Damage Functions: Translating Climate Hazards into Economic Losses and Credit Risk for Banks

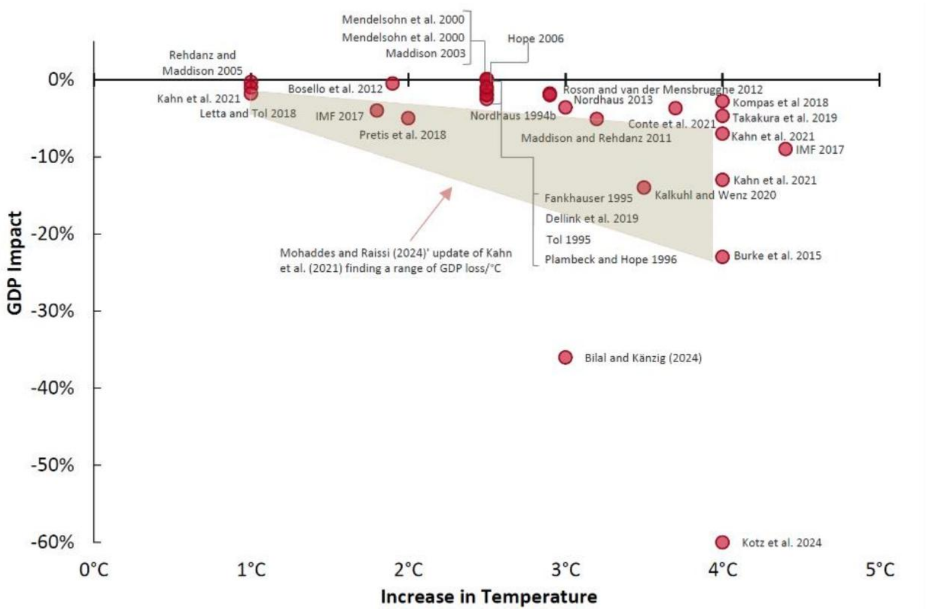
Climate damage functions translate acute and chronic physical hazards into economic losses, ranging from those that quantify the deterioration in the value of specific assets to those that estimate the impact on GDP resulting from income losses. Because no single function captures every hazard or transmission channel, banks must select and calibrate them carefully, combine complementary approaches without double counting, and reflect uncertainty when translating productivity, income and asset-value losses into physical climate-risk analysis.

1. What is a Physical Climate-Risk Damage Function?

A physical climate-risk damage function maps the intensity of a climate hazard, both chronic and acute, into an economic loss. Given a climate-related event (such as changes in temperature, droughts, floods, cyclones, or other climate hazards), a damage function estimates the average percentage of damage or the expected monetary loss suffered by a specific asset (e.g., a building, factory, or crop), portfolio of assets or the whole economy's GDP. In this regard, **Figure 1** reproduces a meta-analysis from a 2025 IMF review of the estimated effects of rising temperatures on GDP. It depicts a robust relationship between rising temperatures and GDP losses relative to a baseline scenario, although the range of estimates is also substantial.[1] Additionally, **from a banking perspective**, damage functions provide a key bridge for incorporating physical climate risks into financial models by estimating how asset losses and business disruptions affect the financial flows of households and firms.

1: In the long run, climate change is not neutral for GDP and could be positive | BBVA Research. 16 February 2026.

FIGURE 1. GDP IMPACT OF INCREASES IN TEMPERATURE. META-ANALYSIS OF ECONOMIC LITERATURE



Source: Mitra et al. (2025), Figure 9, based on Kahn et al. (2021), Mohaddes and Raissi (2024), Tol (2024) and IPCC AR6 WGII, Chapter 16.
Note: Projected GDP per capita impact is for some future year, typically 2100. The shaded area represents the income losses from Mohaddes and Raissi (2024) with upper/lower bound assuming adaptation/no adaptation.

2. From Aggregate Damage Functions to Granular Evidence

The workhorse models in Climate Change Economics, where damage functions are embedded, are the Integrated Assessment Models (IAMs). They provide the main framework used by economists to analyse the interactions between economic activity and climate change **(Box 1. Integrated Assessment Models**).

However, estimating the economic impact of climate change, and accurately calibrating the damage functions within models like Dynamic Integrated Climate-Economy (DICE), is a complex empirical exercise. The standard approach involves estimating a response function using historical data to measure how economic outcomes react to climatic conditions, which is then used to simulate counterfactual scenarios. Even considering recent improvements in the quantitative toolkit (dynamic panel modelling, local projections) and data availability and quality, a radical challenge remains: identifying long-run climate change effects, while controlling for adaptation, is much harder than identifying the short-run effects of temporary weather shocks.

Enhanced availability of granular data is transforming climate-risk modelling. Physical climate risks are inherently local and heterogeneous. Two properties in the same city may suffer different losses because of elevation, construction, use or protection measures. Two companies in the same sector may respond differently because of site concentration, operating flexibility, insurance or liquidity. Integrating these richer, empirically estimated micro-level damage functions into IAMs is a promising avenue of analysis for climate damage functions.

Historically, physical-risk models were constrained by limited spatial and economic information. Asset locations were often incomplete, vulnerability data were generic and company accounts could not be allocated to individual sites. **This constraint is gradually weakening,** with high-resolution hazard information being increasingly combined with more granular data at firm-level like Caggese et al. (2026). It argues that integrating firm-level evidence and indirect channels into Integrated Assessment Models (IAMs) would provide more accurate, and higher estimates of both the economic damages of climate change and the social cost of carbon (**Box 2** for details).

3. A banking perspective. From Physical Climate Hazard to Credit Losses

For banks, a damage function is not the final output of physical-risk analysis. It is an intermediate step connecting a climate hazard to economic damage and, ultimately, to the variables used to measure credit risk. The analytical chain therefore runs from hazard, to physical and economic loss, to borrower financial performance and collateral recovery, and finally to credit losses: **Climate science** estimates the probability and intensity of hazards; **damage functions** translate those hazards into physical and economic losses; and **credit-risk models assess how the resulting shocks affect default and recovery**. Within this architecture, economic losses enter credit-risk models through two main channels: collateral and recoveries, affecting LGD (Loss Given Default); and borrower cash flow and debt-service capacity, affecting PD (Probability of Default)[2] (**Figure 2**).

FIGURE 2. FROM PHYSICAL CLIMATE HAZARDS TO EXPECTED CREDIT LOSS

Source: BBVA Research based on Incorporating physical climate risks into banks' credit risk models BIS Working Paper No. 1274.

2: **- PD (Probability of Default)**: The estimated likelihood that a borrower will fail to meet their debt obligations (default) over a specified time horizon, typically one year.
- LGD (Loss Given Default): The percentage of the outstanding loan that a lender expects to lose if the borrower defaults, after accounting for recoveries such as collateral or repayments.
- Together with EAD (Exposure at Default), these are the core parameters used to estimate Expected Loss (EL):
Expected Credit Loss = PD × LGD × EAD.
- Physical events may also affect EAD, for example when borrowers draw committed credit facilities to cover business interruption, working-capital needs or reconstruction expenditure.

The LGD channel begins with damage to collateral or other recoverable assets. Physical damage may reduce market value, increase repair and workout costs, lower marketability or extend the time required to sell an asset. Insurance can reduce the final loss, but deductibles, exclusions, coverage limits and settlement delays also need to be considered. The resulting shock may therefore affect collateral value, recovery timing and cost-to-recover.

The PD channel operates through the borrower's capacity to meet its financial obligations. Business interruption may reduce sales while fixed costs continue. Extreme heat may lower productivity or increase energy expenditure. Drought may reduce output, raise input costs or increase working-capital needs. Asset replacement and resilience expenditure may also increase financing requirements. These effects weaken variables already used in credit assessment, including EBITDA, liquidity, leverage, interest coverage and covenant headroom.

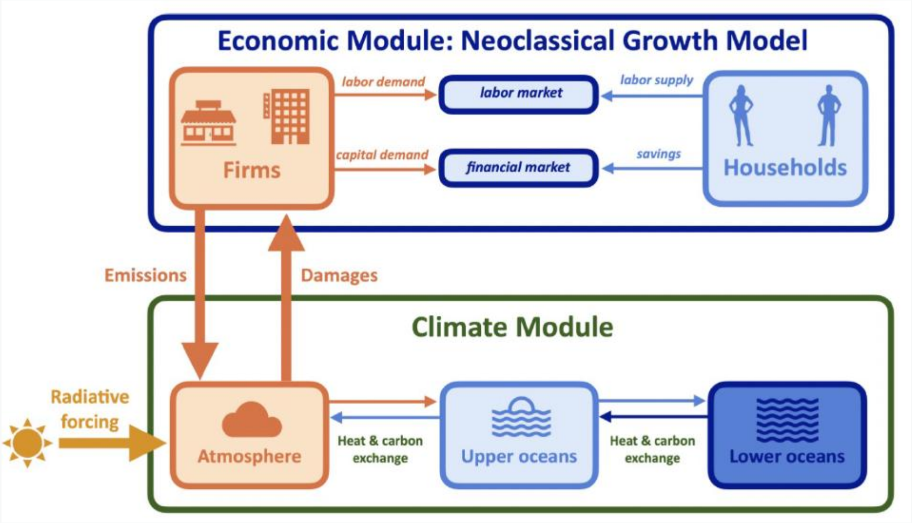
Banks consequently need two complementary perspectives as regards damage functions. Bottom-up analysis captures asset- and borrower-specific losses, while top-down analysis captures systematic and indirect effects. These perspectives should be reconciled carefully, as a regional scenario may already incorporate productivity, infrastructure or capital-loss channels that are also represented in the borrower-level calculation. See **Box 3. Alternative damage functions for different impact channels.**

Last but not least, given uncertainty about hazards, vulnerability, adaptation and indirect effects, banks should assess ranges of plausible outcomes rather than rely on a single climate-loss estimate. The objective is not to create a separate category of climate credit risk, but to show transparently how physical hazards modify the conventional drivers of creditworthiness and recovery. This allows damage functions to support underwriting, pricing, collateral management, provisioning, stress testing and capital assessment.

Box 1. Integrated Assessment Models

One of the earliest IAMs was the Dynamic Integrated Climate Economy (DICE) model proposed by William Nordhaus, which earned him the Nobel prize for integrating climate change into long-run macroeconomic analysis. This model combines a standard neoclassical economic growth model with a climate model, allowing researchers to assess the long-term trade-offs between economic growth, emissions, climate damages and mitigation policies. See **Figure B1**.

Figure B1 Dynamic Integrated Climate Economy model diagram



Source: BBVA Research based on Andrea Caggese's lecture "Climate Change, Firms, and the Green Transition".

Within the DICE framework, gross output is represented by a conventional Cobb–Douglas production function that combines capital (K) and labour (L) as factors of production, while technological progress is captured through total factor productivity (A). Unlike in standard economic growth models, however, gross output is adjusted for two climate-related effects: the **economic damages** caused by climate change (D_t) and the **cost of emission abatement** (Λ_t):

$$Y_t = A_t \, K_t^{\gamma} \, L_t^{1-\gamma}$$

$$Q_t = [1 - D_t] \, [1 - \Lambda_t] \, Y_t$$

Net output (Q_t) therefore reflects the central intertemporal trade-off embedded in the model: devoting resources to mitigation reduces the output available for consumption and investment in the short-term, but it also limits emissions and, consequently, future climate damages.

Box 2. Climate Change, Firms, and Aggregate Productivity [3]

Caggese et al. (2026) develop a model that links firm-level responses to temperature shocks with aggregate productivity, explicitly incorporating both direct productivity effects and indirect losses arising from input adjustment frictions. Empirically, the authors combine matched firm-level data for over one million Italian firms with high-resolution climate data to estimate how extreme temperatures affect sales, productivity, and the marginal products of capital, labor, and materials. They find that extreme heat and cold reduce firm productivity and sales, while capital adjusts much less than labor or materials, creating allocative inefficiencies that amplify aggregate losses.

Using these estimated firm-level semi-elasticities, they construct an aggregate climate damage function and simulate future warming scenarios, accounting for changes in both average temperatures and temperature variability, as well as firms' adaptation. Their results show that climate change generates substantially larger productivity losses than representative-firm models or standard Integrated Assessment Models (IAMs), with indirect allocative effects in the preferred scenario accounting for roughly one-fifth of total losses and adaptation reducing damages only modestly. The authors conclude that incorporating firm heterogeneity, input adjustment frictions, and micro-founded damage functions into IAMs is essential for obtaining more accurate estimates of the economic costs of climate change and the social cost of carbon.

3:“Climate Change, Firms, and Aggregate Productivity”. Andrea Caggese et al.

Box 3. Alternative damage functions for different channels of impact

No single damage function is suitable for every banking application. Damage functions differ in the climate variable they use, the economic outcome they estimate, their geographical resolution and the transmission channel they capture.

Aggregate macroeconomic functions commonly relate temperature or another broad climate indicator to GDP or consumption. They provide a scenario-consistent measure of economy-wide risk and are useful for comparing climate pathways and conducting top-down stress tests. However, an aggregate GDP loss does not reveal which hazards, assets, sectors or borrowers generate the loss.

Impact-specific damage functions provide a first level of decomposition. Boitier et al. (2025),[4] for example, compile European evidence for coastal and river flooding, labour productivity, drought, agriculture, forestry, fisheries, and energy demand and supply, and estimate country-level functions for five of these channels. Their results show that the appropriate relationship differs by impact. Sea-level-rise costs tend to accelerate with global warming, labour-productivity losses are more closely related to local temperature, and agricultural impacts can be non-linear, with moderate warming initially benefiting some locations before losses increase. A single temperature-to-GDP curve may therefore conceal economically important differences among channels and countries.

Spatially explicit damage functions add information about where losses occur. Ignjačević et al. (2026)[5] combine NUTS-2 macroeconomic damage functions with high-resolution projections of temperature, economic activity and urban heat. The resulting estimates reveal regional and urban concentrations of risk that would be obscured by a single European damage function. Such models are particularly useful for identifying geographic concentrations in a bank's portfolio and for defining systematic regional scenarios. Nevertheless, **their outputs remain regional GDP-equivalent losses rather than direct estimates of damage to an individual asset or borrower**.

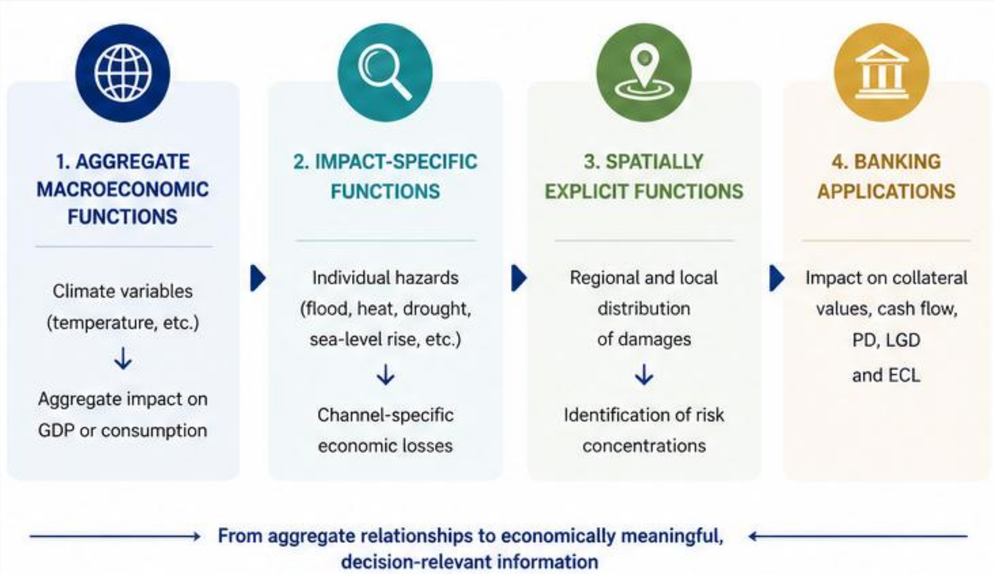
The final layer consists of asset- and borrower-level functions and financial translation models. These estimate how flood depth, heat, drought or other hazards affect repair costs, collateral values, production, sales, operating expenses, investment needs and business interruption. The resulting financial shocks can then be introduced into the conventional determinants of PD and LGD.

These layers are complementary, but their outputs should not be added mechanically. Before combining top-down and bottom-up estimates, banks should prepare a channel inventory identifying the physical losses, indirect effects, adaptation assumptions and market responses already embedded in each model. For example, **if a**

4: "Projected climate impacts and impact-specific damage functions for EU countries: A review and estimation" Boitier et al. Climatic Change. 20 October 2025.
5: "Spatially-Explicit Economic Impacts and Risks of Climate Change in Europe" Ignjačević et al. Economics of Disasters and Climate Change. 11 June 2026.

regional GDP scenario already incorporates labour-productivity losses, flooding or destruction of capital, applying the same shocks in full to borrower cash flows would double count them. A practical approach is to use the top-down model as a scenario-consistent benchmark for systematic effects and the bottom-up model to allocate and differentiate losses across assets and borrowers. Only effects absent from the top-down scenario should be treated as incremental. Insurance, adaptation and recovery assumptions should likewise be applied at the layer where they operate, and results should be reported as ranges rather than as a single point estimate.

Figure B3. Complementary damage functions from macroeconomic scenarios to credit risk



Source: BBVA Research, based on Boitier et al. (2025), Ignjačević et al. (2026)

Highlights of the Week

Global	Global Critical Minerals Outlook 2026 - Event - IEA. **16 July 2026.** Critical minerals have moved to the forefront of energy, economic and national security agendas in recent years.
Global	Home | Statistical Review of World Energy. **30 June 2026.** Global electrification reaches a tipping point as energy demand hits record highs and regional paths diverge.
Global	Renewable energy statistics 2026. **14 July 2026.** Renewable Power Generation Records Its Fastest Growth Ever.
Europe	The green transition – benefits and barriers. **ECB Frank Elderson Keynote Speech. 2 July 2026**. Accelerating the green transition provides substantial economic, environmental and social benefits.

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