CDRI
Coalition for Disaster Resilient Infrastructure

Global Infrastructure
Resilience Working Paper

Economic Impacts

Downstream consequences of infrastructure failures

GIR ECONOMIC IMPACTS
2025 WORKING PAPER

This work is a product of the Coalition for Disaster Resilient Infrastructure (CDRI), as part of a working paper series under the ambit of the second Global Infrastructure Resilience Report (GIR 2025). This Working Paper on "*Economic Impacts: Downstream consequences of infrastructure failures*", examines the cascading economic effects that arise from disruptions and failures in critical infrastructure systems. It may be accessed at https://cdri.world/resilience-dividend/global-infrastructure-resilience-report-second-edition/

This document is a launch edition and may undergo minor changes subject to updates in the analysis.

All papers under the GIR 2025 Working Paper Series are available on the CDRI website, accessible on the web link mentioned above. They provide detailed background material, methodologies, analyses, and case studies for each chapter of the report. The papers will be released sequentially starting November 2025 through 2026.

All queries should be addressed to the Global Infrastructure Resilience (GIR) Report Team, CDRI Secretariat, Coalition for Disaster Resilient Infrastructure, e-mail:biennialreport@cdri.world

Authors
Andrea Bassi and Edvin Andreasson (KnowlEdge Srl)

Copyediting
The Clean Copy

Global Infrastructure
Resilience Working Paper

Economic Impacts

Downstream consequences of infrastructure failures

GIR **ECONOMIC IMPACTS**
2025 WORKING PAPER

Contents

List of Figures

List of Figures

Acronyms

AAL	Average Annual Loss
ADB	Asian Development Bank
BAU	Business-as-Usual
CDS	Copernicus Climate Data Store
CGE	Computable General Equilibrium
DCR	Debt Coverage Ratio
ESM	Earth System Models
GDP	Gross Domestic Product
GEM	Green Economy Model
GHG	Greenhouse Gas
GIRI	Global Infrastructure Risk Model and Resilience Index
IMF	International Monetary Fund
InVEST	Integrated Valuation of Ecosystem Services and Tradeoffs
IPCC	Intergovernmental Panel on Climate Change
IRR	Internal Rate of Return
LEDS	Low-Emission Development Strategy
NbS	Nature-based Solutions
NDCs	Nationally Determined Contributions
NIR	National Inventory Report
NPV	Net Present Value
NZNP	Net-Zero and Nature Positive
PE	Partial Equilibrium
PRIMES	Price-Induced Market Equilibrium System
SD	System Dynamics
SDGs	Sustainable Development Goals
SEEA	System of Environment and Economic Accounts
SIDS	Small Island Developing States
SPI	Standardized Precipitation Index
TFP	Total Factor Productivity
WASP	Wien Automatic System Planning Package
WMO	World Meteorological Organization

Key Messages

1 The economic impacts of disasters go beyond damage to infrastructure. Prolonged failures of infrastructure services affect business operations, the livelihoods of communities, and other public services, such as education and health, that depend on functioning water, electricity, and transport services.

2 The report combines Global Infrastructure Risk Model and Resilience Index (GIRI) with the Green Economy Model (GEM) to understand the indirect impacts of infrastructure failures due to disasters. A review of eight diverse countries in different regions shows that the indirect economic costs are, on average, 7.4 times larger than the cost of direct damages to infrastructure assets. They can be as large as 16 times for some countries. This means that investments in resilience can lead to much larger savings to the economy than if they are calculated considering only the direct impact on infrastructure.

3 The infrastructure failures due to disasters can cause an average annual loss of about 5.2 percent GDP growth between 2025 and 2050. By 2050, the GDP loss will reach 7.4 percent on average and could be as high as 12.9 percent for the Philippines and 14.5 percent for Bangladesh. These results highlight the significance of the economic implications of inadequate infrastructure resilience.

4 The speed of recovery and reconstruction directly influences the economic consequences of infrastructure failures due to disasters. If a country implements a full reconstruction over 10 years—rather than a long and partial reconstruction process, which is common for many climate-related disasters—the average GDP impact in 2050 among the eight countries modelled declines by more than half: from 7.4 percent to 3 percent.

5 If countries can (i) set up financial mechanisms to mobilize necessary funding and ensure institutional arrangements for rapid reconstruction and (ii) reduce recovery timelines from 10 to 4 years, the economic impact would reduce further to an average GDP loss of 2.27 percent. Preparedness for rapid and full reconstruction after disasters pays, and even more so if reconstruction is adapted to future climate risks.

1 Introduction

Infrastructure resilience is a critical determinant of economic stability and sustainable development. Climate and geological hazards cause damage to physical assets, reducing their availability and efficiency to provide services and further disrupting economic activity.

Recognizing that approaches focused on post-disaster reconstruction often fail to take into account the broader macroeconomic consequences of infrastructure failure, this report adopts a systemic perspective, examining how proactive investments in reconstruction can mitigate long-term economic losses.

Understanding the macroeconomic implications of such hazards requires integrated modelling approaches that capture not only direct damages but also the systemic, long-term effects of disrupted capital on productivity and output. This report presents simulation results from the Green Economy Model (GEM), parametrized and calibrated to align with the Global Infrastructure Resilience Index (GIRI). The analysis specifically examines three key areas:

- How do climate-related and geological hazards impact the economy, both in terms of damage to infrastructure assets and their role in enabling economic activity?
- To what extent does the speed of reconstruction matter for recovery after a disaster?
- Do all disasters affect the economy in the same way, or do rare but severe events pose different challenges?

The findings show that investments should be planned not only taking into account damage to infrastructure but also the cascading effects of this damage on economic activity that emerge over time.

1.1. Context for the Use of Simulation in Climate Impact Analyses

Over the past decade, the frequency of extreme weather events and their impacts on socioeconomic systems have increased significantly (EM-DAT, 2021). The findings published by the Intergovernmental Panel on Climate Change (IPCC) indicate that Earth is on track to breach the 1.5°C global warming threshold by 2030 rather than by 2100 as originally assumed. In the absence of decisive action, temperature increases by the end of the century are expected to be much higher (IPCC, 2021).

Climate change affects every aspect of modern societies and threatens both current as well as future sustainable development efforts. Although extreme climate and weather events, such as droughts, floods induced by erratic precipitation, and tropical cyclones, are the most obvious, frequent and low-severity events also have impacts on economic activity. The costs associated with the latter are unexpected and unbudgeted, leading to higher debt and reduced planned expenditure. As temperatures rise, the frequency and severity of these events are expected to increase, causing significant loss of human lives and livelihoods, as well as disrupting infrastructure, supply chains, and consequently, entire economies.

Decision makers must choose between facing the consequences of climate change and decarbonizing our economies to prevent further climate-related damage. Climate action can also have significant impacts on development outcomes. The economic benefits of investing in climate mitigation and adaptation are substantial, both in terms of the future climate-related costs avoided and the enhanced productivity and economic growth that can be realized. In addition, climate action can help reduce pollution and, consequently, health-related impacts and costs. Thus, from a systemic perspective, low-carbon investments offer clear benefits. However, in reality, a clear economic rationale is not always apparent because stakeholders are unwilling to change the status quo, political economy issues need to be addressed, and there is uncertainty about future climate trends. Evidence is, therefore, needed to stimulate action.

Many assessments of the impacts of extreme climate and weather events are available. For example, Guha-Sapir (2018) suggests that these events caused 3.7 million deaths and economic losses worth $2.4[1] trillion over the past 50 years. The World Meteorological Organization (WMO) estimated the human and economic costs of extreme climate and weather events to be almost 2 million lives and $2.4 trillion between 1970 and 2012 (WMO, 2015). Climate trends and disaster statistics show that, while the human mortality associated with such events has declined over time, economic costs have increased (Mühlhofer, 2019). This indicates that although it is possible to increase the adaptive capacity of communities, the number of assets at risk continues to grow.

The Paris Agreement on Climate Change was adopted by 193 countries in 2015. This agreement envisaged a bottom-up process where governments committed to nationally determined contributions (NDCs) to reduce their greenhouse gas emissions by 2025–2030 (Schaeffer et al., 2020). Moreover, the Paris Agreement also set the long-term goal of limiting the increase in the global temperature to below 2°C, and endeavouring to limit it further to 1.5°C. Countries have also committed to implementing a set of Sustainable Development Goals—or SDGs—to help eradicate poverty, protect the global environment, and promote inclusive economic development. Many countries are also aiming to achieve net-zero emissions by 2050 and 2060 (EEAS, 2020; Climate Action Tracker, 2021).

Taking action on climate change has several benefits, as demonstrated by existing investments in climate adaptation and mitigation (Climate Action Tracker, 2015; IISD, 2020). The main benefits of mitigation include reduced current costs, which can enhance growth by freeing up resources for new investments. Adaptation can also reduce future costs and thus encourage growth because it allows resources that would have otherwise been spent on emergency response to be directed to other projects.

When estimating the impacts of climate change, as well as when assessing the outcomes of investments in both mitigation and adaptation, it is not enough to focus solely on direct costs and benefits. The complexity of the socioeconomic system in which infrastructure operates, and uncertainties related to future changes in climate, necessitate an integrated approach. The environmental and socioeconomic outcomes of adaptation and mitigation programmes need to be assessed not only in terms of the return on investment but also the societal benefits from low-carbon development and adaptation plans. Such evaluation can provide insights on the contribution that an investment delivers not only to investors, but to society as a whole (Bassi et al., 2017). It will provide a comprehensive view of the direct, indirect, and induced investment outcomes across sectors and actors, as well as over time (BAPPENAS, 2019). Consequently, knowledge across scientific silos needs to be integrated to generate a set of indicators that are inherently interconnected and can be used for analysis. Cross-sectoral and multidimensional methods and tools that facilitate knowledge integration are essential to assist policymakers in exploring strategic options and formulating policies and policy packages that can help realize the many benefits of climate action while avoiding the side effects that could arise when systems are viewed in isolation.

This paper describes the use of a multi-method approach that (i) includes both qualitative and quantitative methods, (ii) can be strengthened through co-development with local experts and policymakers, and (iii) has been successfully implemented in more than 50 countries over the past 10 years. It focuses on the features of GEM that are essential for assessing climate impacts, with an emphasis on infrastructure assets. A more comprehensive overview of GEM can be found, for instance, in documents related to the Green Economy, Net-Zero and Nature Positive (NZNP) plans, as well as NDCs and Long-term Low Emission Development Strategy (LEDS) documents (Bassi, 2015; Bassi et al., 2024; Pallaske et al., 2023). Systems thinking and system dynamics (SD), the underlying methodologies used to create GEM, are discussed in several books and papers, including Probst and Bassi (2014) and Sterman (2000).

1.2. Literature Review: Available Methods and Models

Various methods and models are available for conducting a systemic assessment of low-carbon development and climate action pathways. A review of the existing literature indicates that most of the models used are sector-specific and have a narrow focus (Bassi, 2015). For instance, models are available for each emission category found in the IPCC manual and National Inventory Report (NIR) (Intergovernmental Panel on Climate Change, 2019). The energy sector has been extensively studied, with optimization models primarily used to identify the lowest-cost options that deliver the energy service required (UNEP, 2014; UN, 2021). Land-use models are available to estimate potential carbon sequestration from reforestation and afforestation. These models most often use optimization to determine the best-suited areas for land cover change (UN, 2021). There is also a suite of models that are purely environmental, which are used to estimate ecosystem service provisioning and their economic value (UNEP, 2014; UN, 2021). Models for macroeconomic trends either optimize for selected economic variables given some model closure rule (e.g., computable general equilibrium [CGE] models) or extrapolate historical trends (e.g., macro-econometric models). While all these models provide useful insights into specific policy challenges, they fail to provide a comprehensive view of how diverse investments across sectors deliver value or produce side effects at the systemic level. Some integrated approaches exist, combining different sectors through nested models or integrating sectoral dynamics within a single framework. The following paragraphs provide an overview of these models and how they have been used to inform decision-making. For illustrative purposes, some of the approaches used to assess low-carbon-development interventions are described.

1.2.1.1. Partial equilibrium models

Partial equilibrium (PE) models are a group of models that focus on a single sector, offering a much more detailed analysis than economy-wide models. They range from single-sector, single-country models to single-sector, multi-country models (FAO, 2006). PE models typically use a 'bottom-up' approach, emphasizing individual technologies and estimating the impacts of their adoption on demand and production in a given sector. At their simplest level, PE models can be conceptualized as the interaction of supply and demand in a single market. The MARKet ALlocation (MARKAL) model is a PE model that optimizes energy supply to minimize production costs, or, more specifically, a partial equilibrium bottom-up energy system technology optimization model employing perfect foresight and solved using linear programming (Loulou et al., 2004). MARKAL represents the entire energy chain, from primary energy resources to energy service demands, and operates under perfect foresight assumptions to optimize energy flows. However, it does not cover economic sectors, macroeconomic dynamics, and the externalities generated by the energy sector. Other examples of PE energy models include the Wien Automatic System Planning Package (WASP) (2010) (García & Giuliano, 2012), Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE) (IAEA, 2008), and Price-Induced Market Equilibrium System (PRIMES) (E3MLab/ICCS, 2014).

1.2.1.2. General equilibrium approach

A general equilibrium approach models supply and demand behaviours across all markets in an economy. Analysis is typically conducted using CGE models (see, for instance, Lofgren & Diaz-Bonilla (2010)). These models are widely used to analyse the aggregate welfare and distributional impacts of policies, especially those that affect multiple markets or involve various instruments such as taxes, subsidies, quotas, or transfers (Sue Wing, 2004). CGE models optimize utility for economic actors, and the three conditions of market clearance, zero profit, and income balance are employed to solve simultaneously for the set of prices and the allocation of goods and factors that support general equilibrium. They are generally 'top-down' models, meaning that variables such as energy consumption are determined by parameterized equations rather than analyses of individual technologies. The main benefit of this approach is that it estimates indicators for a range of impacts across an economy—not only impacts on household incomes, but also macroeconomic effects, such as inflation—and estimates how specific economic sectors will be affected.

1.2.1.3. Econometric models

Econometric models collect historical data on a range of variables and use economic theory and statistical techniques to determine how changes in one variable correlate with changes in others. Data on past correlations are then used to project future changes. A macro-econometric model takes this approach with regard to macroeconomic variables. Thus, these models are not based on theoretical predictions of how an economy works, but on how it has actually evolved, based on real data. They are top-down models primarily used to evaluate policy impacts on economic variables, while also capturing impacts on greenhouse gas (GHG) emissions and energy demand, which can be linked to a core macroeconomic module. Macro-econometric models are typically used to evaluate issues similar to those evaluated by CGE models and can be applied at both the national and regional levels.

1.2.1.4. *Project finance models*

Project finance models calculate the internal rate of return (IRR), net present value (NPV), and debt coverage ratio (DCR) of a project, among others. Essentially, they determine if an investment is economically viable for investors using a bottom-up approach. When adding externalities—that is, those outcomes of the investment that are not intended and do not directly affect the investment itself—the analysis can be extended to estimate societal outcomes and whether the project generates value for society. This means that an intervention will be evaluated based not only on its financial attractiveness, but also on its contribution to societal development (e.g., by linking the investment to the SDGs). According to the International Institute for Sustainable Development (IISD), in the context of the Sustainable Asset Valuation (SAVi) project (IISD, 2021), these models can be used for (i) assessing value for money for the beneficiary government, public and private funds, and other lenders, not just at the point of financial closure, but throughout the project's/asset's life cycle; (ii) identifying and quantifying environmental, social, economic, and financial risks and externalities that can affect the financial performance of the asset or project; and (iii) taking a risk-based approach and conducting due diligence on the technical feasibility analyses of the proposed project and its demand and revenue estimates; it can also help estimate counterparty, pricing, commercial or market risks, and environmental and social risks; climate risks and related resilience characteristics; and financing risks.

1.2.1.5. *Spatially explicit models*

Spatially explicit models can be used to estimate land-cover changes and their impacts on the provisioning of ecosystem services. In other words, these models enable the evaluation of nature-based solutions (NbS) within the System of Environment and Economic Accounts (SEEA) framework (Vallecillo et al., 2019), helping to quantify the extent of ecosystems, conditions, and services, as well as providing an economic valuation of ecosystem service benefits. An example of a spatially explicit model is the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) toolset, which can be used to quantify, map, and value the benefits provided by marine, freshwater, and terrestrial systems (Nelson et al., 2009). It includes models for carbon storage, water provisioning and purification, habitat quality, and nutrient and sediment retention. Results are provided in terms of both biophysical quantities, such as tons of carbon stored, and economic terms, such as the NPV of the carbon stored.

When considering climate loss and damage, several features of each must be incorporated into each model. These include macroeconomic impacts due to damage to critical assets (e.g., public infrastructure, productive capital). Based on their location and related economic activity, they may be affected by a variety of climate hazards. Therefore, an integrated approach is required—one that combines a probabilistic analysis using climate models, based on events and return periods, with a time-explicit analysis more relevant for economic planning. The approach proposed in this report uses GEM as a knowledge integrator, as explained in the following sections.

2. Modelling Approach

GEM is a systems-based model designed to evaluate the wide-ranging impacts of climate change, as well as the diverse effects of climate action and low-carbon development interventions (Bassi et al., 2024; Pallaske et al., 2023). It is particularly relevant in the context of changing precipitation and temperature trends and the increase in extreme weather events, as it can help inform policies that balance climate mitigation and adaptation strategies on the one hand and sustainable development on the other.

GEM was designed to capture the full spectrum of outcomes—direct, indirect, and induced—that can arise in scenarios of inaction and action (e.g., investments in climate mitigation can help reduce emissions while adaptation can build resilience-). The use of a systemic approach is essential because the impacts of climate change and the benefits of climate action emerge across social, economic, and environmental indicators, reflecting both tangible and intangible economic impacts, and influence various economic sectors in different ways (Pallaske et al., 2023).

Practically, GEM offers an integrated representation of socioeconomic and environmental dynamics and the capitals (built, social, human, and natural) that support them, at the country level (BAPPENAS, 2021; Bassi, 2015; Barros et al., 2020). It has been used to inform policymaking that prioritizes sustainable development, linking top-down (macroeconomic) and bottom-up (asset-level, for infrastructure and technology) approaches. It has been applied to more than 50 countries after being tailored to local contexts (KnowlEdge Srl, n.d.).

Figure 1 shows the basic structure of GEM, illustrating how the four types of capital—natural, physical, human, and social—are connected and can shape future economic, social, and environmental trends. Some feedback loops (i.e., circular relations in the system) promote growth and development, while others can hinder it. For example, investments can boost infrastructure and create jobs, leading to increased economic activity and further investment. Conversely, growth can also lead to side effects such as air pollution and GHG emissions, which can, in turn, limit it; the former can directly affect labour productivity through its adverse effects on human health, while the latter may cause more frequent and severe extreme weather events, affecting both people and infrastructure, and thus, the economy. Climate change affects society, the economy, and the environment in myriad ways: floods can damage roads and bridges, making it harder for people to work and for businesses to operate, while droughts can reduce crop yields, affecting farmers' incomes and food prices. The impacts ripple through the economy, affecting households, businesses, and governments. Climate and geological hazards have similar impacts in the model, affecting infrastructure, people, and nature, and hence influencing production through effects on capital, land, and labour productivity.

GEM can simulate scenarios of inaction, as well as various policies and investments—such as flood-resilient infrastructure, water-efficient farming, renewable energy, and education programmes—to assess how they could reduce climate risks, support sustainable growth, and make the economy more resilient over time.

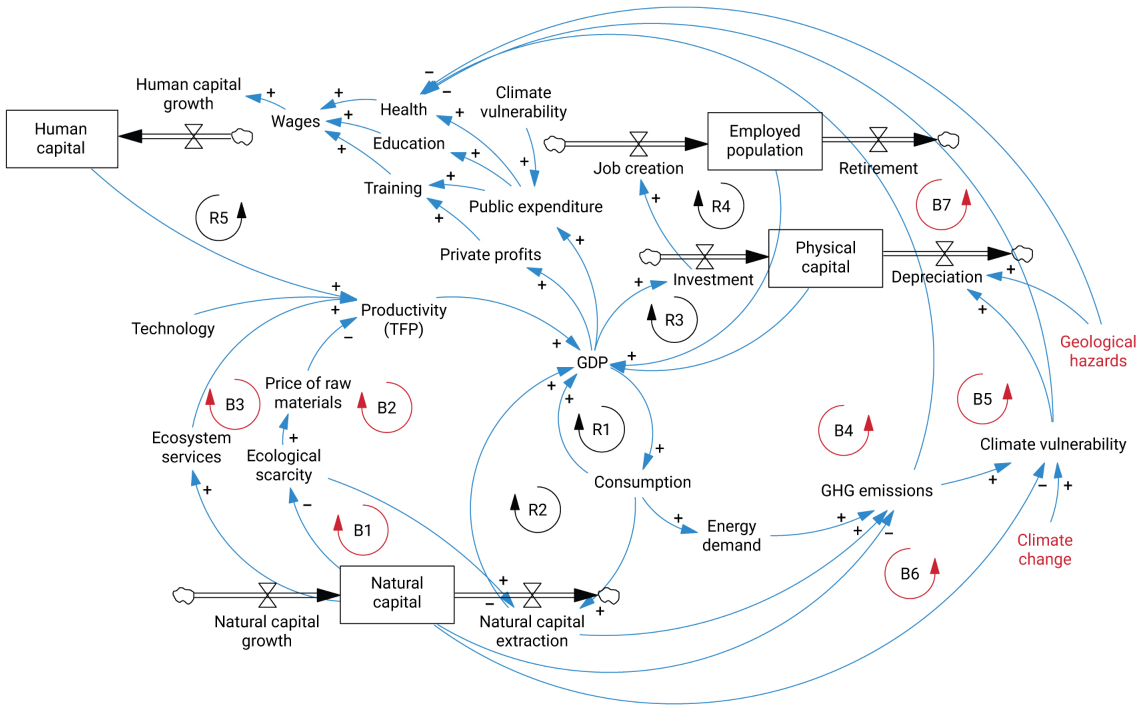

Figure 1: Overview of the main dynamics underlying GEM

Source: Bassi (2015); Bassi et al. (2024)

GEM is developed using the system dynamics (SD methodology and functions primarily as a knowledge integrator (Forrester, 2002; Meadows, 1980; Randers, 1980; Richardson & Pugh, 1981). SD is a form of computer simulation modelling designed to facilitate development planning in the medium to long term. This approach helps integrate knowledge from different research domains and policy areas, enabling long-term strategic planning. It works by testing 'what if' scenarios, showing how problems evolve over time across the social, economic, and environmental domains. This serves as a starting point to analyse the impacts and effectiveness of various intervention strategies. GEM uses SD to connect different areas of analysis—for example, how climate dynamics affect infrastructure and how infrastructure affects economic activity—providing a clearer understanding of how climate actions today can shape future outcomes. The main components of GEM are presented in Figure 2.

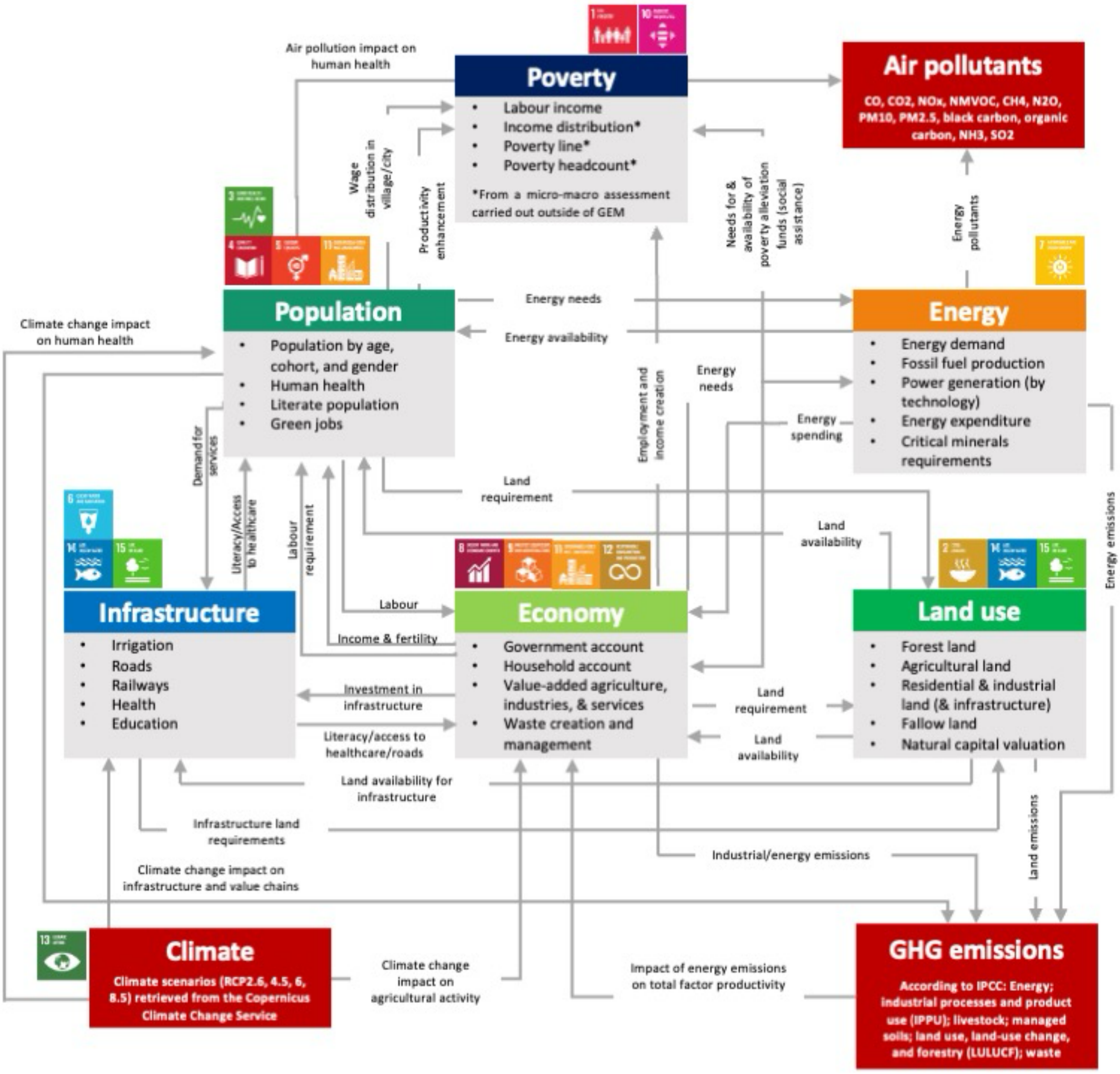

Figure 2: Sub-system diagram presenting the key sectoral components of GEM

Source: Authors' elaboration based on Golechha et al. (2024)

2.1. Estimating Climate Vulnerability by Asset

Extreme weather events pose a growing risk for critical infrastructure, agricultural land, and people, with climate change intensifying the frequency and severity of hazards such as floods, landslides, wildfires, storms, and droughts. By integrating geospatial datasets, including hazard maps, land cover information, and infrastructure layers, GEM is equipped with information on the extent to which infrastructure assets, agricultural land, and people are at risk from climate hazards.

As a first step, hazard maps are used to identify areas prone to extreme weather impacts. Land cover maps help identify agricultural zones and settlement areas that may be exposed to climate risks. Additionally, infrastructure maps include transportation networks, such as roads, railways, airports, and ports, as well as buildings in key sectors, including education (schools and universities), healthcare (hospitals and clinics), and energy (power plants). Power transmission lines are also incorporated into the analysis to assess vulnerabilities in energy distribution networks and the economic impacts of power shortages.

The analysis focuses specifically on the impacts of river floods, coastal floods, landslides, storms, and droughts, which are assessed in terms of their effects on populations, buildings, power plants, transmission lines, roads, and cropland. It evaluates these impacts across a range of return periods and under different climate scenarios. The outputs of this analysis include estimates of the physical value and the percentage of infrastructure assets at risk at the national level (e.g., the length (in kilometres) of roads and the percentage of the road network) at different return periods. Country-level maps are also generated to illustrate the spatial distribution of assets exposed to climate hazards.

The first step involves collecting and harmonizing geospatial datasets related to both hazards and exposed assets. These datasets are sourced from globally recognized databases to ensure a standardized methodology. Hazard datasets include maps of river floods, coastal floods, landslides, storms, and droughts. These hazard layers are available for multiple return periods (10, 25, 100, 250, and 1,000 years) and for different climate scenarios that reflect present and future climate conditions (Table 1). Asset datasets include georeferenced layers showing population distribution, building footprints, locations of power plants and transmission lines, road networks, and cropland areas (see Table 2). All datasets are standardized into a consistent spatial resolution and projection system, enabling accurate spatial overlay and integration.

Table 1: Sources used for the climate hazards

Climate impact	Name of source
Floods	WRI flood Aqueduct
Landslides	Global Landslide Hazard Map (GRI)
Storm surges	WRI Aqueduct
Sea level rise	WRI Aqueduct
Drought	WorldPop

Source: Authors' compilation

Table 2: Sources used for the infrastructure, asset, and population georeferenced layers

Sector	Name of Database
Population	WorldPop
Buildings	Open Street Map (OSM) Open Buildings
Roads	Global Roads Inventory Project (GRIP)
Power generation	ResourceWatch: The Global Power Plant Database
Transmission lines	OSM Transmission Lines (GEOFABRIK)
Cropland	EU Copernicus Global Landcover project
Agriculture yield	Pre-processed and bias-adjusted yield data from ISIMIP3b simulations of the agriculture sector
Livestock	FAO Gridded Livestock of the World
Water	HydroATLAS

Source: Authors' compilation

The hazard and asset datasets are integrated using geographic information system (GIS) tools. This process includes overlaying each hazard layer with each asset layer to identify where and to what extent assets intersect with hazard-prone zones. For example,

- road segments intersecting river or coastal flood zones;
- buildings located in storm-prone or landslide-prone areas;
- cropland falling within regions susceptible to drought; and
- power plants and transmission lines exposed to multiple hazard types.

This spatial integration is carried out for each hazard type and return period, enabling an asset-specific risk profile to be obtained.

Let us consider Kenya and riverine flooding as an example. The spatial analysis reveals that approximately 4–5 percent of buildings are at risk of riverine flooding over time, with the percentage varying across scenarios (Figure 3, left).

This estimate is derived from overlaying hazard maps with building footprint data, enabling the measurement of physical exposure for various flood intensities and frequency projections. When flood risk data were overlaid on a geographic map, it showed that the highest concentrations of exposed buildings are located near the coast and in western Lake Victoria, with additional areas of risk further downstream along major river systems. These results are based on model outputs using a 250-year return period under the historical climate snapshot (Figure 3, right).

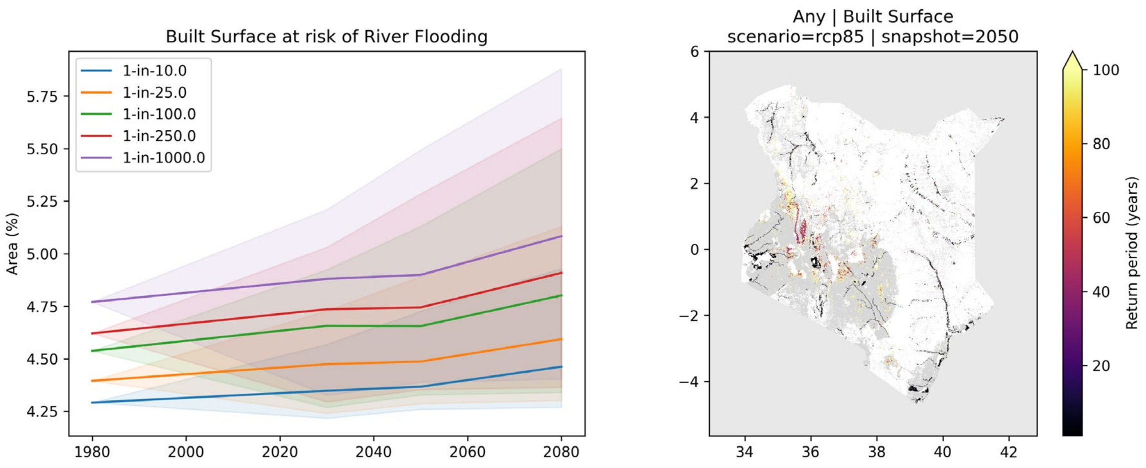

Figure 3: Buildings at risk of river flooding in Kenya (left); spatial overlay for all climate hazards in Kenya under the RCP8.5 scenario (right)

The spatial overlays are converted into quantitative exposure and vulnerability metrics that indicate how much each asset type is affected by each hazard. These exposure statistics include the following:

- **Population**: Number and percentage of people living in hazard-prone zones, for each hazard type.
- **Buildings**: Number and percentage of buildings exposed to each hazard type.
- **Power infrastructure**: Number and percentage of power plants and length of transmission lines affected.
- **Transport infrastructure**: Length (in kilometres) and percentage of road networks within hazard zones.
- **Agricultural land**: Area (in hectares) and percentage of cropland exposed to floods, drought, or landslides.

This quantitative analysis is disaggregated by hazard type, return period, and climate scenario, resulting in a detailed risk matrix. This step converts raw geospatial data into actionable indicators that can aid in policy analysis, infrastructure planning, and investment prioritization decisions.

The exposure and vulnerability indicators are directly input into GEM to estimate potential infrastructure losses and damage, macroeconomic losses, and the benefits of reconstruction or resilience-building interventions (e.g., NbSs, climate resilient infrastructure) across various scenarios.

GEM uses one input per asset, meaning that asset vulnerability—such as buildings at risk—is not disaggregated by individual hazards such as landslides or floods. Since these hazards often originate from the same underlying cause, such as extreme wet events, their hazard data (including return periods, standard deviations, and spatial layers) are aggregated into a single time series for the period 1980 to 2080. Finally, the aggregation method varies by country. Where the proportion of buildings at risk overlaps significantly across hazards—such as landslides, storms, coastal flooding, and river flooding—the time series data are averaged for those hazards at each time step. In cases where overlap is minimal or a single hazard dominates (possibly due to country-specific conditions or data gaps in the estimation of assets at risk), a more customized aggregation approach is used, tailored to national conditions.

2.2. Estimating Climate Impacts on the Economy

GEM uses a supply-side production function based on (i) capital accumulation, (ii) employment, and (iii) an index that combines various additional factors affecting economic activity, including technology, human health (through air pollution, the spread of infectious diseases, and extreme temperature and humidity), the availability of roads for access to markets, the delivery of electricity via transmission lines, and energy spending (these are grouped under total factor productivity (TFP) in GEM).

As a result, climate-induced damage is represented in two ways: (i) as direct damage to buildings, impacts on industry, and disruption of services due to reduced production capacity (i.e., capital) and (ii) as damage to other infrastructure assets (e.g., roads, power generation and distribution), which results in the underutilization of capital and impacts GDP via a reduction in productivity. GDP is therefore affected by both the direct and indirect effects of climate change. The situation is similar in agriculture, where extreme weather events and unfavourable weather conditions directly affect land productivity, ultimately affecting production and GDP. This allows GEM to generate forecasts of GDP for scenarios both with and without climate impacts.

GEM quantifies these impacts using monthly data on precipitation and temperature from the Copernicus Climate Data Store (CDS). This data is used to determine the probability of extreme weather events and, together with asset risk estimates, helps quantify impacts from floods, droughts, and extreme heat on people, livestock, land, and infrastructure.

Table 3 presents the climate impacts currently included in the model. Specifically, impacts on infrastructure, land, and population have the following economic repercussions in GEM (see also Table 3):

- **Power generation and load factors**: Climate change can affect power generation capacity and efficiency, as extreme weather events and increased variability in weather patterns can affect power generation and delivery. For example, high temperatures can reduce the efficiency of thermal power plants, and droughts can disrupt hydropower production. These impacts mean that electricity is produced less efficiently and often at a higher cost. As energy expenses rise, businesses and households face higher operating costs, which decrease the productivity of capital and slow overall economic activity. Over time, this translates to lower GDP growth.

- **Transmission networks**: Climate impacts can compromise the reliability and efficiency of transmission networks, increasing the risk of damage and disruption due to extreme weather events. If the electricity supply is unreliable, downtime increases for businesses and households that rely on electricity. For factories, this results in interrupted production lines, reducing output and driving up costs as workers and equipment are forced to remain idle. Over time, these interruptions reduce the productivity of capital—machines, buildings, and technology—and lower GDP. In addition, frequent shortages deter new investment, as firms expect higher operating risks and costs, further hindering economic growth.

- **Roads and buildings**: Infrastructure, such as roads and buildings, is increasingly becoming vulnerable to damage from extreme weather, resulting in higher repair and maintenance costs and reduced usability over time. Furthermore, when roads are damaged, businesses face reduced market access, as they are forced to take longer and less efficient routes. For sectors that depend on tight timing—such as agriculture, where fresh produce must reach markets quickly, or services that rely on punctual delivery—these disruptions can lead to lost sales, higher costs, and declining competitiveness.

- **Industry and service capital**: Climate impacts can result in increased depreciation and loss of capital in the industry and service sectors. Extreme events (e.g., floods or earthquakes) as well as more insidious climate stresses (e.g., rising temperatures) can damage buildings and machinery, reducing their lifespan and effectiveness. This can lower production capacity and output, reducing value added and GDP. The effects go beyond immediate losses: businesses may cut jobs as production drops, and investors may delay or scale back future investments due to higher risks and uncertainty. Over time, this creates a cycle of slower economic growth.

- **Labour productivity**: Climate change can reduce labour productivity by directly affecting workers' health and working conditions. Rising temperatures and more frequent heatwaves increase heat stress, causing fatigue, lower concentration, and a higher risk of accidents, especially in outdoor sectors such as agriculture, construction, and transport. Even in indoor workplaces, discomfort can reduce performance. Overall, these impacts lower labour productivity, reducing economic output and value added.
- **Yield and livestock**: Agriculture and livestock are highly sensitive to changing climate conditions. Shifts in rainfall patterns, longer and more frequent droughts, and changes in temperature can reduce crop yields and stress animals, leading to lower productivity. Food production becomes less predictable, causing uncertainty for farmers and pushing up prices for consumers. Over time, this can affect income creation and value added in the primary sector.

Table 3: Selected climate change damages included in GEM, offering the possibility of linking bottom-up and top-down assessments of infrastructure resilience

Sector/Impact	Impact	Inputs
Agriculture	Impact of extreme drought on crop yields	Mean weighted temperature (rural weighted)
		90th percentile of temperature (rural weighted)
		Impact of temperature on crop yields
	Impact of heat on crop yields	Mean weighted temperature (rural)
		Threshold for yield impacts
	Effect of extreme wet events on crop productivity	Extreme wet events percentile (Standardized Precipitation Index (SPI))
		90th percentile of SPI
		Reduction in yield from extreme rain
	Impact of temperature on labour productivity (agriculture)	Wet-bulb globe temperature (rural weighted)
		Effect of temperature on labour productivity
Infrastructure	Effect of extreme precipitation on buildings	Extreme wet events percentile (SPI)
		95th percentile of SPI
		Share of buildings susceptible to floods
	Flood damage to roads	Extreme wet events percentile (SPI)
		95th percentile of SPI
		Effect of flood damage on roads
	Flood impacts on power generation capacity	Extreme wet events percentile (SPI)
		99th percentile of SPI
	Wind impacts on power generation capacity	Mean wind speed (surface weighted)
		95th percentile of mean wind speed
	Flood impacts on transmission lines	Extreme wet events percentile (SPI)
		99th percentile of SPI
	Wind impacts on transmission lines	Mean wind speed (surface weighted)

		95th percentile of mean wind speed
Macroeconomy	Impact of temperature on labour productivity (industry and services)	Wet-bulb globe temperature (urban weighted)
		Effect of temperature on labour productivity
	Effect of floods on industry and services capital	Extreme wet events percentile
		Effect of extreme rain on capital

Source: Authors' elaboration

Figure 4 illustrates the GEM modelling approach. GEM is first set up for each country, using key indicators such as the proportion of assets exposed to extreme weather. These are estimated using maps that show the areas that are affected by climate hazards, and the assets, land, and people located there (left). GEM then links these assets to economic activity: infrastructure drives value added in agriculture, industry, and services; the quality and size of agricultural land affect agricultural output; and labour productivity influences industry and services (centre). By running simulations under different climate scenarios, GEM forecasts GDP up to 2050, explicitly accounting for economic losses caused by climate-related impacts (right). This national-level analysis is informed by detailed spatial data and explicitly accounts for the contribution of infrastructure to economic activity.

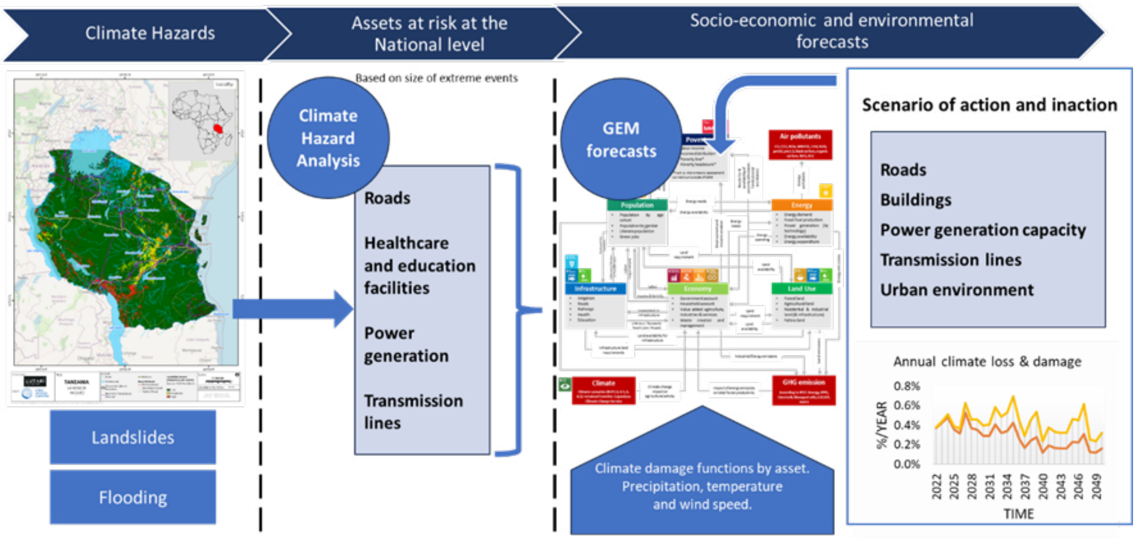

Figure 4: Proposed approach for the estimation of the socio-economic and environmental impacts of climate change, considering bottom-up impacts on several infrastructure assets, land, and people

Source: Authors' elaboration

The study focuses on eight countries, which were selected to provide a geographically balanced and comprehensive perspective on the economic impacts of climate change, with representation across Asia, Africa, the Pacific, and the Caribbean. South and East Asia are represented by Bangladesh, Bhutan, and the Philippines, thus including both low-lying flood-prone areas and mountainous regions vulnerable to landslides. Africa is represented by Ghana, Kenya, and Madagascar, reflecting coastal, inland, and island contexts with differing exposure to droughts, floods, and cyclones. The particular vulnerabilities of island nations to sea-level rise and extreme storms are studied through the analysis of Small Island Developing States (SIDS) in the Pacific (Fiji) and the Caribbean (Barbados).

At the same time, the choice of countries also enables the analysis of diverse development contexts, characterized by different economic structure and conditions. It also allows different types of climate impacts to be assessed—including the effects of seasonal events (e.g., cyclones and typhoons) as well as more erratic ones (e.g., floods and landslides).

3. Scenarios Simulated

To assess the macroeconomic effects of climate and geological hazards, a series of five scenarios was formulated. Together, they help in understanding both the short-term and long-term economic consequences of climate impacts, as well as the potential role of policy measures in reconstruction and climate adaptation.

The first simulation corresponds to a baseline calibration of GEM, incorporating all climate-related hazards (but no geological hazards). These hazards are applied not only to infrastructure but also to land, livestock, and people. The analysis takes into account the current level of financing available for disaster recovery based on existing national allocations, including the National Disaster Risk Reduction and Management Fund in the Philippines and the domestic disaster management spending in countries such as Kenya and Ethiopia. This simulation serves as a reference point to compare current funding levels with the resources needed for rapid recovery after disasters. It also offers a comprehensive view of climate change impacts across the economy, enabling a comparison of projected GDP effects and findings from existing studies and the literature.

The second simulation narrows the focus by restricting the application of climate hazards to infrastructure alone. Unlike the broader baseline, this version excludes impacts on agriculture, livestock productivity, and labour, thereby isolating the consequences of physical damage to infrastructure assets such as roads, buildings, power generation facilities, and transmission lines. This scenario enables better alignment of the model with the specific goals of CDRI on infrastructure resilience, as well as GIRI estimates of the average annual loss (AAL) for infrastructure assets, as well as resilience assessments that typically focus on infrastructure systems.

The third simulation introduces the dynamics of reconstruction timing to understand the benefits of faster repair and restoration of infrastructure services after disasters, including its influence on economic recovery. The model assumes that full reconstruction of damaged infrastructure is achieved and considers three different time frames for full recovery: 1 year, 4 years, and 10 years. This design makes it possible to evaluate how quickly restored capital stocks can reduce GDP losses over time and to quantify the economic costs of prolonged disruption.

Each of these simulations has a distinct purpose. Simulation 1 provides a benchmark against which GEM results can be compared to the existing literature, confirming the validity of the model and its alignment with empirical studies. Simulation 2 better reflects the analytical focus on infrastructure, allowing decision makers to understand the direct macroeconomic consequences of damage to physical assets. Simulation 3 represents a pathway based on well-designed financial and disaster recovery frameworks, showing the potential benefits of rapid and comprehensive reconstruction. By comparing scenarios where reconstruction occurs in 1, 4, and 10 years, it demonstrates the critical importance of financing capacity and institutional readiness in minimizing GDP losses after a climate event.

4. Results

4.1. Estimating Climate Change Impacts on the Economy (Simulation 1)

Table 4 provides a comparative assessment of projected GDP losses across countries between 2025 and 2050, accounting for impacts on infrastructure assets, land, livestock, and people. The results show substantial variation both in absolute and relative terms. Bangladesh and the Philippines emerge as the most severely affected economies, with average annual GDP losses of over $88 billion and $118 billion, respectively, representing declines of 10.6 percent and 10.1 percent on average between 2025 and 2050. These figures translate to cumulative GDP losses exceeding $2.2 trillion for Bangladesh and $3 trillion for the Philippines by 2050—equivalent to 6.5 and 7.4 years of the current GDP.

In contrast, smaller economies such as Bhutan and Fiji register much lower absolute losses. However, these are still relevant when compared to the size of their economies: respectively, $70 million and $363 million lost on average annually; GDP reductions of 3.9 percent and 4.0 percent in the year 2050; and cumulative GDP losses in the range of $1.8 billion and $9.4 billion.

Table 4: Summary analysis of Simulation 1 (with the inclusion of all climate impacts)

Country	GEM average annual GDP loss: 2025–2050 ($ million/year)	GEM average annual GDP loss: 2025 and 2050 (%)	GEM cumulative GDP loss: 2025–2050 ($ million)	Equivalent years of GDP loss (year) based on current GDP
Bangladesh	88,144	10.6	2,291,750	6.5
Barbados	662	8.8	17,203	3.6
Bhutan	70	3.9	1,808	1.7
Fiji	363	4.0	9,442	1.8
Ghana	8,767	6.5	227,936	3.3
Kenya	9,383	4.4	243,970	2.8
Madagascar	728	4.9	18,938	2.7
Philippines	118,548	10.1	3,082,250	7.4
Average (simple)	28,333	6.6	736,662	3.72

Source: Authors' elaboration

Table 5 compares GDP loss estimates generated by GEM with results from the recent literature. Across the eight countries examined, GEM estimates average annual GDP losses of 6.6 percent between 2025 and 2050, with losses rising to 9.2 percent by 2050. These results align closely with the ranges reported in studies conducted by the World Bank, International Monetary Fund (IMF), Asian Development Bank (ADB), and other institutions.

At the country level, Bangladesh and the Philippines are projected to face the steepest impacts, with GEM estimates of GDP losses by 2050 being 15.2 percent and 13.2 percent, respectively. These values correspond well with the ADB's projection of an "up to 15 percent" loss for Bangladesh and the World Bank's finding of a 13.6 percent loss for the Philippines by 2040. The losses are similar for Barbados, with GEM projections showing a 13.3 percent decline in GDP by 2050. This is situated within the wide range of 13.9 percent to 37.6 percent found in the literature, with the latter reflecting potential losses related to tourism in a net zero scenario.

GEM results also fall within or close to the ranges reported by external sources for Bhutan, Fiji, Ghana, Kenya, and Madagascar. For example, GEM projects a 6.5 percent GDP loss in Bhutan by 2050, consistent with

World Bank and IMF findings of between 3 percent and 6.6 percent. In Ghana, the model projects a 6.7 percent loss, aligning with literature estimates of 1.9 percent to 7.2 percent. Similarly, Madagascar's GEM estimate of a 5.5 percent loss is close to the World Bank's projection of 5.8 percent.

Table 5: Comparing GEM results with the literature (Simulation 1)

Country	GEM average annual GDP loss: 2025 and 2050 (%)	GEM GDP loss: 2050 (%)	Literature review on GDP loss by 2050	Source
Bangladesh	10.6	15.2	Up to 15% by 2050	ADB (2024)
Barbados	8.8	13.3	Between 13.9% to 37.6% by 2050	Bueno et al. (2008); Gourdel & Monasterolo (2022)
Bhutan	3.9	6.5	Between 3% (World Bank) and 6.6% (IMF) by 2050	World Bank (2025); Kahn et al. (2019)
Fiji	4.0	6.1	More than 6.5% of GDP from cyclones	Government of Fiji & World Bank Group (2017)
Ghana	6.5	6.7	Between 1.9% and 7.2% by 2050	Hooda (2022)
Kenya	4.4	6.9	Between 3.61% and 7.25% by 2050	World Bank Group (2023)
Madagascar	4.9	5.5	5.8% by 2050	World Bank Group (2024)
Philippines	10.1	13.2	13.6% by 2040	World Bank Group (2022)
Average	6.6	9.2		

Source: Authors' elaboration

Overall, the comparison confirms that GEM projections are consistent with those in the literature. Therefore, the GEM model is reliable, and it can be used to analyse the impacts of disasters on built infrastructure.

4.2. Assessing the Effect of Infrastructure Damage on Macroeconomic Performance (Simulation 2)

Table 6 compares the total climate hazard impact, which accounts for damages to infrastructure, land, livestock, and people (Simulation 1), with the infrastructure-only impact, where losses are restricted to physical assets (Simulation 2). As expected, the infrastructure-only estimates are consistently smaller because they exclude the indirect but substantial effects of climate change on agriculture, livestock productivity, and labour. Simulation 1 yields an average annual GDP loss of 6.6 percent between 2025 and 2050, rising to 9.2 percent in 2050. When the analysis is narrowed to infrastructure impacts only, the losses decline to 5.2 percent between 2025 and 2050 and 7.4 percent by 2050.

For some countries, the difference between Simulations 1 and 2 is small, whereas for others, it is somewhat larger. These differences are related to the role of agriculture in the economy and the level of economic diversification.

For example, Bangladesh experiences a 15.2 percent GDP loss by 2050 for the scenario where all sectors (infrastructure, agriculture, livestock, and health) are considered, compared to 14.5 percent when only infrastructure is considered. In Kenya, the contrast is more pronounced, with GDP losses of 6.9 percent and just 3.2 percent, respectively. This shows that in countries with climate-sensitive agricultural systems, and in those where agriculture contributes substantially to the economy, the reduction in GDP due to climate impacts is comparatively larger.

Small island economies such as Barbados and Fiji remain highly vulnerable in both simulations, with GDP losses exceeding 9 percent and 6 percent, respectively, by 2050, reflecting their reliance on infrastructure for tourism and trade. In these countries, even modest physical damage could have significant reverberations across the economy. This is in contrast to the situation in larger and more diversified economies, such as Kenya and Ghana, where greater relative differences between the two simulations are seen, highlighting the importance of including labour and agricultural channels to capture the whole macroeconomic picture.

Table 6: Climate impacts on the economy when considering infrastructure alone versus the total impact

	Total climate hazard impact (Simulation 1)		**Infrastructure impact alone (Simulation 2)**	
Country	GEM average annual GDP loss: 2025 and 2050 (%)	GEM GDP loss: 2050 (%)	GEM average annual GDP loss: 2025 and 2050 (%)	GEM GDP loss: 2050 (%)
Bangladesh	10.6	15.2	9.9	14.5
Barbados	8.8	13.3	6.9	9.5
Bhutan	3.9	6.5	3.0	5.6
Fiji	4.0	6.1	3.8	6.0
Ghana	6.5	6.7	3.5	3.5
Kenya	4.4	6.9	1.6	3.2
Madagascar	4.9	5.5	3.3	4.3
Philippines	10.1	13.2	9.7	12.9
Average	**6.6**	**9.2**	**5.2**	**7.4**

Source: Authors' calculations

4.3. The Relevance of Urgency in Post-Disaster Reconstruction (Simulation 3)

An important factor shaping the macroeconomic impacts of climate hazards is the availability of financing for recovery and the speed at which reconstruction can be completed. In the baseline situation, the analysis incorporates the current level of disaster recovery funding—on average, around 0.2 percent of GDP per year. This figure is based on national allocations, including the National Disaster Risk Reduction and Management Fund in the Philippines and domestic disaster management spending in countries such as Indonesia, Perú, and several SIDS (Disaster Risk Financing & Insurance Program, 2021; GFDRR, 2014; JICA, 2022). The literature on disaster recovery and resilience financing (UNDRR, 2025), along with GIRI results, shows that these levels are modest compared with the estimated needs following major climate- or hazard-related events, which often amount to several percentage points of GDP, depending on the scale of damage and the affected sectors. In GEM, after this initial reconstruction effort using available resources, the model allows the infrastructure stock to increase and gradually expand over time, driven by demand (e.g., population and economic growth requiring more roads, power generation and distribution, and investment accumulating into industry and services capital stocks). Since these resources are often channelled into national resilience funds, GEM assumes that they are used if necessary or otherwise accumulated over time. However, since they are insufficient to cover the scale of damages associated with severe climate events, the recovery process is a slow and partial one, where infrastructure remains impaired for extended periods, magnifying the economic costs of disasters over time.

To understand the benefits of a stronger recovery, Simulation 3 considers a complete reconstruction pathway. In this simulation, it is assumed that all required financing for reconstruction is made available, either through external support, insurance mechanisms, or an extraordinary mobilization of domestic resources. Within this scenario, three different reconstruction timelines are tested: 1 year, 4 years, and 10 years. The aim is to evaluate how the speed of recovery influences the long-term economic trajectory. The results show that complete and faster reconstruction significantly reduces GDP losses, as the capital stock is restored more quickly, enabling production to be resumed sooner. This avoids the compounding of effects over time.

When comparing Scenario 2 with Scenario 3 using the 10-year reconstruction time frame, the results show a clear difference in projected economic impacts. Simulation 2, which assumes limited post-disaster reconstruction, results in significantly higher GDP losses across all countries. For example, Bangladesh is projected to experience an average annual GDP loss of 9.9 percent between 2025 and 2050, reaching 14.5 percent in 2050, when compared to a scenario where there is no climate impact; the Philippines faces losses of 9.7 percent on average, rising to 12.9 percent in 2050. In contrast, Simulation 3, which assumes complete infrastructure reconstruction over a 10-year period, shows substantially lower economic impacts. In this scenario, Bangladesh's average annual GDP loss between 2025 and 2050 drops to 3.98 percent, with a loss of 5.13 percent in 2050, and the Philippines' losses reduce to 2.53 percent on average and to 2.73 percent by 2050. This shows that complete infrastructure reconstruction can significantly mitigate long-term economic losses. Although the exact reduction varies by country, the overall trend is consistent: investing in complete reconstruction over a decade reduces GDP losses by roughly half or more compared to a scenario with limited recovery efforts. Across countries, the GDP impact in 2050 drops from 7.4 percent (Simulation 2) to 3.04 percent (Simulation 3).

The timing of reconstruction is also important. As indicated above, when reconstruction is spread over a 10-year period, the average annual GDP loss between 2025 and 2050 amounts to approximately 3.04 percent. However, reducing the recovery period to 4 years reduces the average GDP losses to 2.27 percent, while the most rapid reconstruction scenario—achieving full recovery within 1 year—lowers losses further to 1.93 percent. This progressive reduction underscores the compounding effects of foregone production: each additional year of unfinished infrastructure recovery further increases losses, including diminished capital services, reduced productivity, and slower economic growth.

Figure 5 presents the results across the eight countries for each simulation (and the different reconstruction time horizons in Simulation 3). It also shows the range of economic impacts calculated by other models in the literature (circles). The progressively smaller impacts on GDP estimated when (i) considering all impacts versus built infrastructure alone and (ii) when assuming a shorter reconstruction time (e.g., 1 year vs. 4 years vs 10 years) can be clearly seen. Furthermore, it shows that, for small and undiversified economies, the benefits of rapid reconstruction are particularly significant, as each year of delay magnifies losses and compounds vulnerability. Larger and more diversified economies show more nuanced dynamics, as slower reconstruction may sustain GDP growth through prolonged investment and employment triggered by reconstruction.

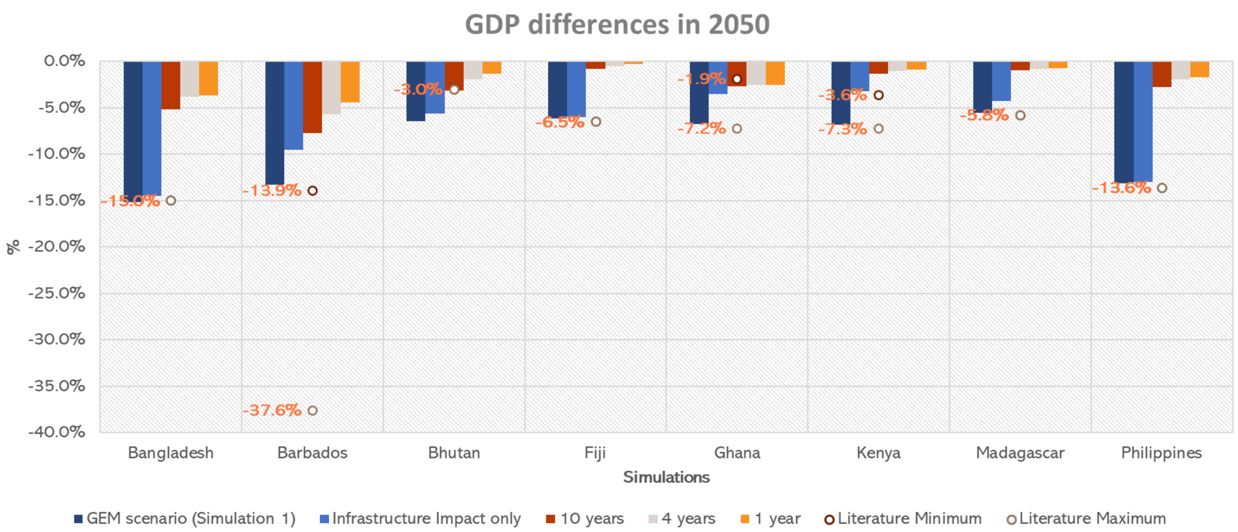

Figure 5: GDP impacts under different scenarios, compared to the range identified by the literature

Source: Authors' calculations

4.4. Comparing Loss and Damage to Impacts on Value Added

The results, across simulations, show that the macroeconomic impacts are substantially larger than the costs of direct infrastructure losses alone. Between 2025 and 2050, in the 10-year reconstruction scenario (Simulation 3), the ratio of GDP loss to AALs is estimated to range from as low as 1.2 in Bhutan to as high as 16.1 in Ghana, with an average of 7.42 across countries (Table 7). When all climate impacts are considered, these values increase further, with an average of 12.76 (Simulation 1).

Table 7: Comparing AAL to GDP impacts (Simulation 3)

Country	GEM average annual GDP loss between 2025 and 2050 (%) (10-year reconstruction scenario)	GDP loss vs. AAL loss (ratio)
Bangladesh	4.0	4.4
Barbados	5.0	11.3
Bhutan	2.4	1.2
Fiji	0.9	2.5
Ghana	2.91	16.1
Kenya	0.7	8.2
Madagascar	1.1	5.7
Philippines	2.5	10.0
Average	**2.4**	**7.42**

Source: Authors' elaboration

This set of simulations and related results comparing GDP loss and AAL serves two purposes. First, it highlights how loss and damage shape macroeconomic outcomes: that is, the societal costs go well beyond the immediate damage to assets; they are compounded over time if recovery is delayed. Second, it demonstrates the importance of proactive investments, either by enhancing climate resilience beforehand—so that damages are less severe when hazards occur—or by ensuring that financial mechanisms such as insurance, contingency funds, or international support are in place to enable rapid response and reconstruction. In both cases, the simulations show that the availability of financial resources and timing of recovery are critical determinants of long-term economic resilience to climate change.

4.5. Geological Hazards

While the simulations have primarily focused on climate-related hazards, the analysis also considers the macroeconomic implications of geological hazards. Earthquakes, though less frequent, have the potential to cause catastrophic losses to infrastructure and disrupt economic development trajectories for years. To capture these risks, we analyse the impacts of a one-time earthquake event, with a reconstruction time of 5 or 10 years.

In this scenario, an earthquake is simulated for 2030 for the Philippines, with damage calibrated at 50 times the AAL reported in GIRI. This corresponds to a total economic damage of $110 billion, which would make the event one of the most destructive disasters in recent history. For comparison, the estimated damages for the 2004 Indian Ocean tsunami were between $7 and $9 billion (Associated Press, 2014; Jalan, 2022), while the 2011 Great East Japan earthquake and tsunami resulted in losses of $210 to $235 billion (Japan Reconstruction Agency, n.d.). While the Philippines' projected losses are significantly higher than those observed in Indonesia in 2004, they are still lower than the catastrophic economic damages recorded in Japan in 2011.

Relative to the national economy, the impact is significant. The estimated damages amount to approximately 8.8 percent of the total capital stock of the industry and services sectors and about 13 percent of the GDP forecast for the Philippines in 2030. These ratios indicate a highly disruptive, although not unprecedented, event. For example, the 2010 earthquake in Haiti caused damages equivalent to 120 percent of GDP (GFDRR, 2022), leading to an economic contraction of around 8 percent. In Japan, damages of a smaller relative magnitude (around 3–4 percent of GDP (GFDRR, 2013)) still resulted in a GDP decline of 3.7 percent in 2011, showing that the scale of disruption caused by disasters can be significant even for advanced economies.

To improve the estimate of capital loss, assumptions are made about the usability of damaged infrastructure. It is assumed that 60 percent of the infrastructure is either completely destroyed or requires major repair to be functional, while the remainder continues to be partially usable. This adjustment reduces the immediate effective capital loss from 8.8 percent of the capital stock to 5.3 percent, which more accurately reflects the share of assets directly and immediately withdrawn from productive use.

The macroeconomic implications of such an earthquake are significant. The model predicts that the earthquake would cause a short-term reduction in GDP growth of up to approximately 4 percentage points in 2030. However, due to the Philippines' high baseline growth rate of 6.2 percent in the business-as-usual (BAU) scenario, the event does not trigger a recession. Instead, the economy is expected to continue growing, albeit at a slower pace (Figure 6). It is important to recognize that earthquakes can cause severe localized economic disruption, with damages concentrated in the affected region (e.g., GDP loss in an island of the Philippines could reach 20 - 30 percent or more of the GDP, as in the case of Haiti mentioned above). Yet their impact on the national GDP is often relatively small as losses are diluted across the broader economy.

Specifically, in 2030, the modelled earthquake leads to an immediate decline in GDP for the Philippines of 2.6 percent under a 5-year reconstruction horizon and 3.6 percent under a 10-year reconstruction horizon, relative to a no-earthquake baseline. The pace of recovery varies significantly across the two scenarios. In the 5-year case, GDP growth rates return to their BAU levels within three years, allowing the economy to gradually close the gap with the baseline. In contrast, under the slower 10-year reconstruction scenario, the GDP remains, on average, 2.9 percent lower than BAU levels, with the gap persisting until at least 2040 (Figure 7).

The slower response in the 10-year case triggers a series of compounding effects. Prolonged reconstruction delays lower production and value added, which in turn decrease new investment, slow down capital accumulation, and further affect economic activity in subsequent years. As a result, the economy does not fully return to BAU levels by 2040, with the long-term GDP to AAL ratio stabilizing at 2.4 through 2050. In contrast, in the 5-year reconstruction case, the economy manages to realign with pre-disaster growth trajectories.

Reconstruction activity itself provides a temporary boost to GDP growth, creating a rebound effect. This rebound occurs between 2031 and 2033 under the 5-year reconstruction scenario, while in the 10-year case, it extends until 2037 due to the prolonged reconstruction cycle. Employment levels remain high during reconstruction in both scenarios, as rebuilding activity generates additional demand for labour. In contrast, employment losses are expected in production sectors, as economic activity declines due to damaged infrastructure and equipment, reducing output. Furthermore, in the 10-year case, the extended reconstruction phase fails to translate to a sustained recovery in GDP, with the cumulative negative effects of delayed investment and slower capital replacement outweighing the temporary stimulus from rebuilding (Figure 8).

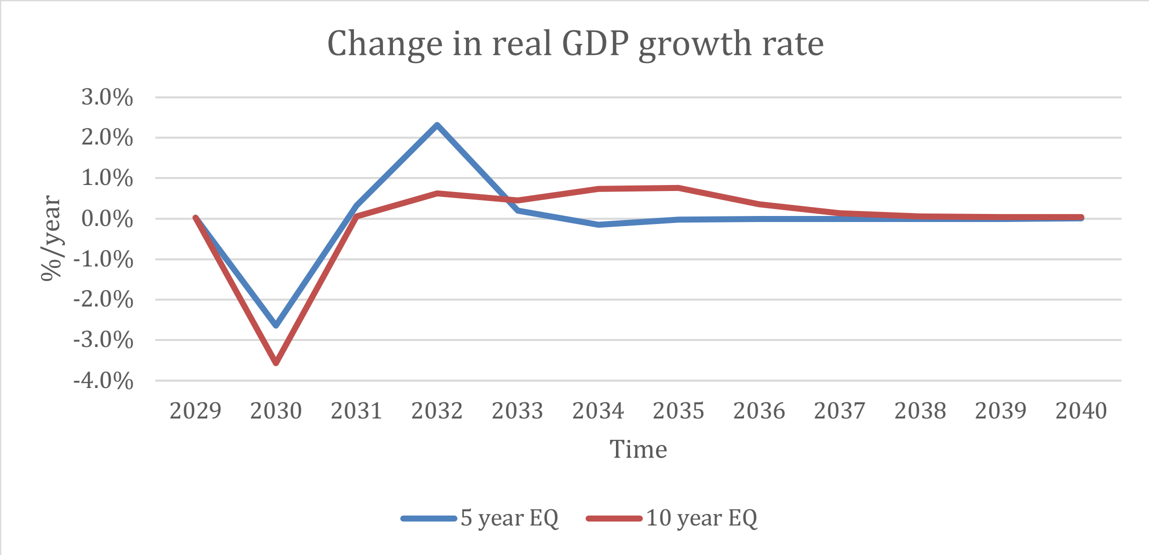

Figure 6: Impact of an earthquake taking place in 2030 on GDP growth in the Philippines

Source: Authors' elaboration

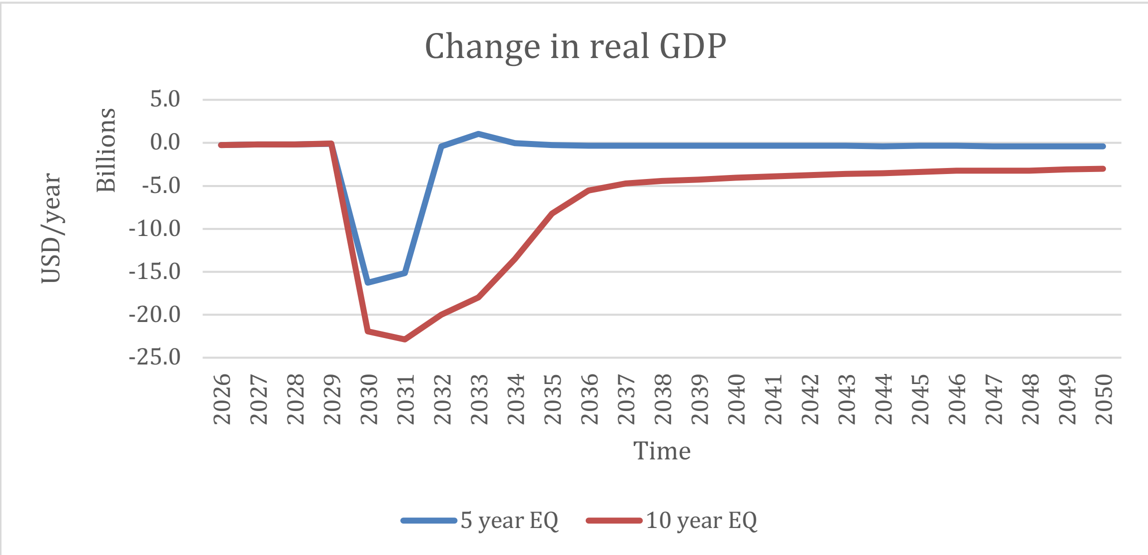

Figure 7: Impact of an earthquake taking place in 2030 on GDP in the Philippines

Source: Authors' elaboration

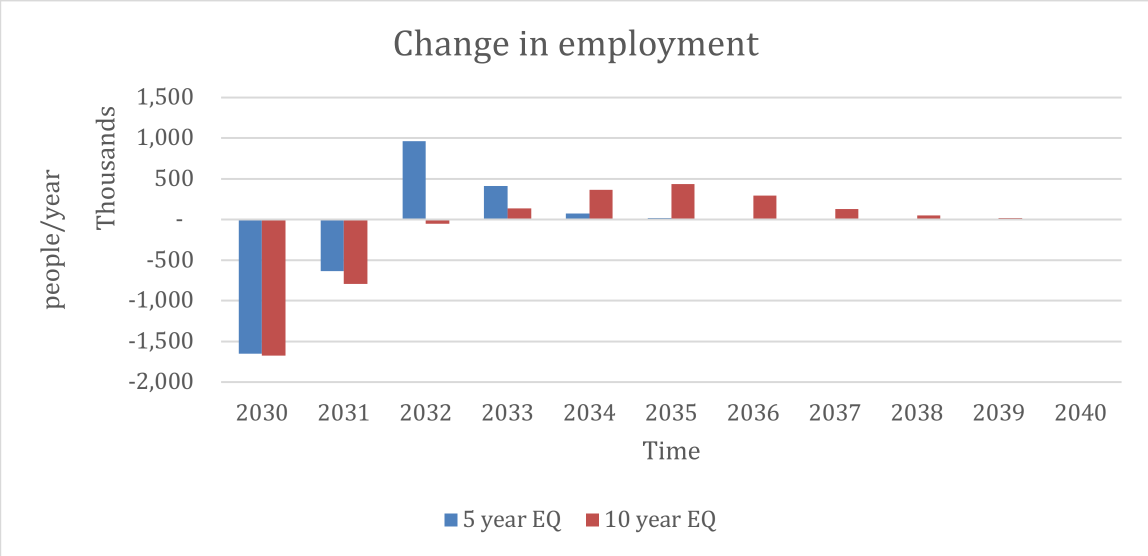

Figure 8: Impact of an earthquake taking place in 2030 on employment in the Philippines

Source: Authors' elaboration

4.6. Discussion

The interpretation of the results presented requires careful consideration of the assumptions underpinning each simulation. While both Simulations 1 and 2 provide valuable insights into the relationship between climate impacts, financing, and reconstruction, there are some limitations that should be kept in mind when interpreting the results.

First, the results of Simulations 1 and 2 may exaggerate the long-term macroeconomic impacts of climate hazards. This is because these scenarios assume that only the currently available public budget—equivalent to around 0.2 percent of GDP—is allocated to reconstruction. In reality, recovery efforts are often financed not only through public funds but also through private investment, concessional loans, and the issuance of bonds. These additional resources can significantly accelerate recovery and ease the economic burden on public accounts. Moreover, reconstruction in these scenarios is influenced by demand dynamics: damaged infrastructure is repaired, beyond the 0.2 percent of GDP, if the population and businesses require it (e.g., if the population and GDP grow over time).

In contrast, the results of Simulation 3 may underestimate the economic impact of climate hazards. This is due to the optimistic assumptions made to simplify the dynamics of post-disaster recovery. In this scenario, all damaged assets are assumed to be fully reconstructed, regardless of actual financing capacity or demand conditions. Construction is assumed to begin within a year, even when the overall recovery process extends over 4 or 10 years. Furthermore, the act of reconstruction itself is modelled as a direct contributor to economic growth: job creation and new investment in capital stock are assumed to push GDP upwards. Finally, the required investments are treated as having no implications for public finances, thereby ignoring both short-term budgetary constraints and longer-term risks associated with debt accumulation. While these assumptions help illustrate an optimistic pathway for recovery, they may downplay the fiscal and institutional challenges that many countries face in practice.

A more realistic and effective strategy would be designing reconstruction programmes that build back better. Such programmes aim not only to replace damaged assets but also to incorporate higher resilience standards and adaptation measures to prepare for future climate hazards. This approach would deliver multiple benefits simultaneously: stimulating short-term economic growth through investment and employment, reducing the scale of loss and damage for subsequent events, and reducing the frequency and magnitude of future reconstruction needs.

Finally, the analysis highlights the importance of proactive climate adaptation. Anticipatory investments reduce the need for repeated short-term reconstruction and enhance the stability of long-term growth trajectories. In this sense, proactive adaptation represents not only a defensive measure against climate impacts but also a forward-looking growth strategy that generates economic co-benefits.

5. Conclusion

This chapter adopts a systemic approach to assess the macroeconomic impacts of climate-related and geological hazards. Using GEM, calibrated with GIRI, the analysis focuses on three key questions: the overall economic impact of these hazards, how the speed of reconstruction influences recovery, and the differing effects of high-impact, low-frequency events (e.g., geological hazards) and more common, but also more diverse, extreme events (e.g., climate hazards).

GEM was tailored to assess the impact of climate hazards on infrastructure in eight countries, representing different geographies and development contexts. The model integrates data on hazard exposure, infrastructure vulnerability, and its contribution to economic activity to estimate potential loss and damage at the physical level and foregone GDP at the macroeconomic level. It employs a multi-hazard, multi-asset approach.

Results show that damage to infrastructure accounts for about 80 percent of the economic impact of climate hazards across the eight countries analysed. The remaining 20 percent is attributable to damage to land, livestock, and labour. While the results vary by country, based on their reliance on agriculture and the exposure of the labour force to extreme heat, they underscore the importance of infrastructure resilience.

Furthermore, the analysis shows that both climate change–related and geological hazards have consequences that extend far beyond the immediate replacement cost of damaged assets. When rebuilding is delayed, it creates a ripple effect: lost productive capacity in the short term reduces output, which in turn lowers investment and slows capital accumulation, reducing economic growth over time. The stock-and-flow dynamic used in GEM, by highlighting how sound infrastructure promotes economic activity, illustrates why foregone value addition over time surpasses the initial infrastructure damage. Therefore, relying solely on asset-based assessments provides an incomplete picture of the financial investments required to promote climate resilience. Decision-making based only on direct damages underestimates the true economic costs of inaction and may lead to underinvestment in reconstruction and climate resilience.

The simulations also show that mobilizing adequate funding in the immediate aftermath of disasters can significantly reduce long-term GDP losses. Rapid reconstruction, enabled by sufficient financial resources, helps to restore productive capacity and limit the scale of compounding economic impacts. The analysis further implies that proactive investment in climate resilience could reduce the severity of damages and lower the frequency of reconstruction needs, easing pressure on public finances and boosting economic resilience.

Ultimately, the findings underscore that building resilience should be viewed not merely as an operational or engineering concern but as a core economic strategy. Mobilizing resources today to strengthen infrastructure resilience—through both traditional and nature-based approaches—can result in long-term benefits, safeguarding growth, stabilizing public finances, and ensuring that economies remain robust in the face of climate and geological risks. Being prepared for short-term mobilization and making strategic, forward-looking investments in resilience are therefore essential to ensure sustainable development and to minimize the economic and social costs of future disasters.

Bibliography

Adalja, A. A., Watson, M., Bouri, N., Minton, K., Morhard, R. C., & Toner, E. S. (2014). Absorbing citywide patient surge during Hurricane Sandy: A case study in accommodating multiple hospital evacuations. *Annals of Emergency Medicine, 64*(1), 66–73.e1. https://doi.org/10.1016/j.annemergmed.2013.12.010

Asian Development Bank (ADB). (2024). *Asia-Pacific Climate Report 2024: Catalyzing finance and policy solutions*. Asian Development Bank. https://dx.doi.org/10.22617/SGP240498-2

BAPPENAS (Indonesian Ministry of National Development Planning). (2021). *A green economy for a net-zero future: How Indonesia can build back better after COVID-19 with the Low Carbon Development Initiative (LCDI)*. Indonesian Ministry of National Development Planning. https://lcdi-indonesia.id/wp-content/uploads/2021/10/GE-Report-English-8-Oct-lowres.pdf

Basel Committee on Banking Supervision. (2021). *Climate-related risk drivers and their transmission channels*. Bank for International Settlements. https://www.bis.org/bcbs/publ/d517.pdf

Bassi, A. (2015). Moving towards integrated policy formulation and evaluation: The green economy model. *Environment and Climate Technologies 16*(1). https://www.researchgate.net/publication/295181846_Moving_Towards_Integrated_Policy_Formulation_and_Evaluation_The_Green_Economy_Model

Bassi, A., Garrido, L., Harsono, A., & Pallaske, G. (2024). *Informing national climate action with the Green Economy Model: A technical description of the structures and processes*. World Resources Institute (WRI). https://www.wri.org/research/national-climate-action-green-economy-model-technical-note

Bessette-Kirton, E. (2019). *Landslides triggered by Hurricane Maria: Assessment of an extreme event in Puerto Rico*. The Geological Society of America. https://rock.geosociety.org/net/gsatoday/science/G383A/article.html

Blimpo, M. P., Postepska, A., & Xu, Y. (2020). Why is household electricity uptake low in Sub-Saharan Africa? *World Development, 133*, 105002. https://doi.org/10.1016/j.worlddev.2020.105002

Brei, M., Mohan, P., Perez Barahona, A., & Strobl, E. (2024). Transmission of natural disasters to the banking sector: Evidence from thirty years of tropical storms in the Caribbean. *Journal of International Money and Finance, 141*, 103008. https://doi.org/10.1016/j.jimonfin.2023.103008

Bueno, R., Herzfeld, C., Stanton, E. A., & Ackerman, F. (2008). *The Caribbean and climate change: The costs of inaction*. Stockholm Environment Institute (SEI). https://www.researchgate.net/publication/237321245_The_Caribbean_and_climate_change_The_costs_of_inaction

Chen, H., Jin, L., Wang, M., Guo, L., & Wu, J. (2023). How will power outages affect the national economic growth: Evidence from 152 countries. *Energy Economics, 126*, 107055. https://doi.org/10.1016/j.eneco.2023.107055

Chowdhury, H., Malik, I., Sun, H., & Ali, S. (2022). *Natural disasters and corporate default risk*. https://acfr.aut.ac.nz/__data/assets/pdf_file/0004/712399/H-Sun-ND_and_default-risk_manuscript.pdf

De Bandt, O., Kuntz, L., Pankratz, N., Pegoraro, F., Solheim, H., Sutton, G., Takeyama, A., & Xia, F. D. (2023). The effects of climate change-related risks on banks: A literature review. *Journal of Economic Surveys, 39*(4). https://onlinelibrary.wiley.com/doi/10.1111/joes.12665

Eickmeier, S., Quast, J., & Schüler, Y. S. (2024). Macroeconomic and financial effects of natural disasters. Deutsche Bundesbank Discussion Paper No. 45/2024. https://doi.org/10.2139/ssrn.5066005

Enei, R., Doll, C., Klug, S., Partzsch, I., Sedlacek, N., Kiel, J., Nesterova, N., Rudzikaite, L., Papanikolaou, A., & Mitsakis, V. (2011). *Vulnerability of transport systems – Main report.* Fraunhofer-ISI. https://www.researchgate.net/publication/270571786_Vulnerability_of_transport_systems

Forrester, J. (2002). *Road Maps: A guide to learning system dynamics.* System Dynamics Group, Sloan School of Management, MIT. https://ocw.mit.edu/courses/15-988-system-dynamics-self-study-fall-1998-spring-1999/43abb8809f08667bba3c9c61b7735bad_part1.pdf

García, D. S., & Giuliano, J. M. (2012). Operating strategies of solar thermal power plants with molten-salt storage. IEEE Transactions on Sustainable Energy, 3(3), 392–399. https://doi.org/10.1109/TSTE.2012.22.5639900

Golechha, A., Raman, A., Srivastava, A., Bassi, A., Pallaske, G., Cholayil, N., & Dayal, S. (2024). *A green economy model for India: Technical summary of methods and data used.* World Resources Institute. https://www.wri.org/research/green-economy-model-india-technical-summary-methods-and-data-used

Gourdel, R., & Monasterolo, I. (2022). *Climate physical risk, transition spillovers and fiscal stability: An application to Barbados.* Task Force on Climate, Development and the IMF. https://gdpcenter.org/TaskForce

Government of Fiji & World Bank Group. (2017). *Climate vulnerability assessment: Making Fiji climate resilient.* World Bank. https://documents1.worldbank.org/curated/en/163081509454340771/pdf/Climate-vulnerability-assessment-making-Fiji-climate-resilient.pdf

Gramlich, D., Walker, T., Zhao, Y., & Bitar, M. (2023). After the storm: Natural disasters and bank solvency. *International Journal of Central Banking, 19*(2): 199–249. https://www.ijcb.org/journal/ijcb23q2a4.pdf

Guffanti, M., Mayberry, G. C., Casadevall, T. J., & Wunderman, R. (2009). Volcanic hazards to airports. *Natural Hazards, 51*(2), 287–302. https://doi.org/10.1007/s11069-008-9254-2

Hallegatte, S., & Walsh, B. (2021). Natural disasters, poverty and inequality. In É. Laurent & K. Zwickl (Eds.), *The Routledge handbook of the political economy of the environment* (1st ed., pp. 111–131). Routledge. https://doi.org/10.4324/9780367814533-10

Hallegatte, S., Rentschler, J., & Rozenberg, J. (2019). *Lifelines: The resilient infrastructure opportunity.* World Bank. https://documents1.worldbank.org/curated/en/111181560974989791/pdf/Lifelines-The-Resilient-Infrastructure-Opportunity.pdf

Hamm-Rodríguez, M. (2018). *The effects of displacement on Puerto Rican K–12 students in Florida after Hurricane Maria.* Natural Hazards Center. https://hazards.colorado.edu/quick-response-report/the-effects-of-displacement-on-puerto-rican-k-12-students-in-florida-after-hurricane-maria

Haraguchi, M., & Lall, U. (2015). Flood risks and impacts: A case study of Thailand's floods in 2011 and research questions for supply chain decision making. *International Journal of Disaster Risk Reduction, 14*(3), 256–272. https://doi.org/10.1016/j.ijdrr.2014.09.005

Hashemi, M. (2022). How would residential electricity consumers respond to reductions in power outages? *Energy for Sustainable Development, 69*, 1–10. https://doi.org/10.1016/j.esd.2022.05.004

Hickford, A., Blainey, S., Pant, R., Jaramillo, D., Russell, T., Preston, J., Hall, J., Young, M., & Glasgow, G. (2023). *Decision support systems for resilient strategic transport networks in low-income countries*. University of Southampton. https://transport-links.com/hvt-publications/final-report-decision-support-systems-for-resilient-strategic-transport-networks-in-low-income-countries

Hooda, N. (2022). *Ghana – Green Growth PASA: CCDR AFOLU background note.* World Bank Group. https://documents1.worldbank.org/curated/en/099205110162231409/pdf/P17598909706d00209477090f387ca35f1.pdf

Japan International Cooperation Agency (JICA). (2024). *JICA Global Agenda for No. 20: Disaster Risk Reduction (DRR) through Pre-disaster Investment and Build Back Better (GA-DRR).* Japan International Cooperation Agency. https://www.jica.go.jp/activities/issues/disaster/__icsFiles/afieldfile/2025/04/23/agenda_03_1.pdf

Kahn, M. E., Mohaddes, K., Ng, R. N. C., Pesaran, M. H., Raissi, M., & Yang, J.-C. (2019). Long-term macroeconomic effects of climate change: A cross-country analysis (IMF Working Paper No. 2019/215). International Monetary Fund. https://www.imf.org/en/Publications/WP/Issues/2019/10/11/Long-Term-Macroeconomic-Effects-of-Climate-Change-A-Cross-Country-Analysis-48691

Kesete, Y. Y., Raffo, V., Pant, R., Koks, E. E., Paltan, H., Russell, T., & Hall, J. W. (2021). *Climate change risk analysis of Argentina's land transport network.* World Bank. https://doi.org/10.1596/36504

Kishore, N. (2018). Mortality in Puerto Rico after Hurricane Maria. *The New England Journal of Medicine*, *379*(2). https://doi.org/10.1056/NEJMsa1803972

Klomp, J. (2014). Financial fragility and natural disasters: An empirical analysis. *Journal of Financial Stability, 13,* 180–192. https://doi.org/10.1016/j.jfs.2014.06.001

Koks, E., Pant, R., Thacker, S., & Hall, J. W. (2019). Understanding business disruption and economic losses due to electricity failures and flooding. *International Journal of Disaster Risk Science, 10*(4), 421–438. https://doi.org/10.1007/s13753-019-00236-y

Kousky, C. (2016). Impacts of natural disasters on children. *The Future of Children, 26*(1), 73–92. https://doi.org/10.1353/foc.2016.0004

Mahul, O., Signer, B., & Boudreau, L. (2014). *Financial protection against natural disasters: From products to comprehensive strategies: An operational framework for disaster risk financing and insurance.* The World Bank and Global Facility for Disaster Reduction and Recovery. https://www.gfdrr.org/sites/default/files/documents/Financial%20Protection.pdf

Meadows, D. (1980). The unavoidable a priori. In J. Randers (Ed.), *Elements of the system dynamics method* (pp. 23–57). MIT Press. https://www.academia.edu/113594342/Elements_of_the_System_Dynamics_Method

Mensah, J. (2016). *Bring back our light: Power outages and industrial performance in Sub-Saharan Africa*. French Association of Environmental and Resource Economists. https://ideas.repec.org/p/fae/wpaper/2016.20.html

Mensah, J. (2018). *Jobs! Electricity shortages and unemployment in Africa*. World Bank Group. https://documents1.worldbank.org/curated/en/659751524142624281/pdf/Jobs-electricity-shortages-and-unemployment-in-Africa.pdf

Niles, S. (2019). *Social vulnerability and the role of Puerto Rico's healthcare workers after Hurricane Maria*. Natural Hazards Center. https://hazards.colorado.edu/quick-response-report/social-vulnerability-and-the-role-of-puerto-ricos-healthcare-workers-after-hurricane-maria

O'Meara, S. L. (2014). *The 2004 Indian Ocean tsunami: An examination of the effectiveness of warnings, preparatory measures, and evacuation behaviors in coastal Sri Lanka* [Senior thesis, Scripps College]. Claremont Colleges Scholarship. https://scholarship.claremont.edu/cgi/viewcontent.cgi?article=2844&context=scripps_theses

Pallaske, G., Bassi, A. M., Garrido, L., & Guzzetti, M. (2023). Exploring the virtuous interdependencies existing between climate action and sustainability in the context of low-carbon development. In F. J. López, M. Mazzanti, & R. Zoboli (Eds.), *Handbook on innovation, society and the environment* (pp. 281–308). Edward Elgar. https://uis.brage.unit.no/uis-xmlui/bitstream/handle/11250/3104647/no.uis%3Ainspera%3A152006185%3A6715431.pdf?sequence=1&isAllowed=y

Poaponsakorn, N., & Meethom, P. (2013). Impact of the 2011 floods, and flood management in Thailand. ERIA Discussion Paper Series. https://www.eria.org/ERIA-DP-2013-34.pdf

Praktiknjo, A. J., Hähnel, A., & Erdmann, G. (2011). Assessing energy supply security: Outage costs in private households. *Energy Policy, 39*(12), 7825–7833. https://doi.org/10.1016/j.enpol.2011.09.028

Randers, J. (1980). *Elements of the system dynamics method*. MIT Press. https://www.academia.edu/113594342/Elements_of_the_System_Dynamics_Method

Rentschler, J., Braese, J., Jones, N., & Avner, P. (2019). *Three feet under: The impacts of flooding on urban jobs, connectivity, and infrastructure*. World Bank. https://documents1.worldbank.org/curated/en/410661560796289323/pdf/Three-Feet-Under-The-Impact-of-Floods-on-Urban-Jobs-Connectivity-and-Infrastructure.pdf

Richardson, G., & Pugh, A. (1981). *Introduction to system dynamics with Dynamo*. Productivity Press. https://scispace.com/pdf/introduction-to-system-dynamics-modeling-with-dynamo-17tvfgrkuh.pdf

Rodriguez-Llanes, J. M., Ranjan-Dash, S., Degomme, O., Mukhopadhyay, A., & Guha-Sapir, D. (2011). Child malnutrition and recurrent flooding in rural eastern India: A community-based survey. *BMJ Open, 1*(2), e000109. https://doi.org/10.1136/bmjopen-2011-000109

Romeiro, V., Pinheiro, B., Genin, C., Feltran-Barbieri, R., Barros, C., Bassi, A., & S., K. (2020). *A new economy for a new era: Elements for building a more efficient and resilient economy in Brazil*. WRI Brasil. https://newclimateeconomy.net/sites/default/files/2023-08/wribrasil_neweconomyforanewera_en.pdf

Schulze, S. S., Fischer, E. C., Hamideh, S., & Mahmoud, H. (2020). Wildfire impacts on schools and hospitals following the 2018 California Camp Fire. *Natural Hazards, 104*(1), 901–925. https://doi.org/10.1007/s11069-020-04197-0

Stock, A., Davidson, R. A., Kendra, J., Martins, V. N., Ewing, B., Nozick, L. K., Starbird, K., & Leon-Corwin, M. (2023). Household impacts of interruption to electric power and water services. *Natural Hazards, 115*(3), 2279–2306. https://doi.org/10.1007/s11069-022-05638-8

Teperman, S. (2013). Hurricane Sandy and the greater New York health care system. *Journal of Trauma and Acute Care Surgery, 74*(6), 1401–1410. https://doi.org/10.1097/TA.0b013e318296fa9f

Verschuur, J., & Hall, J. (2024). *Systemic impacts of disruptions at maritime chokepoints* [in review]. https://doi.org/10.21203/rs.3.rs-5234319/v1

Verschuur, J., Koks, E. E., & Hall, J. W. (2023). Systemic risks from climate-related disruptions at ports. *Nature Climate Change, 13*(8), 804–806. https://doi.org/10.1038/s41558-023-01754-w

World Bank. (2011). *Thai flood 2011: Rapid assessment for resilient recovery and reconstruction planning.* World Bank Group. https://documents.worldbank.org/en/publication/documents-reports/documentdetail/677841468335414861

World Bank. (2025). *Bhutan: Country climate and development report.* World Bank. https://reliefweb.int/report/bhutan/bhutan-country-climate-and-development-report

World Bank and State Secretariat for Economic Affairs (SECO). (2021). *Fact Sheet 3: Managing disaster funds for response and recovery.* The World Bank Disaster Risk Financing & Insurance Program. https://www.financialprotectionforum.org/sites/default/files/SECO%20Factsheet%2003_22July2021.pdf

World Bank Group. (2022). *Philippines country climate and development report.* World Bank Group. http://hdl.handle.net/10986/38280

World Bank Group. (2023). *Kenya country climate and development report.* World Bank. https://documents1.worldbank.org/curated/en/099110923164513587/pdf/P179792078f54c060099260c32008ca87f7.pdf

World Bank Group. (2024). *Madagascar country climate and development report.* World Bank. http://hdl.handle.net/10986/42263

Xie, W., Li, N., Li, C., Wu, J., Hu, A., & Hao, X. (2014). Quantifying cascading effects triggered by disrupted transportation due to the Great 2008 Chinese Ice Storm: Implications for disaster risk management. *Natural Hazards, 70*(1), 337–352. https://doi.org/10.1007/s11069-013-0813-9

Yang, Y., Liu, H., Mostafavi, A., & Tatano, H. (2025). Review on modeling the societal impact of infrastructure disruptions due to disasters. *Reliability Engineering & System Safety*, *257*(PB). https://ideas.repec.org/a/eee/reensy/v257y2025ipbs0951832025000833.html

Annex: Documentation of the Analysis of Climate Hazards

Assets and Hazards Coverage

Asset type	River flood	Coast flood	Landslide (rainfall)	Storm	Drought
Population	✓	✓	✓	✓	-
Rural population	✓	✓	✓	✓	✓
Built surface	✓	✓	✓	✓	-
Power plants	✓	✓	✓	✓	-
Transmission lines	✓	✓	✓	✓	-
Roads	✓	✓	✓	✓	-
Cropland	✓	✓	✓	✓	✓
Livestock	✓	✓	✓	✓	✓
Lakes	-	-	-	-	✓

Coverage Summary

- 9 asset types covered
- 5 hazard types covered
- Total combinations: 33 asset–hazard pairs supported in addition to a cross-hazard category ‘Any’ not included in the table.

Hazards

The hazards typically derive from Earth system models (ESMs), satellite altimetry, and/or impact models. They often include an error estimate, either directly provided as percentiles or as an ensemble of models.

Hazard	Data source	Spatial resolution	Future scenarios	Data format	Units	Risk threshold	Error estimate
River flood	WRI Aqueduct v2 (Ward et al., 2020)	~1 km	Historical, RCP8.5	Return periods	Flood depth (m)	>0 m	3 percentiles + (future only) 5 ESMs
Coastal flood	WRI Aqueduct v2 (includes land subsidence) (Ward et al., 2020; World Resources Institute, 2020)	~1 km	Historical, RCP8.5	Return periods	Flood depth (m)	>0 m	3 percentiles
Landslide (rainfall)	World Bank Global Landslide Hazard Map (earthquakes not included) (Arup et al., 2023)	~1 km	Historical only (1980–2018)	Mean annual frequency			
Storm	STORM v3 (Bloemendaal, de Moel, Dullaart, et al., 2022;	~10 km	Historical, Climate change	Return periods	Wind speed (m/s)	> 121 km/h (33.6 m/s)	4 ESMs (future only)

Hazard	Data source	Spatial resolution	Future scenarios	Data format	Units	Risk threshold	Error estimate
	Bloemendaal, de Moel, Muis, et al., 2022)						
Drought	ISIMIP2 (Lange et al., 2020)	0.5° (~50 km)	Historical (2004), RCP6.0	Annual time series	Event occurrence (0/1)		4 ESMs + 8 impact models

- **Future scenarios**: For the future snapshots for 2030, 2050, and 2080, we used the RCP6.0 scenario whenever possible, but most hazards only provide projections for the RCP8.5 scenario. When projections are not available, historical data is held constant into the future.

- **Spatial processing**: All hazard data is re-gridded to a consistent (~1 km) resolution for analysis using bilinear interpolation (see the note on droughts below).

- **Risk threshold**: Flood and storm hazards are available for various return periods. We define risk thresholds (e.g., >0 m flood depth, >121 km/h wind speed) and interpolate between return periods *R* to estimate exceedance probabilities. The annual frequency $f = 1/R$ is used as an interpolant. For a set of return periods *R*(I = 1, …, *n*), we use the middle-point annual frequency $f = (R_r + R_{r-1})/2$, where R_r is the first return period for which the risk threshold is crossed. In the case of droughts, Lange et al. (2020) defined a drought event with respect to a pre-industrial baseline and provided an annual time series of events until 2100. For each of the snapshots, we take a 31-year window and compute the annual frequency as "number of drought events/31." This approach can resolve return periods up to 30 years. Landslides are already provided as an annual frequency of events.

- **Error estimate**: We call 'realization' any combination of an ESM, an impact model, and a percentile. Each realization is associated with its own annual frequency of the event. It should be noted that the realizations are not consistent across hazards. Therefore, we calculate the minimum, median, and maximum of all realizations for each grid cell. For landslides, as there is no error estimate, these values are equal. It should be noted that for the CSV file, whenever possible (i.e., all but not the 'any' category), we calculate the percentage of assets at risk for each realization separately and calculate the median, minimum, and maximum values on the national aggregates.

- **Multi-hazard**: In addition to single hazards, an 'any' hazard category estimates the annual frequency of any hazard occurring under an independence assumption, $f = 1 - \Pi_i(1 - f_i)$. This calculation is done separately for the median, minimum, and maximum.

- **Return period**: For a given hazard and snapshot, a grid point is considered at risk for a return period R if the annual frequency $f > 1/R$. This definition, based on the annual frequency of occurrence, can be made for each hazard (including 'any') and each error level (median, minimum, or maximum).

Considerations

- The drought dataset uses a relative definition for droughts, measuring a change compared to the pre-industrial period. As a result, a dry country may appear to experience less droughts than a wetter country if the wetter country had a stronger historical trend toward drying. Moreover, that hazard is defined for return periods less than 30 years (the next value is 0). On the maps, any value greater than 30 is thus the result of interpolation when re-gridding from 10 km onto 1 km. It is reasonable to expect some non-zero probability in the vicinity of a drought-impacted region, so we treat that as a calculation assumption rather than as an error.

- Climate hazards are not truly independent in general—and true correlations cannot easily be calculated and accounted for—so the calculation of the 'any' hazard category is inaccurate and must be interpreted carefully. If two events with risk *f* = 0.1, each, were 100 percent correlated, their resulting risk would be the same as each event taken individually: that is, 0.1. In our calculation, this would result in an overestimate: $ f = 1 – (1 – 0.1) (1 – 0.1) = 0.19 $. This suggests that the 'any' category will tend to overestimate risk. However, not all hazards are included in this analysis.

Assets

Asset type	Data source	Spatial resolution	Quantitative fields	Coverage
Population	WorldPop (built-settlement growth model (BSGM)) (Bondarenko et al., 2020)	~100 m	Population count	2020
Rural population	WorldPop (BSGM) (Bondarenko et al., 2020) and Global Human Settlement Layer (R2023) (Copernicus, n.d.; Pesaresi et al., 2024)	~100 m + 1 km	Population count	2020 + 2025
Built surface	Global Human Settlement Layer (GHS built-up surface grid) (R2023) (Copernicus, n.d.; Pesaresi et al., 2024)	100 m (Mollweide)	Built surface area (m^2)	2025
Power plants	WRI Global Powerplant Database v1.3.0 (Byers et al., 2021)	Point locations	Capacity (MW)	up to 2021
Transmission lines	OpenStreetMap (2025)	Vector lines	Length (km)	
Roads	GRIP4 Global Roads Database (GLOBIO) (GLOBIO, n.d.; Meijer et al., 2018)	Vector lines	Length (km)	
Cropland	Copernicus/ESA Land Cover v3 (Copernicus et al., 2019)	~100 m	Cropland area (m^2)	2019
Livestock	Gridded Livestock of the World (GLW4) (FAO, n.d.; Gilbert et al., 2018)	~10 km	Livestock count	2010
Lakes	HydroLAKES v1.0 (HydroSHEDS, n.d.; Messager et al., 2016)	Vector polygons. All global lakes with a surface area of at least 10 ha	Lake area (m^2)	

The assets are aggregated onto the 1-km hazard grid. They are summed using nearest-neighbour co-location in each grid cell.

Considerations

- The power plant dataset may contain inaccurate entries. In the individual cases we reviewed, we found geolocalization errors of up to 15 km. The authors of that dataset noted that governmental communications were incomplete, and they had used various sources and reconstruction techniques for both power generation data and geolocalization (Byers et al., 2021).

Administrative Boundaries

The geometries used for the countries included were taken from Natural Earth (1:10 m) or from GADM. GADM provides a much higher level of detail and also includes administrative boundaries within the countries. In this work, a balance was struck between the level of detail and speed of computation.

[1] The dollar sign indicates US dollars throughout this paper.

Coalition for Disaster Resilient Infrastructure (CDRI)

email biennialreport@cdri.world, info@cdri.world **Website** www.cdri.world

CDRI_world coalition-for-disaster-resilient-infrastructure coalitionfordri

GIR ECONOMIC IMPACTS
2025 WORKING PAPER

This document is a launch edition and may undergo minor changes in design.