Network for Greening the Financial System

Information Note

Leveraging physical climate risk data

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Central Banks and Supervisors
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Foreword

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The NGFS Expert Network on Data (EN Data) is pleased to share this Information Note on Leveraging Physical Climate Risk Data.

As the physical impacts of climate change on the economy and the financial system intensify, the NGFS has been supporting physical risk analysis through its short- and long-term scenarios. It has also examined the implications of climate adaptation for central banks and supervisors, as outlined in its Conceptual Note on Adaptation. With this Information Note, we take an important step forward by exploring the data challenges associated with physical climate risk assessment, drawing on the experiences of the Expert Network's members. Similar to the NGFS Note on Improving Greenhouse Gas Emissions data, this document provides an in-depth assessment of one of the focus areas identified in the NGFS Final report on bridging data gaps.

Physical risk analysis relies on a wide range of data, including forward-looking information on climate events, details about exposed assets and activities, and their links to the financial system. This diversity presents challenges related to data availability and comparability across metric types, regions, and sectors, often requiring a trade-off between granularity and coverage.

This Note maps the main categories of physical risk data, highlights critical gaps – such as the limited availability of insurance data – and discusses innovative ways to address them. For example, it considers how adaptation datasets can be built using natural language processing techniques applied to corporate reports or through geospatial tools that provide information on nature-based solutions. The Note concludes with practical recommendations to strengthen the foundations of physical risk analysis. This includes enhancing in-house technical expertise, fostering data sharing and collaboration, developing robust data systems, and supporting funding initiatives for climate risk research.

We are grateful to the members of the Expert Network for their contributions and to the members of the NGFS Task Force on Adaptation for their review. We also extend our special thanks to the team lead, Jolien Noels (OECD), for her leadership and her dedication to this work. We are confident that this Information Note is an important step towards enhancing physical risk analysis in the financial sector and can serve as a valuable resource for stakeholders working to address the challenges posed by climate change.

Executive summary

With climate risks intensifying, central banks and financial supervisors increasingly rely on physical climate risk data to assess economic and financial stability consequences. Assessments of physical climate risks to finance are used for a range of different use cases, including macro-economic analysis and banking supervision. However, challenges related to data availability, technical expertise, and modelling capacities hinder their full integration into risk management.

A range of physical climate risk indicators are being developed. These indicators range from country-level proxy metrics to climate-adjusted financial risk metrics, such as probabilities of default due to climate impacts. While some indicators assess the exposure-at-risk, highlighting how climate risk drivers could transmit through the economy and financial system, others also assess vulnerabilities to quantify the scale of past or potential financial sector losses.

Physical climate risk indicators require a combination of complex data and modelling inputs. Data on climate-related hazards, exposure, vulnerability, and adaptation actions from different sources use different methodologies, which can lead to varying results. The accessibility, granularity, and comparability of such data need to be improved across regions and sectors. Key gaps include asset-level exposure data – especially in developing countries – granular damage functions, adaptation efforts, supply chain analyses, harmonized and detailed data on historical losses, and secondary effects.

Physical climate risk data solutions are advancing. Some public databases, open-source initiatives, and pilot studies are contributing to the availability of such data. Tools like the Copernicus Climate Data Store Toolbox and Google Earth Engine facilitate data-intensive climate risk analyses. Several data solutions are emerging to also integrate adaptation efforts in physical climate risk assessments, but these need to be expanded. Examples include adaptation data collected from corporate surveys (e.g. from CDP), corporate reports through NLP and LLMs, or derived from geospatial tools with information on nature-based solutions. Furthermore, data on insurance coverage remains scarce. At asset or liability level, supervisors may conduct *ad hoc* data collections. At more aggregate levels, proxy estimates of insurance coverage can be developed.

Combining the different data and modelling inputs, both bottom-up and top-down approaches need to be used to assess physical climate risks to the financial system. Bottom-up methods focus on detailed financial exposure and vulnerability, while top-down approaches offer macro-level insights into systemic risk. Top-down assessments are generally characterised by macroeconomic modelling challenges more than by data challenges. Ideally, both approaches are combined.

Data challenges and technical barriers to physical climate risk analyses can be addressed through capacity building, data sharing and collaboration, robust data systems, and funding initiatives. Capacity building initiatives such as physical risk training, workshops, and development programs can help enhance climate risk analysis skills across central banks and supervisory institutions. Data sharing and collaboration between central banks, national statistical offices, financial institutions, and research organisations help address data gaps and improve assessments, as demonstrated by the CLIMADA and Digital Twin projects. Robust data systems that integrate multi-source data are essential for providing high-quality, timely information to decision makers. Finally, more funding for climate risk research through national and international funding mechanisms needs to be secured.

1. Introduction

As the impacts of climate change become increasingly evident, central banks and financial supervisors increasingly need to rely on climate change related physical risk data to identify and address economic and financial risks associated with such impacts. Climate impacts are rising, the likelihood of keeping global warming well below 2 °C is decreasing, and the consequences of crossing climate tipping points are uncertain but severe. Climate change risks can have profound impacts on economic activities, asset values, and creditworthiness, posing increasing risks to socioeconomic and financial systems (NGFS, 2024). Traditional risk management frameworks need to be adapted to account for the unique characteristics of physical climate risks. This requires integrating physical climate risk data into financial risk analysis to identify material risks. In turn, this enables the development of robust adaptation and resilience strategies to ultimately safeguard financial stability and ensure the resilience of financial institutions (NGFS, 2024).

Central banks and financial supervisors employ physical climate risk data across various use cases, including:

- Micro-prudential analysis: Assessing the resilience of individual financial institutions to climate-related risks and events.
- Macro-prudential analysis: Evaluating the systemic risks posed by climate change to the financial system.
- Monetary policy: Incorporating climate risk considerations into monetary policy frameworks to ensure long-term price stability.
- Statistical indicators and research: Developing and refining indicators to monitor climate risks and conducting research to inform policy decisions.

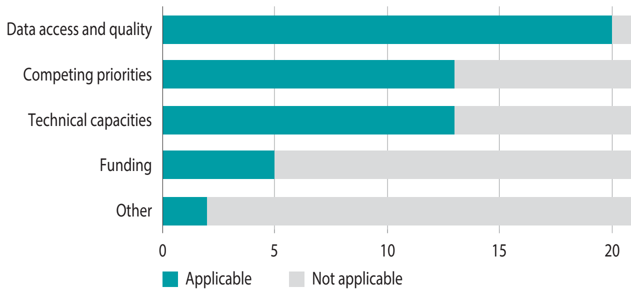
Based on the NGFS 2024 Physical Risk Survey of 21 NGFS members across all continents (see Annex I Figure 1 and 2), central banks and supervisors are already integrating physical climate risk data across use cases although stages of development and implementation across institutions vary. Among survey respondents, physical risk data has been especially relied upon for developing research and statistical indicators, as well as for macro-prudential analysis (Figure 1).

Figure 1 **Different use cases for physical risk data being considered by surveyed institutions**

Notes: Results of 21 NGFS members across all continents responding to the survey. See further details of the scope of the survey in Annex I.
Source: NGFS 2024 Physical Risk Survey.

Many challenges hinder the integration of physical climate risk data across use cases. Nearly all survey respondents pointed to data availability being one of the main challenges to integrating physical climate risk analysis across use cases by central banks and supervisors (Figure 2). Many survey respondents also pointed out different challenges relating to developing internal capacities with respect to climate risk data, including developing comprehensive and reliable climate risk databases, as well as expanding in-house technical expertise and modelling approaches.

Figure 2 **Challenges in integrating physical climate risk data across use cases by central banks and supervisors**



Note: Results of 21 NGFS members across all continents responding to the survey. See further details of the scope of the survey in Annex I.
Source: NGFS 2024 Physical Risk Survey.

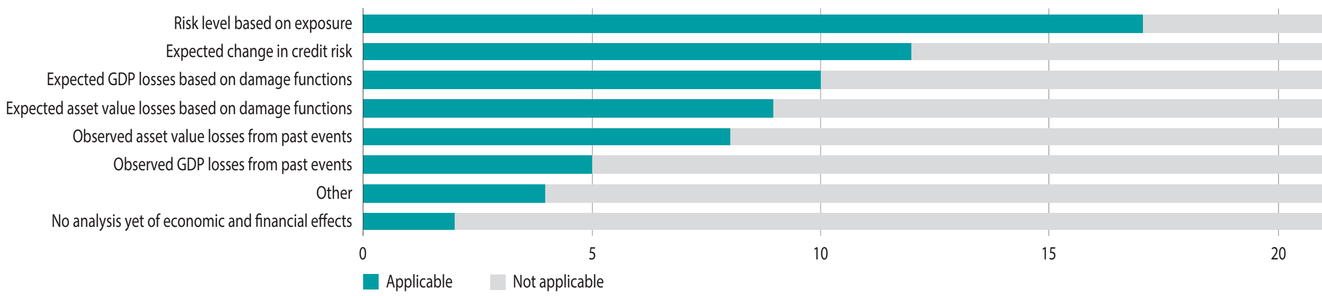
To help address these challenges, this information note takes stock of available approaches, indicators, and data used in physical risk analyses by central banks and supervisors, pointing to options for enhancing physical climate risk analyses. The note provides an overview of existing (leading) practices across central banks and financial supervisors, pointing to best-available harmonized datasets, metrics and models (considering comparability across jurisdictions). Where relevant, this note points to potential solutions and further steps to be taken to improve physical climate risk data for climate-related financial analyses by central banks and supervisors. It complements other NGFS work focused on GHG emissions data (NGFS, 2024) and integrating adaptation indicators into transition plans (NGFS, 2025). Building climate resilience and adaptive capacity to physical climate risks must be seen in conjunction with climate transition. Stepping up climate adaptation is indispensable to cope with the effects of climate change and minimise climate damages and losses[1]. At the same time, successful mitigation limits further warming, climate extremes and environmental degradation. The availability of high-quality climate data is critical to supporting the integration of climate-related risks in the operation and risk management of the financial sector.

1 In terms of intertemporal policy choices, adaptation presents society and decision makers with a need to choose between how much to invest in it versus how much residual risk, and economic and financial losses, it is prepared to accept (Mongelli, Ceglar, & Scheid, 2024). Thus, there are trade-offs among adaptations' costs, benefits, and residual damages.

2. Indicators of financial risks from physical climate risks

The assessment of climate-related physical risks to the financial system requires evaluating economic and financial impacts at multiple levels, from individual counterparties to the macroeconomic context. Figure 3 displays the variety of economic and financial impacts assessed by respondents to the survey, highlighting that more data and modelling intensive approaches (e.g. expected change in credit risk) are being implemented by NGFS members.

Figure 3 **Economic and financial impacts assessed by central banks and supervisors**



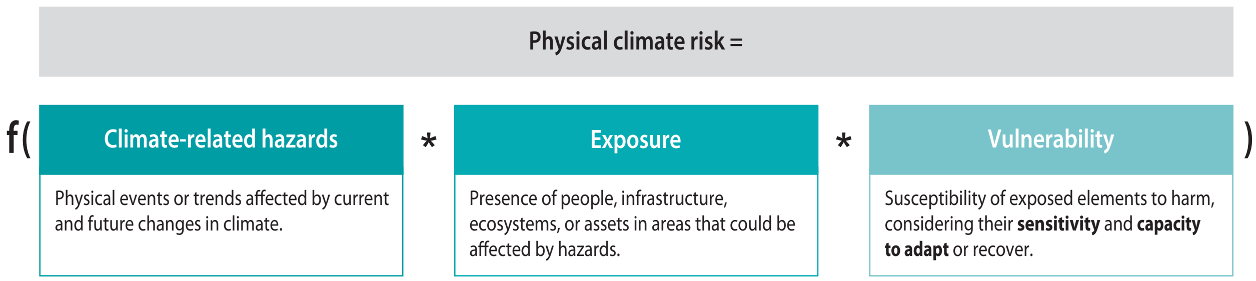
Note: Results of 21 NGFS members across all continents responding to the survey. See further details of the scope of the survey in Annex I.
Source: NGFS 2024 Physical Risk Survey.

Physical climate risk indicators for the financial sector measure financial risks and losses that can arise from the adverse effects of current or future climate conditions. Such risks can stem from climate change-induced natural hazards (such as floods, wildfires, and storms) and chronic phenomena (like heat and water stress).

Physical climate risks result from dynamic interactions between climate hazards, exposure and vulnerability (Figure 4).

- Climate-related **hazards** are physical events or trends affected by current and future changes in climate. Hazards can be sudden (also referred to as acute hazards) or slower onset (also referred to as chronic hazards).
- **Exposure** refers to the presence of people, infrastructure, ecosystems, or assets in areas that could be affected by hazards. This concept highlights the "what" and "where" that are subject to potential harm.
- **Vulnerability** describes the susceptibility of exposed elements to harm, considering their sensitivity and capacity to adapt or recover. Vulnerability factors can be physical (e.g. the structural integrity of buildings), social (e.g. income inequality, education), financial (e.g. the presence of insurance coverage), or systemic (e.g. reliance on fragile supply chains).

Figure 4 **Elements of physical climate risk**



Source: Authors, based on (Ara Begum, et al., 2022).

A range of physical climate risk metrics are being developed, with examples summarised in Table 1. They may be developed by central banks – as is the case of the portfolio loss metrics developed by the European System of Central Banks (ESCB)[2], namely Potential Exposure at Risk (PEAR), Normalised Exposure at Risk (NEAR), and collateral-adjusted exposure at risk (CEAR). Several other institutions, private companies, and researchers have been developing other metrics to incorporate physical climate risks into risk assessments. For example, Climate Analytics have developed acute physical risk metrics, in partnership with the NGFS.

This report – and Table 1 in particular – distinguishes *proxy*, *exposure-at-risk*, and *risk* metrics, in broad alignment with the FSB analytical framework to assess climate transition and physical risks (FSB, 2025)**, but with slight nuances so as to reflect specificities of physical risks.**

- *Physical climate risk* ***proxy*** metrics provide an *indication of potential drivers of physical risk* (FSB, 2025). In Table 1, aggregate proxy metrics are classified as such as they allow to identify the most material impacts for an economy (e.g. Climate Impact Explorer) or provide a starting point for quantitative risk analyses (e.g. macroeconomic impacts in NGFS scenarios).
- ***Exposure-at-risk*** metrics are a suggested adaptation of the FSB *exposure* metric concept to the specificities of physical climate risks. Physical climate exposure-at-risk risk metrics only assess the intersection of hazards and exposure, which may include financial exposure. They identify what is at risk without yet evaluating the susceptibility of the exposed elements. Portfolio and asset-level exposure metrics do so for specific financial portfolios or assets. Such approaches may allow for granularly assessing potential vulnerabilities, even when the lack of vulnerability data does not allow for assessing potential losses.
- ***Risk*** metrics take a step further by integrating vulnerability into the analysis. They account for both what is exposed to hazards and how likely it is to suffer harm, given its specific characteristics and resilience. They thus account for the vulnerability of exposure with respect to hazards. When considering the financial consequences of physical impacts, this allows more specificity to compute *financial risk* metrics or financial sector loss metrics, which aim to quantify how risks transmit to the financial sector. The FSB framework definition of risk focuses on such financial risk metrics; such approaches are the most methodologically and data intensive, but are often a desired final output of climate risk analyses for the financial sector.

2 The first set of these indicators was developed by the European System of Central Banks (ESCB) as part of the European Central Bank (ECB)'s climate and nature plan, initiated in 2021. The indicators were first published in January 2023 and have since been refined in subsequent releases (see ECB's website: "Analytical indicators on physical risks").

Table 1 **Examples of financial indicators of physical climate risks**

Indicator	Explanation and examples
Aggregate proxy metrics	
Historical aggregate losses from climate hazards	***What?*** Records of historical economic and insured losses, per event. ***Use case?*** Assessing past protection gaps, defining starting points for exposure at risk. ***Example?*** EM-DAT database.
Forward-looking aggregate losses from climate hazards	***What?*** Provides forward-looking acute risk estimates under various climate scenarios (e.g. flood damage to assets under different Representative Concentration Pathways). ***Use case?*** Assessing future increases in risk to infrastructure. ***Example?*** Climate Analytics' Climate Impact Explorer.
Synthetic exposure at risk scores	***What?*** Measures country-level climate vulnerability and readiness. ***Use case?*** By financial institutions to prioritize investment in adaptation projects. ***Example?*** ND-GAIN Index.
Hazard and exposure cross-analysis	***What?*** Combines hazard data with socio-economic exposure. ***Use case?*** To assess risks for multinational operations or sovereign investments. ***Example?*** OECD Country Risk Analysis.
Portfolio and asset-level exposure metrics	
Portfolio potential exposure at risk	***What?*** Evaluates financial exposure to debtors with activities in areas susceptible to hazards, without considering their vulnerability and adaptation strategies. ***Use case?*** To assess risk distribution across different financial portfolios and regions in a harmonized way. ***Example?*** Potential exposure at risk (PEAR) in ECB analytical physical risk indicators.
Portfolio exposure to different hazard intensities	***What?*** Indicate value and percentage of portfolio associated with debtors located in areas of varying physical risk. Compared to a 'potential financial exposure at risk' metric, there is additional information on hazard intensity (but not on vulnerability). ***Use case?*** Risk scores provide valuable insights for assessing relative risk levels across countries, climate scenarios, and variations within the same hazard type. ***Example?*** Risk scores in ECB analytical physical risk indicators use a scale from 0 (no risk) to 3 (high risk).
Regional Hazard-Exposure Proxy	***What?*** Combines hazard data with asset exposure for regional analyses. ***Use case?*** By banks to evaluate real estate portfolio risks. ***Example?*** S&P Physical Risk Heat Map.
Asset-Level Potential Exposure	***What?*** Assesses the exposure of corporate assets to regional hazards. ***Use case?*** In corporate credit rating adjustments. ***Example?*** Moody's Climate Risk Data.
Financial sector loss metrics	
Direct losses to physical assets	***What?*** Asset-level loss estimates from extreme events, through natural catastrophe models. May be forward-looking, *inc.* with respect to evolution of exposure. ***Use case?*** By insurers to assess underwriting risks, price premiums, assess reinsurance needs, or as an input to other financial risk metrics. ***Example?*** Munich Re NatCatSERVICE.
Input credit risk metrics – Climate-Adjusted Probability of Default (PD), Climate-Adjusted Loss Given Default (LGD)	***What?*** Adjusts the traditional PD and LGDs to incorporate the impact of physical climate risks on borrowers' creditworthiness, considering factors such as increased default risk due to extreme weather that can disrupt businesses and reduce repayment capacity. ***Use case?*** Integrating climate risk into credit risk models and stress testing. ***Example?*** PD adjustments provided in NGFS short-term scenarios (especially the Disasters & Policy Stagnation scenario, capturing extreme weather events impacts).
Input market risk metrics – Climate-Adjusted Equity prices, Climate-Adjusted corporate & sovereign spreads	***What?*** Adjusts market risk metrics to incorporate the impact of physical climate risks on counterparties' value, e.g. through increased indebtedness and reduced future cash flows. ***Use case?*** Integrating climate risk into market risk models and stress testing. ***Examples?*** Equity adjustments & climate-adjusted corporate/sovereign spreads provided in NGFS short-term scenarios, MSCI Climate Value at Risk (VaR) for listed companies.
Underwriting risk	***What?*** Impact of physical climate risks on insured people and assets. ***Use case?*** Climate stress testing, risk management by insurers. ***Example?*** Evolution of insurance loss ratios may relate forward-looking estimates of insured losses to hypotheses on premium pricing, which may take into account the reactions of policyholders (see ACPR 2023-2024 climate exercise).
Other input financial risk metrics	***What?*** Other metrics needed to capture financial impacts across assets in financial institutions' portfolios. ***Example?*** Shocks to risk-free rates in NGFS short-term scenarios.
Portfolio-level expected losses	***What?*** Estimates the expected loss in FI's portfolios, at a given time horizon and in a given scenario, for credit & market risk. Credit risk indicators may take into account physical and financial collateral. ***Use cases?*** Climate-induced credit or market risk estimation. ***Examples?*** (1) ECB analytical physical risk indicators, especially Normalised exposure at risk (NEAR) and Collateralised exposure at Risk (CEAR). (2) Expected Credit Loss under climate stress scenarios (EL = PD × LGD × Exposure at Default (EAD), adjusted for the effects of physical risks under specific climate scenarios).

Source: Authors, based on (FSB, 2025), ECB, (Bank of England, 2021), Climate Analytics, NGFS, World Bank, OECD, Munich Re, S&P, Moody's, EM-DAT.

Physical climate risk metrics initially focused on exposure-at-risk, with further work needed to integrate vulnerability elements. Granular exposure metrics include the Potential Exposure at Risk (PEAR), which evaluates the financial exposure of institutions to areas affected by physical climate hazards by capturing the geographic and financial overlap of portfolios with hazard zones. This indicator can be applied across different financial portfolios and regions. In practice, it currently focusses on non-financial companies and does not yet take into account households. It also does not incorporate vulnerability and typically does not reflect risk mitigation or adaptation strategies, discussed in Chapters 3 and 4. Financial sector loss metrics include the Normalized Exposure at Risk (NEAR) metric, which estimates the financial losses that institutions might face if borrowers are unable to fulfil their loan obligations due to the destruction of their physical assets by a natural disaster. This metric incorporates hazard intensity by utilizing damage estimation functions, discussed in Chapter 3. NEAR factors in the likelihood of hazards occurring, enabling the calculation of expected losses. These losses can be reported both on an annual basis and over the remaining duration of financial instruments, providing insights into differences arising from the maturity profiles of banks' portfolios. The Collateralized exposure at risk (CEAR) metric is an extension of NEAR which accounts for the loss absorption capacity of collateral. The indicator also accounts for the exposure to physical risk of the collateral itself.

Data quality is critical in assessing physical climate risks, which requires understanding the underlying methodological assumptions and inputs of different data sources available to central banks and supervisors. Quality of data encompasses considerations such as granularity, scope, and methodological transparency and reliability. A range of commercial data vendors already provide ready-to-use physical climate risk scores and assessments. Such physical risk scores can differ significantly across providers (Hain, Kölbel, & Leippold, 2022). At the same time, several central banks and supervisors have started to develop their own methods leveraging in-house data, allowing for more control over methodological assumptions. However, such data is resource intensive to collect. Central banks and supervisors also can rely on physical risk assessments done by financial institutions. The next chapters unpack the different elements that go into a physical risk indicator and assessment, which inform both commercial and in-house physical climate assessments.

3. Data needs to assess climate hazards, exposure, and vulnerability

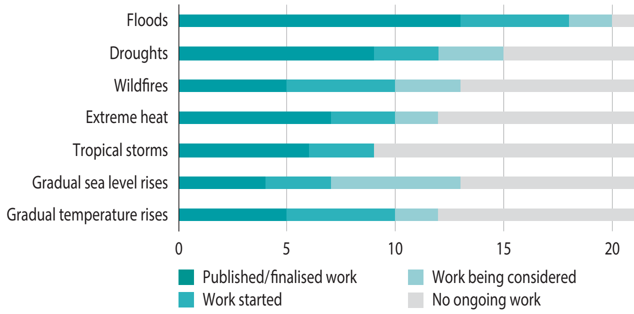
Physical risk metrics require different types of data inputs, namely climate-related hazard information (Section 3.1), exposure data (Section 3.2), and vulnerability data (Section 3.3). Together, such data enable more accurate risk assessments and can guide investment decisions. Data on forward-looking climate projections are critical for integrating long-term risk considerations into planning processes, while historical data helps validate models and identify patterns of past climate impacts. Integrating such comprehensive physical risk data into decision-making frameworks is pivotal for achieving resilience and equitable development.

3.1 Climate-related hazard metrics and data sources

Climate-related hazards are diverse, requiring the use of a combination of different data sources. Climate-related hazards range from wildfires and extreme temperatures to floods and droughts. The general framework on climate-related hazard indices from the Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report (AR6) has identified 28 Climatic Impact Drivers (CID) grouped into seven main types (IPCC, 2022). The categories are heat and cold, wind, coastal, wet and dry, snow and ice, open ocean, and other. Hazards can be acute or chronic. *Acute hazards* are sudden, short-term, extreme weather events, like hurricanes and floods, that cause immediate and severe infrastructure damage and economic disruption. *Chronic hazards* are long-term changes that gradually affect climate patterns, such as rising temperatures and sea-level rise that gradually erode asset values and challenge business sustainability.

Survey responses indicate that central banks and supervisors are already assessing a wide range of climate-related hazards, including gradual sea level rises, temperature increases, wildfires, droughts, floods, storms, and extreme heat (Figure 5). The prioritisation of such hazards will depend on the geographic and sectoral context of an analysis. For example, Banco de España and the Spanish Macroprudential Authority Financial Stability Council (AMCESFI) assess risks from droughts, floods, and extreme heat among others (Álvarez-Román, Mayordomo, Vergara-Alert, & Vives, 2024; AMCESFI, 2023), while the Deutsche Bundesbank evaluates the probability of future flooding and wildfire risks.

Figure 5 **Climate-related hazard assessed by central banks and supervisors**



Note: Results of 21 NGFS members across all continents responding to the survey. See further details of the scope of the survey in Annex I.
Source: 2024 Physical Risk Survey.

A range of open-source cross-country geospatial data sources, metrics, and tools are already available for various hazards. Climate-related hazards are assessed by looking at hazard-specific climate metrics (Table 2), which can vary even for the same hazard. Differing datasets can follow different approaches and methodologies, providing data on historical or projected climate-related hazards. Aside from several open-source global data sources, tools have been developed to facilitate their use. For example, the Copernicus Climate Data Store Toolbox and Google Earth Engine enable large-scale spatial analysis to monitor climate trends and simulate event-specific impacts while offering insights for scenario analysis. At the same time, national data is typically more precise to localize hazards. However, national data sources are not yet available for all countries and face interoperability limitations.

Despite significant advances, spatial data analysis for physical risk assessment could be hampered by several challenges. A major obstacle lies in the lack of high-quality granular data, particularly for emerging economies, where climate risks are often more acute. This limitation hampers accurate modelling of some acute hazards, such as floods, and chronic hazards, like sea-level rise. Validation of spatial data models poses another challenge, as discrepancies between satellite data and ground-based measurements can lead to inaccuracies in risk estimations. To address these issues, investment in open-access geospatial datasets, enhanced modelling capabilities, and collaborative frameworks between climate and financial experts are critical.

Table 2 **Examples of data sources to measure climate exposure of physical assets**

Climate hazard	Metric	Source	Temporal perspective	Geographic coverage
Extreme heat	Universal Thermal Comfort Index (UTCI)	Copernicus ERA5-HEAT (reanalysis)	Historical (1979-present)	Global
	Hot days	NASA NEX-GDDP-CMIP6	Forward-looking	Global
	Heatwave occurrence	EURO-CORDEX	Historical (1970-2005), forward-looking (20062100)	Europe
	Mean, minimum, maximum Temperature, hot days, tropical nights	Copernicus ERA5-Land	Historical (1979 to present)	Global
Drought	Meteorological drought: Standardised Precipitation and Evapotranspiration Index (SPEI)	Global SPEI database	Historical	Global
	Meteorological drought: Standardised Precipitation and Evapotranspiration Index (SPEI)	World Bank	Forward-looking	Global
	Agricultural drought: Risk of Drought Impacts for Agriculture (RDrl-Agri)	European Commission Joint Research Centre (JRC)	Historical (2013-present)	Global
	Meteorological drought	HELIX	Historical	Global
	Hydrological drought	European Commission Joint Research Centre (JRC)	Historical	Global
	Volumetric surface soil moisture	Copernicus ERA5-Land	Historical (1979-present)	Global
River flooding	Flood prone areas: Flood depth (m)	WRI Aqueduct flood hazard maps	Historical, forward-looking	Global
	Flood depth (m) and probabilities of occurrence	European Commission Joint Research Centre (JRC)	Historical	Global/Europe
	Flood depth (m) and probabilities of occurrence	Delft University of Technology	Historical (1971-2000), forward-looking (2021-2050)	Europe
Coastal flooding	Flood depth (m)	Deltares	Historical	Global
	Flood prone areas: Flood depth (m)	WRI Aqueduct flood hazard maps	Historical, forward-looking	Global
	Flood prone areas: Flood depth (m)	World Bank Global Coastal Flood Hazard Maps	Historical	Global
	Flood depth (m), probabilities of occurrence, storm surge heights	Delft University of Technology	Historical (1971-2000), forward-looking (2021-2050)	Europe
Wildfire	Danger rating: Fire danger index	Copernicus ERA5	Historical (1979-present)	Global
	Danger rating: Fire danger index	Copernicus CORDEX	Forward-looking	Global
	Burned area	MODIS/Terra and Aqua MCD64A1 product	Historical (2000-present)	Global
	Active fire data	NASA	MODIS: Historical (2000-present) VIIRS: Historical (2012-present)	Global
Extreme wind	Wind speed	EURO-CORDEX	Forward-looking	Europe
	Maximum 10 m wind gust	Copernicus ERA5	Historical (1979-present)	Global
	Mean wind speed at a height of 10 / 100 m above the surface (m s-1)	Copernicus ERA5	Historical (1979-present)	Global
	Tropical cyclone track data	NOAA	Historical (1841-present)	Global
	Pacific hurricane catalog	NOAA	Historical (1851 present)	Atlantic, Pacific

Source: Adapted from (Noels, Bernhofen, Jachnik, & Touboul, 2024), based on (Maes, *et al.*, 2022; Freeman, *et al.*, 2024; ECB, 2024).

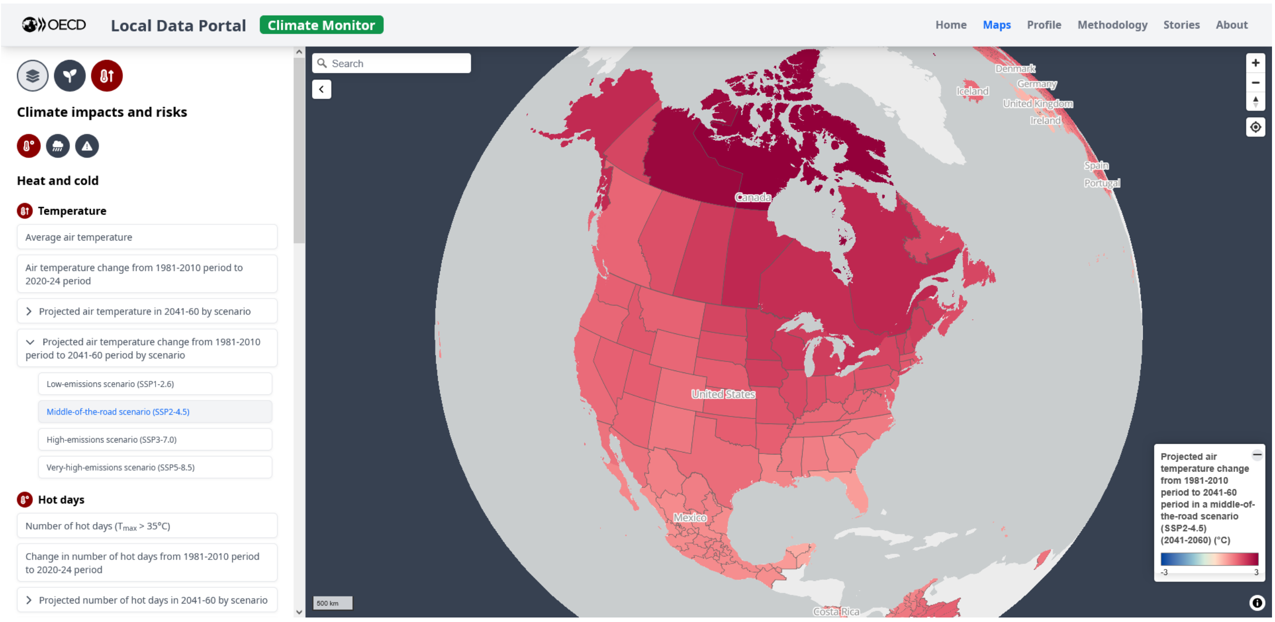
Box 1

Climate indicators in the OECD Local Data Portal

The OECD Local Data Portal is an interactive platform designed to help policymakers, researchers, and the public explore and compare subnational data across 41 countries. It provides access to over 100 indicators across 10 key themes, including demography, environment, climate change, energy, transport, economy and labour, territorial organisation, housing, services, and public finance. Developed by the OECD Laboratory for Geospatial Analysis, the OECD Local Data Portal allows to visualise and compare subnational data at different territorial levels across 41 countries, in close to 225,000 municipalities and local areas, 3,000 regions, and 1,500 cities.

The portal features a sub tool called the **Climate Monitor**, which allows users to visualise indicators related to climate mitigation, impacts, and risks, including future climate projections. This tool enhances local-level understanding of climate challenges and helps guide effective adaptation and sustainability strategies at the local level.

Figure 6 **Climate impacts and risks available in the OECD Local Data Portal – Climate Monitor**



Source: OECD Local Data Portal, https://localdataportal.oecd.org/.

3.2 Climate-related exposure data

While climate-related exposure data is used to identify the presence of a range of socio-economic and environmental systems, the focus here is on economic activities and related physical assets. Climate-related exposure data broadly relates to people, activities, assets, or ecosystems that could be affected by hazards. Climate-related analysis serving different purposes may focus on different elements. Here, the focus is on physical assets and economic activities.

Granular and consistent asset-level data on exposure to climate-related hazards are needed to accurately assess risks. In practice, banks often have access only to the registered address of a borrower (e.g., a corporate headquarters). The headquarters may however not be where critical assets, such as factories or warehouses, are located. A company with operations spread across multiple regions faces varying physical risks at each site. Therefore, banks and other market participants may underestimate or misjudge risks. A more precise assessment requires information on the exact geographical location of the company's assets. Excluding physical assets and locations other than headquarters grossly underestimates exposure to climate hazards, with existing research having estimated that up to 70% of expected investor losses may be missed (Bressan, Đuranović, Monasterolo, & Battiston, 2024). The specific location of assets is important, but depending on the type of hazard, more or less precise data is needed. For example, the impact of river floods varies significantly for an asset that is 10 meters versus 100 meters away from the river, making very granular information on assets necessary. In case of windstorms, location data at ZIP-code level might suffice.

Aside from the location of assets, other types of information on individual physical assets are needed, such as the asset type and characteristics, value, and (corporate) owner. Different types of physical assets can be affected by climate-related hazards in different ways. Examples of physical asset types include production plants for the manufacturing sector, power plants for the energy sector or mines for the mining sector, as well as various types of infrastructure, buildings, and agricultural assets. Information on asset characteristics – such as year of construction, building materials, and protection measures (e.g. elevation above ground level for flood resilience, or structural resistance to earthquakes) – are also essential, as these factors affect how well assets can withstand extreme events. Asset damage functions determine damage costs based on the value of an asset, which can be valued for example at replacement value. Finally, asset-level data needs to be connected to the corporate owner (to later aggregate for entity level and financial portfolio analysis).

Privacy concerns limit the accessibility of asset-specific data across regions.[3] In many cases, asset data on location, asset type, value, and (corporate) owner of the individual assets of a counterparty constitute private information.

- With respect to households, location information on postal codes may be sufficient for analysis of certain hazards. Generally, household data is privacy protected, making it difficult to localize precisely households' assets or sources of income.
- With respect to firms, central banks and financial supervisors have access to databases that localize corporate establishments and economic activity. For example, the European System of Central Banks has a comprehensive database of corporates (RIAD) which includes information on the location of headquarters, and on total assets for each company. The Banco Central do Brasil can identify economic activities through its internal credit bureau (Box 2). However, most databases lack geographical information on physical assets other than corporate headquarters, as well as information on the asset types (ECB-ESRB, 2023). For any company operating across multiple locations, such gaps lead to risk mismeasurement as the physical risk of the company headquarters is usually not representative of the company as a whole[4], especially for companies with multiple branches, which make up a significant part of financial institutions' balance sheet. Hence, the database needs to be complemented with data on production premises (De L'Estoile, Kerdelhué, & Verdier, Fortcoming; Loberto & Russo, 2024).

Existing commercial data providers of physical climate risk assessments in finance tend to have access to very granular in-house or commercial data of physical assets. Several providers of physical climate risk ratings integrate asset data that was collected in-house, based on corporate reporting in annual reports, publicly available reporting submitted to regulators such as 10-K forms in the US, or corporate websites, as well as from vendor or regulatory data (Noels, Bernhofen, Jachnik, & Touboul, 2024). In most cases, information on location, size, tangible fixed asset value, asset type, and ownership is collected. Some may also collect data on revenue, usually collected at the firm level and attributed to assets based on for example production shares.

Emerging asset-specific datasets on asset locations and ownership links enable physical risk analysis. While microdata on physical assets are generally scarce or not publicly available, there are increasingly public and open-source initiatives (Table 3). Some public databases on locations of physical assets are available, with increasing efforts by NGOs and academia (Noels, Bernhofen, Jachnik, & Touboul, 2024). Such facility-level data is also collected under emissions trading schemes in specific jurisdictions,

3 Discussions at the OECD-NGFS Workshop on Assessing the Climate Resilience of Finance: From physical risk to resilience alignment.

4 A complementary analysis by ECB and Banque de France staff however showed that for analyses at portfolio level, this assumption may be reasonable (Borea, *et al.*, 2024).

Table 3 **Examples of data sources on locations of physical assets that include information on ownership linkages**

Database	Establishments type covered	Sectors covered	Corporate owner indicators	Region
ETS platforms (e.g., from EU or Chile)	Production facilities	Manufacturing and energy	Legal Entity Identifier (LEI), Reporting Unit Identifier (RUI), other (depending on jurisdiction)	Global
Global Energy Monitor	Production facilities	Energy and steel	Own Identifier	Global
Orbis	Headquarters	All sectors	Legal Entity Identifier (LEI), Own *Identifier*	Global
Register of Institutions and Affiliates Data (RIAD)	Headquarters	All sectors	Legal Entity Identifier (LEI), International Securities Identification Number (ISIN), RIAD code	EU
Spatial Finance Initiative GeoAsset Databases	Production facilities	Beef abattoir, cement, iron and steel, petrochemicals, paper and pulp, waste management	Legal Entity Identifier (LEI), International Securities Identification Number (ISIN)	Global
S&P Global Platts	HQ and production facilities	Energy and mining	Legal Entity Identifier (LEI), International Securities Identification Number (ISIN)	Global

Source: Adapted from (Noels, Bernhofen, Jachnik, & Touboul, 2024).

such as in the context of the EU ETS. However, these types of data sources do not allow to analyse all establishments of some major multinational manufacturing and energy companies, which typically own physical assets across multiple countries, not all of which have an emissions trading scheme or detailed public data. Moreover, such data does not cover all sectors and geographies. This approach can be complemented by global data being collected for specific sectors (Table 3). Existing public data tends to be collected for specific sectors such as steel, cement, and coal, and often covers advanced economies more comprehensively than emerging markets and developing economies. Additionally, small companies may not always be sufficiently represented in such datasets.

Finally, satellite data could also be used to estimate the geographical exposure of asset values. For example, the ETH Zurich uses a combination nightlight intensity and population data to provide gridded asset exposure data (litpop).[5] However, the main challenge with this type of approach is that the estimated **exposure** data is not matched to specific debtors. Additionally, these kinds of estimations of asset value tend to be very rough and do not account for asset value within buildings such as machinery and equipment.

5 https://www.research-collection.ethz.ch/handle/20.500.11850/331316.

Box 2

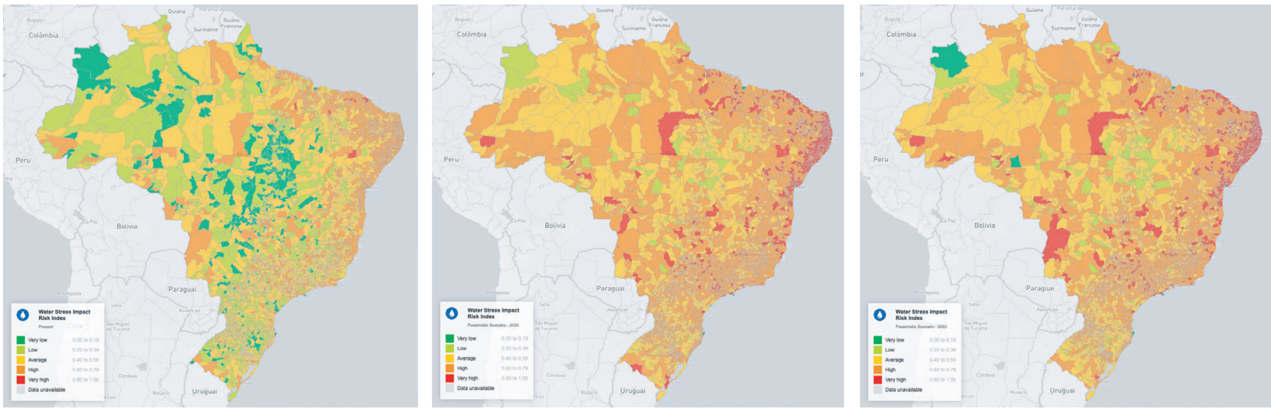
Sensitivity analysis to drought risk: Brazilian case study

The Banco Central do Brasil (BCB) has explored a sensitivity analysis to drought risk following a three-step method, namely (i) projection of climatic changes effects; (ii) estimation of climate risks in each municipality in the stressed scenario; (iii) identification of economic activities with most intense use of water in its production processes or services. The analysis assessed the share of current credit portfolios consisting of loans granted to debtors in municipalities and economic sectors expected to be significantly impacted by an extreme drought scenario projected for 2030-2050. The meteorological projections and estimations of climatic impact risks (steps i and ii) are obtained from the Sistema de Informações e Análises sobre Impactos das Mudanças Climáticas (AdaptaBrasil MCTI portal), whereas data needed for step iii, regarding credit books distributions are obtained from the BCB's credit bureau – Sistema de Informações de Crédito (SCR).

…/…

Figure 7 **Risks from extreme drought in Brazil**

Risk of impacts in water resources – Current | **Risk of impacts in water resources – 2030 Scenario (Pessimistic)** | **Risk of impacts in water resources – 2050 Scenario (Pessimistic)**



Source: (Banco Central do Brasil, 2022).

3.3 Climate-related vulnerability metrics and data sources

The vulnerability of an exposed asset is influenced by its physical characteristics, function, and level of adaptation (Noels, Bernhofen, Jachnik, & Touboul, 2024). Physical characteristics include the structure's design, the material used in its construction, the quality of its construction, or the age of the asset. For example, older and poorly maintained structures are more likely to be susceptible to climate impacts. The function of an asset also determines its vulnerability. For example, a storage facility for materials is generally less vulnerable to extreme heat than a building where hundreds of employees work. Furthermore, the asset's dependence on its surrounding environment and infrastructure is crucial. For example, an asset used as a logistical hub would be more vulnerable to the flooding of nearby roads and transportation networks than a data centre asset, which is less reliant on such external conditions.

For assessing direct capital impacts, granular damage functions are a key component linking the intensity of hazards with the corresponding costs. An example of using damage functions for bottom-up analysis can be found in the ESCB analytical physical risk indicators: damage functions were used for river and coastal floods as well as for windstorms.[6] The damage functions that were used for river and coastal floods were based on historical flood data (Huizinga, De Moel, & Szewczyk, 2017) and provided loss percentages per flood depth, differentiated by macro-region and by type of land cover (e.g. residential vs commercial). Damage functions for windstorms were based on a damage model by (Koks & Haer, 2020). For other climate-related hazards, there is still a lack of granular bottom-up damage functions. Some national sources (e.g. INRAE damage functions in France) may complement regionally or globally calibrated damage functions, as they may be more tailored to the specificities of the exposure in one's economy.

Current approaches for incorporating vulnerability into assessments of risk vary depending on the type of analysis being carried out as well as the hazard that is being assessed. Certain sectors and activities will be more vulnerable to certain hazards than others (Addoum, Ng, & Ortiz-Bobea, 2023; Graff Zivin & Neidell, 2014). For certain hazards (such as flooding and extreme wind) there is more data on vulnerability than others. This is partially the case because modelling the relationship between economic damage and hazards is more complex for some hazard types. The following examples of using damage functions for different hazards can inform further analysis (Noels, Bernhofen, Jachnik, & Touboul, 2024):

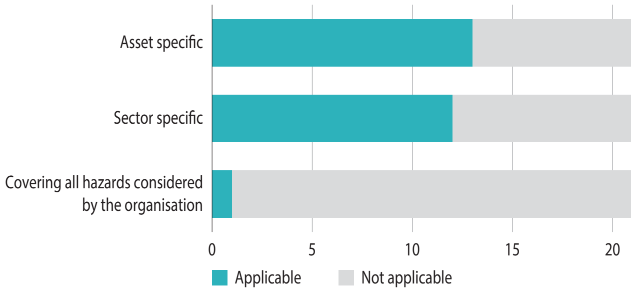
- **Extreme heat** significantly lowers labour productivity and increases energy costs, especially in smaller firms (Costa, Franco, Unsal, Mudigonda, & Caldas, 2024;

6 https://www.ecb.europa.eu/pub/pdf/scpsps/ecb.sps48~e3fd21dd5a.en.pdf p. 72.

Ponticelli, Xu, & Zeume, 2023). Assessments will typically use different heat vulnerability functions and draw on different empirical literature depending on whether they assess impacts on office workers, outdoor workers, or the intensity of the workload.

- Damage functions for **flooding** relate the intensity of a flood to the level of damage that it causes. Typically, flood depth is used to represent the intensity of the flood in vulnerability functions, but flood velocity and flood duration can also be used. The most frequently used open vulnerability datasets in assessments of flood risk have been developed by combining various national-level datasets (Huizinga, De Moel, & Szewczyk, 2017). These were also used in the ECB's economywide climate stress test (Alogoskoufis, *et al.*, 2021).
- For **extreme winds and storms**, vulnerability functions relate wind speed to the level of damage that it causes. A widely used windspeed vulnerability function is a function derived using storm insurance claims data in the US (Emanuel, 2011). This function was extended to further regions globally using empirical data on global historical storm losses (Eberenz, Lüthi, & Bresch, 2021). These regional functions are integrated into open-source tropical cyclone risk assessment tools (Bresch & Aznar-Siguan, 2021) and have been used extensively in assessments of climate financial risk (Bressan, Ðuranović, Monasterolo, & Battiston, 2024).

Figure 8 **Characteristics of climate damage functions used by central banks and supervisors**



Note: Results of 21 NGFS members across all continents responding to the survey. See further details of the scope of the survey in Annex I.
Source: 2024 Physical Risk Survey.

Box 3

CLIMADA tool

CLIMADA (CLIMate ADAptation) is an open-source Python-based tool to assess financial risks and economic impacts of climate-related hazards, as well as to appraise adaptation options (Aznar-Siguan & Bresch, 2019; Bresch & Aznar-Siguan, 2021).[1] It can be used to assess different types of climate-related hazards. It provides an event-based probabilistic approach, meaning it can simulate many individual climate-related events – both actual historical events and synthetic plausible events – and assign a probability to each, to estimate how likely it is to cause damage. CLIMADA is globally consistent and suitable from country-level to detailed local assessments.

Central banks and supervisors can use CLIMADA's probabilistic framework to calculate a range of physical climate risk indicators. For example, average annual expected losses for specific economic assets and financial asset classes, as well as annual exceedance frequency curves to stress test extreme but plausible climate events. CLIMADA also informs the floods and cyclones acute risk modules of the Phase IV of NGFS long-term climate scenarios (NGFS, 2023).

1 https://climada.ethz.ch/.

3.4 Physical climate risk from value chains

Aside from direct physical climate risks, firms can also be affected by climate risks indirectly through its value chains. Such risks can represent a significant share of a firm's overall physical climate risk. There are two types of value chain risks, namely supply chain risks and market risks (Noels, Bernhofen, Jachnik, & Touboul, 2024). Supply chain risks include trade and transport infrastructure disruptions due to climate-related hazards. Market risks include changes in availability of goods and services, macroeconomic damages, and global systemic risks due to climate-related hazards.

Measuring climate risks across the value chain of a given company is complex and data intensive. It requires identifying suppliers and customers of a given facility or entity, assessing the volume or value of products and services exchanged, evaluating the risks associated with their production, and analysing the substitutability of the product or supplier (Noels, Bernhofen, Jachnik, & Touboul, 2024). For physical goods, the climate resilience of their transportation modes, trade route and related infrastructure are also critical factors (NGFS, 2024). Most companies do not (at the moment) fully disclose their supply chain dependencies, and their supply chains can span hundreds of firms across multiple countries, making it hard to track vulnerabilities. A very limited number of research studies have yet been developed to assess value chain risks by combining multiple micro-level data sources. One study used detailed customer-supplier relationships data from FactSet Revere, with financial performance data from Worldscope and geographic location and establishment-level data from FactSet Fundamentals and Moody's Orbis (Pankratz & Schiller, 2023). Another study shows central banks can leverage detailed administrative data already available to them (see Box 4).

Aggregated country-sector climate risk indicators have been used to address data challenges to capture supply chain risks (Noels, Bernhofen, Jachnik, & Touboul, 2024)**.** Some analyses rely on the OECD Inter-Country Input-Output Database (OECD, 2023), while others use multiregional input-output (MRIO) analysis. MRIO combines regional and national input-output tables to map global economic interdependencies between sectors and economies. The Input-Output Trade Analysis (IOTA) model is a hybridized physical-financial MRIO modelling framework, providing both the commodity specificity and resolution of production that is available in global trade databases, as well as the full supply chain coverage of MRIO analysis (Adams, Benzie, Croft, & Sadowski, 2021). While this approach can provide an industry-average estimate of physical risk exposure in the value chain, it does not reflect information on specific asset locations.

Box 4

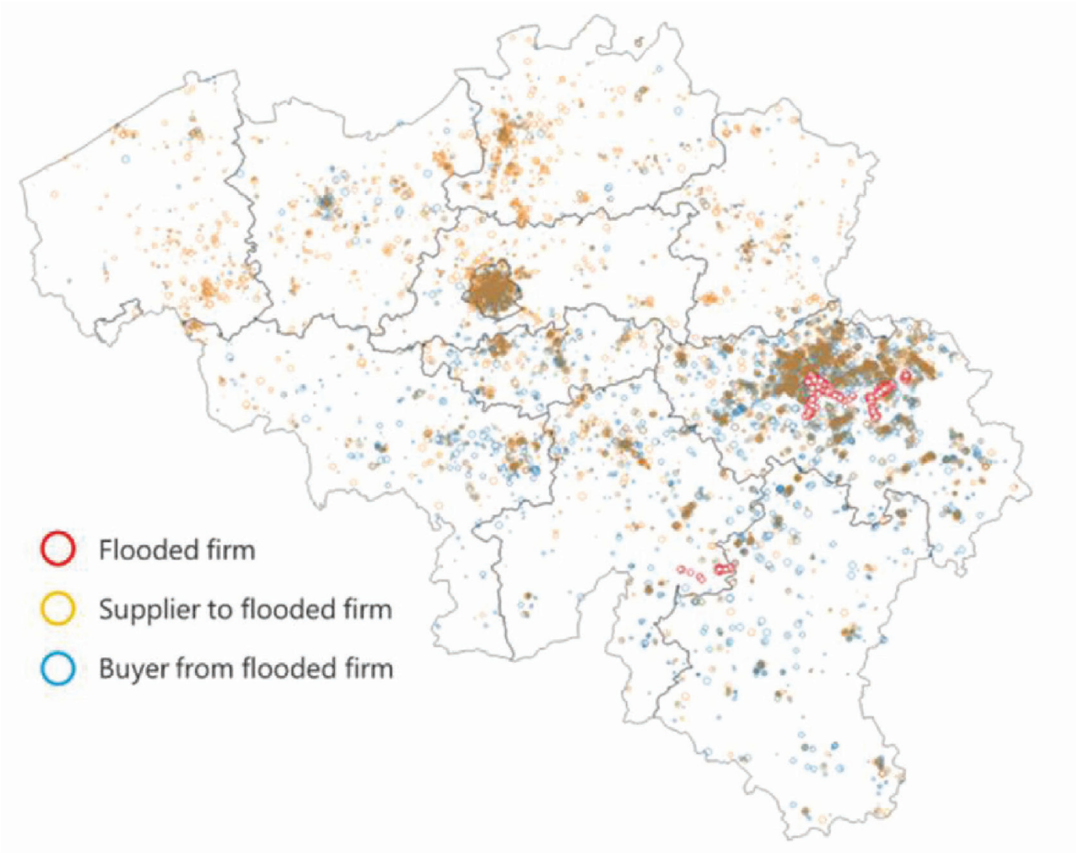
Data to identify supply chain risks of climate-driven natural disasters: Belgian case study

To identify supply chain risks from climate-related natural disasters, multiple administrative micro-level data sources need to be combined. A study of physical climate supply chain risks combines six data sources from the National Bank of Belgium (Bijnens, Montoya, & Vanormelingen, 2024), namely: (i) VAT declarations, which track sales, investments, and intermediate inputs on a quarterly basis; (ii) Social Security data, offering information on employment and wage bills; (iii) Business-to-Business (B2B) transaction data, which captures buyer-supplier linkages through VAT customer listings; (iv) the Crossroads Bank of Enterprises (CBE), containing firm characteristics such as location and incorporation details; (v) Annual Accounts, which provide financial statements, including balance sheets and profit-and-loss data, particularly for large firms; and (vi) Trade Data, which includes firm-level imports and exports categorized by product and country. These datasets are linked using a unique firm identifier, enabling the construction of supply chain networks and assessment of disruptions. Additionally, flooding data from the Public Service of

.../...

Wallonia, derived from satellite and aerial imaging, helps geolocate affected firms. By filtering firms in the most severely impacted areas and mapping their proximity to flooded zones, researchers can identify supply chain disruptions and assess resilience. This approach allows to assess both direct and indirect economic impacts of climate-related disasters on firms and supply chains.

Figure 9 **Locations of flooded firms, their clients in suppliers in Belgium**



Notes: The red dots represent the flooded firms as described. The blue dots represent the connected buyers of these firms. The orange dots represent the connected suppliers. The size of the dots is weighted according to thier level of trade exposure.
Source: (Bijnens, Montoya, & Vanormelingen, 2025).

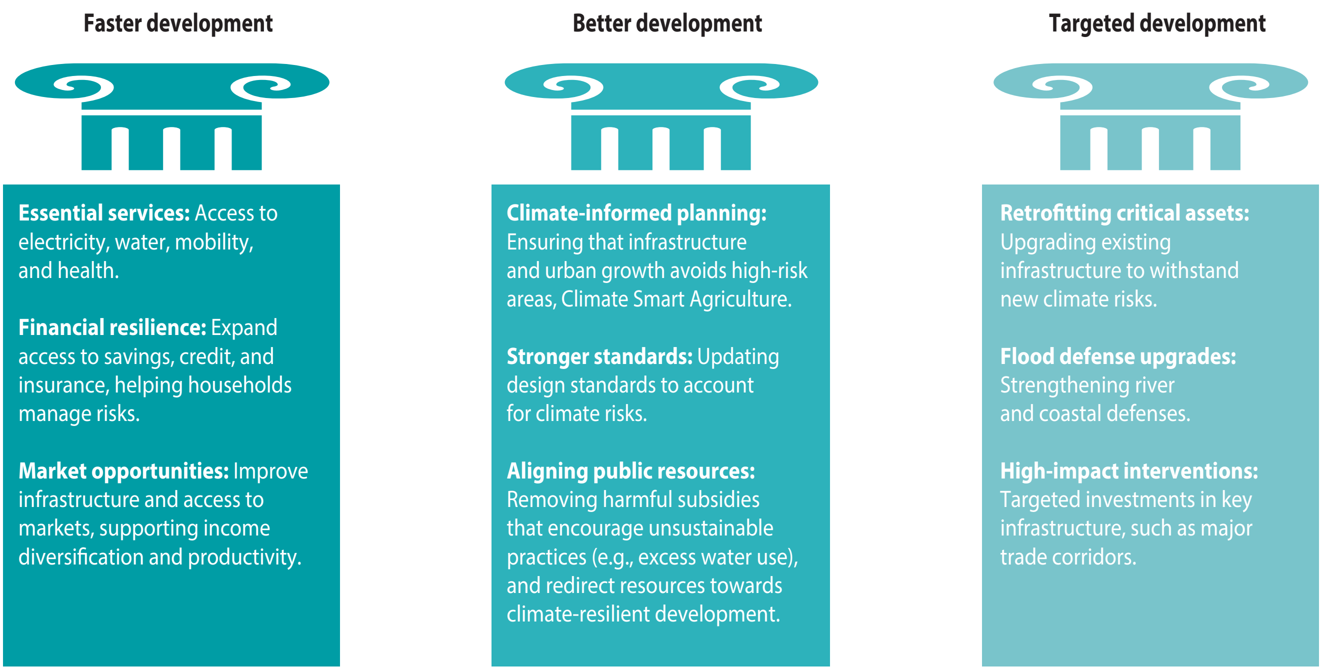
4. Data considerations on climate change adaptation and resilience

Adaptation and resilience are an important step in addressing physical climate risks (NGFS, 2024). *Climate adaptation* is the process of adjusting ecological, social, or economic systems in response to actual or expected climatic change and its effects, aimed at reducing vulnerability and building resilience (Ara Begum, *et al.*, 2022). This includes a wide range of actions at individual, community, and systemic levels. *Climate resilience* refers to the capacity of social, economic, and environmental systems to cope with hazardous events or trends related to climate change (Ara Begum, *et al.*, 2022).

Adaptation can either be incremental or transformational implying different levels of ambition. *Incremental adaptation* maintains the integrity of existing systems, through measures such as no-regret actions (e.g., early warning systems to alert the population of looming climate hazards), climate-smart infrastructure (i.e., infrastructures that are climate resilient and might prove cost-effective over longer periods), and low-cost preparatory and early actions (Mongelli, Ceglar, & Scheid, 2024). *Transformational adaptation* envisages changes in the fundamental attributes of a system in anticipation of further climate change and more severe impacts (World Bank, 2024; Möller, *et al.*, 2022).

Building climate resilience and adaptive capacity has a symbiotic relationship with good development, and often separating the two for the purpose of monitoring and tracking adaptation efforts can be challenging. Minimizing the present and future impacts of climate change and building resilience requires (1) achieving faster development to close socioeconomic gaps and provide essential services, (2) better development that integrates climate risk management into growth and sectoral strategies, and (3) targeted adaptation interventions to address climate vulnerabilities of the most at-risk sectors, populations and communities. These three pillars need to work together to build resilience and support equitable development in a changing climate (World Bank, 2024).

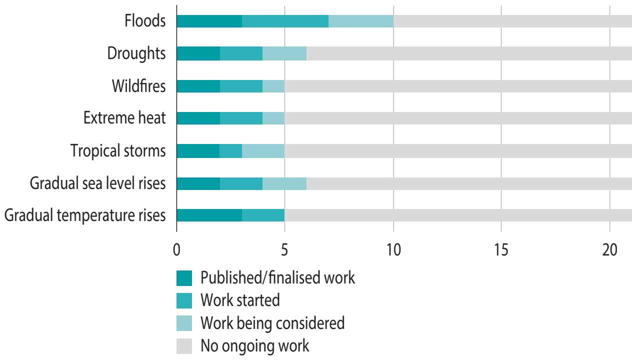
Figure 10 **Pillars of climate resilient development**



Source: (World Bank, 2024).

Across hazards, central banks cannot yet comprehensively account for adaptation actions and resilience strategies. A select number of central banks and supervisors have started to include adaptation actions, such as upgrading physical assets with flood defences, for all hazards but mainly for floods (Figure 11). This for example, includes upgrading physical assets with flood defences.

Figure 11 **Hazards for which adaptation actions are included in the physical climate risks analysis**



Note: Results of 21 NGFS members across all continents responding to the survey. See further details of the scope of the survey in Annex I.
Source: 2024 Physical Risk Survey.

Adaptation metrics can be developed through a maturity pathway (NGFS, 2025). As adaptation-related data and metrics are still developing, approaches for identifying key adaptation metrics should be practical and recognise the need for a step-by-step approach. This approach can commence with a stocktake (understanding data and coverage status) to facilitate a baseline of adaptation metrics and targets, and progress towards a meaningful set of metrics: from baseline exposure and vulnerability to inputs applied towards adaptation activities, to output-led metrics that quantify the impact of adaptation activities and set these against a target. While data is not yet fully available for all these metrics, this chapter identifies best available data for baseline and input metrics on corporate adaptation actions and resilience strategies (Section 4.1), which reflect physical resilience, and on insurance coverage (Section 4.2), which can contribute to financial resilience.

4.1 Types and sources of data on adaptation actions and resilience strategies

Little data is available to integrate current and potential future adaptation efforts in physical climate risk assessments. Limited data availability partially reflects limited guidance on disclosure needs on corporate climate adaptation actions and targets currently available (Noels, Bernhofen, Jachnik, & Touboul, 2024). Some initial guidance has included some disclosure requirements on adaptation strategies (IFRS ISSB, 2023). Some adaptation frameworks highlight the importance of monitoring and evaluating adaptation and resilience across different scales (World Bank, 2023).

Climate resilience needs to be measured and tracked globally at a country level, institutionally, and at a project level (World Bank, 2023). For example, global and country-level indicators already estimate the number of people highly vulnerable to climate risks with low resilience due to limited access to systems like financial tools and healthcare. Institutional-level indicators can assess the number of people benefiting from enhanced resilience through institutional interventions, such as improved infrastructure, disaster response, and enabling frameworks for climate risk management. Project-level indicators are used to monitor resilience outcomes in economic, environmental, and social systems, linked to specific project interventions and beneficiary impacts.

Different data initiatives are already collecting information on actions undertaken by companies to reduce physical climate vulnerability. Some information on physical climate risk management is already collected in the context of ESG scores (Boffo, Marshall, & Patalano, 2020). Such data is almost exclusively collected by commercial data providers. For example, MSCI has data on risk management as part of its ESG metrics. These tend to be sector specific. In addition, some commercial data providers are starting to also include data on how physical assets are being adapted as a response to increasing climate related hazards. For example, Moody's RMS assessments include information on the characteristics of infrastructure and how it changes over time to increase resilience (Moody's, n.d.).

New solutions are being developed to collect information on adaptation actions and plans by companies. Initial data on corporate climate resilience strategies to reduce vulnerability is collected through corporate questionnaires (Section 4.1.1.). Some initiatives are relying on Large Language Models (LLMs) to assess adaptation progress disclosed in corporate reports (Section 4.1.2.). Nature-based solutions also form a solution to reduce physical climate risks, with efforts to compile data being scaled up (Section 4.1.3.). In addition, information on how exposed assets are being upgraded to decrease their vulnerability is needed. Some commercial data providers are starting to also include data on how physical assets are being adapted as a response to increasing climate related hazards. For example, Moody's RMS assessments include information on the characteristics of infrastructure and how it changes over time to increase resilience.

4.1.1 Adaptation data collected from corporate surveys

Corporate questionnaires are one source of data on corporate climate change adaptation and resilience. Through the CDP annual climate questionnaire, information can be collected on these actions.[7] For example, the questionnaire collects information on the development of climate adaptation, resilience and insurance risk solutions, or on the share of aligned assets contributing to climate change adaptation based on capital expenditure of investees in the reporting year. Companies are increasingly reporting on adaptation actions and resilience strategies (Box 5). However, there are continued challenges to addressing and tracking adaptation coherently and comprehensively.[8]

Box 5

Corporate adaptation progress analysis based on CDP climate questionnaires

An analysis of corporate climate disclosures from the 2022 CDP climate questionnaire shows that companies are increasingly recognising the financial risks of climate change and investing in adaptation and resilience (Chau, *et al.*, 2023). Of the 18,700 companies that responded to the CDP Climate Change Questionnaire, 25% reported physical climate risks and assessed the potential costs of inaction. Many have detailed the adaptation measures they are financing to mitigate these risks, including supply chain resilience measures, water use monitoring and efficiency, flood protection, and decentralized energy generation and storage.

4.1.2 Adaptation data collected from corporate reports through LLMs

Large Language Models (LLMs), such as GPT-4, and specialized Climate Language Models (CLMs), including ClimateBERT, are providing new ways to collect and analyse adaptation data from corporate reports. These models enable the automated analysis of adaptation measures disclosed in corporate reports, which are often aligned with global frameworks such as the Task Force on Climate-related Financial Disclosures (TCFD). LLMs leverage Natural Language Processing (NLP) to automate the identification of adaptation measures within corporate reports. These tools can scan thousands of pages of disclosures, extracting information such as "flood management systems", "green infrastructure investments", or "drought resilience programs". Specialized models like ClimaText enhance this process by focusing on climate-specific data, while FinBERT caters to financial contexts, offering tailored insights into how companies are addressing climate-related risks. This automation enables greater efficiency in analysing corporate preparedness, ensures compliance with reporting standards, and provides a standardized approach to evaluating adaptation strategies across industries and geographies.

7 https://www.cdp.net/en.

8 Discussions at the OECD-NGFS Workshop on Assessing the Climate Resilience of Finance: From physical risk to resilience alignment, including presentation on 'Indicators of Corporate and Financial Strategies to Reduce Physical Risks and Increase Resilience Alignment' by Clare Everett.

LLMs are increasingly being deployed to assess climate disclosures due to their scalability. For example, researchers at the University of Oxford and the University of Zurich have developed the 'Adaptation Alignment Assessment Framework' to assess corporate adaptation plans using LLMs (see Box 6). Another example is ClimateGPT, which uses its NLP capabilities to classify and quantify corporate adaptation initiatives, aiding stakeholders in understanding companies' climate readiness (Thulke, *et al.*, 2024). ClimateBERT is another model fine-tuned on climate-related datasets that can provide more granular insights on adaptation strategies (Webersinke, Kraus, Bingler, & Leippold, 2022). These tools significantly enhance the ability to perform climate-related financial risk analysis, aligning disclosures with regulatory and market expectations while providing actionable insights for investors and regulators.

Box 6

Adaptation Alignment Assessment Framework

Researchers at the University of Oxford and the University of Zurich have developed a framework to harness AI to assess corporate adaptation plans (Spacey Martín, Ranger, Schimanski, & Leippold, 2024). Specifically, their work uses LLMs to retrieve and analyse adaptation information from corporate sustainability reporting. To prevent hallucination in the analysis, they rely on Retrieval Augmented Generation (RAG). RAG systems include external, verifiable information into the input of an LLM and let the model answer only upon this information, not on potentially flawed internal knowledge.

Indicators in this framework relate to foundations, governance, risk, implementation, and metrics and targets. Examples of indicators include:

- Do the climate change adaptation targets set by the company reference/align with external goals/targets?
- Does the company report what assumptions it works with when assessing physical risks arising from nature loss?
- How often does the company report to carry out an assessment of physical risks arising from nature loss?
- Has the company defined a baseline against which its progress on specific climate change adaptation targets is measured?
- Does the company require a physical climate-related risk or opportunity assessment as part of key business operations, such as procurement?

An initial analysis of 100 companies identified as systemically important for nature loss and at high risk of physical climate hazards, shows that on average, these companies report against half of the proposed 65 indicators. Among these companies, there is a high degree of variation in disclosure, with the worst-performing company only reporting against 6 of our 65 indicators and the best-performing company reporting against 52.

Box 7

Project Gaia: Enabling climate risk analysis using generative AI

Project Gaia – a collaboration between the Bank for International Settlements (BIS), the Bank of Spain, the Deutsche Bundesbank and the European Central Bank – leverages AI and LLMs to facilitate the analysis of climate-related risks in the financial system (BIS, 2024). By automating the extraction and categorization of climate-related data, including climate resilience measures, Project Gaia can help address the challenges of unstructured data and inconsistent reporting in the financial sector. For example, the AI-driven approach can help identify adaptation strategies such as early warning systems or infrastructure resilience efforts from unstructured corporate reports.

Despite their potential, LLMs face challenges in adaptation analysis, including limited access to high-quality, standardized corporate disclosures and the need for further fine-tuning to improve domain-specific accuracy. The integration of LLM outputs into financial risk models and regulatory frameworks remains a work in progress. Quality assurance questions need to be addressed. Expanding publicly available datasets and enhancing model interpretability can drive effectiveness of LLMs in adaptation data analysis.

4.1.3 Data on nature-based solutions

Nature-based solutions (NBSs) are actions of ecosystem improvements that decrease climate risk (NGFS, 2024). They influence biological processes as well as climatic, hydrological, and biochemical cycles, maintaining environmental conditions that benefits human life through avoided damage on livelihoods caused by severe storms, droughts, flooding, and wildfires among others. Households, non-financial companies and financial institutions benefit from NBSs in terms of lower economic losses, mitigation costs and insurance rates. For example, NBSs can affect water storage, infiltration and evapotranspiration processes limiting surface runoff, increase water retention and quality, and provide flood protection during storms. Further examples of processes associated to NBSs and climate physical risks are shown in Table 4.

Data plays a key role in the modelling of the impacts of NBSs on physical climate risk and ecosystem services. The System of Environmental and Economic Accounting for Ecosystem Accounts of United Nations (SEEA EA) emphasizes the use of biophysical models – such as the Soil and Water Assessment Tool (SWAT), the Integrated Valuation of Ecosystem Services and Trade-offs (INVEST), or Nature Braid, among others – whose application is highly data-intensive (UN, 2022). Applications at urban scale also highlight the need of data for expert models and methods (EEMs) such as FLUENT-ANSYS, EMVI-met, TEB-met, and RaynMan model, among others (Bouzouidja, *et al.*, 2021). New modelling approaches such as machine learning rely on geospatial big data to identify statistical relationship or generate new metrics and indicators for NBSs (Vasiliev, Bornmalm, & Stevens, 2024).

While developed countries have tended to obtain NBSs spatial data and metrics from governmental and transnational bodies, EMDEs face data limitations due to financial and technological constraints. Publicly available global sources of geospatial data can help to reduce this data gap. In Europe, the Joint Research

Table 4 **Examples of nature-based solutions (NBS) for climate physical risk**

NBS Type	Hazard regulation processes		
	Flooding	Drought	Heat
Urban and upland forests	Reducing runoff, reflecting energy, slowing water flow, reducing wave height	Regulating water storage and flow, Affecting evapotranspiration, shading, recharging groundwater	Shading, affecting evapotranspiration
Rivers and floodplain restoration	Storing water, slowing water flow, enhancing infiltration	Enhancing infiltration, affecting evapotranspiration, shading, storing water	Shading, absorbing heat, affecting evapotranspiration
Urban green	Storing water, enhancing infiltration	Affecting evapotranspiration, shading, infiltration, storing water	Shading, affecting evapotranspiration
Ponds, lakes, and small water bodies	Storing water	Storing water	Absorbing heat, reducing evaporation
Inland wetlands	Storing water, slowing water flow, reducing wave height	Recharging groundwater	Affecting evapotranspiration
Mangrove forests	Reflecting energy, slowing water flow, reducing wave height	n.a.	n.a.
Reef ecosystems	Reflecting energy, slowing water flow, reducing wave height	n.a.	n.a.
Submerged aquatic vegetation	Slowing water flow, reducing wave height	n.a.	n.a.

Source: (van Zanten, *et al.*, 2023).

Centre Data Catalogue, the European Environment Agency Data Hub and the Copernicus Monitoring Land System are some of the main sources of geospatial data and metrics for NBS assessment. Moreover, geospatial data inputs can be derived from Sentinel-2 and Landsat time series satellite collections, open-access imagery collections from the European Space Agency (ESA) and the National Aeronautic & Space Administration (NASA). Additional sets of information come from research that use remote sensing data to develop additional spatial parameters and data inputs for biophysical and economic modelling of NBS. Some of the most relevant global open-source data for such purposes are summarized in Table 5.

Cost-benefit assessments of NBSs require costing investments in nature solutions and infrastructure which may be public or private provided. For example, the economic benefits from flooding-prevention NBSs in Netherlands were estimated based on cost data provided by regional water authorities (Vogelsang, Weikard, van Loon-Steensma, & Bednar-Friedl, 2023), while estimations in Italy were based on costs acquired from private providers (Staccione , Essenfelder, Bagli, & Mysiak, 2024). Firms such as EC-Harris or BCIS International, provide information on building reconstruction costs extracted from country-specific cadastral estimates per type of building.

Biophysical models need granular historical data and validation exercises. It is important to calibrate biophysical models using observed data from field sampling or monitoring stations when they are available. Coarser sources of information can lead to biased estimates for ecosystem services. Therefore, sufficiently granular information needs to feed into biophysical modelling. Exercises to validate and contrast model results with baseline data are necessary. Moreover, lack of data in water streams imposes challenges regarding calibration and validation of the models to assess NBSs.

Table 5 **Examples of nature-related data for assessing Nature Based Solutions**

Data Input	Source	Link
Data infrastructure for the topographic structure of the land, such as the slope, elevation, aspect, and surface flow direction	Alos Palsar's Digital Elevation Model (DEM) data with a 12.5 m spatial resolution	https://asf.alaska.edu
	Copernicus DEM and FABDEM (Forest and Buildings removed Copernicus DEM) data, both with a 30 m spatial resolution	https://gee-community-catalog.org/projects/fabdem/
Normalized Difference Vegetation Index	Landsat Collection 2 Surface Reflectance-derived spectral indices	https://espa.cr.usgs.gov/
Land Use and Land Change	WorldCover v200, Sentinel satellite data for worldwide land cover map	https://esa-worldcover.org/en
	DynamicWorld	https://developers.google.com/earth-engine/datasets/catalog/GOOGLE_DYNAMICWORLD_V1
	MapBiomas Project with a resolution between 10 m and 30 m	https://countryname.mapbiomas.org/
Precipitations	Global Satellite Mapping of Precipitation, a global hourly rain rate with a 0.1 x 0.1-degree resolution	https://developers.google.com/earth-engine/datasets/catalog/JAXA_GPM_L3_GSMaP_v8_operational
	ERA5-Land dataset, providing data on evolution of land variables, including precipitation with a 0.1 x 0.1-degree resolution	https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land?tab=download
Rainfall erosivity	Global rainfall erosivity 30 arc-seconds (~1 km at the Equator)	https://esdac.jrc.ec.europa.eu/content/global-rainfall-erosivity
Soil information	ISRIC is the World Data Centre for Soils	https://data.isric.org/geonetwork/srv/eng/catalog.search#/home
Mangrove extent	Global Mangrove Watch	https://www.globalmangrovewatch.org/
Impervious surface	Global 30 m Impervious-Surface Dynamic Dataset	https://zenodo.org/records/5220816

Source: Authors.

Technological innovations can foster collaboration to generate local driven data. For example, the OpenET[9] project, a community-driven effort generates and shares evapotranspiration data at a field scale built upon Google Earth Engine platform and open-source software tools that facilitate collaboration governmental agencies, scientific teams, and private agents.

Data on the nexus between nature improvement and ecosystem service to assess NBSs is scarce. For example, empirical evidence on the effects on water resources coming from improvements in the quality of forest is limited, but improving (World Bank, 2022). While more research needs to be done, collected, and made public in this matter, data is still a constraint for the studies and the application of new technological approaches such as machine learning.

4.2 The role of insurance data

Insurance coverage, or lack thereof, is a key determinant of financial vulnerability to climate hazards at the counterparty, portfolio, and macroeconomic levels. As a risk-sharing mechanism, insurance can reduce certain physical risk transmission channels. By providing post-disaster liquidity to companies, households or other policy beneficiaries such as banks, it limits direct capital losses and reduces business interruption and recovery length (NGFS, 2024, p. 21). At financial and macroeconomic level, insurance may help preserve the value of affected counterparties' securities, limit contagion effects within value chains by accelerating reconstruction, enhancing the eligibility of corporate assets as collateral, and reducing the need for public financial intervention.

Growing physical climate risks make gaps in insurance coverage even more consequential. For example, only about a quarter of climate-related catastrophe losses are currently insured in the EU. This insurance protection gap could widen in the medium to long term as a result of climate change, partly because repricing of insurance contracts in response to increasingly frequent and intense events may lead to such insurance becoming unaffordable (ECB-EIOPA, 2023). It is estimated that, compared to a scenario with full insurance coverage, the absence of such coverage would lower Europe's GDP by 2 percentage points (pp) in 2050 and by 8 pp in 2100 (Fache Rousová, *et al.*, 2021).[10] Assessing insurance protection levels accurately is therefore essential for physical risk analysis at both counterparty and macroeconomic levels. However, this assessment presents specific data challenges.

At asset or liability level, data on insurance coverage is typically not accessible. For instance, European prudential requirements for the insurance sector do not include information that would allow for granular identification of liabilities (EUR-Lex, 2009). Conversely, prudential requirements on assets, whether in the banking or insurance sectors, do not specify whether assets are insured. For example, centralized ESCB statistical data such as the AnaCredit (bank loans to corporates) and SHS-S (bank equity holdings) databases, do not include asset-level information on insurance coverage such as whether or not bank's collateral is insured. Supervisors, however, may conduct *ad hoc* data collections. For example, the Australian Prudential Regulation Authority (APRA) is developing analysis on how the affordability of general insurance may change due to climate risks in collaboration with the five largest general insurers in Australia (APRA, 2024). Such *ad hoc* data collection exercises may face other data challenges. Supervised banks often face challenges to collect and update these data mostly due to the lack of accessible regional/national insurance databases, lack of national laws on insurance protection, non-standardized insurance policies, lack of standardized definitions, as well as personal data protection laws.

At the jurisdiction level, proxy estimates of insurance coverage may be developed. For example, the European Insurance and Occupational Pensions Authority (EIOPA) assessed natural catastrophe protection gaps by collecting historical data on economic and insured losses and current estimates of insurance penetration (see Box 8). Another example is the Australian Competition and Consumer Commission which calculates the median home insurance premiums across regions and assess insurance affordability concerns due to physical climate risks (ACCC, 2024).

9 https://etdata.org/.

10 In an RCP 4.5 emissions trajectory, aligned with the NGFS *Current Policies* scenario. In an RCP 8.5 emissions trajectory, figures would be 3 pp and 14 pp, respectively.

Developing forward-looking assessments of insurance coverage remains a challenge. Insurance protection gaps are influenced by both demand-side factors (e.g., policyholders' responses to rising premiums) and supply-side factors (e.g., insurers' geographical or peril exclusions, reinsurance market dynamics), which are difficult to predict. Future levels of insurance coverage may also be affected by the types of policies implemented to address protection gaps, such as different configurations of public intervention in insurance systems (e.g., subsidies to premiums, public reinsurance, last resort guarantees, full public internalization of some perils) or more generally adaptation policies. Considering those evolutions in forward-looking assessments of insurance coverage adds another layer of complexity and uncertainty. While comprehensive analyses are thus challenging, targeted ones may shed light on some drivers. For example, in its 2023-2024 climate exercise for the insurance sector, the French supervisory authority (ACPR) introduced district-level "unaffordability thresholds" of premiums to insured values ratios, above which participating insurers would terminate contracts in their projections (ACPR, 2023).

Improving data collection on insurance protection gaps will require collective efforts across jurisdictions (IAIS, 2023). Supervisors may collect – and potentially share – data on insured losses (and uninsured losses, to the extent available). These data collection efforts could be centralized (*e.g.*, through EIOPA) or coordinated among multiple authorities in jurisdictions where no single supervisor oversees all insurers.

Box 8

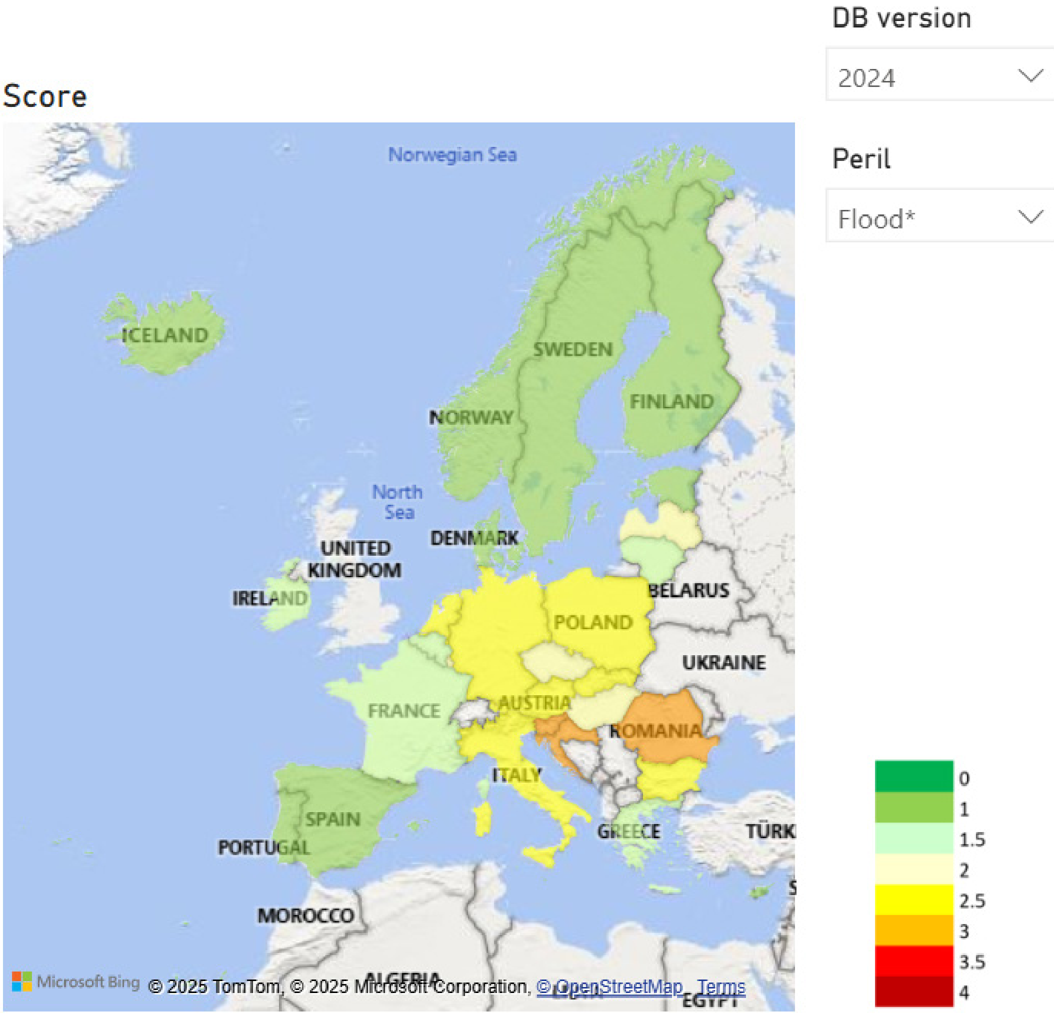
Assessing insurance protection gaps: EIOPA Dashboard on insurance protection gap for natural catastrophes

EIOPA developed a first assessment on insurance protection gaps for natural catastrophes (EIOPA, 2024). The dashboard summarizes data on economic and insured losses, risk estimates, and insurance coverage from 30 European countries to present the drivers of climate-related insurance protection gaps and contribute to identifying measures to increase resilience. For example, the dashboard presents national estimates on current protection gaps for flooding across the EU (Figure 12). In developing this data, EIOPA followed two types of approaches:

- **An historic loss coverage approach** (*"Historical view"*), which relies on estimates of economic and insured losses (e.g., the EM-DAT database, which is open-source). While useful for country-level estimates, historical loss databases face challenges such as uneven geographical coverage and inconsistencies in the scope of recorded "economic losses" (European Commission, 2021).
- **A contemporary estimates of insurance penetration approach** (*"Current view"*), based on data provided by individual supervisors. Supervisors were asked to indicate, for each peril, a bracket of insurance coverage level in their jurisdiction: 0-25%, 25%-50%, 50%-75% or 75%-100%. Those brackets synthesized information on both household and corporate insurance.

.../...

Figure 12 **Current protection gap score for flooding**



Source: (EIOPA, 2024).

5. Data challenges with estimating climate-related physical risk to the financial system

Combining the different elements discussed in the previous chapters, an assessment of physical climate risks to the financial system can follow a bottom-up or top-down approach. Bottom-up methods focus on granular financial exposure and vulnerability metrics, while top-down approaches start from macroeconomic-level insights. These two approaches present distinct data requirements, advantages, and limitations. While bottom-up approaches offer climate risk estimates tailored to granular exposure data, top-down approaches better represent general equilibrium effects and are less data intensive. Ideally, these two approaches are combined, as physical risks affect both micro and macro channels.

5.1 Data challenges in developing bottom-up physical climate risk metrics

A bottom-up approach to assessing financial risks from physical climate risks first evaluates the financial impacts on counterparties across economic sectors – and of their related securities and liabilities – and then aggregates those risks. As discussed in Chapter 3, data challenges differ depending on hazard type and the required level of granularity of exposure and vulnerability data. Capital-destructive hazards (*e.g.,* floods and windstorms) warrant the use of asset-level data, especially tangible fixed asset data, and require damage functions for loss assessments. Other hazard transmission channels may make detailed balance sheet data less necessary. For example, a sectoral approach may be sufficient to assess the impact of heatwaves on labour productivity. Ideally, the assessment of financial impacts on counterparties would leverage financial information beyond assets (*e.g.* profits, company or household indebtedness), which also brings modelling challenges.

With respect to assessing the vulnerability of financial securities or liabilities linked to specific counterparties, data and methodological challenges vary across types of financial instruments.

- For **insurance liabilities**, the relationship is straightforward from the perspective of the insurer, as the insured asset and the case of payout is clearly defined in the insurance contract. However, there are data challenges associated with granular insurance coverage information at liability and asset level (see section 4.2), which also affects financial vulnerability assessments for the corporate assets mentioned below.
- For **corporate assets** (equities, bonds, and loans)**,** the transmission of physical risk to the financial institution is more difficult to assess. In these cases, the value of the financial asset depends on the overall health of the counterparty, not just a single physical asset. The full exposure of the counterparty needs to be understood, but the necessary information is often lacking – warranting e.g., imputation of the existing data to calculate actual risk metrics. Data on overall assets of the company are needed, which can be taken from the balance sheets of public companies. Furthermore, data on the ownership links and group consolidation of the counterparty is needed. Even if a parent company does not operate physical assets affected by physical risk, its financial health is still affected by the physical risk of its subsidiaries. However, in practice, data on how the physical risks of subsidiaries are distributed within corporate groups is often very limited. Therefore, the ECB analytical indicators on physical risk, for example, focus on the single-entity level for now (ECB, 2024, p. 12).
- For **corporate loans** specifically, information on **collateral** may help refine the analysis. In the case of the ESCB, information on collateralized corporate assets is available in the AnaCredit database, however not at the same level of granularity as for company headquarters. This includes information on the nature of collateral (physical or financial), and on its location (at postal code, or by default regional level). Additionally, the collateral may be insured or not: but as for assets, that information is typically not available at counterparty level (see section 4.2).
- For exposure to **households** (e.g., residential mortgages), data availability is lower compared to corporate counterparties,. In the ESCB, counterparty-level information on household lending and its collateral is currently not collected.

Different approaches may be implemented to address these data and methodological challenges:

- **When physical vulnerability is not quantifiable, financial vulnerability assumptions may be directly derived from hazard and exposure information.** For example, in the ECB 2022 bottom-up stress test, non-financial company-level flood risk scores were aggregated to build geographical zones with different flood risk levels, which served as shocks in a short-term scenario (ECB, 2022).
- **A direct link between physical vulnerability and financial vulnerability could be assumed.** For example, the ESCB physical risk indicators assume that the impact of capital-destructive perils to the securities of counterparties is proportional to the impact of those perils on related financial assets (ECB, 2024). Collateral, and the physical risk it is exposed to, is also accounted for. Insurance is only accounted for an aggregate level, through applying correcting mechanisms at country-level. As greater under-insurance could be expected in more vulnerable areas, this could underestimate risks to vulnerable populations.
- **Additional data may allow to consider risk transmission channels in more refined ways.** Areas for progress include: (1) leveraging insurance data at more granular levels (see section 4.2), (2) developing data and methods for assessing the counterparty-level impact of business interruptions, and (3) considering more detailed information on the characteristics of assets. As an illustration of that last point, the Banque de France use case of the Digital Twins tool distinguishes between property damage and transferable assets damage (Box 9). Impacts to the former affect the LGD linked to owner firms, while impacts to the latter affect the PDs linked to occupier firms. Company indebtedness is considered to refine assessments of financial vulnerability.
- **Anonymised data collections may help address privacy concerns, especially for residential data.** For their analysis of flood risk to residential lending portfolios, Bank of Canada leveraged on anonymized information on mortgage loans and home equity lines of credit (HELOC), across a total of 63 financial institutions (Johnston, *et al.*, 2023). This information included the postal code of the property used as collateral, but not the address or other personal information.

Aggregating counterparty-level estimates to the level of financial institutions, sectors, or jurisdictions brings additional data challenges, but allows central banks and supervisors to address macroprudential challenges including portfolio concentration or cross-border exposures. Data challenges are linked to international ownership relationships, and the zoning and comparability of regulatory reporting. Cross-border data sharing agreements can contribute to bridging data gaps. Moreover, two main approaches can be used to aggregate counterparty-level estimates.

- A first approach is to directly aggregate financial losses at counterparty level to portfolio level. This approach can be implemented when granular portfolio data is available. This was the case, for example, for the ESCB 2024 approach, which uses European prudential data (Anacredit/SHS-S databases) (ECB, 2024).
- A second approach is to use sample granular data to calibrate aggregate shocks, which may then be applied back to granular data. This is the approach of the ECB 2022 bottom-up stress test, in which flood impacts on PDs are calibrated at district level, using representative samples of companies in each district, to compute geographical shocks that may be applied by financial institutions to their own portfolios. Shocks are thus more easily applicable than in the first approach but may lose information on impacts at NFC level.

Box 9

Digital Twins tool

This box presents a collaborative tool for supervision authorities to assess climate risks, adapting the concept of "Digital Twins" (de l'Estoile, Kerdelhué, & Verdier, 2024). Digital Twins are virtual representations of physical objects that can be used to simulate shocks to their physical counterpart, using frequently updated or near real-time data. The project develops a generic and modular tool to assess physical risks even when information is lacking. It was initiated under the BIS Innovation Network, and jointly led by De Nederlandsche Bank (DNB), Hong Kong Monetary Authority (HKMA), and Banque de France (BdF).

The structure of the tool is based on the hazard-vulnerability-exposure-finance framework commonly used in the insurance sector. The project promotes a bottom-up approach to physical risks analysis: each of the participating institutions used the common tool to study a use case adapted to its needs and data resources. Both DNB and BdF worked on flooding, yet their approaches highlight different dimensions of the transmission of climate hazards to financial risks.

- BdF's use case estimates potential flood risks to the banking system in France through the non-financial corporation (NFC) channel. It combines data on climate

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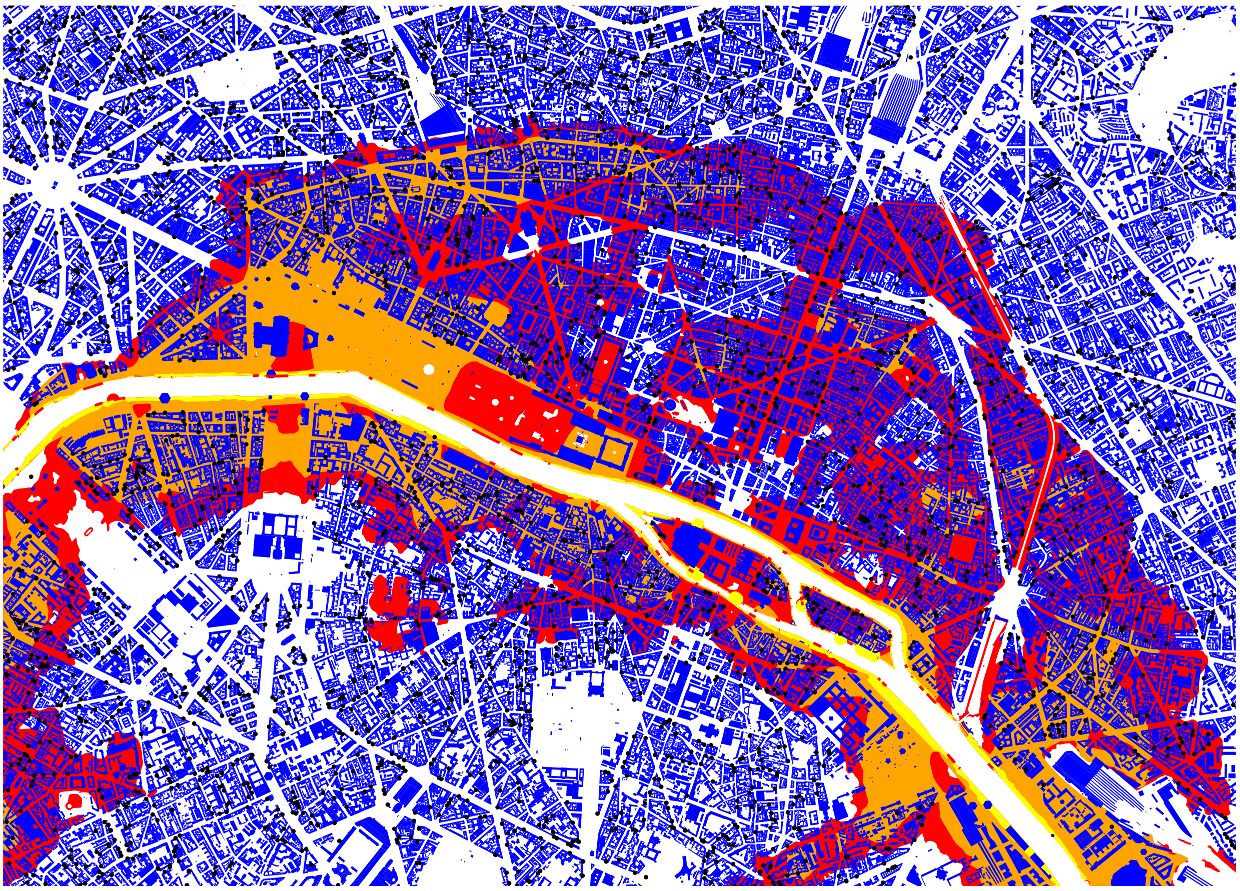
Figure 13 **Flood hazard, buildings and firms' establishments in Paris**



Note: Each colour corresponds to a return period (probability of annual occurrence) of flooding: yellow for 10 years, orange for 100 years, red for 1,000 years. Black dots represent firms' establishments.
Source: Géorisques, Sirene, BNDB.

hazards (scenarios or real-time), the geolocation of physical (real estate and transferable) assets of NFCs, and the financial information of exposed NFCs and their creditors. The results show the importance of granularity in assessing physical risk. First, the potential economic losses when considering all firms' producing premises are much higher than when covering only headquarters. Second, the losses associated with tangible assets are greater than those associated with property assets. The deterioration of both asset types affects the banking system through different channels. Property damage reduces the assets of the owning NFC and increases the loss given default (LGD) associated with the property, while transferable damage (to machinery, inventories or productive capital) may affect the cash and leverage of the occupying NFC. France's current insurance scheme reduces vulnerability to flooding directly for companies and limits the amplification of vulnerability through the banking system.

- DNB's use case analyses how floods in the Netherlands could impact financial stability through a credit risk channel (Caloia & Jansen, 2021). Using geocoded data on real estate exposures, it evaluates 38 adverse flood scenarios and finds that property damages typically lead to bank capital declines of 30-50 basis points. However, the severity of impacts varies significantly based on location and financial vulnerabilities. For instance, severe floods in densely populated areas, particularly the western Netherlands, could trigger much larger capital depletion – exceeding 700 basis points in extreme cases. The study highlights that loan-to-value (LTV) ratios are a critical driver of these outcomes, as higher LTVs amplify losses when collateral values decline due to flood damage.

5.2 Challenges with top-down assessments of physical climate risk

Top-down assessments of physical climate risk start with macroeconomic assessments of physical risk impacts to an economy, and then downscale them if necessary. Such approaches can thus be combined with bottom-up approaches, for example in climate stress testing. The decision to downscale or not depends on the target metric. Economy-level estimates may provide an aggregate proxy metric, while downscaling would be necessary to build financial sector loss metrics.

Top-down assessments are generally characterized by macroeconomic modelling challenges more than by data challenges. As top-down assessments of physical climate risks tend to rely on more aggregate data, they do not face as many data challenges as a bottom-up assessment. However, top-down assessments require complex modelling inputs, including macroeconomic damage functions and aggregate estimates of physical risks (see example in Box 10). There are three key modelling inputs, which are difficult to model but are all integrated in the NGFS scenario modelling:

- **Macroeconomic country-level or sector-level damage functions.** Macroeconomic damage functions have been used in NGFS long-term climate scenarios since their inception. Such damage functions generally identify empirical relationships between macroeconomic and climate data, and project those relationships in the future climate. The scope of climate phenomena modelled in such damage functions vary, but macroeconomic damage functions typically cover chronic risks (*e.g.* mean temperature and precipitation patterns evolution) more than acute risks. While NGFS scenarios rely on country-level damage functions, users can also resort to sector-level damage functions (see NGFS (2024) for a review of the literature on damage functions).
- **Aggregate estimates of acute physical risk.** The Phase IV of NGFS long-term scenarios provides country-level GDP impacts of storms, floods, heatwaves and droughts (NGFS, 2023). Storms and floods were modelled using the CLIMADA natural catastrophe modelling framework, using national-level proxy exposure data (*e.g.* spatially disaggregated GDP) (Box 11).
- **Integrated macroeconomic and financial modelling of extreme weather events.** The NGFS short-term scenarios model acute physical risks through adverse and *ad hoc* storylines fit with the time horizon (*e.g.* extreme compound events occurring successively in different macro-regions) (NGFS, 2025). The feedback loop between the economy and financial sector is modelled, and results are provided with sectoral and financial granularity.

While such estimates may be used to build preliminary exposure-at-risk metrics at country-level, more advanced uses typically require sectoral and financial downscaling, or adjustments reflecting different jurisdiction contexts and needs. Notably, long-term scenarios may need to be tailored depending on the analysis needs and country contexts, as several institutions have already done (see e.g., Box 11) and as recommended by the NGFS itself (NGFS, 2024). However, the NGFS short-term scenarios now entail a reduced need for downscaling, as they offer sectoral and financial granularity by design.

Sectoral downscaling approaches may aim to differentiate impacts depending on physical risk transmission channels, which comes with modelling and data challenges. Contrary to transition risk, for which there are some established methods (e.g., modelling the transmission of energy price shocks through input-output tables and models), approaches for downscaling physical risk are more experimental. Approaches generally aim to identify the transmission channel(s) associated with an aggregate estimate such as a macroeconomic damage function, and the differentiated sectoral impact those channels may have. For example, the NGFS long-term scenarios heatwaves module estimates GDP impacts through the channel of lower labour productivity (estimates that are also available on the Climate Impact Explorer[11]). Academic sources on relative impacts of heatwaves across sectors may then be used to distribute those impacts. Such an approach has been implemented in the 2023-2024 ACPR insurance climate exercise (ACPR, 2024), while ECB/ESCB work previously leveraged data on labour productivity impacts to build a short-term heat-stress scenario (ECB/ESRB, 2022).

At financial level, financial modules used in stress testing frameworks may translate the macro/sectoral physical risk impacts into financial shocks. This is the approach of the 2023-2024 ACPR insurance climate exercise, in which the sectoral and financial downscaling framework from (Allen, *et al.*, 2020) is applied to derive the financial impacts associated with the chronic physical risk impacts from NGFS scenarios (ACPR, 2024).

Box 10

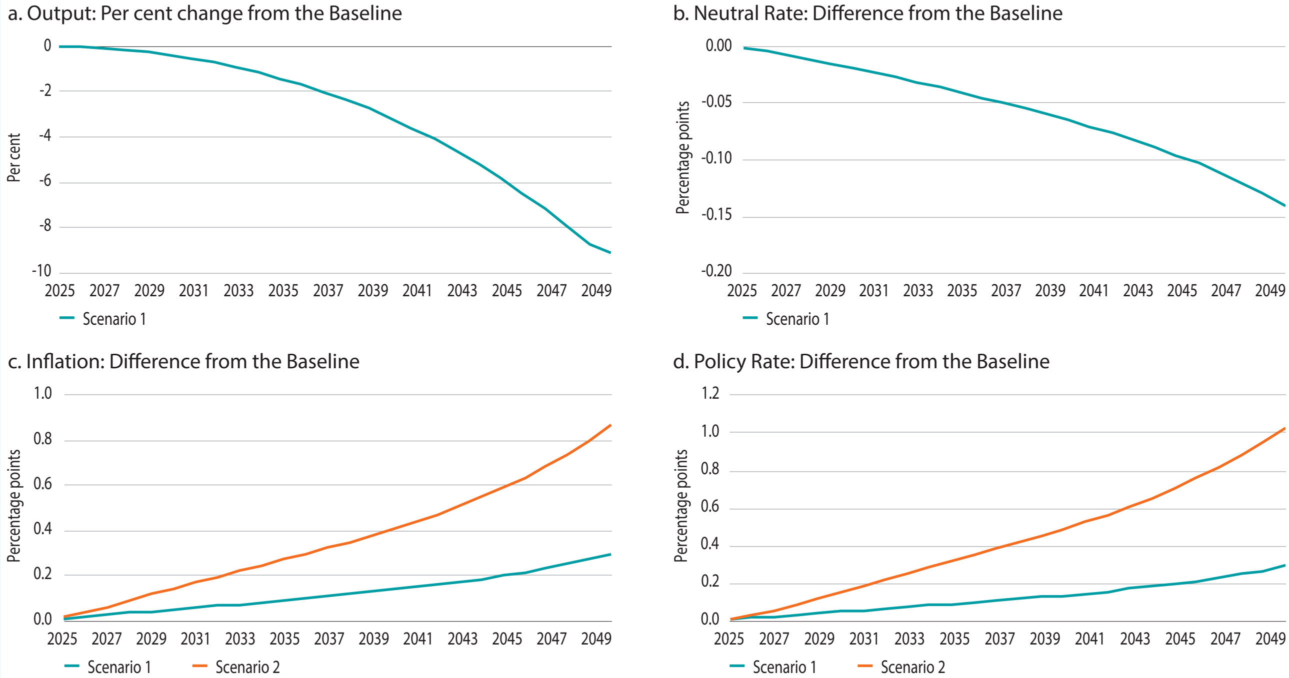
Estimating macroeconomic effects of climate change in India

The Reserve Bank of India (RBI) estimated the counterfactual macroeconomic impact of climate change (Scenario 1) vis-à-vis a no climate change scenario (Baseline) using a new-Keynesian model that incorporates a physical climate risk damage function calibrated with aspects of the National institute Global Econometric Model (NiGEM) (Figure 14). Without climate change mitigation policies, GDP is projected to be 9% lower by 2050 compared to a no-climate-change scenario with full pass-through of the physical risks of climate change to the economy. Both inflation and its volatility may increase over time. Frequent shocks to inflation will necessitate tighter monetary policy even with a lower natural rate of interest. If inflation hysteresis (persistent inflationary effects) occurs, it could de-anchor inflation expectations, undermining central bank credibility. Restoring such credibility would require even higher interest rates, leading to greater output losses (Scenario 2).

…/…

11 https://climate-impact-explorer.climateanalytics.org/.

Figure 14 **Impacts of physical risks of climate change**



Source: (RBI, 2024).

Box 11

Forward-looking climate scenarios for physical risk analysis

Central banks and supervisors use a variety of scenarios for forward-looking physical climate risk analysis, including NGFS and IPCC scenarios. These scenarios provide a structured framework to assess the potential impacts of climate change under different assumptions and pathways. For example, Banco de España complements ESRB-ECB scenarios (which are mainly based on NGFS estimates and narratives) with additional macroeconomic variables and sectoral impacts necessary for their stress tests (ECB, 2022). This approach allows to capture a more comprehensive picture of the potential economic and financial impacts of climate change.

Many institutions adapt published scenarios to better fit their specific needs and contexts. Banco de España, for instance, uses its CATS (Carbon Tax Sectoral) model to estimate sectoral impacts in line with published scenario narratives and paths (Aguilar, González, & Hurtado, 2022). This model enables the projection of different growth paths for various sectors under different climate scenarios, providing detailed insights into how climate risks might evolve over time. The Federal Reserve's pilot climate scenario analysis exercise in 2023 is another example of how institutions tailor scenarios to their needs. Participants in this exercise used external vendor models, including catastrophe models, to define physical shocks such as hurricanes and extensive flooding (FED, 2024). They then calculated climate-adjusted credit risk parameters to understand the potential impacts on their real estate portfolios. Similarly, the Deutsche Bundesbank employs standardized flood risk and wildfire risk metrics on a regional level, combined with regional data on company facilities, to assess future risks (Deutsche Bundesbank, 2024). They use company-level physical risk scores and physical risk estimations as a percentage of revenue to evaluate the potential impacts under different climate scenarios. This detailed approach helps them understand the specific vulnerabilities and risks faced by different sectors and regions.

These forward-looking scenarios are crucial for central banks and supervisors to anticipate and mitigate the long-term risks posed by climate change. By using a combination of published and adapted scenarios, institutions can develop more accurate and relevant risk assessments, guiding their decision-making processes and policy responses.

Top-down estimates would ideally be combined with bottom-up approaches, especially in the context of climate scenario analysis. In that way, the data and methodological advantages specific to both a top-down and a bottom-up approach may compensate each other. The NGFS encourages users to complement scenarios with their own data (e.g. national meteorological institute data), to model additional sources of risk (NGFS, 2024). For example, in their 2024 climate risk stress test, the Peruvian Superintendencia de Banca assessed the impact of chronic and acute physical risks on probabilities of default (PD) and probabilities given default (LGD) (Romero, Salinas, & Trujillo, 2024). The assessment relied on district-level panel data models. This identification strategy allows them to leverage on some advantages of both top-down and bottom-up approaches.

The optimal mix between a top-down and a bottom-up approach to physical risk assessment depends on the type of exposure. For climate scenario analyses which cover insurance liabilities (e.g., 2021 Bank of England Climate Biennial Exploratory Scenario (BoE, 2022)), granular approaches to physical risk assessment by participants are in any case essential. On the asset side, both bottom-up and top-down approaches may be relevant depending on the objective: the former brings a granular view of acute impacts on assets, and the latter may allow to capture general equilibrium effects with lower data needs.

6. Lessons learned and potential next steps

Recognising the growing economic and financial threats posed by climate change, central banks and financial supervisors need to scale up data to assess such risks. They already rely on physical climate risk data for macro-prudential analysis and statistical indicators and research, and increasingly also for micro-prudential supervision and monetary policy analysis. Despite significant progress, central banks and supervisors continue to face data availability, technical capacity, and funding challenges to enhance physical climate risk analyses.

This information note highlighted several challenges and potential next steps for central banks and financial supervisors to integrate high-quality and granular physical climate risk data in financial risk analysis.

- **More granular data on the location and characteristics of corporate and residential physical assets is needed to assess physical risks more accurately.** Data on the location of assets can be improved by leveraging a growing number of publicly-available data sources, such as the Global Energy Monitor for energy facilities across the world. For corporate exposure, better data on companies' activities and the role of assets across their activities, such as the contribution of a given production site to the level of activity, may also allow better modelling of the impact of climate hazards on business interruption. However, the cost of comprehensively estimating the vulnerability of a company's assets and processes to physical risks remains a challenge, including for data providers. For residential exposure, anonymised data collection can help address privacy concerns, for instance, by collecting geographical information at a coarse enough level to prevent identification.
- **Damage functions are often a "bottleneck" of bottom-up loss assessments, as they lack granularity and peril coverage.** Further efforts to calibrate damage functions can build on increasingly available data on historical losses linked to natural catastrophes. However, the availability and consistency of such data remains a challenge in both developed and developing countries.
- **Central banks and supervisors can build on emerging initiatives to integrate data on climate change adaptation actions and resilience strategies.** Some information on climate adaptation actions is already collected through corporate surveys, namely by CDP. New methods, leveraging large language models, are being developed to collect information on and assess corporate adaptation plans. Several initiatives are developing data on nature-based solutions, which can further inform climate resilience assessments. Finally, any improvement to the granularity of insurance data would help better account for the consequences of hazards on counterparties' financial situation.
- **Top-down physical risk assessments are generally characterized by macroeconomic modelling challenges more than by data challenges.** Technological tools and collaborative projects – such as Climada and Digital Twins – can support central banks across regions to enhance their physical risk analyses across use cases.
- **Physical climate risk assessments need further development to capture compound and secondary effects, as well as feedback loops.** This helps identify risk hotspots and avoid underestimating financial risks.[12] Greater availability of data on companies' value chains enables better assessment of potential contagion effects. Data solutions can build on three approaches. First, the use of customer-supplier relationships data, such as from FactSet Revere, can be further leveraged. Second, central banks and supervisors have access to more detailed administrative data. Third, industry-average estimates of physical risk exposure in the value chain, based on multiregional input-output (MRIO) analysis, provide useful estimates. For this purpose, the OECD Inter-Country Input-Output Database can be used.

To bridge data gaps, technical capacity and funding barriers need to be addressed.

- **Technical Challenges:** Designing robust models to analyse physical climate risks requires advanced technical expertise, which needs to be developed further. For example, Banco de España uses various existing natural hazard indices and metrics, such as the Aridity

12 OECD-NGFS Workshop on Assessing the Climate Resilience of Finance: From physical risk to resilience alignment.

index for drought and extreme heat, while acknowledging the need to develop more precise indicators and damage functions for different climate hazards. Deutsche Bundesbank, for instance, also emphasizes the need for domain-specific knowledge, such as geoscience, to link geospatial data to company data effectively.

- **Limited Funding:** Conducting comprehensive climate risk analyses requires adequate resources. Financial constraints can hinder the ability to build up the necessary data infrastructure and technical capabilities. In the NGFS 2024 Physical Risk Survey, some central banks, such as the Central Bank of Brazil, indicated ongoing funding needs to continue the development of methods for measuring physical risk.

Adopting approaches that utilise effective data collection and analysis is essential for developing comprehensive physical climate risk management and climate resilience strategies based on improved data management. To overcome these challenges, institutions can adopt several strategies:

- **Capacity building:** Skills development and knowledge sharing is crucial to build capacity within organisations. Further investments in training and development programs are needed to enhance technical expertise in climate risk analysis by central banks and supervisors. This includes workshops, seminars, and collaborative projects with academic and research institutions. For example, the Joint Committee on Climate Change in Malaysia organises regular knowledge sharing and training sessions, providing materials and resources to enhance understanding of climate risk data (see JC3 Training Materials). The Deutsche Bundesbank also suggests e-learning on open-source geographic information systems and discussing economic impacts to better understand where to prioritise insurance. The NGFS Expert Network on Data, which supported the drafting of this note, fosters information sharing among central banks and supervisors on environmental data, notably through regular webinars. The NGFS also recently established an Expert Network on Capacity Building, with the objective of intensifying capacity building efforts across all streams of NGFS work, including data.
- **Data sharing and collaboration:** Leveraging partnerships with other central banks, financial institutions, and research organisations to share data and best practices can help address data gaps and improve the quality of assessments. For example, central banks and supervisors, including Norges Bank, seek to gain better insights into how other authorities address climate risk issues through knowledge sharing facilitated by the NGFS, as indicated in the NGFS 2024 Physical Risk Survey. The CLIMADA tool and digital twin project were developed to facilitate the calculation of a range of physical climate risk indicators for central banks and supervisors. Further, cooperation and coordination between public and private institutions can help optimise the generation of existing and new data for different physical climate risk metrics. Additionally, systematic data collection in open-source databases enhance the transparency of physical climate risk analyses. Finally, a data directory for research on physical climate risks and adaptation actions could facilitate the access to relevant methodologies, information and data needed for risk and opportunity assessments. Some initiatives are already being developed. For NBSs, for example, Climate Advisers' list of guidance and reports for nature-based solutions[13], the Nature Based Solutions Initiative[14], and the Global database on urban ecosystem services assessments' (GLOBIO) overview of papers assessing urban ecosystem services[15].
- **Robust data systems:** To effectively provide physical risk data to end users and decision-makers, robust data systems must be developed and maintained. These systems should integrate multi-source data, including remote sensing, ground-based observations, and socio-economic datasets, ensuring high-resolution and timely information. Open-access platforms and dashboards are essential to disseminate data widely and enable user-friendly access for diverse stakeholders. Advanced analytics tools, such as artificial intelligence and machine learning, should be leveraged to process large datasets and generate actionable insights. Data interoperability standards and APIs must be established to ensure seamless integration across sectors and systems. Furthermore, capacity-building programs

13 https://www.climateadvisers.org/list-of-guidance-and-reports-for-nature-based-solutions/.

14 https://www.naturebasedsolutionsinitiative.org/.

15 https://www.globio.info/global-database-on-urban-ecosystem-services-assessments.

are critical to equip users with the skills to interpret and apply this data in policy, planning, and project design effectively.

- **Funding initiatives:** Securing dedicated funding for climate risk research and analysis through national and international funding mechanisms. This can include grants, public-private partnerships, and international aid. For example, the Financial Market Commission of Chile is actively engaged in national and supra-national working groups to discuss solutions for obtaining highly granular and reliable climate-related risk data.

Together, these four strategies help address data challenges and technical barriers to physical climate risk analyses as outlined in this paper. This, ultimately, strengthens the ability of central banks and supervisors to more accurately identify financial risks due to climate change, guide policy responses, and support the resilience of the financial system.

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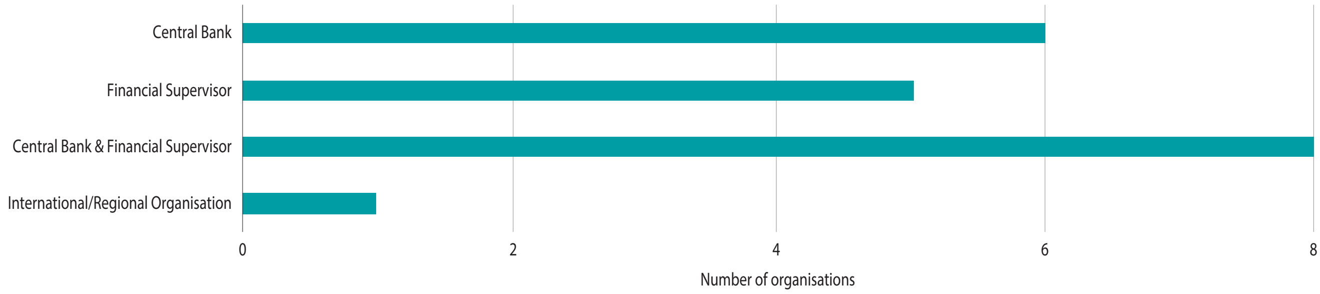
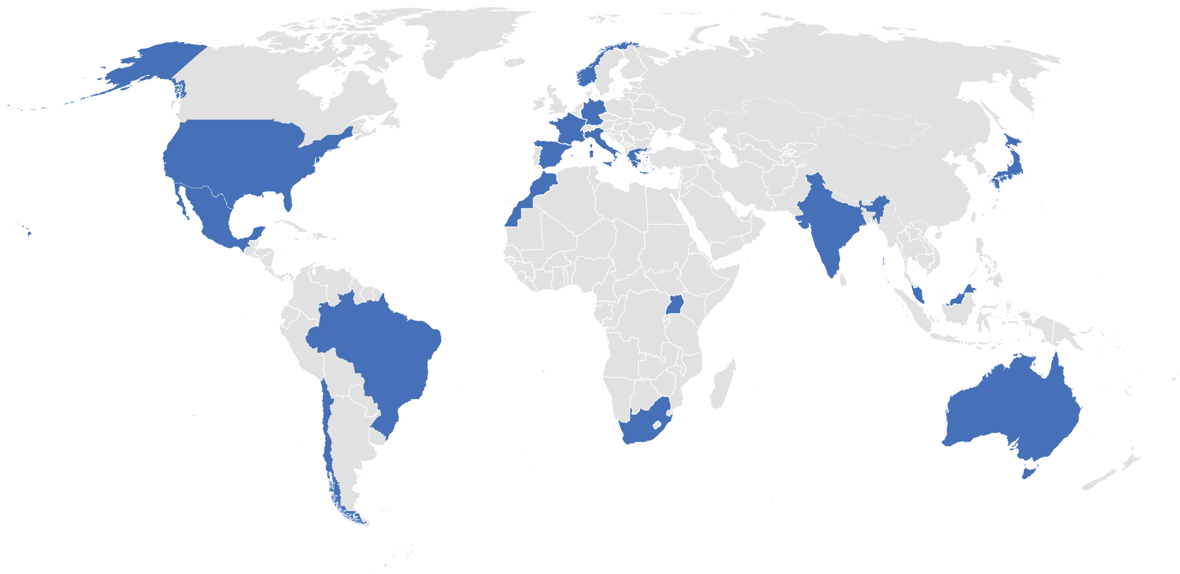
9. Annex I – Survey respondents

Figure 15 **Survey respondents by type of institutions**



Source: 2024 Physical Risk Survey.

Figure 16 **Geographical distribution of survey respondents**



Source: 2024 Physical Risk Survey.

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