, 3.2]	Low	Low
GNQ	3.1	3.1	[2.7, 3.4]	Low	Low
KGZ	3.1	3.1	[3, 3.2]	Low	Low
LKA	3.1	3.1	[3, 3.1]	Low	Low
MDA	3.1	3.2	[3, 3.3]	Low	Medium
CHN	3	3.2	[2.9, 3.6]	Low	Medium
DMA	3	3	[2.8, 3.4]	Low	Low
TUN	3	3	[2.9, 3.1]	Low	Low
TUV	3	3	[2.5, 3.5]	Low	Low
WSM	3	3	[2.8, 3.1]	Low	Low
SUR	3	3.2	[2.7, 3.6]	Low	Medium
ARG	2.9	3	[2.9, 3.1]	Low	Low
ARM	2.9	3	[2.8, 3.1]	Low	Low
FJI	2.9	2.9	[2.9, 2.9]	Low	Low
JAM	2.9	2.9	[2.8, 3]	Low	Low
MNG	2.9	3	[2.8, 3.1]	Low	Low

Country	Score	Median	Range	Category	Dominant
BDI	5.6	5.6	[5.5, 5.8]	High	High
MDG	5.5	5.6	[5.3, 5.8]	High	High
IRN	5.4	5.6	[5.3, 5.8]	High	High
COL	5.3	5.6	[5.1, 6.2]	High	High
IND	5.3	5.4	[5.2, 5.6]	High	High
PHL	5.3	5.7	[5.2, 6.1]	High	High
AGO	5.2	5.3	[5.1, 5.4]	High	High
GTM	5.1	5.6	[5, 5.8]	High	High
TZA	5.1	5.1	[5, 5.2]	High	High
UKR	5.1	5.2	[4.7, 6]	High	High
COG	5	4.9	[4.7, 5.2]	High	High
EGY	4.9	5	[4.8, 5.3]	High	High
MEX	4.9	5	[4.8, 5.2]	High	High
DJI	4.9	4.7	[4.4, 5]	High	Medium
AZE	4.8	4.7	[4.5, 5.1]	Medium	Medium
LBY	4.8	4.7	[4.3, 4.9]	Medium	Medium
HND	4.8	4.9	[4.7, 5]	Medium	High
PER	4.8	5	[4.7, 5.1]	Medium	High
TUR	4.8	5.1	[4.6, 5.5]	Medium	High
ECU	4.7	4.8	[4.6, 5.1]	Medium	Medium
VEN	4.7	4.6	[4.5, 4.7]	Medium	Medium
BRA	4.6	4.6	[4.5, 4.7]	Medium	Medium
CIV	4.6	4.6	[4.3, 4.9]	Medium	Medium
IDN	4.6	4.7	[4.5, 5]	Medium	Medium
GIN	4.5	4.5	[4.3, 4.7]	Medium	Medium
LBR	4.5	4.6	[4.3, 5]	Medium	Medium

Country	Score	Median	Range	Category	Dominant
MYS	2.9	3	[2.9, 3.1]	Low	Low
SRB	2.9	2.9	[2.8, 3.1]	Low	Low
TKM	2.9	2.8	[2.6, 3]	Low	Low
CUB	2.8	3.3	[2.8, 3.4]	Low	Medium
BTN	2.8	2.9	[2.7, 3.1]	Low	Low
LCA	2.8	2.9	[2.7, 3]	Low	Low
TTO	2.8	2.8	[2.6, 2.9]	Low	Low
BGR	2.7	2.8	[2.6, 2.9]	Low	Low
MNE	2.7	2.7	[2.6, 2.9]	Low	Low
PLW	2.7	2.8	[2.5, 3.2]	Low	Low
PRY	2.7	2.7	[2.5, 2.8]	Low	Low
BWA	2.6	2.7	[2.5, 2.9]	Low	Low
CYP	2.6	2.6	[2.4, 2.9]	Low	Low
GRC	2.6	2.7	[2.6, 2.7]	Low	Low
NRU	2.6	2.6	[2.3, 2.9]	Low	Low
ROU	2.6	2.6	[2.5, 2.7]	Low	Low
STP	2.6	2.8	[2.4, 3.1]	Low	Low
VCT	2.6	2.7	[2.6, 3.2]	Low	Low
ITA	2.5	2.6	[2.5, 2.6]	Low	Low
KWT	2.5	2.3	[2.2, 2.6]	Low	Low
OMN	2.5	2.5	[2.3, 2.6]	Low	Low
POL	2.5	2.6	[2.4, 2.8]	Low	Low
AUS	2.4	2.4	[2.3, 2.5]	Low	Low
BRN	2.4	2.4	[2.3, 2.5]	Low	Low
CAN	2.4	2.5	[2.4, 2.6]	Low	Low
CPV	2.4	2.2	[1.9, 2.5]	Low	Low

Country	Score	Median	Range	Category	Dominant
SLB	4.5	4.6	[4.3, 5]	Medium	Medium
ZAF	4.5	4.5	[4.5, 4.6]	Medium	Medium
MWI	4.4	4.5	[4.2, 4.9]	Medium	Medium
RUS	4.4	4.1	[3.8, 4.5]	Medium	Medium
THA	4.4	4.4	[4.3, 4.6]	Medium	Medium
TJK	4.4	4.5	[4.4, 4.5]	Medium	Medium
BEN	4.3	4.3	[4.1, 4.5]	Medium	Medium
KHM	4.3	4.3	[4.1, 4.5]	Medium	Medium
MRT	4.3	4.3	[4.1, 4.5]	Medium	Medium
TGO	4.3	4.3	[4, 4.5]	Medium	Medium
RWA	4.2	4.2	[4, 4.4]	Medium	Medium
SLE	4.2	4.3	[4.1, 4.6]	Medium	Medium
VUT	4.2	4.4	[4.1, 4.8]	Medium	Medium
DOM	4.1	4.6	[4.1, 4.8]	Medium	Medium
LBN	4.1	4.3	[3.9, 4.9]	Medium	Medium
MHL	4.1	4.1	[3.5, 4.7]	Medium	Medium
NIC	4.1	4.1	[4, 4.3]	Medium	Medium
NPL	4.1	4.5	[4.1, 4.6]	Medium	Medium
PRK	4.1	4.1	[3.9, 4.4]	Medium	Medium
SEN	4.1	4.1	[4, 4.2]	Medium	Medium
ZWE	4.1	4.3	[4, 4.5]	Medium	Medium
SLV	4	4.3	[3.9, 4.4]	Medium	Medium
GNB	3.9	4	[3.7, 4.3]	Medium	Medium
ZMB	3.9	4	[3.7, 4.2]	Medium	Medium
JOR	3.8	4	[3.6, 4.6]	Medium	Medium
NAM	3.8	3.9	[3.7, 4.1]	Medium	Medium

Country	Score	Median	Range	Category	Dominant
DEU	2.4	2.5	[2.4, 2.7]	Low	Low
FRA	2.4	2.4	[2.3, 2.6]	Low	Low
HRV	2.4	2.5	[2.4, 2.5]	Low	Low
LVA	2.4	2.4	[2.2, 2.6]	Low	Low
ATG	2.3	2.4	[2.3, 2.9]	Low	Low
ESP	2.3	2.3	[2.3, 2.4]	Low	Low
JPN	2.3	2.7	[2.3, 3.3]	Low	Low
GRD	2.2	2.3	[2.2, 2.5]	Low	Low
MDV	2.2	2.6	[2.1, 2.8]	Low	Low
MKD	2.2	2.2	[2.1, 2.3]	Low	Low
BEL	2.1	2.2	[2, 2.5]	Very Low	Low
BHS	2.1	2.2	[2.1, 2.7]	Very Low	Low
GBR	2.1	2.2	[2.1, 2.3]	Very Low	Low
NLD	2.1	2.3	[2, 2.7]	Very Low	Low
MUS	2.1	2.1	[2.09, 2.5]	Very Low	Very Low
SVK	2.1	2.1	[2, 2.2]	Very Low	Very Low
URY	2.1	2.1	[1.9, 2.2]	Very Low	Very Low
BRB	2	2	[2, 2.1]	Very Low	Very Low
PRT	2	2	[1.9, 2]	Very Low	Very Low
KNA	1.9	2.2	[1.9, 2.8]	Very Low	Low
AUT	1.9	2	[1.9, 2.1]	Very Low	Very Low
HUN	1.9	1.9	[1.9, 2]	Very Low	Very Low
KOR	1.9	2	[1.8, 2.4]	Very Low	Very Low
LTU	1.9	1.9	[1.8, 2.1]	Very Low	Very Low
SWE	1.9	1.9	[1.8, 2]	Very Low	Very Low
BLR	1.8	1.7	[1.6, 1.8]	Very Low	Very Low

Country	Score	Median	Range	Category	Dominant
KIR	3.7	3.9	[3.6, 4.1]	Medium	Medium
PSE	3.7	3.9	[3.5, 4.4]	Medium	Medium
VNM	3.7	4	[3.6, 4.3]	Medium	Medium
BLZ	3.6	3.7	[3.3, 4.2]	Medium	Medium
BOL	3.6	3.6	[3.5, 3.8]	Medium	Medium
DZA	3.6	3.6	[3.5, 3.7]	Medium	Medium
GMB	3.6	3.7	[3.4, 3.9]	Medium	Medium
GUY	3.6	3.5	[3.4, 3.7]	Medium	Medium
LSO	3.6	3.6	[3.3, 3.9]	Medium	Medium
MAR	3.6	3.7	[3.6, 3.7]	Medium	Medium
PAN	3.6	3.7	[3.5, 3.8]	Medium	Medium
SAU	3.6	3.6	[3.3, 3.8]	Medium	Medium
TLS	3.6	3.7	[3.5, 3.9]	Medium	Medium
GEO	3.5	3.5	[3.4, 3.7]	Medium	Medium
GHA	3.5	3.5	[3.4, 3.7]	Medium	Medium
LAO	3.5	3.5	[3.4, 3.7]	Medium	Medium
COM	3.3	3.4	[3.1, 3.7]	Medium	Medium
SWZ	3.3	3.3	[3.1, 3.5]	Medium	Medium

Country	Score	Median	Range	Category	Dominant
CZE	1.8	1.9	[1.7, 2]	Very Low	Very Low
ISR	1.8	1.9	[1.8, 2]	Very Low	Very Low
ARE	1.7	1.8	[1.6, 2.1]	Very Low	Very Low
IRL	1.7	1.7	[1.6, 1.9]	Very Low	Very Low
MLT	1.7	1.8	[1.6, 1.9]	Very Low	Very Low
NOR	1.7	1.7	[1.7, 1.8]	Very Low	Very Low
EST	1.6	1.6	[1.5, 1.8]	Very Low	Very Low
ISL	1.6	1.7	[1.6, 1.8]	Very Low	Very Low
SVN	1.6	1.6	[1.6, 1.6]	Very Low	Very Low
FIN	1.5	1.5	[1.5, 1.6]	Very Low	Very Low
SYC	1.5	1.5	[1.4, 1.7]	Very Low	Very Low
BHR	1.4	1.4	[1.3, 1.6]	Very Low	Very Low
CHE	1.4	1.5	[1.4, 1.6]	Very Low	Very Low
DNK	1.4	1.5	[1.4, 1.6]	Very Low	Very Low
NZL	1.4	1.6	[1.4, 1.7]	Very Low	Very Low
QAT	1.4	1.4	[1.3, 1.6]	Very Low	Very Low
LUX	1.1	1.2	[1.1, 1.3]	Very Low	Very Low
LIE	1	1.1	[1, 1.4]	Very Low	Very Low
SGP	0.7	0.8	[0.7, 0.9]	Very Low	Very Low

Note: Cells highlighted in light blue indicate a difference between nominal risk category and the most frequent risk category assigned during the uncertainty analysis.

Source: European Commission's Joint Research Centre, 2024.

6 Conclusions

This statistical audit covers the INFORM Risk index developed by JRC. The INFORM Risk Index is an essential tool for risk management and policy planning, providing crucial insights into risk, exposures and vulnerabilities in various regions and countries. INFORM Risk currently covers 191 countries that are given a risk class based on their index score. The index includes three sub-indices: “Hazard & exposure”, “Vulnerability” and “Lack of coping capacity”. These sub-indices include several levels of aggregation and 74 indicators.

In this report, we examined the statistical soundness of the calculations and assumptions used to arrive at the final index scores and rankings. The CC-COIN team of JRC found the INFORM Risk documentation provided good coverage and understanding for its users in terms of the metadata and data properties including the data availability, timeliness and imputation strategies as well as the treatment of outliers, denomination and normalisation.

On these topics, CC-COIN finds that the INFORM Risk Index of 2024 is based on recent data, has an excellent data coverage with almost 90% observed data points, and appropriately treats outliers and denominates most indicators. There are two categorical indicators and two composite indicators included as individual indicators, which is not desirable from a statistical point of view. In terms of aggregation, the CC-COIN team recognises the developers have followed previous recommendations to use the geometric mean. The CC-COIN team would like to follow-up on previous work and further recommend adding a smaller constant within the geometric aggregation formula.

In this audit the CC-COIN team also examined the statistical coherence of the INFORM Risk index. The correlation structure are good or adequate for the majority of aggregates. The “Vulnerability” and “Lack of coping capacity” dimensions are statistically coherent in terms of correlations and allow information from most indicators to be reflected in the overall index scores. Furthermore, 23 of the 29 aggregates in the index meet stringent criteria for statistical coherence in a principle component analysis. However, the “Natural Hazard” category shows some room for improvement due to weak or negligible correlations within its subcomponents or with its parent dimension. The CC-COIN team recommends that the developers analyse to what extent changes can be made to improve the statistical coherence, noting this is a difficult feat within the constraints of policy and stakeholder needs, the data space and the conceptual framework.

The CC-COIN team also examined the uncertainty of scores and risk class created by the INFORM Risk index. The CC-COIN team used Monte Carlo simulation of alternative version of the index to create confidence intervals around the scores and ranks and to assess the uncertainty in risk class assignment. In all these tests, the INFORM Risk Index shows a low level of uncertainty in the scores and risk class. Therefore, the CC-COIN team concludes that the current methodology is robust to changes in weights, geometric aggregation formula and imputation and is an accurate portrayal of a range of scenarios.

Overall, the statistical audit of the INFORM Risk Index shows the scores and risk classes which reflect the underlying information, are robust to alternative specifications and are precise enough to be interpreted as meaningful differences from a statistical point of view. The CC-COIN team has given suggestions within the report that could further enhance the positive properties of the INFORM Risk index. However, such decisions must always be made with the conceptual coherence in mind.

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