MarshMcLennan

Marsh McLennan Flood Risk Index Methodology

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Overview And Structure

The Marsh McLennan Flood Risk Index provides a global overview of flood risk at the national level. Utilizing disaster risk assessment concepts as a foundation, the Index provides a comprehensive analysis of the threat posed by flooding across countries by estimating scores for the hazard, exposure, and vulnerability components of flood risk:

- **Hazard** refers to the physical processes that may cause loss of life, injury or other health impacts, property damage, social and economic disruption, or environmental degradation through flooding.
- **Exposure** indicates the people, infrastructure, housing, production capacities and other tangible assets located in hazard-prone areas.
- **Vulnerability** refers to the conditions determined by physical, social, economic, and environmental factors or processes which increase the susceptibility of communities, assets, or systems to the impacts of hazards.

Hazard scores are presented for riverine (fluvial), coastal, and rainfall (pluvial) flooding. Scores for these dimensions were calculated resorting to 100-year return period hazard maps under different climate change scenarios (present day, +1.5 °C, +2 °C, and +3.5 °C) obtained from projections of flood risk in 2010, 2030, 2050, and 2080 respectively. Total hazard scores were calculated by averaging the scores for the three components of the hazard. Exposure and vulnerability scores were calculated for their human and economic components. Total exposure and vulnerability scores were estimated as the average of the corresponding human and economic scores. Exposure scores were estimated under different climate change scenarios (present day, +1.5 °C, +2 °C, and +3.5 °C). Vulnerability scores were only estimated for present-day conditions.

The scores for hazard (total, riverine, coastal, rainfall), exposure (total, human, economic), and vulnerability (total, human, economic) range from 1 to 10, with higher values indicating higher risk.

Hazard, exposure, and vulnerability are shaped by several underlying drivers that can mitigate or exacerbate the impacts of flooding. Due to the unique set of factors that influence each component, the structure of the Index is meant to primarily support comparative analysis of countries within each indicator, rather than across.

Selection Criteria

Index indicators were selected to provide a reliable and easy to understand snapshot of the components of flood risk in each country according to the following principles:

- **Robustness** Indicators are chosen from reputable sources with the most current information available.
- **Parsimony** A small number of indicators with high levels of explanatory power have been selected to preserve simplicity and avoid cross-indicator redundancy. Included indicators represent critical elements of flood risk based on underlying risk drivers.
- **Reliability** Selected datasets have high coverage and are obtained from reputable institutions.

Data Sources

The Index uses various data sets to estimate proxies for hazard, exposure, and vulnerability at the country level. The World Bank Official Boundaries[1] data set was used to aggregate geospatial information and calculate country statistics.

The indicator scores were derived from publicly available data sources and are summarized in Exhibit 1. The layers and the country statistics presented in the Overlays section of the webtool were generated from the data sets listed in Exhibit 2.

1 The World Bank. (n.d.). World Bank Official Boundaries. Retrieved July 28, 2021. The choice of this dataset does not imply any endorsement by Marsh McLennan concerning the legal status of any country or territory or the delimitation of frontiers or boundaries.

Exhibit 1: Index components, indicators, and data sources

Index component	Indicator	Data sources
Hazard scores	Riverine (fluvial) hazard	100-year return period hazard maps from the World Resources Institute (WRI)'s Aqueduct Floods[2] which incorporate information from 5 CMIP5 models (GFDL-ESM2M, HadGEM2-es, IPSL-CM5A-LR, MIROC-ESM-CHEM, NorESM1-M) under an RCP8.5 forcing scenario for different time horizons: 2010, 2030, 2050, 2080. Further details can be found in the WRI Aqueduct Floods methodology document.[3]
	Coastal hazard	100-year return period hazard maps from WRI Aqueduct Floods[4] which incorporate information from the Global Tide and Surge Reanalysis (GTSR) dataset and model future coastal subsidence. Further details can be found in the WRI Aqueduct Floods methodology document.[5]
	Rainfall (pluvial) hazard	100-year return period precipitation maps estimated from CMIP5 model simulations and ECMWF ERA-Interim[6] data made available by the Climdex project[7] ECA&D E-OBS,[8] WMO CCI/WCRP/JCOMM ETCCDI HadEX3,[9] and USGS/CHC CHIRPS.[10]
Exposure scores	Human exposure	Global Human Settlement Layer (GHSL) 2015[11] from the European Commission's Joint Research Center. Hazard maps from data sets listed in the "Hazard scores" section of this table.
	Economic exposure	Capital Stock data from the United Nations Office for Disaster Risk Reduction (UNDRR)'s Global Exposure Database GAR 2015.[12] Hazard maps from data sets listed in the "Hazard scores" section of this table.
Vulnerability scores	Human vulnerability	Human Development Index from the United Nations Development Programme (UNDP) Human Development Data 2020.[13] Non-life insurance premium volume to GDP data from the World Bank's Global Financial Development Database 2019.[14]
	Economic vulnerability	Quality of infrastructure from the Global Competitiveness Index Historical Dataset (2017-2018) with underlying data from the World Economic Forum's Executive Opinion survey (EOS).[15] Non-life insurance premium volume to GDP data from the World Bank's Global Financial Development Database 2019.[16]

Source: Marsh McLennan Advantage

2 Ward, P. J., Winsemius, H. C., Kuzma, S., Bierkens, M. F. P., Bouwman, A., Moel, H. D., Loaiza, A. D., Englhardt, J., Erkens, G., Gebremedhin, E. T., Iceland, C., Kooi, H., Ligtvoet, W., Muis, S., Scussolini, P., Sutanudjaja, E. H., Beek, R. V., Bemmel, B. V., Huijstee, J. V., Vatvani, D., Verlaan, M., Tiggeloven, T., Luo, T. (2020). Aqueduct Floods Methodology.

3 Ibid.

4 Ibid.

5 Ibid.

6 Berrisford, P., Dee, D. P., Poli, P., Brugge, R., Fielding, M., Fuentes, M., Kållberg, P. W., Kobayashi, S., Uppala, S., & Simmons, A. (2011). The ERA-Interim archive Version 2.0. ECMWF.

7 University of New South Wales. (n.d.). Climdex. Retrieved April 20, 2022.

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11 European Commission. References: GHS-POP. EU Science Hub. Retrieved July 22, 2021.

12 Bono, A. D., & Chatenoux, B. (2014). A Global Exposure Model for GAR 2015. UNEP/GRID-Geneva.

13 UNDP. Human Development Reports – Human Development Index. Retrieved March 30, 2022.

14 The World Bank. (2020). Global Financial Development Database. Retrieved March 30, 2022.

15 World Economic Forum. The Global Competitiveness Report 2017-2018. Retrieved 10 March 2021.

16 The World Bank. (2020). Global Financial Development Database. Retrieved March 30, 2022.

Exhibit 2: Overlay components and data sources

Layer	Data sources
Riverine hazard	100-year return period hazard maps from WRI Aqueduct Floods.
Coastal hazard	100-year return period hazard maps from WRI Aqueduct Floods.
Rainfall hazard	100-year return period precipitation maps estimated from the data sets listed in the "Hazard scores," "Rainfall (pluvial) hazard" section in Exhibit 1. Only areas with extreme precipitation ≥200mm/day are shown.
Urban areas	Surface covered by urban areas derived from FAO's Global Land Cover (GLC-SHARE).[17]
Rural areas	Surface covered by agriculture derived from FAO's Global Land Cover (GLC-SHARE).[18]
Power plants	WRI's Global Power Plant Database.[19]
International ports and airports	International Ports[20] and International Airports[21] databases from the World Bank's Data Catalog.

Source: Marsh McLennan Advantage

Score Calculation

Scores for Hazard, Exposure, and Vulnerability are calculated at the country level. Global and country group averages are then calculated by aggregating information across countries. Group averages were calculated by classifying countries by income and geography using the World Bank's World by Income and Geography data set.[22] The lists of countries included in the calculation of regional and income group averages are available in the data file made available on the Rethinking Flood landing page.

Hazard

Background

Hazard scores represent a measure of the potential threat of flooding, in terms of severity and likelihood, and are based on information on 100-year return period flooding.

The scores reflect information on the following components:

- **Riverine flooding**, caused by overflowing of rivers due to intense precipitation, ice jams, and melting of snow and ice.

17 Latham, J., Cumani, R., Rosati, I., & Bloise, M. (2014). Global land cover share — FAO. Food and Agricultural Organization of the United Nations. Retrieved March 30, 2022.

18 Ibid.

19 Global Energy Observatory, Google, KTH Royal Institute of Technology in Stockholm, Enipedia, World Resources Institute. (2018). Global Power Plant Database. Published on Resource Watch and Google Earth Engine. Retrieved March 30, 2022.

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22 The World Bank. (2022). The World By Income and Region. World Development Indicators. Retrieved March 30, 2022.

- **Coastal flooding**, triggered by storm surges, extreme tidal events, and subsidence.
- **Rainfall flooding**, occurring when extreme precipitation leads to flash floods or surface water floods.

The 100-year return period riverine and coastal inundation maps were obtained from WRI's Aqueduct Floods. Coastal inundation maps incorporate the effect of coastal subsidence. Further details can be found in the WRI Aqueduct Floods methodology document.[23] The 100-year return period maps for rainfall flooding were calculated by performing an extreme value analysis of the annual maximum values of daily precipitation from multiple observational, reanalysis, and climate model data sets.

Calculation

Fluvial and coastal hazard scores

Step 1. The 100-year riverine and coastal inundation maps available in Aqueduct Floods for present-day conditions and for years 2030, 2050, 2080 under an RCP8.5 forcing were analyzed to calculate riverine and coastal hazard scores for the four scenarios in the Index. The 2030, 2050, and 2080 time horizons were assumed to correspond to +1.5 °C, +2 °C, and +3.5 °C warming levels.

Step 2. The area-weighted average value of flood depth for riverine flooding in each country was estimated for each warming level. The average riverine flood depth in each country for each warming level was mapped to a riverine hazard score (ranging from 1 to 10) using the deciles of the distribution of the 2080 average riverine flood depth values across countries.

Step 3. A similar analysis was performed to calculate coastal scores. In this case, however, the area-weighted average values of coastal flood depth were estimated from a 30-km coastal buffer in each country. Excluding areas outside this buffer ensures comparability across countries with very different areas.

Rainfall hazard scores

Step 1. The present-day 100-year return period map for extreme rainfall was calculated by performing an extreme value analysis of the annual maximum values of daily precipitation in the 30-year period 1991–2020 from multiple observational and reanalysis data sets with different geographical coverages: ECA&D E-OBS, WMO CCI/WCRP/JCOMM ETCCDI HadEX3, USGS/CHC CHIRPS, and ECMWF ERA-Interim. The best extreme rainfall estimate at each location was obtained by selecting the first available estimate from the data sets in the order of preference corresponding to their listing order above. Such estimates were then merged to generate a map with global coverage, and the area-weighted average value of extreme rainfall in each country was calculated.

Step 2. A set of eight present-day 100-year return period maps for extreme rainfall was calculated from CMIP5 climate model simulations of annual maximum values of daily precipitation under historical forcing conditions. The CMIP5 model output was made available by the Climdex project.[24] Seven of the 15 models in the project were excluded from the analysis as they failed to represent global precipitation patterns under present-day conditions. The eight CMIP5 models used to calculate extreme rainfall values (from the last 30 years of each historical run) were bcc-csm1-1, CanESM2, CCSM4, CNRM-CM5, GFDL-CM3, HadGEM2-ES, IPSL-CM5A-MR, and MRI-CGCM. The eight extreme rainfall maps were then averaged to produce a multi-model estimate of extreme rainfall under present-day conditions.

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23 Ward, P. J., Winsemius, H. C., Kuzma, S., Bierkens, M. F. P., Bouwman, A., Moel, H. D., Loaiza, A. D., Englhardt, J., Erkens, G., Gebremedhin, E. T., Iceland, C., Kooi, H., Ligtvoet, W., Muis, S., Scussolini, P., Sutanudjaja, E. H., Beek, R. V., Bemmel, B. V., Huijstee, J. V., Vatvani, D., Verlaan, M. Tiggeloven, T., Luo, T. (2020). Aqueduct Floods Methodology.

24 University of New South Wales. (n.d.). Climdex. Retrieved April 20, 2022.

Step 3. The present-day 100-year return period map for extreme rainfall calculated from observations and reanalysis data in step 1 was divided by the multi-model extreme rainfall map for present-day conditions calculated in step 2. The resulting map of bias correction factors was used to rescale extreme rainfall values calculated from CMIP5 models under future warming scenarios (see step 4).

Step 4. The 100-year return period maps for extreme rainfall under future warming scenarios (+1.5 °C, +2 °C, and +3.5 °C) were calculated by performing an extreme value analysis of the annual maximum values of daily precipitation in the 30-year periods centered on 2030, 2050, and 2080 respectively, as simulated by the eight CMIP5 model simulations from the Climdex project. The eight extreme rainfall maps for each warming scenario were then averaged to produce a multi-model estimate. The multi-model averages were then rescaled by multiplying them by the bias correction factor map calculated in step 3. The area-weighted average value of extreme rainfall in each country for each warming scenario was then calculated.

Step 5. The area-weighted average value of extreme rainfall in each country for each warming level (as calculated in steps 1 and 4) was mapped to a rainfall hazard score (ranging from 1 to 10) using the deciles of the distribution of the 2080 extreme rainfall values across countries.

Step 6. Observational, reanalysis, and model simulation data had different resolutions. Performing the operations described in steps 1 to 4 required to reinterpolate data to the highest resolution among all data sets (E-OBS).

The total hazard score for each country was estimated by averaging the riverine, coastal, and rainfall hazard scores.

Limitations

The 2030, 2050, and 2080 time horizons were assumed to correspond to +1.5 °C, +2 °C, and +3.5 °C warming levels based on CMIP5 multi-model global temperature projections, without accounting for different climate sensitivities across the CMIP5 ensemble.

Information on flood defenses was not included in the analysis.

Different resolutions of the data sets used to estimate rainfall flooding impacted their representation of pluvial extremes.

CMIP5 climate models may underestimate or overestimate rainfall extremes, and correction factors were applied to reduce such biases. Bias correction factors are assumed constant in time.

Exposure

Background

Exposure scores reflect information on the following components:

- **Human exposure**, an estimate of the percentage of population exposed to flooding in each country.
- **Economic exposure**, an estimate of the percentage of assets exposed to flooding in each country.

Exposure scores were calculated by intersecting population and asset distribution data with a layer obtained by combining the 100-year return period global inundation maps for riverine, coastal, and rainfall flooding for each warming scenario. No changes in time of the population and asset distributions were assumed when estimating exposure scores for future climate change scenarios, thus only incorporating information on changing hazard.

Calculation

Step 1. An aggregated 100-year hazard map was created by combining the riverine, coastal, and rainfall inundation maps across each of the climate scenarios. For rainfall, extreme precipitation exceeding 200mm/day was used as a threshold to identify at-risk areas. The 2030, 2050, and 2080 time horizons were assumed to correspond to +1.5 °C, +2 °C, and +3.5 °C warming levels.

Step 2. Asset value data from GAR was aggregated to a raster layer (1km x 1km) to provide a continuous representation of exposure.

Step 3. The global population (GHSL) and asset (GAR) layers were then clipped to the boundaries of the combined 100-year riverine, coastal, and rainfall inundation maps.

Step 4. A zonal statistics operator was applied to sum the values of population and assets in the inundated areas, thus calculating the total values of exposed population and assets in each country.

Step 5. The same zonal statistics operator was applied to calculate the total assets and population values in each country.

Step 6. The percentages of people and assets threatened by flooding were calculated for each country by dividing the numbers estimated in steps 4 and 5.

Step 7. Human and economic exposures scores for each country (ranging from 1 to 10) were estimated from the two percentage values by comparing them to the deciles of the corresponding distribution of percentages across countries in 2080. Scores for the four scenarios (present day, 2030, 2050, 2080) were all estimated using the deciles of the 2080 distributions.

Step 8. Total exposure scores were calculated by averaging the human and economic exposure scores.

Limitations

The 2030, 2050, and 2080 time horizons were assumed to correspond to +1.5 °C, +2 °C, and +3.5 °C warming levels based on CMIP5 multi-model global temperature projections, without accounting for different climate sensitivities across the CMIP5 ensemble.

Due to the difficulty in estimating flood exposure, there was a limited choice of available datasets. Data sources chosen to calculate exposure represent best available information that can be viewed as proxies for data that would otherwise be created or utilized exclusively for the purpose of flood risk modelling and assessment.

The choice of 200mm/day as a threshold to identify areas prone to rainfall flooding is arbitrary, and does not incorporate information on soil type, local topography, and other factors that may affect risk.

Vulnerability

Background

Vulnerability scores reflect socioeconomic susceptibility to flooding and are based on the following indicators:

- **The Human Development Index (HDI***),* which captures three dimensions of human development that are highly relevant to human vulnerability (life expectancy, access to knowledge, and per capita income).[25]
- **Quality of Overall Infrastructure**, which estimates the quality of transport, energy and telephony systems and uses them as a proxy for economic vulnerability of infrastructure to flood events.
- **Non-Life Insurance Premium Volume to GDP***,* which in the absence of global natural catastrophe insurance penetration data provides a view of the insurance environment and corresponding levels of protection within each country.

Calculation

Step 1. The Human Development Index (HDI, ranging from 0 to 1), the Quality of Overall Infrastructure (Q, between 1 and 7), and the Non-Life Insurance Premium Volume to GDP (I) were rescaled to the range 0 to 100, with 0 indicating the highest performance in each dimension (HDI = 1, Q = 7, I = maximum among all countries) and 100 the lowest performance (HDI = 0, Q = 1, I = minimum among all countries). In the case of Q, data was first cleaned to account for countries with missing values. If no data was available for the most recent year of the dataset, data from previous years was included. No data before 2015 was included.

Step 2. Human vulnerability values were calculated from HDI and Non-Life Insurance Premium Volume to GDP using the following formula:

$$\frac{HDI_{RESCALED} + 0.5 \times I_{RESCALED}}{1.5}$$

Step 3. Economic vulnerability values were calculated from Quality of Overall Infrastructure and Non-Life Insurance Premium Volume to GDP using the following formula:

$$\frac{Q_{RESCALED} + 0.5 \times I_{RESCALED}}{1.5}$$

Step 4. The resulting human and economic vulnerability values were then mapped to scores (ranging from 1 to 10) using the decile values of the two distributions.

Step 5. Total vulnerability scores were calculated by averaging human and economic vulnerability scores in each country.

Limitations

Vulnerability to flood risk can be represented by many indicators. The indicators included in the analysis do not explicitly factor in mitigation and adaptation measures and are not to be viewed as an exhaustive portrayal of vulnerability to flooding.

No information on climate scenarios was incorporated due to lack of reliable projections on the proxies used.

25 Details regarding the calculation of HDI can be found here.

Overlays Statistics Calculation

Background

The Overlays section of the Index shows the global inundation maps for riverine and coastal flooding (100-year return period maps from WRI's Aqueduct Floods), and the rainfall inundation maps generated through from the process described in the Hazard Calculation section of this document. The Overlays section also presents data on the global distributions of urban areas, rural areas, and critical infrastructure assets, accompanied by key country-level statistics:

- **Urban Areas**, with the percentage of urban areas at risk of flooding.
- **Rural Areas**, with the percentage of rural areas at risk of flooding.
- **Power Plants**, with the percentage of power generation capacity at risk of flooding.
- **Ports and Airports**, with the percentages of international trade volumes (ports) and international seats (airports) at risk of flooding.

Calculation

Step 1. An aggregated 100-year hazard map was created by combining the riverine, coastal, and rainfall inundation maps across each of the climate scenarios. For rainfall, extreme precipitation exceeding 200mm/day was used as a threshold to identify at-risk areas. These maps were intersected with World Bank boundary data and the data sets listed in steps 2 to 4 to estimate the percentages of urban/rural areas and critical assets at risk.

Step 2. The total percentages of urban and rural areas exposed to flooding in each country were calculated from the FAO's Global Land Cover SHARE (GLC-SHARE) database.

Step 3. The percentage of power generation affected by flooding in each country was estimated from the WRI's Global Powerplant Database.

Step 4. The percentages of trade volumes (for international ports) and seats (for international airports) at risk were estimated from the World Bank's data catalog on international ports and airports.

Limitations

The 2030, 2050, and 2080 time horizons were assumed to correspond to +1.5 °C, +2 °C, and +3.5°C warming levels based on CMIP5 multi-model global temperature projections, without accounting for different climate sensitivities across the CMIP5 ensemble.

The data sets used for the analysis only offer an approximate representation of the distribution on the assets at risk at flooding. Data gaps and incorrect reporting of locations may lead to underestimation/overestimation of the percentages affected.

The choice of 200mm/day as a threshold to identify areas at risk of rainfall flooding is arbitrary, and does not incorporate information on soil type, local topography, and other factors that may affect risk.

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