

RISK INDEX FOR CLIMATE DISPLACEMENT (RICD)

# Macro-level Analysis: Case Study of the Philippines

PREPARED BY UNIVERSITY OF THE PHILIPPINES RESILIENCE INSTITUTE

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This analysis was produced as part of the RICD partnership, led by the Organization for Migration (IOM), University of the Philippines Resilience Institute (UP RI) and the Asian Institute of Technology (AIT)



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## Executive Summary

This report presents the **macro-level analysis for the Philippines under the Risk Index for Climate Displacement (RICD) initiative**. Using the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) risk framework, the study evaluates risk as a function of hazard, exposure, and vulnerability. The analysis focuses on **flood risk across all 1,634 cities and municipalities in the Philippines**, identifying priority areas for further analysis and field data collection.

Flooding was modeled using simulated 100-year return period rainfall events. A Mean Hazard Index (MHI) was generated for each city and municipality by combining simulated flood data with population and settlement information. Exposure was assessed based on the percentage and number of affected populations, using high resolution population data. Vulnerability **was analyzed through two components: sensitivity** (e.g. poverty, age, structure and expenditure) and **adaptive capacity** (e.g. access to healthcare, sanitation, electricity). The composite risk index, which equally weights hazard, exposure, and vulnerability, shows that over 63% of cities and municipalities fall under a high-risk category. Very few areas are classified as low risk, highlighting the systemic nature of displacement drivers.

The macro-level analysis represents the first step in the RICD methodology framework, providing a **standardized index of flood risk across the Philippines**. This index holds significant potential for **informing policymaking, guiding development planning, and integrating into national disaster risk and displacement datasets**. The next phase, the micro-level analysis, will build on this foundation by **examining community-level displacement triggers and tipping points** to capture the nuanced dynamics that lead to displacement on the ground.

This work was developed through a co-creation partnership between the International Organization for Migration (IOM), the University of the Philippines Resilience Institute (UP RI), and the Asian Institute of Technology (AIT), with contributions from a network of regional and global academic and government partners. It draws on publicly accessible datasets and was informed by technical engagements with several key national government agencies, including the Department of Social Welfare and Development (DSWD), the Climate Change Commission (CCC), the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA), the National Mapping and Resource Information Authority (NAMRIA), the Bureau of Soils and Water Management of the Department of Agriculture (BSWM-DA), the Department of Trade and Industry (DTI), the Philippine Statistics Authority (PSA) and the National Disaster Risk Reduction and Management Council (NDRRMC).

# 1. Introduction and Objectives

The Philippines is among the world's most disaster-prone countries, regularly experiencing floods, typhoons, landslides, and other climate-related hazards. With over 50% of its population living in low-lying coastal areas, the country faces a heightened risk of displacement from both slow- and rapid-onset hazards. Recent events such as Severe Tropical Storm Paeng and Typhoon Tisoy have led to significant internal displacement, highlighting the urgency of improving foresight and preparedness.

In response, the International Organization for Migration (IOM)'s Climate Mobility Innovation Lab (CMIL), the University of the Philippines Resilience Institute (UP RI), and the Asian Institute of Technology (AIT) are jointly leading the development of the Risk Index for Climate Displacement (RICD). In the Philippines, consultations were conducted jointly by IOM Philippines and UPRI with the Climate Change Commission (CCC) and the Department of Social Welfare and Development (DSWD) to discuss the RICD initiative and ensure alignment of its pilot implementation in the Philippines with national priorities.

This initiative was co-created with a network of academic partners such as the University of Indonesia, Nanyang Technological University, and the University of Sydney, among others. The analysis is informed by consultations and data inputs from relevant national agencies, including the Department of Social Welfare and Development (DSWD), the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA), the National Mapping and Resource Information Authority (NAMRIA), the Bureau of Soils and Water Management of the Department of Agriculture (BSWM-DA), the Department of Trade and Industry (DTI), the Philippine Statistics Authority (PSA) and the National Disaster Risk Reduction and Management Council (NDRRMC). While formal partnerships with National Government Agencies (NGAs) were not established during this phase, the process integrated publicly available data and was informed by technical engagement with relevant institutions. This modular tool is designed to assess and map the risk of climate-induced displacement at national and subnational levels. By combining scientific modeling with institutional engagement, RICD aims to inform planning, policy, and investment decisions in high-risk areas.

The macro-level analysis forms the foundational layer of RICD. It provides a broad overview of flood risk by evaluating three key dimensions: hazard, exposure and vulnerability. These components are aligned with the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) framework, which defines risk as the interaction of hazard intensity and frequency, exposure of populations and assets, and the vulnerability of affected systems.

This case study for the Philippines focuses on floods as a rapid-onset hazard and uses high-resolution spatial and socioeconomic data to calculate risk scores across all cities and municipalities. It also includes a preliminary correlation analysis using actual displacement data from the Disaster Response Operations Management, Information and Communication (DROMIC). This approach enables a structured, data-driven understanding of displacement risk from climate hazards, starting with floods as the initial focus, expanding the focus over time to other hazards.

The results are intended to inform both the development of the RICD tool and strategic initiatives such as the Climate Catalytic Fund (CCF), which supports anticipatory action and climate resilience investments in high-risk contexts.

## The objectives of this macro-level analysis in the Philippines are:

1. To identify and quantify indicators for flood-related hazard, exposure, and vulnerability;
2. To generate composite risk scores for all local government units (LGUs) using standardized methodologies;
3. To identify flood risk hotspots and priority areas for further validation and integration into the RICD tool;
4. To inform the design and prioritization of micro-level analysis by identifying high-risk areas for detailed fieldwork, allowing for a coherent, layered approach to displacement risk from national to community scale.

This analysis, developed through a co-creation process involving technical experts, implementing agencies, and government partners, draws from multiple institutions, including national statistics offices, disaster management authorities, and academic partners, to ensure relevance, data accuracy, and alignment with national priorities. The

methodology and indicator selection were refined through iterative consultations, enabling the model to reflect local risk contexts while maintaining consistency with global risk frameworks. This collaborative approach supports the tool's intended use across sectors and scales, from national planning to local implementation.

# 2. Methodology

The macro-level analysis serves as the foundation for the development of the RICD tool, focusing on quantifying the drivers of displacement as outlined in the conceptual framework presented in Figure 1.

It adopts the IPCC Fifth Assessment Report (AR5) framework, which defines climate risk as the interaction of three components: hazard, exposure, and vulnerability. Risk is conceptualized as:

$$\text{Risk} = f(\text{Hazard} \times \text{Exposure} \times \text{Vulnerability})$$

This structure enables a systematic evaluation of flood risk across all cities and municipalities in the Philippines.

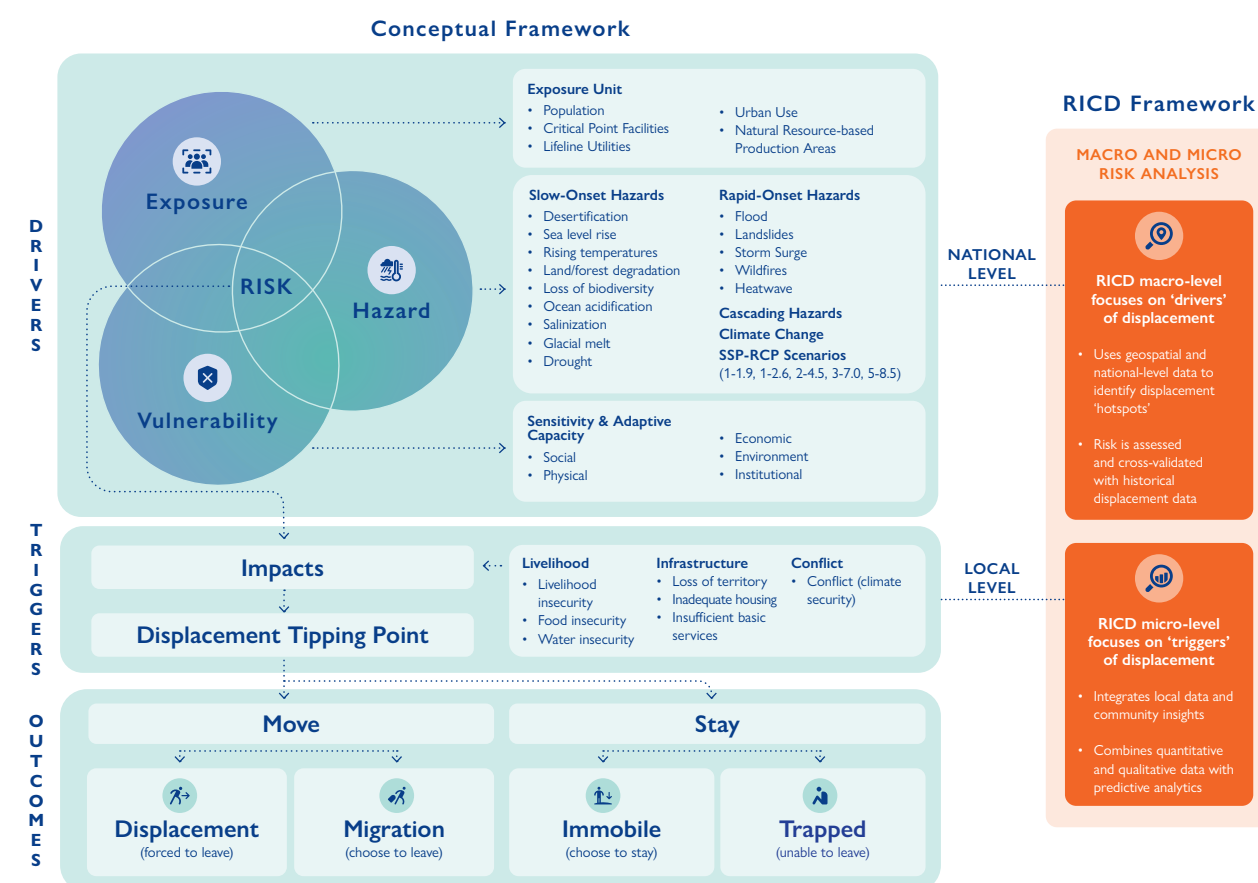


Figure 1. Conceptual Framework for the Risk Index for Climate Displacement (RICD) tool

The methodology reflects contributions from multidisciplinary partnership spanning hazard modelling, migration studies, and disaster risk management co-led by IOM, UP RI and AIT.

## 2.1. Spatial and Temporal Scope

The analysis covers all 1,634 cities and municipalities in the Philippines. The hazard component focuses on flooding, one of the most frequent and impactful rapid-onset climate hazards affecting the country. Flood simulations were conducted based on 100-year return period rainfall events, following national flood modeling standards. Displacement data were

drawn from the Department of Social Welfare and Development Disaster Response Operations Management, Information and Communication (DSWD DROMIC), covering events from 2014 to early 2024. All scoring and risk analyses were conducted at the municipal level, ensuring consistency in the application of indicators and classification methods.

## 2.2. Indicator Selection and Data Sources

Indicators were selected to reflect national priorities, scientific literature, and the availability of disaggregated data. They are grouped under the following components:

- **Hazard:** Flood hazard levels identified by simulating rainfall data from PAGASA with elevation and land classification data from NAMRIA.
- **Exposure assessed using two key indicators:**
  - Proportion of affected population, based on flood overlays with population data from the Philippines Statistics Authority (PSA) represented in the spatial extent of the Facebook High Resolution Settlement Layer (HRSL)
  - Number of affected people
- **Vulnerability** (sourced from the Philippine Statistics Authority (PSA):
  - **Sensitivity** indicators included:
    - › Poverty Index Score
    - › Age Dependent Population Score
    - › Poor Wall Construction Materials Score
    - › Poor Roof Construction Materials Score
    - › Large Household Size Score
    - › Poor State of Building Score
    - › Year of Construction Score
    - › House and Lot Tenure Score
    - › Housing Backlog Score
  - **Adaptive capacity** indicators included:
    - › Highest Education Attainment Score

- › Literacy Rate Score
- › Internet Access Score
- › Ownership of Household Convenience Score
- › Improved Water Sources Score
- › Electrified Houses Score
- › Cities and Municipalities Competitive Index (CMCI) Score (sourced from DTI)
- › Urbanization Score

The datasets used were primarily drawn from official sources including PAGASA, PSA, NAMRIA, DTI and DSWD. While these were accessed via public platforms, technical consultations were held with selected agencies to guide data interpretation and model relevance.

The selection of indicators for the Philippines was guided by relevance, data availability, and alignment with established risk frameworks. However, differences in data availability, resolution, and format across sectors and regions presented challenges for full standardization. Rather than limiting the analysis to a narrow set of indicators available in all contexts, the assessment used the best available national datasets to maximize spatial coverage and indicator validity. This approach ensures a more accurate and context-specific representation of flood risk, while acknowledging that some trade-offs in cross-country comparability were necessary.

## 2.3. Index Construction and Scoring

Each indicator was normalized using the Min-Max method, in line with methodologies such as the UNDP Human Development Index.



Rainfall data provided by PAGASA were used in the development of hydrometeorological models. Additionally, elevation and land cover data from NAMRIA, along with soil type data generated by the BSWM, were also included as input parameters in the hydrometeorological simulations.

Using a 100-year return period rainfall simulation, the hazard layer was constructed based on the flood extent and severity resulting from heavy precipitation, as shown in Figure 2. Flood hazard was assessed by calculating the Mean Hazard Index (MHI) for each city and municipality. The MHI represents the average flood severity derived from simulated rainfall exposure across administrative boundaries. Flooded residential zones were identified by overlaying the HRSL onto simulated flood extents. Each administrative unit was assigned a score from 1 (lowest hazard) to 5 (highest hazard), using equal interval classification. The scoring assumed that all structures and populations within flood-prone areas are equally exposed, consistent with the hazard definition in the IPCC AR5 framework.

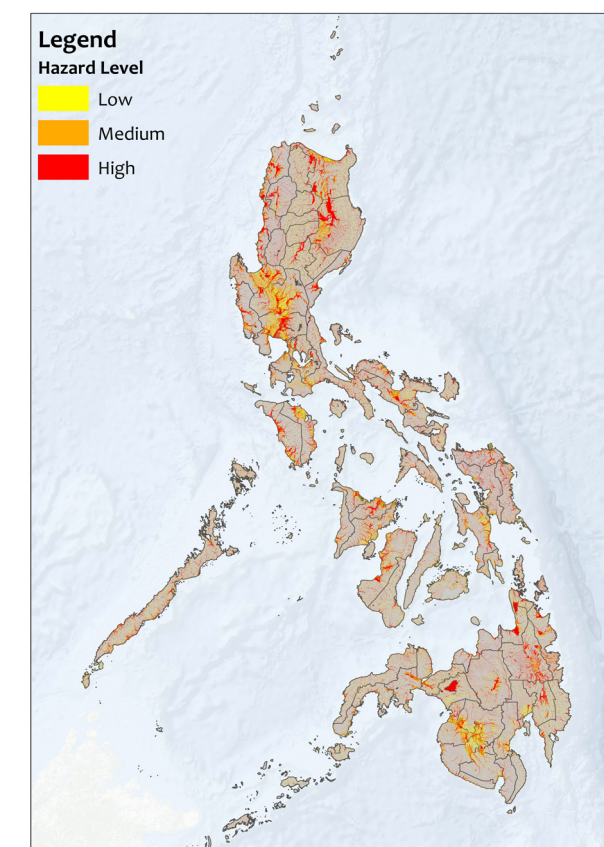


Figure 2. Flood hazard map based on 100-year return period rainfall simulation in the Philippines



## Exposure

The exposure dimension captures the concentration of people living in flood-prone areas. This analysis used high-resolution population data to determine both the proportion of people affected and the density of affected populations within each city and municipality.

Two key indicators were used to calculate the exposure index:

1. Percentage of population exposed to flooding (shown in Figure 3 – left);
2. Number of affected individuals within each administrative unit (shown in Figure 3 – right).

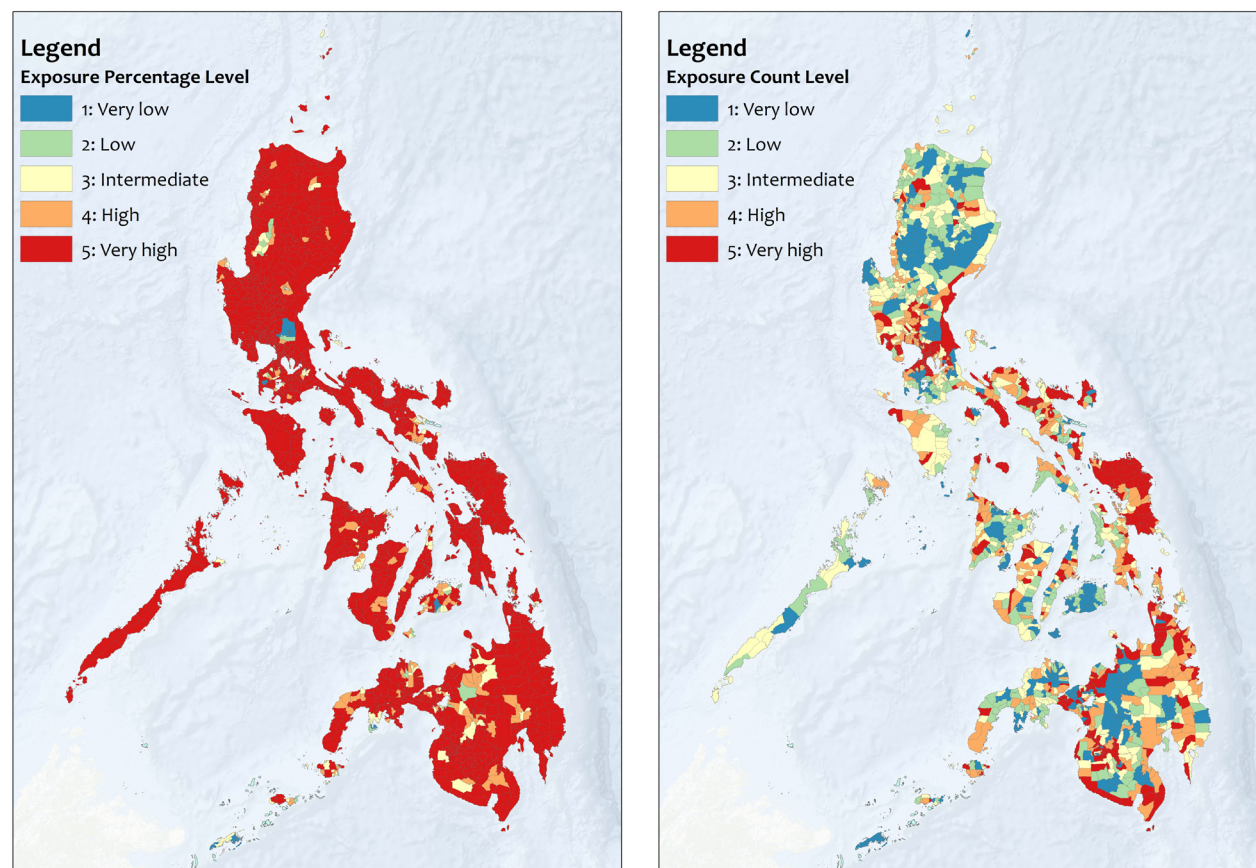


Figure 3. Exposure percentage (Left) and count levels of affected people per city and municipality (Right)

The flood extent from the 100-year return period rainfall simulation was overlaid onto population data—using the spatial distribution from the Facebook High Resolution Settlement Layer (HRSL) and population figures from the Philippine Statistics Authority (PSA) at the administrative unit level – to

identify areas where residents are likely to be directly affected. These two indicators were normalized using the Min-Max method and then averaged to produce the final Exposure Index, scaled from 1 (lowest exposure) to 5 (highest exposure).



## Vulnerability

Vulnerability was assessed through two subcomponents: sensitivity and adaptive capacity. Data regarding various vulnerability indicators were obtained from the 2020 Census of Population and Housing and First Semester 2021 Poverty Statistics released by the PSA. These dimensions capture socioeconomic conditions that shape how severely populations are impacted by flooding and how well they can recover. Vulnerability scores are presented in Figure 6.

A Cronbach's Alpha test was conducted to assess the reliability of the sensitivity and adaptive capacity indicator sets. These were then further refined

through a pairwise assessment. Lastly, Principal Component Analysis (PCA) was applied to determine the weights for sensitivity and adaptive capacity indicators, ensuring the resulting index reflects the most relevant dimensions of local vulnerability. Sensitivity and adaptive capacity scores are mapped in Figures 7 and 8, respectively.

The composite Vulnerability Index was calculated by averaging the weighted sensitivity and adaptive capacity scores. This layered approach ensures that areas with structural disadvantages are meaningfully reflected in the overall risk profile.

## 2.4. Risk Score Calculation and Classification

The composite Risk Index integrates the three main dimensions of the analysis – hazard, exposure, and vulnerability – to identify areas at highest risk of flood events.

Following the IPCC AR5 framework, the risk score for each city and municipality was calculated using the unweighted average of the three normalized component scores:

$$\text{Risk Score} = 1/3 (\text{Hazard Score} + \text{Exposure Score} + \text{Vulnerability Score})$$

Each component was scaled from 1 (lowest) to 5 (highest), and final risk scores were classified into five categories using equal intervals.

## 2.5. Data Limitations

The analysis relied on the best available datasets at the time of analysis; however, several limitations should be acknowledged.

- Displacement data often **lacks full subnational disaggregation, standard event attribution, or consistent temporal coverage**. This limits the precision of validation efforts.
- Socioeconomic and infrastructure indicators were based on the most recent national surveys and administrative sources, but some variables (e.g., informal housing, internet access, or household sensitivity) may be **underreported or outdated** in certain areas.
- Hazard data, while modelled or compiled from authoritative sources, are often static snapshots and may **not fully reflect localized changes** due to land use or recent climate events.
- Finally, cross-country comparability is **constrained by differences in indicator definitions, spatial resolution, and data frequency**, which informed the decision to prioritize national datasets over uniform global sources.

These limitations underscore the importance of ongoing model refinement, data harmonization, and the incorporation of local knowledge through micro-level analysis.



## 3. Macro-Level Analysis

### 3.1. Hazard Assessment

This macro-level analysis focuses on flooding as the initial hazard of concern due to its high frequency and displacement potential across the Philippines.

This approach reflects a realistic worst-case scenario and is consistent with national disaster modeling practices. Figure 4 presents the hazard score with the most frequent flood events.

The hazard component provides a spatially disaggregated view of flood risk intensity and sets the foundation for integrated exposure and vulnerability analysis in the following sections.

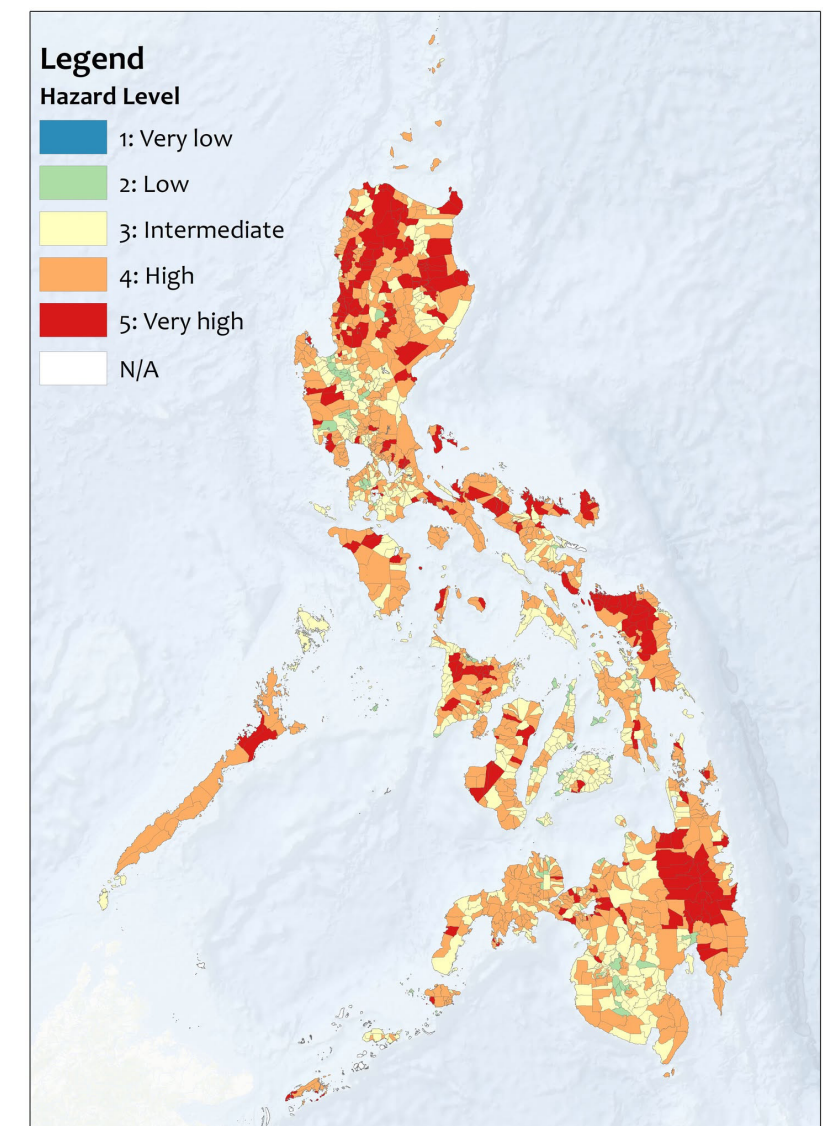


Figure 4. Hazard levels of cities and municipalities in the Philippines

### Key Findings

- The resulting classification shows that flooding is widespread and nationally significant.
- Out of 1,634 cities and municipalities, 1,007 (approximately 62%) received scores of 4 or 5, indicating high or very high hazard scores.
- Hazard scores of 5 were concentrated in low-lying and coastal regions, particularly in parts of Central Luzon, Eastern Visayas, and Bangsamoro.
- Very few areas scored a 1, reinforcing the geographic breadth of flood exposure

### 3.2. Exposure Analysis

The exposure dimension captures the concentration of people living in flood-prone areas. This analysis used high-resolution population data to determine both the proportion of people affected and the density of affected populations within each city and municipality.

Areas with high population density that experienced frequent flooding were scored as exposed to risk as depicted in Figure 5.

This two-dimensional approach to exposure captures both the relative scale of impact (how many) and spatial intensity (how concentrated) – ensuring that both rural and urban vulnerabilities are reflected in the risk calculation.

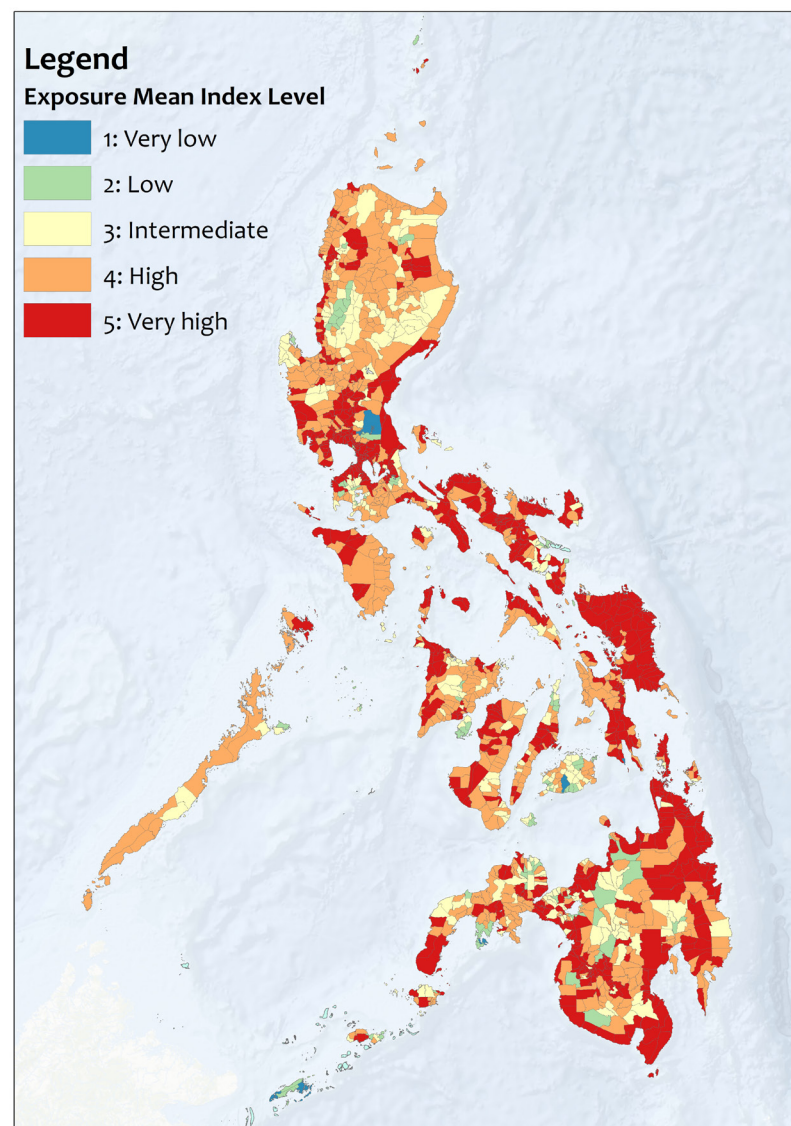


Figure 5. Exposure mean index levels of cities and municipalities in the Philippines

#### Key Findings

- Urban centers such as Metro Manila, Davao City, and Cagayan de Oro scored 5, reflecting both high population concentrations and significant flood-affected areas.
- Many smaller municipalities received mid-range scores due to moderate densities or smaller affected areas.
- Remote areas and highlands typically received scores of 1 or 2, with minimal overlap between population and flood extent.

### 3.3. Vulnerability Analysis

Vulnerability was assessed through two subcomponents: sensitivity and adaptive capacity. These dimensions capture socioeconomic conditions that shape how severely populations are impacted by flooding and how well they can recover.

Figure 6 shows the combined vulnerability levels of cities and municipalities in the Philippines.

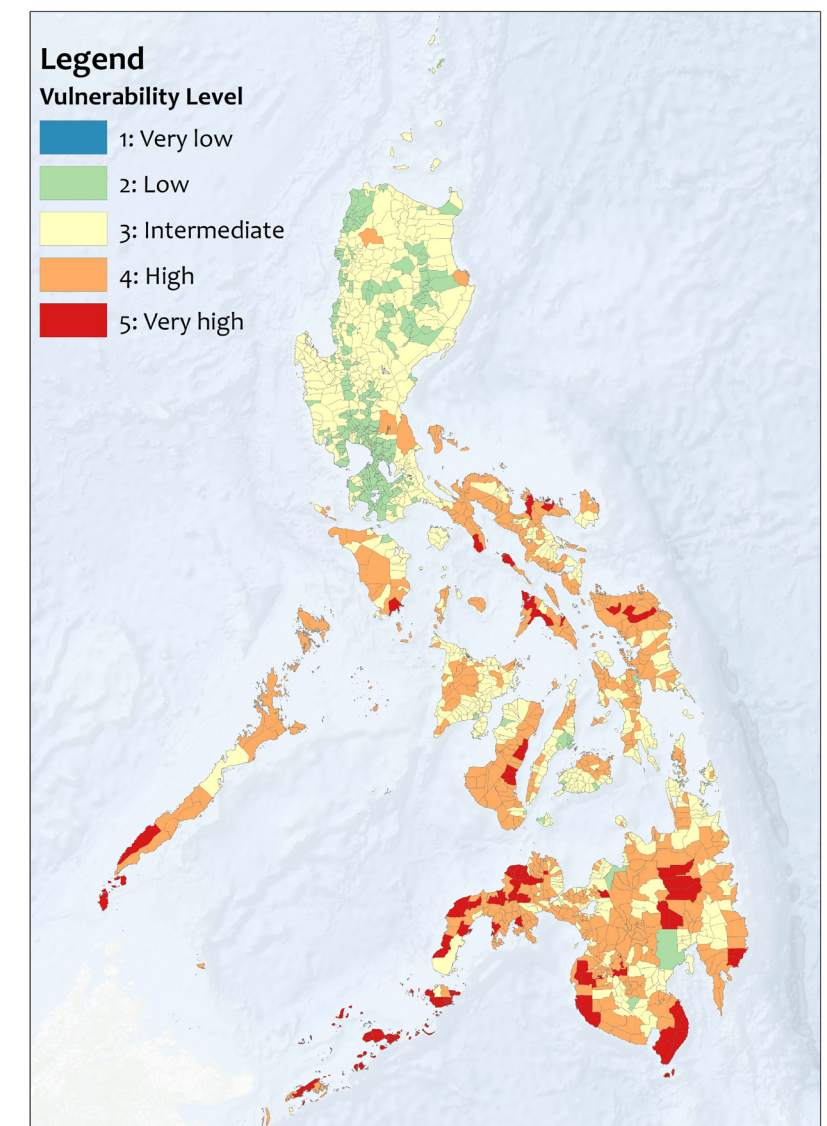


Figure 6. Vulnerability levels of cities and municipalities in the Philippines



### 3.3.1. Sensitivity

Sensitivity reflects how exposed populations may be disproportionately affected by flooding due to underlying socioeconomic disadvantages, as shown in Figure 7.

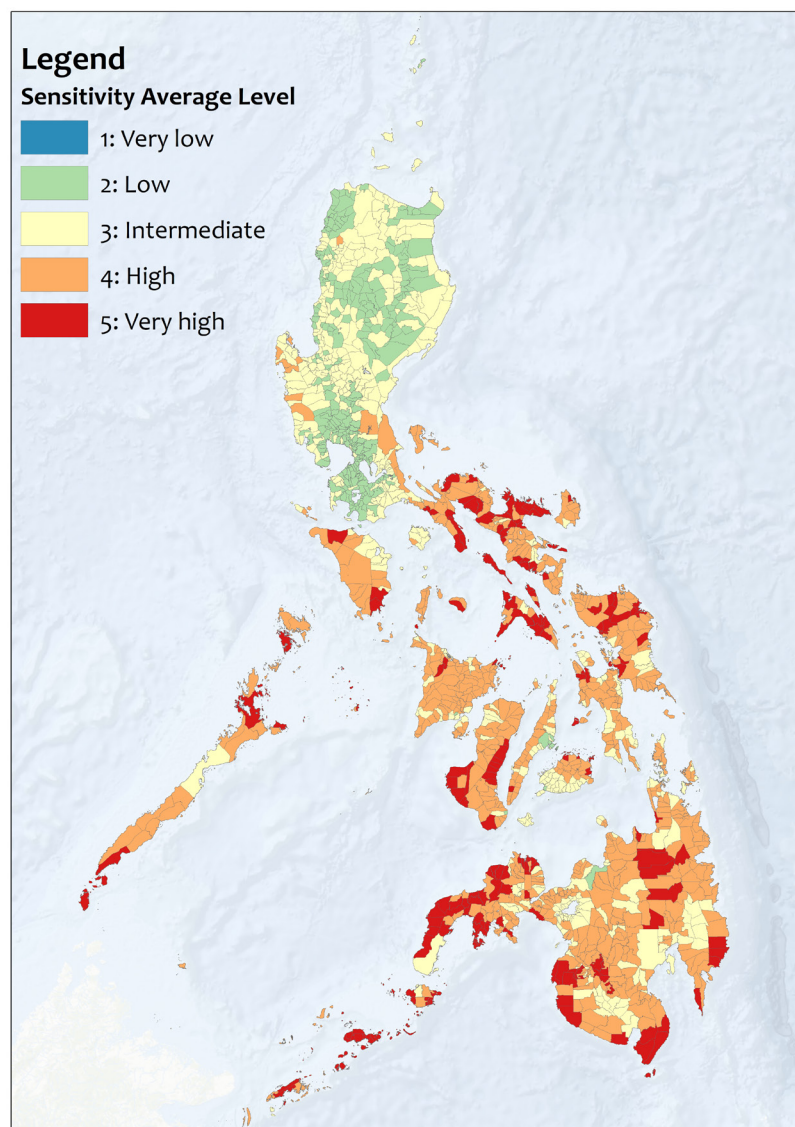


Figure 7. Sensitivity levels of cities and municipalities in the Philippines

#### Key findings

- Visayas and Mindanao regions displayed the highest sensitivity scores, particularly in provinces such as Eastern Samar, Lanao del Sur, and Maguindanao del Norte.
- Municipalities with widespread informal housing and limited household resilience were most affected.
- Several provinces with moderate hazard scores ranked high in sensitivity, amplifying their overall risk.

### 3.3.2. Adaptive Capacity

Adaptive capacity measures the ability of populations to cope with and recover from flood events. It is based on access to services and infrastructure that support resilience. In this case, higher access levels correspond to lower vulnerability levels, as depicted in Figure 8.

The variation in adaptive capacity deepens the spatial inequality in flood risk.

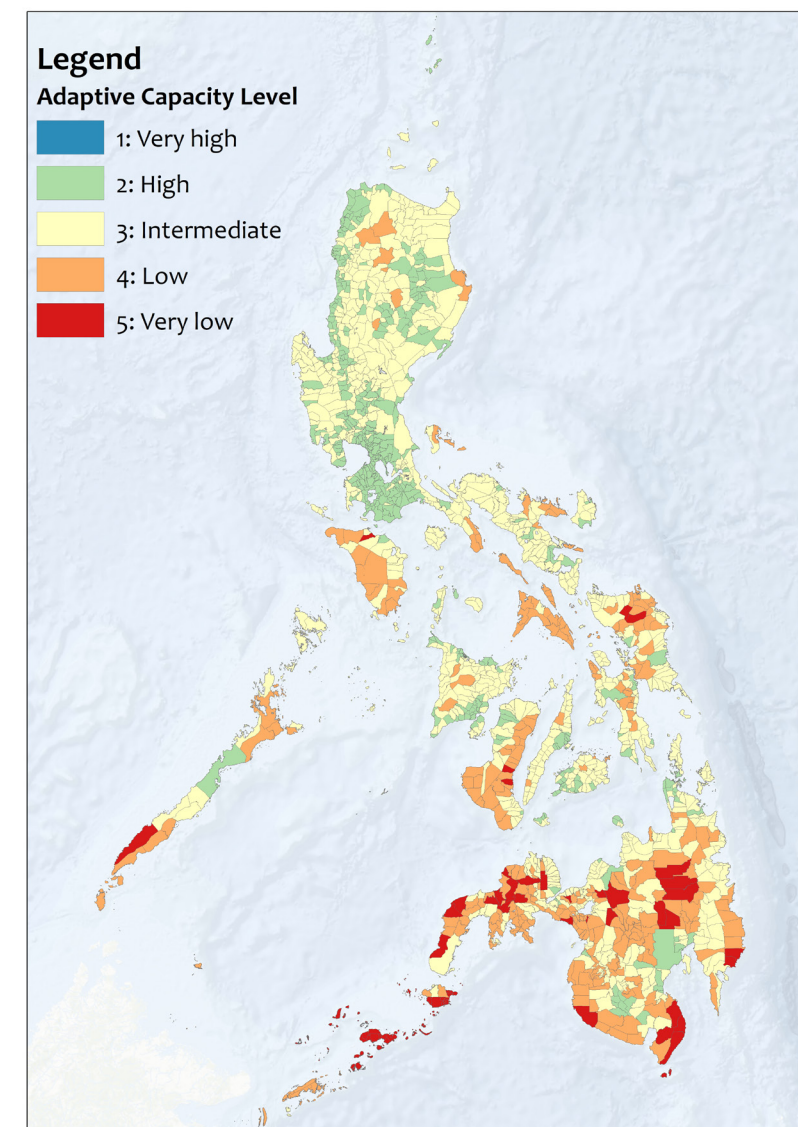


Figure 8. Adaptive capacity levels of cities and municipalities in the Philippines

#### Key findings

- Luzon, particularly regions surrounding Metro Manila, owed higher adaptive capacity due to stronger infrastructure and service access.
- Conversely, parts of Mindanao and rural Visayas exhibited low scores, reinforcing patterns of chronic underinvestment.

### 3.4. Composite Risk Index

Each municipality therefore received three final scores – Hazard, Exposure, and Vulnerability – each ranging from 1 to 5. The final composite risk map is presented in Figure 9.

The variation in adaptive capacity deepens the spatial inequality in flood risk.

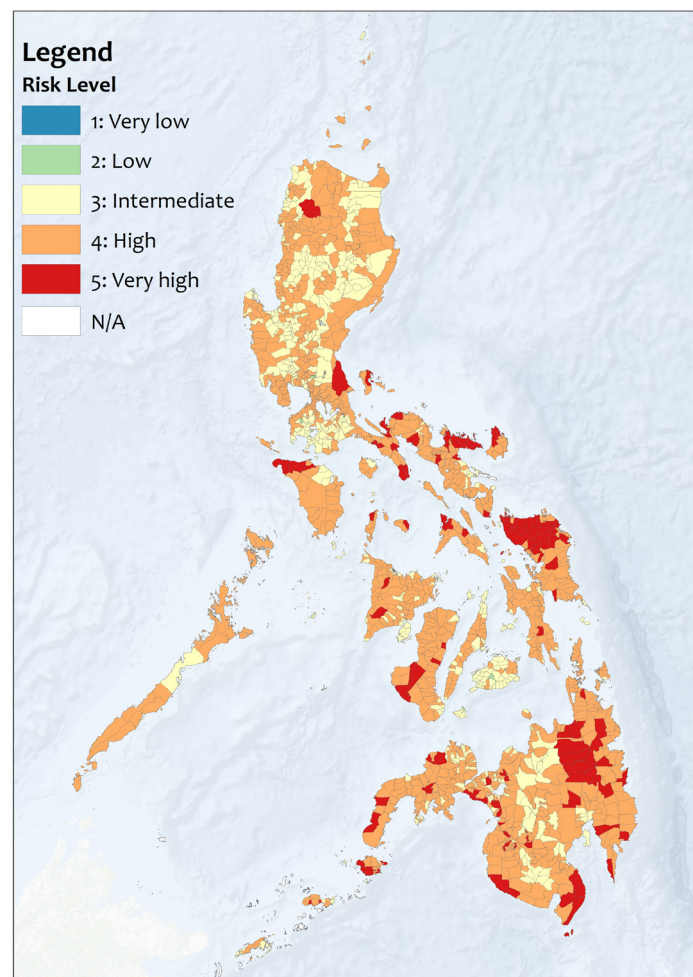


Figure 9. Composite risk scores of cities and municipalities in the Philippines

### Key findings

The results indicate that flood risk is a nationwide concern with strong subnational variation:

- 71% of cities and municipalities received a risk score of 4 and 5, highlighting the systemic nature of flood exposure combined with socioeconomic vulnerabilities.
- The Visayas and Mindanao regions emerged as composite risk hotspots, particularly in areas where high hazard intersects with poor adaptive capacity (e.g., Eastern Samar, Maguindanao, Lanao del Sur).
- Several municipalities with only moderate hazard levels appeared in the high-risk category due to high sensitivity and low adaptive capacity, reinforcing the importance of vulnerability in risk modeling.

Conversely, a small number of municipalities – typically remote highland or low-density areas – received low risk scores, largely due to minimal flood exposure.

The composite risk index supports prioritization by identifying overlapping high-risk zones, which can inform both anticipatory displacement planning and further micro-level validation.

## 4. Correlation of Computed Risk with Displacement Data

To validate the modelled risk scores, a preliminary correlation was conducted using Disaster Response Operations Management, Information and Communication (DROMIC) data on actual displacement events between 2014 and 2024. The analysis focused on major flood-triggering events, including Severe Tropical Storm Paeng, which caused significant displacement in late 2022.

DROMIC data were accessed through the official website of the Department of Social Welfare and Development (DSWD). A meeting was conducted with DSWD and IOM Philippines to discuss past displacement trends, displacement datasets, and its application in this validation process. A formal request for accessing situation reports was also submitted to the NDRRMC. This dataset includes:

- The number of displacement events
- People displaced by flood or storm-related hazards
- Geographical location and severity of each event

Preliminary analysis shows that flooding and storm events are leading drivers of internal displacement in the Philippines, consistent with global displacement trends. In particular, Severe Tropical Storm Paeng (2022) triggered widespread evacuations across multiple provinces. Eight rainfall events with 100-year return periods are currently under review to further understand the alignment between flood risk and displacement patterns. Findings suggest some geographic overlap between high composite risk scores (Figure 10 – left) and documented displacement hotspots (Figure 10 – right).

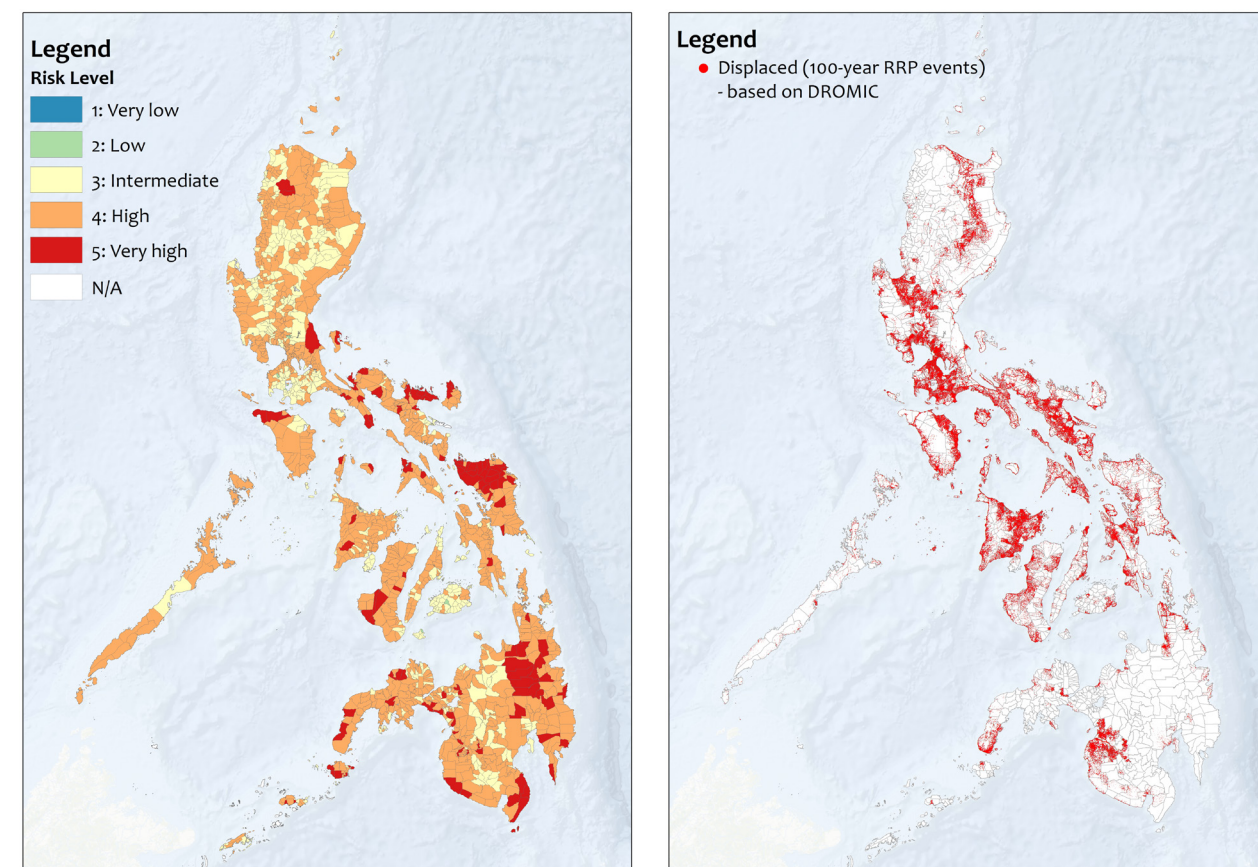


Figure 10. Modelled risk map (Left) and distribution of displaced individuals (Right)

### Key Findings

- Provinces such as Eastern Samar, Maguindanao, and Cotabato exhibit both high displacement figures and high-risk classifications.
- Some highly exposed urban centers (e.g. Metro Manila) also report frequent displacement, though adaptive capacity may mitigate long-term impacts.

The spatial overlap between areas with high displacement figures and those identified as high-risk regions suggests that the model broadly captures key risk patterns, albeit with some inconsistencies. This reinforces the view that macro-level analysis, while useful for identifying structural drivers, is insufficient on its own to fully capture displacement dynamics. Notably, the specific triggers and threshold conditions that lead to displacement have yet to be captured, which will require more granular data. This need for micro-level insights is further explored under the micro-level analysis.

## 5. Conclusions and Next Steps

This macro-level analysis of flood risk in the Philippines confirms that flooding is a systemic and geographically widespread concern. Using the IPCC AR5 framework, risk was assessed as the composite of hazard, exposure, and vulnerability across all 1,634 cities and municipalities.

### Key findings

- **Widespread flood risk:** 71% of cities and municipalities are classified as high or very high risk, underscoring systemic exposure across the country.
- **Geographic concentration of vulnerability:** High-risk areas are concentrated in Visayas and Mindanao, where flood hazards intersect with high sensitivity and low adaptive capacity.
- **Urban hotspots:** Metro Manila, Davao City, and Cagayan de Oro are among the highest-risk urban centers, due to high exposure and population density.
- **Model validation:** General overlap between high-risk areas and actual displacement reinforces the model's relevance.

These findings provide a strategic entry point for anticipatory action, early warning systems, and investment prioritization. They also highlight the importance of addressing vulnerability through targeted improvements in housing, basic services, and livelihoods.

### Future Improvement and Upscaling

- Expand the RICD model to include other hazards (e.g. storm surge, rain-induced landslide).
- Conduct micro-level validation through field data collection in selected high-risk LGUs.
- Refine indicators based on local coping strategies, displacement histories, contextual factors, and updated datasets as needed.
- All future developments of the RICD model will continue to be driven by a strong institutional partnership, ensuring technical robustness, regional relevance and stakeholder ownership.

This macro-level analysis lays the foundation for more granular, actionable displacement risk assessments and supports the Philippines' efforts to build climate resilience through data-driven planning. Future iterations of the RICD macro-level tool may include the integration of dynamic hazard projections (e.g., climate scenario-based flood modelling), improved temporal resolution of displacement data, and enhanced methods for automated model updating. These enhancements would allow for more frequent updates, better predictive capabilities, and closer alignment with real-time risk monitoring needs.

### Broader Use Cases and Future Applications

Beyond informing the CCF and guiding micro-level fieldwork, the RICD has strong potential for wider applications:

- **Policy Design:**
  - Align risk metrics with national adaptation plans and DRR strategies. The risk index provides a standardized, evidence-based metrics that can be integrated into existing frameworks.
  - Assist in identifying priority areas for climate resilience investment: By highlighting regions with high climate risk, the index can guide the allocation of financial and technical resources to target resilience-building interventions.

### • Data Enhancement:

- Complement and enhance existing national datasets: The spatially disaggregated risk scores offer a granular view of flood risk that can fill gaps in current datasets, contributing to a more comprehensive understanding of risk.
- Integrate index into operational datasets used in DRR planning: The composite index enables more data-driven decision-making by key government institutions in DRR planning.
- These applications will benefit from continued collaboration across the RICD partner institutions, enabling harmonized uptake across policy, planning and investment platforms.

### Next Steps

#### Micro-Level Analysis



Conduct community-level fieldwork in high-risk hotspots to assess displacement tipping points. In close collaboration with IOM country offices and local academic partners.



Document past mobility patterns (e.g. evacuation, temporary/permanent displacement, returns, trapped populations).

#### Climate Catalytic Fund (CCF)



Use composite risk scores and micro-level analysis to target Climate Catalytic Fund (CCF) investments in collaboration with local partners.



Inform the design of CCF interventions addressing climate-induced displacement.

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Annexes

Annex 1. Indicators Used in the Risk Index

| No. | Dimensions  | Indicators                             | Definition                                             |
|-----|-------------|----------------------------------------|--------------------------------------------------------|
| 1   | Hazard      | Flood Frequency                        | Average number of flood events per year                |
| 2   |             | Flood Extent                           | Percentage of flooded areas                            |
| 3   | Exposure    | Population Density                     | Number of people per sq.km                             |
| 4   | Sensitivity | Poverty Index Score                    | Percentage of populations living below poverty line    |
| 5   |             | Age Dependent Population Score         | Percentage of populations aged 16 or below and over 65 |
| 6   |             | Poor Wall Construction Materials Score | Percentage of homes with non-durable wall materials    |
| 7   |             | Poor Roof Construction Materials Score | Percentage of homes with non-durable roof materials    |
| 8   |             | Large Household Size Score             | Percentage of households with more than 5 members      |
| 9   |             | Poor State of Building Score           | Percentage of homes in visibly poor condition          |
| 10  |             | Year of Construction Score             | Percentage of homes built before a set cut-off year    |
| 11  |             | House and Lot Tenure Score             | Percentage of households without secure tenure         |
| 12  |             | Housing Backlog Score                  | Share of households with unmet housing needs           |

| No. | Dimensions        | Indicators                                               | Definition                                                 |
|-----|-------------------|----------------------------------------------------------|------------------------------------------------------------|
| 13  | Adaptive Capacity | Highest Education Attainment Score                       | Percentage of population with secondary education or above |
| 14  |                   | Literary Rate Score                                      | Percentage of literate individuals in the population       |
| 15  |                   | Internet Access Score                                    | Percentage of households with internet access              |
| 16  |                   | Ownership of Household Convenience Score                 | Index of access to household appliances or amenities       |
| 17  |                   | Improved Water Sources Score                             | Percentage of households using safe water drinking sources |
| 18  |                   | Electrified Houses Score                                 | Percentage of households with electricity                  |
| 19  |                   | Cities and Municipalities Competitive Index (CMCI) Score | Composite score on local economic competitiveness          |
| 20  |                   | Urbanization Score                                       | Percentage of population living in urban areas             |

Annex 2. Risk Scoring System

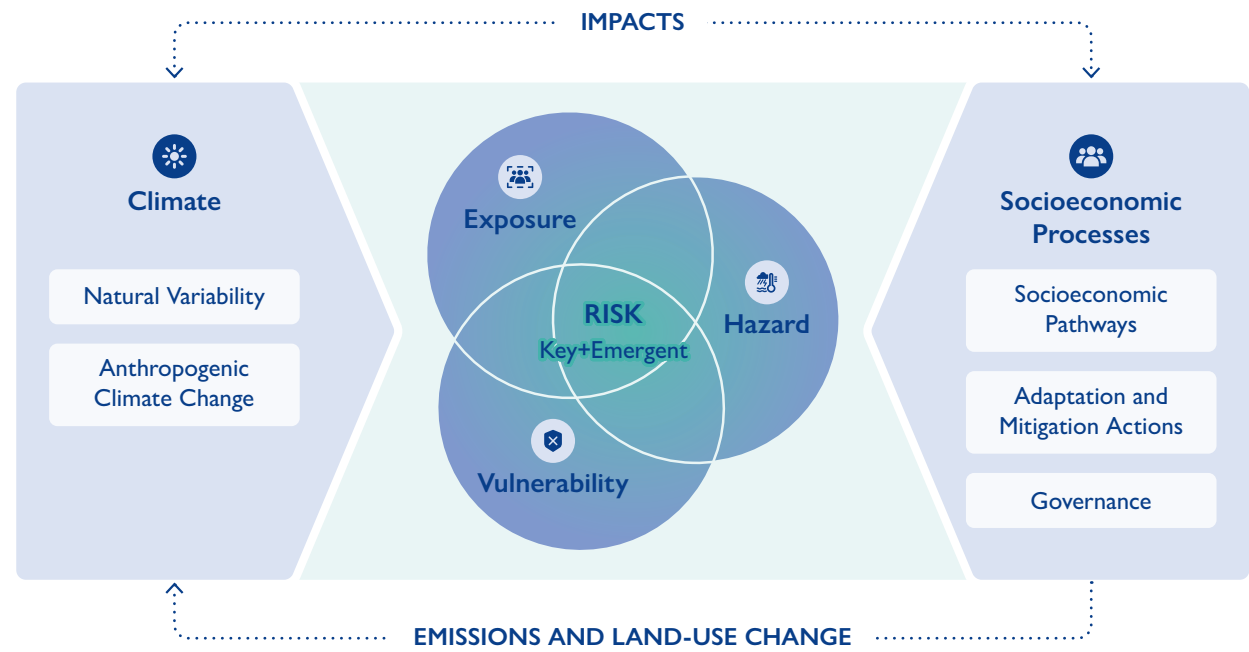


Figure 11. Managing the risks of extreme events and disasters to advance climate change adaptation (SREX) and IPCC AR5 Vulnerability Assessment Framework

The macro-analysis adopts a widely accepted risk assessment framework outlined in the Intergovernmental Panel on Climate Change’s Fifth Assessment Report (IPCC AR5). The framework defines risk as the potential for adverse effects when valuable assets are at stake. Risk is computed based

on Exposure, Vulnerability, and Hazard dimensions. Operationalizing the methodology involves an iterative process that includes determining the indicators for each risk dimension, identifying the data sources, data collection and analysis, and producing outputs in the form of thematic maps and reports



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