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Modelling the impact of physical climate risk and adaptation on sovereign credit ratings

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Abstract

Climate-related extreme weather events create significant fiscal pressures for governments, yet their impacts on sovereign creditworthiness and the risk reduction benefits of adaptation remain poorly quantified. We develop an integrated modelling framework linking acute climate risk, macroeconomic, and sovereign credit rating models to probabilistically assess how climate extremes and adaptation investments impact sovereign creditworthiness. Applying this framework to river flooding in Thailand, we show that flood-induced losses in an extreme year could trigger multi-notch sovereign rating downgrades, substantially increasing borrowing costs. Under future emissions scenarios, these rating impacts increase significantly. However, large-scale government-funded adaptation investments in flood protection can substantially reduce these risks across all climate scenarios. Built using open data and existing macroeconomic tools, our framework provides governments and international institutions with practical methodologies for integrating acute climate risks and adaptation benefits into sovereign debt sustainability analyses, offering climate vulnerable, indebted countries an evidence-based pathway to break the 'climate investment trap'.

Keywords sovereign debt, credit ratings, climate change, physical climate risk, adaptation

JEL codes Q54, G24, E6, C6

I. Introduction

As global temperatures increase, so do the frequency and severity of extreme weather events. In 2024, global losses from natural hazards totalled $417 billion, with 60 individual events exceeding losses of $1

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billion (Gallagher Re, 2025). The influence of climate change on extreme weather events is increasingly apparent. Recent estimates suggest that $143 billion in annual damages can be directly attributable to climate change (Newman and Noy, 2023). For example, the 2022 flooding in Pakistan, which caused $15 billion in damages and over 1,500 deaths, was made 50 per cent more likely due to climate change (Otto *et al.*, 2023). Future increases in risk are compounded by continued population growth in high-risk areas (Andreadis *et al.*, 2022; Rentschler *et al.*, 2023), with developing countries seeing the largest increases in risk exposure under future socioeconomic scenarios (Zhang *et al.*, 2025).

These rising risks have profound financial and macroeconomic implications. Global financial losses are estimated in the tens of trillions by the end of the century if we follow a business-as-usual emissions path (Dietz *et al.*, 2016) and global growth impacts tend to be negative, particularly for poorer countries, albeit with large uncertainty in the magnitude of future impacts (Tol, 2024). While these findings emphasize the importance of mitigating future warming by reducing our emissions, research showing the potential sizeable impacts of climate change on the global economy demonstrates the urgency of adapting to rising climate risks (Burke *et al.*, 2015; Desbordes and Eberhardt, 2024).

This urgency is particularly important at the national scale, where climate change creates fiscal pressures through both revenue and expenditure channels (Volz *et al.*, 2020). On the revenue side, climate impacts reduce economic growth and erode tax bases, while on the expenditure side, governments face mounting costs from disaster response, reconstruction, and the need for proactive adaptation investment. Many of the countries with the most urgent adaptation needs are faced with the dual challenge of rising climate losses and high levels of sovereign debt, which creates a 'climate investment trap' that limits their ability to invest proactively in both mitigation (Ameli *et al.*, 2021) and adaptation (Ranger *et al.*, 2025). Empirical analysis suggests that climate-vulnerable countries already pay a premium on their debt (Beirne *et al.*, 2021; Cevik and Jalles, 2022; Kling *et al.*, 2025; Erhart *et al.*, 2026) all else being equal, further constraining their ability to raise capital to fund adaptation and exacerbating the climate investment trap. Recent research suggests these dynamics extend to nature loss, where vulnerability to biodiversity degradation is associated with increases in sovereign borrowing costs, which disproportionately impacts high-risk, lower-income countries (Wollenweber *et al.*, 2026).

These fiscal pressures directly affect countries' ability to service debt and maintain creditworthiness. Sovereign credit ratings act as a universal metric of a government's ability to repay its debt and determine the terms on which they can access capital markets. Whether and how ratings provided by credit rating agencies currently capture climate-related fiscal pressures is debated. Empirical studies have found that countries with greater exposure to natural disasters have lower ratings (Cappiello *et al.*, 2025) and that climate vulnerability is negatively associated with ratings while adaptation readiness shows positive associations (Cevik and Jalles, 2023; Sun *et al.*, 2023). However, other studies examining similar measures have found no statistically significant relationship (Andersen, 2025). Rating agencies maintain that climate change is already included in sovereign credit ratings where relevant (Moody's, 2016; S&P Global, 2021; Fitch Ratings, 2025) and while we have anecdotal evidence of ex-post rating adjustments following climate related events (Moody's, 2017; Fitch Ratings, 2022) the extent to which ex-ante assessments of climate risk and adaptation influence sovereign ratings is unknown.

To explore how public finances, debt, and sovereign ratings may change under future climate change, Klusak *et al.* (2023) performed the first ex-ante assessment of 109 rated countries under various climate scenarios until 2100. The study combined a predictive model of sovereign ratings with forward-looking climate econometric estimates of GDP growth (Kahn *et al.*, 2021) and found that nearly three-quarters of the countries analysed would experience downgrades by the end of the century in a high-emission (RCP 8.5) scenario. While these assessments capture how aggregate, chronic impacts may affect ratings, they do not capture the effects of extreme events such as flooding. They also do not capture how specific adaptation interventions may reduce the risk.

Our paper addresses these gaps by explicitly incorporating acute physical climate risks and adaptation investments into sovereign credit rating assessment. We focus on Thailand, a country with high and increasing exposure to river flooding (Kiguchi *et al.*, 2021), and develop an integrated modelling framework that links flood risk and adaptation scenarios with macroeconomic impacts and sovereign creditworthiness.

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Our approach makes three key contributions. First, we provide estimates of how acute events may affect sovereign ratings, addressing a gap in existing assessments that focus primarily on the chronic aggregate impacts of climate change. Second, we explicitly model how adaptation investments can reduce these rating impacts, providing actionable insights for climate-resilient fiscal planning. Third, our framework relies on openly available data and employs the Debt-Investment-Growth and Natural Disasters (DIGNAD) model, a macroeconomic tool already used by countries and the International Monetary Fund (IMF) to assess debt sustainability implications of climate shocks and adaptation (Marto *et al.*, 2017). The reproducible nature of our approach enables application to other countries and contexts, or as improved data become available, making our methodology directly applicable to ongoing efforts to integrate climate risk and adaptation into debt sustainability analyses (IMF and World Bank, 2024).

II. The modelling framework

We develop a modelling framework for estimating the impact of flood risk and adaptation measures on sovereign credit ratings in Thailand by linking three types of models. The framework simulates thousands of hypothetical years of flooding. In each simulated year, a flood risk and adaptation model generates sectoral damages to capital stock and economic activity under a given adaptation and climate scenario. These losses serve as shock inputs to a macroeconomic model calibrated for Thailand, which translates them into GDP impacts. The GDP impacts in turn feed a sovereign credit rating model, trained on historical rating movements and macroeconomic fundamentals, which predicts the corresponding change in Thailand's credit rating. The methodological workflow is outlined in Figure 1 and described in detail below.

(i) Flood risk and adaptation model

The national flood risk and adaptation model is developed using global open data to ensure its reproducibility in other contexts and by other users. Flood risk is assessed in two stages. First, flood risk is assessed at each 90m resolution grid cell in Thailand and then aggregated into loss–probability curves at the river basin scale for both baseline and future climate scenarios. Second, national flood losses are simulated using a Monte Carlo approach that accounts for the spatial dependence of flooding across river basins in Thailand. Both these stages are explained in greater detail below.

To generate our basin-scale flood loss–probability (risk) curves, we combine data on hazard, exposure, and vulnerability. For hazard, we use the global river flood hazard return period maps developed by the EU Joint Research Centre (JRC) (Baugh *et al.*, 2024). Return period flood hazard maps estimate the extent and depth of flooding associated with events of a given annual probability. For example, a 100-year flood is one with a 1 per cent annual probability of being equalled or exceeded in any given year. Our JRC flood maps (plotted in Figure 2) exist for seven different return periods, ranging from 10 to 500 years, equivalent to annual probabilities of occurrence of 0.1 and 0.002, respectively.

For exposure, we combine national and subnational economic data with gridded datasets that describe the spatial distribution of exposed assets and activity. National public and private capital stock is taken from the Thai national accounts (NESDC, 2022) for three sectors: agriculture, industry, and services. We disaggregate these national totals across gridded datasets describing the location of the relevant assets: residential and non-residential building volume from the Global Human Settlement dataset (Pesaresi *et al.*, 2024), cropland extent (Potapov *et al.*, 2022), and an infrastructure density layer we derive from OpenStreetMap road networks following Nirandjan *et al.* (2022). Residential and non-residential capital splits are obtained from the GIRI Building Exposure Model (Piller *et al.*, 2023). Subnational economic output is taken from the DOSE database (Wenz *et al.*, 2023), which assembles sectoral output data from 1,661 subnational regions across 83 countries, drawing on national and subnational sources. As with capital stock, we disaggregate these subnational output figures across the relevant gridded datasets to obtain grid-cell-level economic activity. While the capital stock and economic

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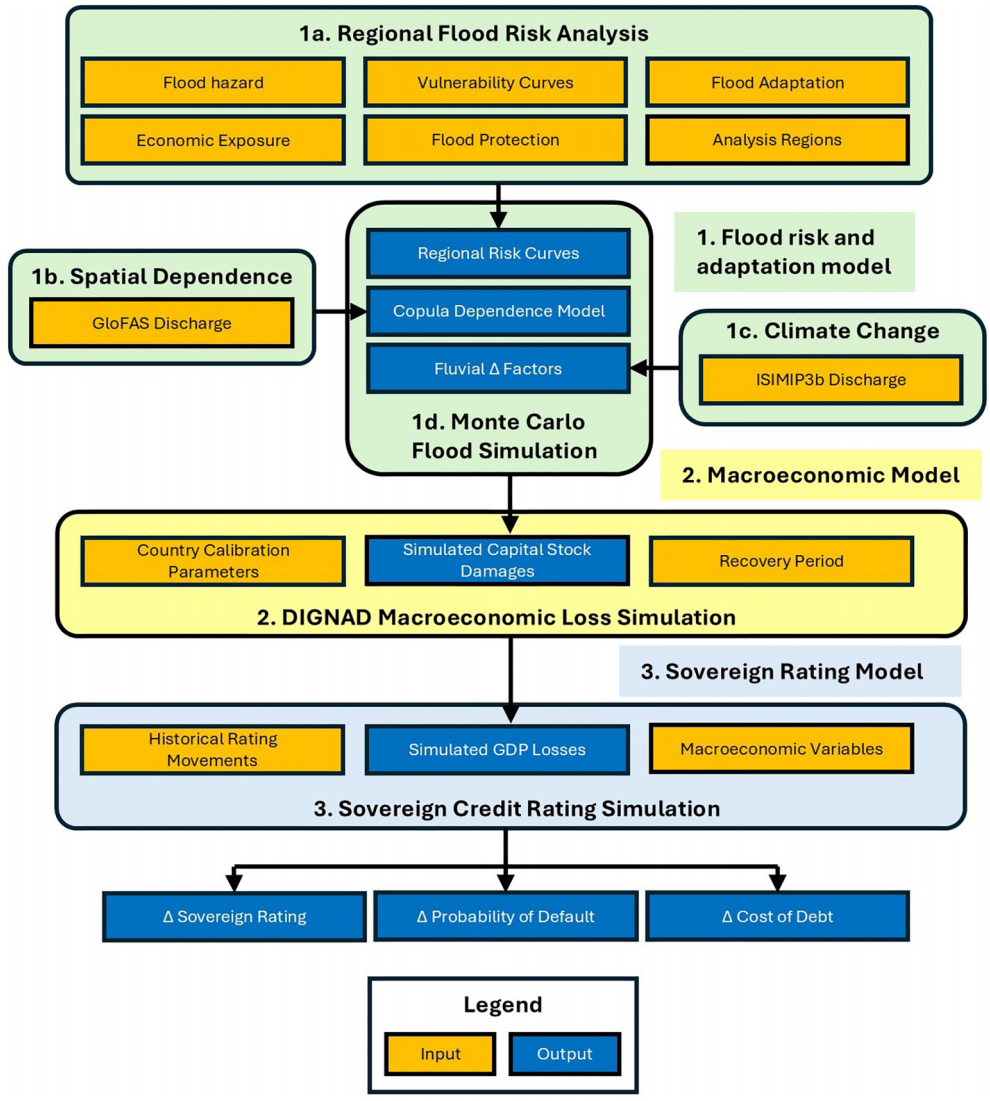


Figure 1 Detailed modelling framework for simulating impacts of flood risk and adaptation on Thailand's sovereign credit rating.

output totals are drawn from official national records and should therefore be reliable, their disaggregation relies on openly available global datasets and requires assumptions about how sectoral value maps onto the residential, non-residential, and infrastructure layers. Sectorally resolved exposure layers would be preferable, but the approach we adopt represents the most comprehensive disaggregation achievable with openly available data, preserving reproducibility of the framework across other contexts.

We overlay the flood hazard and exposure datasets to calculate losses at the grid cell level. For each grid cell i, sector s, and annual exceedance probability p,

$$L_{i,s}(p) = E_{i,s} \cdot D_s(h_i(p)) \tag{1}$$

where $E_{i,s}$ is the exposed economic value for sector s, $h_i(p)$ is the flood depth at i for probability p, and $D_s(\cdot)$ is the depth-damage function for sector s taken from Huizinga *et al.* (2017).

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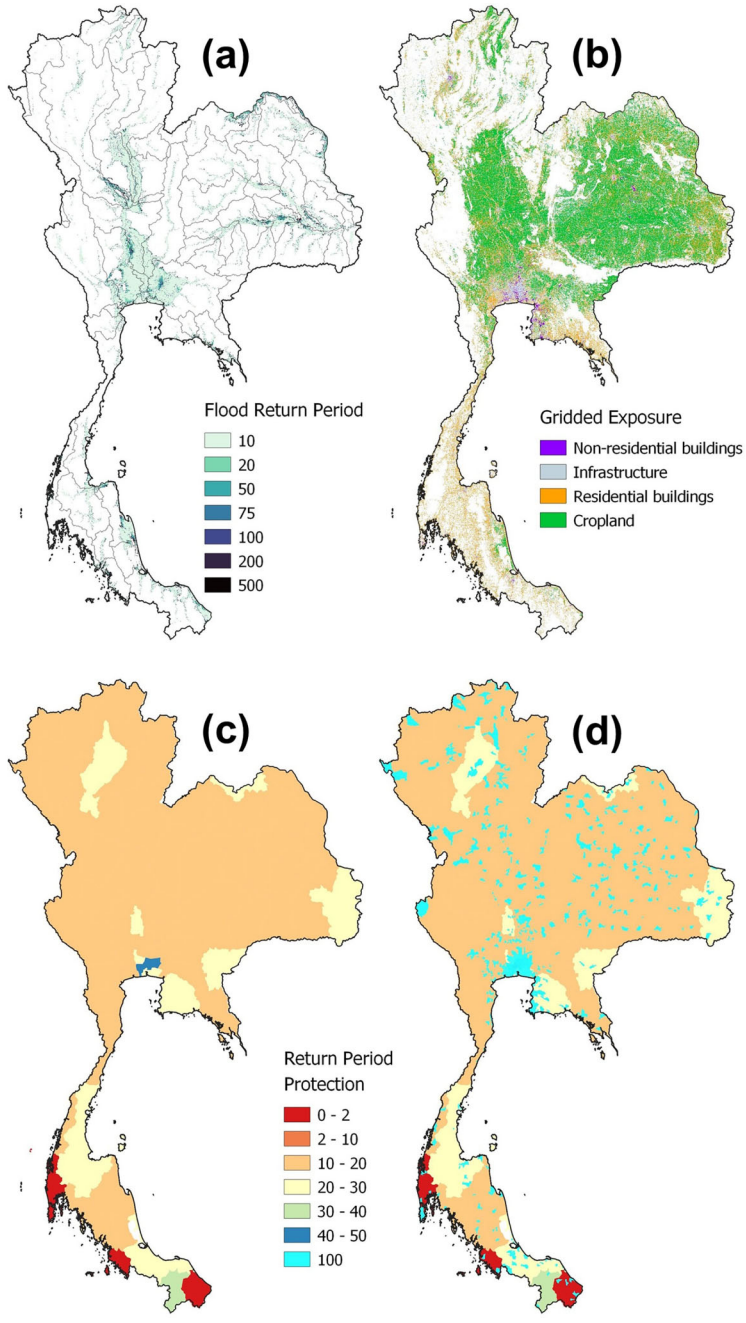


Figure 2 Flood risk and adaptation model inputs. (a) Return period flood hazard maps and level 6 HydroBASINs. (b) Gridded exposure data used to disaggregate sectoral capital stock and economic activity. (c) Baseline (unadapted) FLOPROS river flood protection standards indicating the existing design flood protection level in each subnational region. (d) The adaptation (adapted) scenario where the protection level in all urban areas is raised to protect against a 100-year flood.

Source: Authors, using flood hazard data from Baugh *et al.* (2024), river basin data from Linke *et al.* (2019), building volume data from Pesaresi *et al.* (2024), cropland from Potapov *et al.* (2022), infrastructure derived from OpenStreetMap, flood protection standards from Scussolini *et al.* (2016), and urbanization data from Schiavina *et al.* (2023).

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A challenge with using return period flood hazard maps to understand national tail losses is that a single map does not represent an actual flood event. Return period maps represent a constant probability of flooding across space, whereas real floods exhibit spatial heterogeneity in their extremes (Quinn *et al.*, 2019; Olcese *et al.*, 2024). Aggregating losses directly from national return period maps would therefore assume that flooding of a given probability occurs everywhere simultaneously, overstating the spatial footprint of any single event and inflating estimated national tail losses (Metin *et al.*, 2020). To avoid this, we summarize losses at the river basin scale, using the global nested hydrological basin dataset, HydroBASINs (Lehner and Grill, 2013; Linke *et al.*, 2019). We use HydroBASINs at level 6 hierarchy, as this is the smallest size of basin that we can reliably extract river discharge data from. Within each basin, we assume flooding is fully dependent (a flood of a given exceedance probability affects the whole basin simultaneously) while dependence between basins is modelled explicitly when we aggregate basin losses to the national scale (described later in this section). Basin-scale sectoral losses are obtained by summing over the grid cells in each of the 83 level 6 HydroBASINs in Thailand (Figure 2):

$$L_{b,s}(p) = \sum_{i \in b} L_{i,s}(p) \; L_b(p) = \sum_{s} L_{b,s}(p) \tag{2}$$

The basin-scale loss–probability curves are further adjusted to account for different adaptation scenarios. Two scenarios are considered: (i) an *unadapted scenario* that captures existing flood protection levels (Scussolini *et al.*, 2016) and (ii) an *adapted scenario* where we assume all urban areas in Thailand are protected against a 100-year return period flood, defined using the degree of urbanization dataset (Schiavina *et al.*, 2023). Adaptation is applied by truncating basin-level loss curves at the basin-specific protection probability p_b^*:

$$L_b^{adapt}(p) = \begin{cases} 0, & p \geq p_b^* \\ L_b(p), & p < p_b^* \end{cases} \tag{3}$$

The costs of adaptation are estimated using the formula introduced in Tanoue *et al.* (2021), who created a unit cost database composed of 276 flood protection projects worldwide. For each project, they recorded the total construction cost (converted to real, purchasing power parity (PPP) terms and normalized per kilometre of river protected) alongside its flood protection standard. Fitting a linear regression of unit cost against the $\log_2$ of the protection standard yielded a positive relationship between the two, which we apply to estimate adaptation costs as

$$C_{adapt} = u \cdot L \cdot \log_2(\Delta_{Pr}) \tag{4}$$

where L is the length of river to protect, in kilometres (Lehner and Grill, 2013); u is the unit cost, set at \$2.399 million (Tanoue *et al.*, 2021; Boulange *et al.*, 2023); and Δ_{Pr} is the ratio of the target protection standard (a 100-year return period, in our case) to the baseline level of protection (Scussolini *et al.*, 2016). We evaluate equation 4 separately for each basin and sum across basins to get a total national cost of adaptation.

Future changes in flood risk in our model are calculated using simulations from the third round of the Inter-Sectoral Model Intercomparison Project (ISIMIP3b) (Frieler *et al.*, 2025); the ISIMIP database is used as it combines projections from many models in an interoperable way to capture uncertainties and is also used by the Network for Greening the Financial System (NGFS). In ISIMIP3b, hydroclimatic forcing from five bias-corrected global climate models (GCMs) was used as input for the simulation of nine different hydrological models. We use the simulated outputs of the JULES-W2 hydrological model (Best *et al.*, 2011), which previous model intercomparison research has shown performs best for river flooding in Thailand (Mester *et al.*, 2021). Daily river discharge estimates for three climate scenarios are extracted from the model runs at each native 0.5° grid cell for 135 years (1965–2100). The climate scenarios we use are Shared Socioeconomic Pathways (SSPs), which couple a socioeconomic development storyline with a level of radiative forcing reached by 2100. The three scenarios are SSP126, which is a low-emissions, sustainability-oriented pathway; SSP370, a medium-to-high emissions pathway characterized by regional rivalry; and SSP585, which is a high-emissions, fossil-fuel-intensive pathway (O'Neill

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et al., 2016). We perform a flood frequency analysis using a peak-over-threshold approach and fit a generalized Pareto distribution (Pan *et al.*, 2022) for a baseline period (1965–2014) and multiple future periods with a moving window of 50 years. We index these results using the centre of each 50-year window, t, which represents the midpoint year of the window. Change factors of flood probability are calculated for each of the 83 river basins using baseline and future discharge distributions. These change factors provide us with new basin-scale loss–probability curves for future flooding:

$$L_b^{future}(p,t) = L_b^{baseline}(p \cdot CF_b(t)) \tag{5}$$

where $L_b^{future}(p,t)$ is the future basin-scale loss–probability curve at a future time period t, $L_b^{baseline}(p)$ is the baseline loss–probability curve, and $CF_b(t)$ is the basin-specific fluvial change factor at a future time period t. A detailed description of the change factor calculation is provided in Appendix A1.

To account for the spatial correlation of flooding between river basins, we employ a copula-based approach. Copulas are statistical functions that allow you to join univariate marginal distributions into a multivariate distribution, allowing their dependence structure to be modelled separately from their individual behaviour (Nelsen, 2007). They have been applied widely in hydrology (Chen *et al.*, 2019) and in flood risk assessments to understand the correlation of flooding across space and time (Timonina *et al.*, 2015; Nguyen *et al.*, 2020). Following Kerkhofs *et al.* (2025), we calculate the pairwise correlation of extreme river discharge in the 83 river basins and fit a t-copula to represent the joint dependence. Flood correlations are calculated using daily discharge from the Global Flood Awareness System (GloFAS) v4.0 hydrological reanalysis dataset (Harrigan *et al.*, 2020). This is the same data that forced the underlying flood hazard maps we use in our risk assessment (Baugh *et al.*, 2024). We assume that the dependence structure of extreme discharge remains stationary in the future.

We use the fitted copula to run a Monte Carlo simulation of national flood losses. For each scenario, we simulate 10,000 synthetic years, drawing in each year one 83-dimensional vector of correlated uniform random numbers, with one value for each level 6 HydroBASIN. These draws represent the joint occurrence probabilities of flood events across basins and preserve the estimated spatial dependence in extreme discharge. Each draw is converted to a basin-specific annual exceedance probability and used to sample the corresponding basin loss–probability curve, separately for the baseline and adaptation cases. Annual national losses are then obtained by summing sectoral losses across all basins.

(ii) Macroeconomic model

Various types of macroeconomic model have been used for studying the economic impacts of physical climate change (Botzen *et al.*, 2019; Coalition of Finance Ministers for Climate Action, 2025). These include computable general equilibrium (CGE) models (Tanoue *et al.*, 2020), dynamic stochastic general equilibrium (DSGE) models (Marto *et al.*, 2017; Melina and Santoro, 2021), structural econometric models (Kodzovi Senu *et al.*, 2025), input–output (I-O) models (Hallegatte, 2008), integrated assessment models (IAM) (Calcaterra *et al.*, 2025), and hybrids (Koks *et al.*, 2016).

In our study, we use the DIGNAD macroeconomic model developed by the IMF. DIGNAD is a dynamic general equilibrium model based on the underlying framework of the IMF's Debt-Investment-Growth (DIG) class of models (Buffie *et al.*, 2012) and has been developed to study the impact of natural disasters and adaptation investments on the economies of emerging and developing countries (Marto *et al.*, 2017; IMF, 2022, 2023*a*). It is particularly suited to this paper as it directly examines the relationship between physical capital stocks and a disaster event on the economy. The model is composed of three blocks. The first is a private demand block, consisting of two types of private households maximizing utility: savers who have access to capital markets and who can invest in financial assets and real assets and liquidity-constrained households who have no access to capital markets. The second is a private supply block, consisting of profit-maximizing firms in tradeable and non-tradeable sectors. The final block is a policy block, consisting of a government that invests in standard and adaptation infrastructure, which is financed using a range of fiscal and debt instruments. Through this model, we focus on the impacts of natural disasters on the economy through the following three channels: (1) damages to

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public capital stock, (2) damages to private capital stock, and (3) a reduction in total factor productivity (TFP).

DIGNAD is an aggregated, aspatial model: it represents the economy at the national level, with no geographic structure to its capital stocks or output. In its current set-up, adaptation enters as an investment in resilient infrastructure, whose payoff depends on its cost and on assumed elasticity relative to standard infrastructure linking that investment to reduced disaster damages. However, the model does not consider the locations of the flood protection assets, as well as its location-specific effectiveness. Flood risk, by contrast, is spatially heterogeneous, and the benefit of a specific measure depends on the local hazard, exposure, and protection standard at its location. The challenge is to reconcile a spatially explicit representation of flood risk and adaptation with an aggregate macroeconomic model. We therefore connect these two components by using our national flood risk and adaptation model to simulate the damages and avoided losses from specific interventions and passing the resultant aggregate shocks to DIGNAD. This lets the macroeconomic model reflect the benefits of spatially targeted adaptation.

We refer to Marto *et al.* (2017) and Aligishiev *et al.* (2023) for a detailed overview of the DIGNAD model structure. Below, we outline output-related equations to estimate GDP losses and the specific modifications we have made to link it with the flood risk and adaptation model described in the previous section.

Firms produce tradeable (x) and non-tradeable (n) output following the Cobb–Douglas production function according to

$$y_{j,t} = A_{j,t} K_{g,t-1}^{\psi_j} K_{p,j,t-1}^{\alpha_j} l_{j,t}^{1-\alpha_j} \text{ for } j = n, x \tag{6}$$

where $y_{j,t}$ is sector-specific output, $A_{j,t}$ is the TFP, $K_{g,\,t}$ is the public capital, $K_{p,\,t}$ is the private capital, and $l_{j,t}$is labour, while $\psi_j$and α_j represent the rate of return in public and private capital, respectively. Nominal GDP is the sum of outputs from both sectors according to

$$y_t = P_{n,t} y_{n,t} + P_{x,t} y_{x,t} \tag{7}$$

where $P_{n,t}$ and $P_{x,t}$ are prices for non-tradeable and tradeable goods.

Flood damages from the flood risk and adaptation model enter DIGNAD as exogenous shocks to private capital, public capital, and TFP. Private capital $K_{p,t} = K_{p_x,t} + K_{p_n,t}$ evolves according to

$$(1+g) K_{p_j,t} = \left(\left(1-\delta_j\right) K_{p_j,t-1} + I_{p_j,t}\right) \cdot \left(1 - D_{K_j,t}\right) \text{ for } j = n, x \tag{8}$$

where $I_{p,t}$ is private capital investment, δ_p is the sectoral private capital depreciation rate, and $D_{k_j,t}$ is the fraction of private capital destroyed by the flood (derived from the flood risk model). The term g denotes the long-run growth rate in the absence of a disaster. Public capital ($K_{g,\,t}$) similarly evolves as

$$(1+g) K_{g,\,t} = \left(\left(1-\delta_g\right) K_{g,\,t-1} + s_t I_{g,t}\right) \cdot \left(1 - D_{g,t}\right) \tag{9}$$

where $I_{g,t}$ is public investment, s_t is the efficiency of public investment, and $D_{g,t}$ is the fractional loss to public capital. TFP ($A_{j,t}$) for each respective sector evolves according to

$$A_{j,t} = A_{j,0} \left(1 - D_{A_j,t}\right) \text{ for } j = n, x \tag{10}$$

where $D_{A,t}$ represents the fractional disaster-induced loss in productivity and A_0 is steady-state TFP. Together, these equations capture the dynamics of capital, investment, and growth: public and private capital accumulate along a steady-state path through investment net of depreciation, while a flood destroys a fraction of each stock and temporarily lowers productivity, depressing output until the lost capital is rebuilt and productivity recovered.

Adaptation benefits are incorporated externally by running the flood risk and adaptation model under *baseline* and *adaptation* scenarios, yielding avoided losses ($B_{k,t}$)

$$B_{k,t} = D_{k,t}^{\text{baseline}} - D_{k,t}^{\text{adaptation}} \text{ for } k = p, g, A \tag{11}$$

which are treated as reductions in the effective disaster shocks ($D_{k,t}^{\text{eff}}$) within DIGNAD

$$D_{k,t}^{\text{eff}} = D_{k,t} - B_{k,t} \text{ for } k = p, g, A \tag{12}$$

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DIGNAD represents public capital as two perfectly substitutable types: standard and climate-resilient infrastructure. Because our flood protection benefits are already captured exogenously through the avoided losses described above, we use the resilient infrastructure channel solely to introduce the cost of adaptation. Adaptation investment is routed through this channel by adjusting the parameters so that new resilient infrastructure investments neither reduce disaster damages nor contribute to productive capacity. This imposes the fiscal costs of adaptation on the government without double counting its benefits or otherwise altering the model's structure.

We calibrate the DIGNAD model for Thailand using macro-financial data from the year 2022 collected from multiple sources (Bank of Thailand, 2022; IMF, 2023*b*). The calibration parameters are listed in Appendix Table A1, with the full calibration sheet and sources provided in the replication code. We use Thai national sectoral capital stock tables (NESDC, 2022) to disaggregate losses from the flood risk model into public, private, tradeable, and non-tradeable impacts for input into DIGNAD. For all scenarios, we initialize the DIGNAD run and assume the flood event occurs after 5 years. We set a recovery period of 3 years, which is the central value found in a meta-study of historical disasters (Carpenter *et al.*, 2020). The recovery period defines the horizon over which the economy returns to its pre-disaster path. For the adaptation scenario, we assume a constant level of public adaptation investment over 5 years, equivalent to the total cost of the adaptation measures and assume measures are fully effective when the disaster occurs. The government finances adaptation through both public domestic and external commercial debt. The output of each DIGNAD run is a 20-year time series of national GDP, expressed as the percentage deviation from the no-disaster (steady-state) baseline. From this we compute our measure of GDP impact: the mean percentage deviation from the baseline over the 3 years following the flood. We adopt this short, post-disaster horizon because sovereign credit assessments are most sensitive to near-term macroeconomic deterioration, when fiscal and debt pressures are most acute and most likely to prompt rating action. This averaged GDP impact is the input passed to the sovereign credit rating model, and unless stated otherwise all references to GDP loss in this paper refer to this measure.

(iii) Sovereign credit rating model

Our sovereign credit ratings model is a predictive, empirical model of the rating level. Our approach is based on data from S&P's Sovereign Risk Indicators, and an illustrative specification is as follows:

$$CR_{it} = GDPpc_{it} + \boldsymbol{X}_{it} + \mu_{it} \tag{13}$$

where CR represents the rating level. Rating agencies rely on a 20-notch scale, ranging from AAA (most creditworthy) down to D (least creditworthy, and in default). Our data for CR represent the rating level (often referred to as 'notches') for country i in year t. We regress this onto the log of GDP per capita, and our other control variables, namely real GDP growth, net general government debt/GDP, narrow net external debt/current account receipts, current account balance/GDP, and general government balance/GDP. Our data rely on observations from 109 countries, and over the period 2015–20. We restrict our empirical exercise to 2015–20 precisely because this represents a point in time of relatively stable macroeconomic conditions in between both the financial crisis and the Covid-19 pandemic. This facilitates a more accurate estimation of the relationship between macroeconomic fundamentals and sovereign credit ratings. Were we to extend our sample we might encounter various challenges. One key concern is that extending into the Covid-19 pandemic, the data for debt/GDP may considerably widen for many economies without an appreciable change in any of their ratings (Tran *et al.*, 2021). This may limit the utility of our model as a predictive tool. Our dataset is limited to 109 countries as those are the ones with data coverage from S&P over this time period.

While our study focuses on Thailand, we require data from many other countries in order to produce a predictive model of credit ratings. We explore how climate shocks may impact sovereign ratings by exploiting the cross-sectional variation in macroeconomic condition and rating levels. With this approach we can simulate how a climate-induced change to Thailand's macroeconomy may be predictive of a new rating level. We specify a baseline regression framework and estimate it using a random forest model. Informed by others in the literature (see Markellos *et al.*, 2016, for example), this approach is motivated by

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several considerations. First, sovereign credit ratings are ordinal and exhibit important discontinuities. A one-notch change does not have a uniform economic interpretation across the rating scale. For example, a downgrade from AAA to AA+ may have relatively limited implications for a country's underlying fiscal position, whereas a one-notch move from BBB− to BB+ represents a transition from investment grade to speculative grade, with materially different consequences for borrowing costs and market access. Second, the relationship between ratings and explanatory variables is itself non-linear. This is reflected in how rating agencies communicate their assessments, which often rely on threshold effects or 'bands' of economic performance, particularly for indicators such as GDP levels that map to discrete rating categories (S&P Global, 2024). Third, our objective for this model is prediction, rather than explanation. Machine learning approaches offer the flexibility that parametric approaches do not. Removing these constraints provides a much more accurate model, which is important for our results. Random forest models are particularly well suited to accommodate these different features. Our model and approach is closely aligned with Klusak *et al.* (2023), who simulate sovereign credit ratings under different IPCC climate scenarios, and others in the literature who rely on random forest models for sovereign credit rating prediction (Burke *et al.*, 2024; Holden *et al.*, 2024; Agarwala *et al.*, 2026).

Once we have established a model which appropriately captures the existing ratings distribution, we adjust the macroeconomic data to reflect changes in GDP given by DIGNAD. Changes to our other variables are informed by data from S&P (S&P Global, 2015), which describe how shocks to GDP, from natural hazards, may influence the government performance variables featuring in our model. We rely on these data to establish polynomial relationships between GDP losses and changes to these variables and then interpolate on those relationships for our results from DIGNAD. The advantage of this approach is twofold. First, it allows us to capture variables and data related to historic acute physical risks. Second, it provides practitioner evidence on the expected relationship between GDP losses and these macroeconomic indicators, keeping our methodology closely aligned with real-world practices in credit rating agencies.

III. Validation against 2011 Thai floods

We validate our modelling framework using the 2011 floods in Thailand, the country's most damaging recent flood event. Excessive rainfall from successive monsoons caused major rivers to overflow, affecting 65 out of Thailand's 77 provinces. Analysis of peak river flows suggests the event had a return period between 10 and 20 years (0.05–0.1 annual exceedance probability) (Gale and Saunders, 2013). The total economic impact was estimated at $46.5 billion, with 44 per cent attributed to direct physical damages and 56 per cent to economic losses (World Bank, 2012).

Our validation exercise involves passing the maximum observed flood extent from the 2011 event through our full modelling chain and comparing both (i) physical asset losses generated by the flood risk model and (ii) macroeconomic impacts generated by the DIGNAD model with the World Bank's post-disaster rapid assessment (World Bank, 2012). As our framework is calibrated to Thailand in 2022, differences between 2011 and 2022 socioeconomic conditions are considered when interpreting results.

We use MODIS-derived satellite flood extent from the Global Flood Database (Tellman *et al.*, 2021). Flood depths are estimated by combining the binary flood mask with high-resolution topography (Yamazaki *et al.*, 2019), following the approach of Betterle and Salamon (2024). The resultant flood extent-depth map used for validation is shown in Figure 3.

Running our flood risk model with observed 2011 data yields total capital stock damages of $25.8 billion. This compares with the $21 billion in reported asset damages in the World Bank's assessment. Adjusting reported damages to 2022 values gives $27.3 billion, approximately 106 per cent of our modelled estimate, indicating that the model reproduces observed damages with reasonable accuracy.

Feeding these physical loss estimates into the DIGNAD macroeconomic model yields GDP losses of 0.74 per cent, which peak at 1.2 per cent in the year following the disaster. This is consistent with the 1.2 per cent reduction in GDP growth reported by World Bank (2012). These GDP losses result in negligible rating impacts from our credit risk model. In 2011, the flooding also did not lead to a rating downgrade

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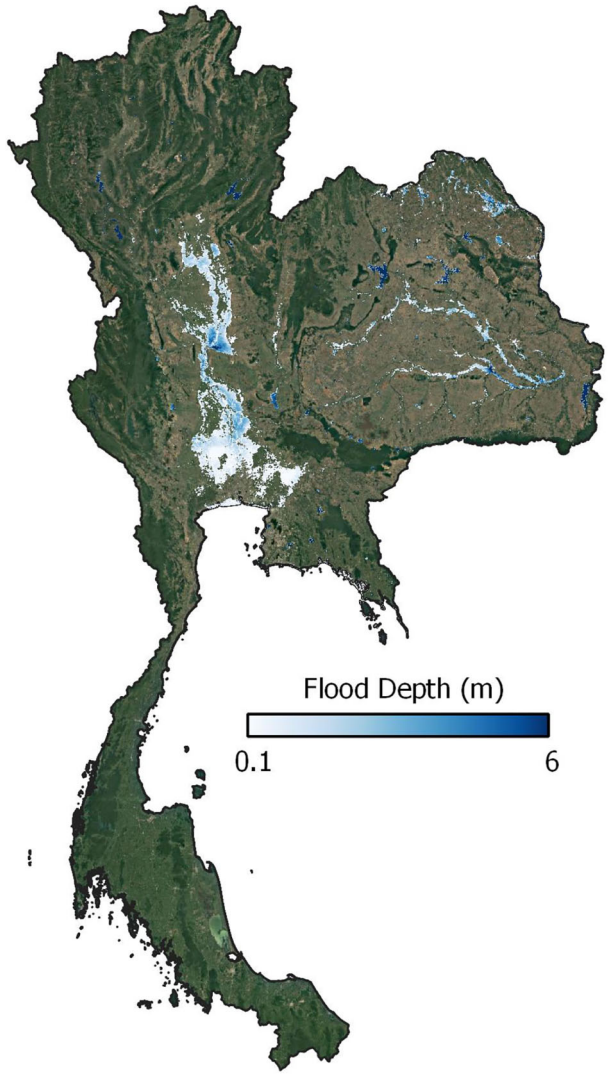


Figure 3 Maximum observed flood extent and derived depths for the 2011 event.
Source: Authors, derived from the Global Flood Database (Tellman *et al.*, 2021) and MERIT Hydro topography (Yamazaki *et al.*, 2019), following the approach of Betterle and Salamon (2024).

for Thailand. In the months following the flood, S&P maintained their stable outlook for Thailand, citing the country's strong fiscal position despite the recent flooding (S&P Global, 2011).

The agreement across all three stages of the modelling chain, from physical damages through GDP losses to the rating outcome, gives us confidence that the integrated framework reproduces the observed impacts of a major flood event with reasonable accuracy.

IV. Simulating current flood risk, GDP losses, and credit impacts

We apply our probabilistic modelling framework to Thailand by simulating 10,000 years of flooding and calculating the damages to capital stock, the resultant impact on GDP, and what this means for

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Table 1 Distribution of flood-risk impacts across physical, macroeconomic, and sovereign credit outcomes in the current climate.

	Mean	Q99
Capital stock damage ($ billion)	9.96	146.40
GDP loss (%)	0.58	10.28
Credit rating impact (notches)	0.09	1.23
Probability of default increase (percentage points)	0.63	1.77
Cost of debt increase (basis points)	65.1	176.8

Note: Values report the mean and 99th percentile of each metric's marginal distribution across baseline simulations. The Q99 values are calculated separately for each outcome and therefore do not necessarily arise from the same simulated year.

the country's sovereign credit rating. In Table 1, we report average (mean) and tail (Q99) metrics from our simulation. The difference between average and tail metrics is substantial. Averaged across all simulation years (the average annual loss, AAL), the capital stock damage is nearly $10 billion, GDP loss is around half a percentage point, and the rating impact is negligible at under a tenth of a notch. Tail losses, by contrast, are more pronounced. The Q99 value for capital stock damages, equivalent to the 100-year return period loss (RP100), exceeds $140 billion, while the Q99 GDP loss exceeds 10 per cent. For sovereign credit outcomes, the Q99 rating impact is a downgrade of more than one notch. The respective Q99 values for the increase in probability of default and cost of debt are approximately 1.8 percentage points and 177 basis points. To illustrate the fiscal significance of this increase, we apply the increase in borrowing costs to Thailand's outstanding debt. With public-sector debt approximately 60 per cent of GDP (around $300 billion) in 2022 (IMF, 2023*b*), a 177-basis-point increase applied to the entire debt stock would raise annual interest costs by roughly $5.3 billion, equivalent to around 1 per cent of GDP. This represents a long-term, full-repricing scenario. In the near term, the increase would be smaller as only the portion of debt that matures, is refinanced, or carries a variable interest rate would be affected.

The full simulation results across our modelling framework are visualized in Figure 4. Each panel plots the outputs of one part of the modelling chain: capital stock damage (top), the resulting GDP loss (middle), and the predicted sovereign downgrade (bottom). Outputs across the modelling chain are ordered by the magnitude of their capital stock damage, meaning every point represents the same simulated flood year across panels, and allows the outputs of the three models to be read together. The three panels show that the linkages between the models are not proportional. While the capital stock curve is smooth by construction (having been ordered by magnitude), the GDP losses display considerable scatter at any given exceedance probability, showing that similar aggregate capital damages can lead to different macroeconomic impacts. This is due to the spatial heterogeneity of economic activity in Thailand and the sectoral differentiated propagation of losses through the macroeconomy, which our spatially explicit model of climate risks is able to capture.

Rating impacts in Figure 4 exhibit a distinct threshold effect rather than a smooth progression. At the 100-year capital stock loss exceedance probability, when GDP losses are in the range of 10 per cent, Thailand's credit outlook becomes markedly more uncertain. These results are significant for three reasons. First, they highlight that rating agency processes may embed implicit thresholds in how economic performance is evaluated, rather than responding proportionally to changes in fundamentals. Second, they show that sovereign risk is not a linear function of economic performance. Instead, there are clear nonlinear and boundary dynamics in creditworthiness that standard macroeconomic models may fail to capture. Third, and most importantly, these thresholds are likely to vary across countries. For Thailand, the analysis suggests a degree of resilience up to around a 10 per cent GDP loss, but identifying where such breakpoints occur in other vulnerable economies is a key priority for policymakers and multilateral development banks.

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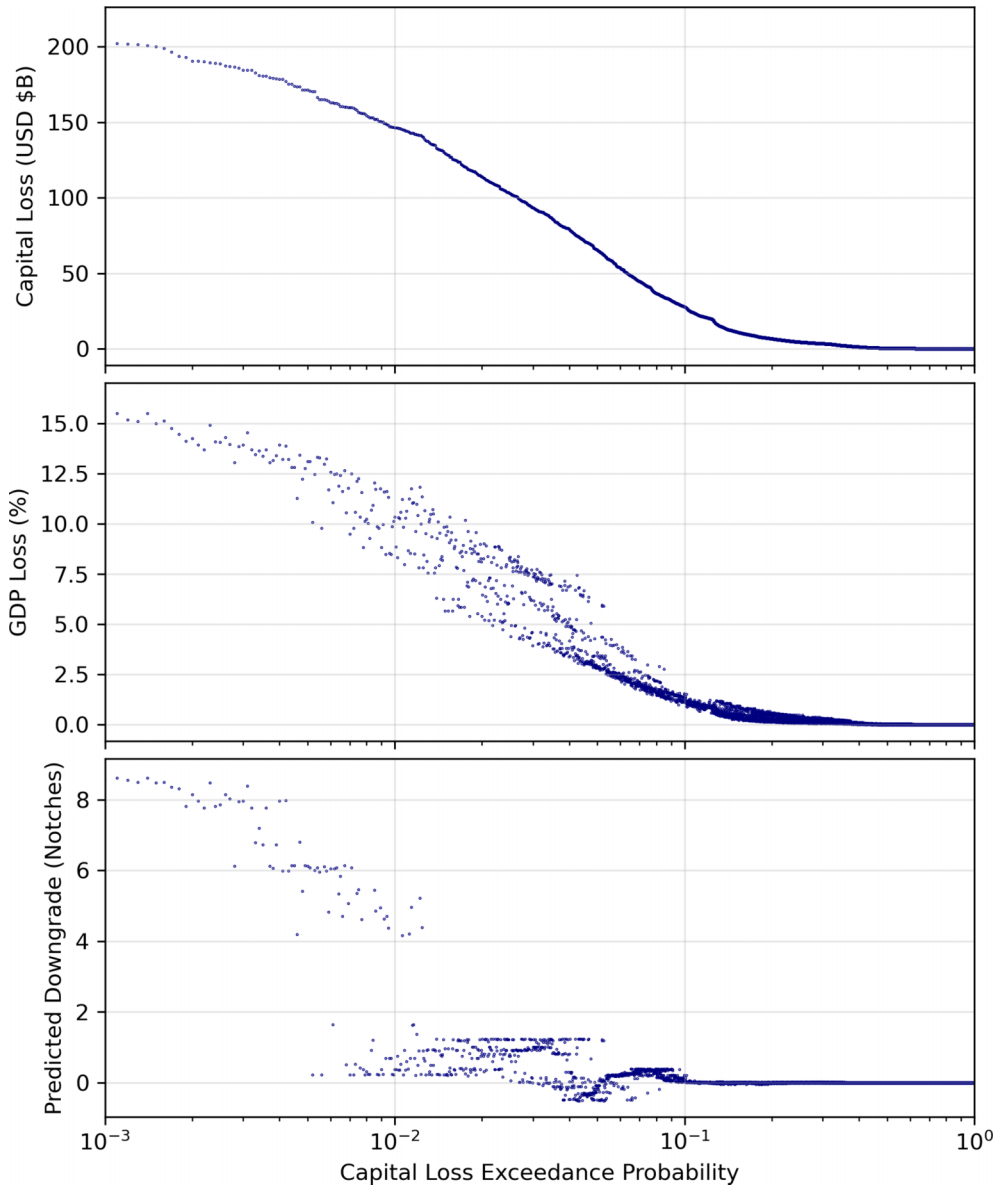


Figure 4 Loss–probability curves for the current climate for capital stock losses (top), GDP losses (middle), and credit rating downgrades (bottom).
Note: All panels share a common x-axis ordered by capital loss exceedance probability, with each point representing the same flood event realization across panels.

V. Rising future flood losses and the benefits of adaptation

We extend our framework to assess how losses and the benefits of adaptation evolve under climate change. We analyse three emissions scenarios spanning low- to high-forcing pathways (SSP126, SSP370, and SSP585) across five future epochs (2030, 2040, 2050, 2060, and 2070), each defined as the centre of a 50-year window. We consider two adaptation conditions: an unadapted case that represents Thailand's

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existing flood protection standards (Scussolini *et al.*, 2016) and an adapted case in which all urban areas are protected against a 100-year return period flood, at a cost of $8.2 billion (1.7% of Thailand's 2022 GDP). Table 2 reports the percentage change in capital stock losses relative to the historical baseline for a select set of scenario combinations, for both the AAL and the 100-year (RP100) loss. An equivalent table for GDP losses is provided in Appendix Table A2.

Under existing protection levels, projected capital stock losses rise with both time and emissions intensity, with AALs reaching nearly 34 per cent above the historical baseline by 2070 under SSP585. The 100-year loss follows the same ordering but with smaller mean increases (up to 11%) and narrower ensemble ranges, while the annual average is both larger and more variable across GCMs. The ensemble ranges are wide, and for lower-emissions scenarios and earlier epochs, span zero, reflecting disagreement across the five GCMs about the direction of change in Thai flood hazard in the near future. Adaptation reduces losses across every scenario and epoch. Protecting urban areas to a 100-year standard reduces AALs to 33–48 per cent below the historical baseline, more than offsetting the climate-driven increases, even under the most severe emissions pathway. The reduction is also substantial for the 100-year loss (roughly 26–29%), though the extreme tail is reduced rather than eliminated, since urban protection does not cover flooding elsewhere in the country. GDP losses follow a similar pattern across scenarios and epochs (Appendix Table A2) with unadapted losses rising under higher emissions and adaptation delivering substantial reductions throughout.

To explore what future climate losses and adaptation mean for Thailand's sovereign credit rating, we focus on the probability of two outcomes: a downgrade and a downgrade below investment grade. The two outcomes represent thresholds of differing severity. Any downgrade raises borrowing costs; a downgrade below investment grade, which from Thailand's current BBB+ rating requires a fall of three or more notches, is far more consequential, as investors restricted to investment-grade assets would be forced to divest. Figure 5 reports both probabilities across scenarios and epochs, relative to the current climate baseline. Under existing protection, the probability of a downgrade rises with both emissions and time: the mean estimate exceeds 2.5 per cent under SSP585 by 2070, with subinvestment grade probability rising from 0.8 per cent at baseline to nearly 1.3 per cent. Although the lower part of the 90th percentile window falls below the current climate baseline, the figure indicates it is highly unlikely that climate change will leave Thailand's downgrade risk below present levels. Uncertainty is substantial and widens under higher emissions and later epochs, with the unadapted downgrade probability exceeding 7 per cent at the upper bound under SSP585. Adaptation reverses this picture across every scenario and epoch, holding downgrade probability below 1 per cent and the subinvestment downgrade probability below 0.5 per cent, in both cases well below the current climate baseline.

Our model shows that the benefits of adaptation are substantial relative to its cost. Upgrading urban flood protection to a 100-year standard, at a cost of $8.2 billion, can lead to reductions in AALs ranging from $3.1 billion to $14.2 billion, across scenarios, epochs, and ensemble quantiles. The undiscounted upfront cost of adaptation would be recovered within 1–3 years through avoided losses alone, well within the multi-decade lifetime of the infrastructure. Although the magnitude of Thailand's future flood risk remains uncertain, adaptation lowers risk below current levels across every scenario and epoch, making it a robust investment regardless of which climate pathway materializes. The benefits of adaptation also extend beyond avoided physical damages. By reducing the probability and severity of downgrades, adaptation keeps borrowing costs lower and preserves fiscal space for investments elsewhere. The stakes are highest at the investment-grade boundary: our model shows a sub-investment-grade downgrade raises borrowing costs by 349 basis points. Applied to our previous illustration of Thailand's $300 billion public-sector debt stock, this would raise annual interest costs by $10.5 billion (around 2% of GDP) under full repricing. Avoiding such a downgrade also avoids harder-to-quantify consequences, including the capital flight that can follow a loss of investment grade status. Adaptation therefore delivers a threefold benefit: it reduces expected damages, narrows the uncertainty around them, and lowers the fiscal tail risk of a costly downgrade.

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Table 2 Projected percentage change in capital stock annual average loss (AAL) and 100-year loss (RP100) relative to the historical baseline, with and without additional adaptation.

		AAL (mean)		RP100 (Q99)	
Scenario	**Epoch**	**Unadapted**	**Adapted**	**Unadapted**	**Adapted**
SSP126	2030	0.1 [−21.8, 43.9]	−46 [−53.4, −32.8]	0.2 [−11.3, 16.7]	−29.4 [−31.9, −25.2]
	2050	16.5 [−7.2, 72.9]	−40.9 [−48.8, −25.1]	6.6 [−2.8, 22.9]	−27.4 [−30.8, −24.6]
	2070	18.6 [−5.3, 70.5]	−39.7 [−47.3, −26.3]	5.8 [−3.2, 22.9]	−27 [−30.3, −23.7]
SSP370	2030	−1.8 [−17.3, 26.9]	−47.7 [−53, −37.8]	0.3 [−8.9, 13.5]	−29.3 [−31.4, −25.3]
	2050	1 [−20.8, 52.4]	−46.4 [−53.8, −30.4]	1.3 [−10.9, 21.3]	−29 [−31.5, −23.7]
	2070	11.4 [−22.9, 107.2]	−42.5 [−54.3, −14.9]	6.2 [−12.9, 31.9]	−27.3 [−32.4, −22.4]
SSP585	2030	5.7 [−11.6, 37.9]	−44.3 [−50.2, −34.3]	3.7 [−5.4, 15.2]	−28.8 [−30.2, −25.2]
	2050	21 [−3.8, 85.6]	−39.8 [−48.1, −22.9]	9 [−1, 27.6]	−26.8 [−29.9, −23.3]
	2070	33.7 [−5.7, 137.4]	−33.4 [−45.8, −5.6]	11 [−5.9, 35.1]	−25.8 [−30.2, −21.9]

Note: Each cell reports the mean across the five-GCM ensemble, with lower and upper bounds of the 90th percentile window in brackets

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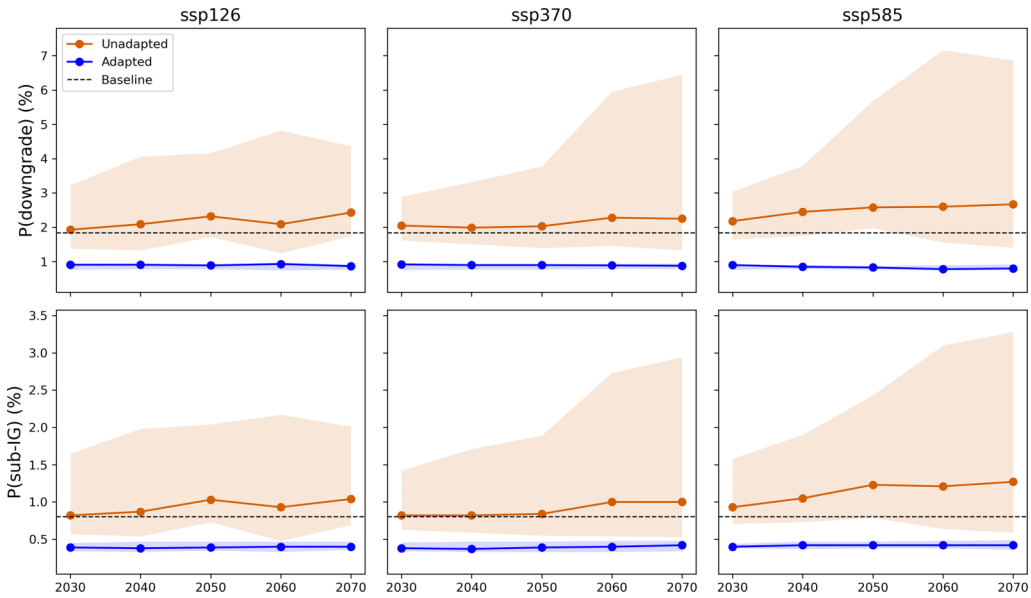


Figure 5 Probability of downgrade (top row) and subinvestment grade downgrade (bottom row) across climate scenarios and future epochs.

Note: Values represent the mean across climate model ensemble members, with shading indicating the 90th percentile window across the ensemble. The dashed line indicates the baseline (current climate) probability.

VI. Discussion

Our analysis has shown that acute climate risks can materially impact economic growth, public debt, and hence sovereign creditworthiness, with extreme flood events potentially triggering multi-notch rating downgrades with significant fiscal consequences in Thailand. Our modelled acute impacts on credit ratings equal and exceed the estimated chronic impacts presented in Klusak *et al.* (2023), demonstrating the importance of including acute physical climate risk in forward-looking assessments of climate financial risk. Crucially, our modelling framework also allows us to explicitly incorporate adaptation into assessments of sovereign credit risk. We show that adaptation can significantly reduce future losses and resultant downgrades in Thailand, providing concrete evidence about the benefits of adaptation investments.

The integration of probabilistic catastrophe models into sovereign risk assessment, as proposed here, represents an evolution in how governments and international financial institutions could approach debt sustainability analysis (DSA). Current DSA frameworks, while sophisticated in their treatment of traditional macroeconomic shocks, often inadequately capture the tail risks associated with climate extremes. Our results show that a 1-in-100 flood loss year (the 99th percentile of our simulation) could reduce Thailand's GDP by 10 per cent in the years following the event and trigger a sovereign downgrade, with rarer events and higher-emission futures pushing ratings towards or below investment grade. These impacts are comparable to or exceed those from chronic climate change alone, highlighting the importance of incorporating climate shocks into fiscal sustainability assessments.

The probabilistic approach we introduce offers several advantages for DSA applications. First, it moves beyond deterministic scenarios to capture the full distribution of acute climate impacts, enabling more comprehensive stress testing. Second, by linking a flood catastrophe model directly to the DIGNAD framework, our methodology maintains consistency with existing IMF and ministries of finance analytical tools, while adding climate and adaptation capabilities. This compatibility is crucial for practical implementation, as it allows decision-makers to extend rather than replace their existing toolkit (Coalition of Finance Ministers for Climate Action, 2025).

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Our findings directly address the 'climate investment trap' where climate-vulnerable countries face a vicious cycle of rising climate damages, eroding growth, and increasing public debt levels, hence deteriorating creditworthiness, and reducing fiscal capacity for adaptation investments. Importantly, by quantifying how specific adaptation measures affect sovereign ratings, we provide an evidence base for breaking this cycle, something that was not possible in previous work that relied on the aggregate macroeconomic impacts of climate change (Klusak *et al.*, 2023). Upgrading urban flood protection to a 100-year standard, at a cost of $8.2 billion, reduces AALs by between $3.1 billion and $14.2 billion across scenarios and epochs. Adaptation also lowers the probability and severity of downgrades, and the associated borrowing costs. These avoided costs are the most consequential at the investment-grade boundary, where a reduction in downgrade probability protects against a disproportionately large increase in borrowing costs and the loss of market access that can follow a fall below investment grade.

The methodology we present is relevant beyond just credit ratings and, we propose, enhances climate scenario analysis capabilities for both public and private financial institutions. Current climate stress testing exercises, such as those conducted by central banks and financial regulators, often struggle to incorporate acute physical climate risks (Ranger *et al.*, 2022) and their cascading effects through sovereign channels. Our framework addresses this gap by providing a reproducible methodology for modelling how extreme weather events propagate from physical damages through macroeconomic impacts to debt sustainability and sovereign ratings. This could be extended to explore the impact of financial sector exposures and the bank–sovereign nexus. This is particularly important for emerging market economies where domestic financial institutions hold substantial debt portfolios (Feyen and Zuccardi, 2019).

The findings of our study are also subject to several limitations, which should be addressed. To preserve reproducibility across countries, our framework is built predominantly on global open datasets. These global datasets have well reported limitations in terms of accuracy and detail (Bernhofen *et al.*, 2018, 2021). The hazard maps, exposure layers, and protection standards could all be improved with national data. Our adaptation scenario is stylized, assuming uniform protection of all urban areas to a 100-year standard rather than a costed portfolio of specific projects. For our assessment of future risks, we hold the Thai economy constant at 2022 levels. Previous research has shown historical urban growth in high flood risk areas, including Thailand (Rentschler *et al.*, 2023). If future urbanization follows historical trends, this could further increase future flood losses, which our model implementation does not capture. Our results are also conditional on a series of modelling choices whose individual contributions to uncertainty we have not fully quantified. At each stage of the chain, we adopt one model from a wider set of plausible alternatives. Each carries its own structural assumptions and a full propagation of uncertainty across the chain, including the sensitivity of results to the choice of model at each step, remains an open question and an avenue for future work. The objective of this analysis is not to deliver definitive estimates of Thailand's credit risk, but to demonstrate how probabilistic quantification can strengthen the evidence base on the fiscal benefits of adaptation. Because the framework is open-source and modular, each component can be replaced or refined as better data and models become available or adapted to the question and country context of interest.

The framework presented here opens several avenues for policy-relevant research. Most immediately, linking our approach to National Adaptation Plans (NAPs) could provide countries with quantitative tools to prioritize adaptation investments based on their fiscal risk reduction potential. This requires that NAPs provide sufficient detail on both planned interventions, costs, and approach for financing measures (Woodruff and Regan, 2019). It would also require working directly with national planning agencies to incorporate country-specific project pipelines and implementation timelines into the modelling framework. Such applications could inform the development of 'adaptation-smart' debt sustainability frameworks that recognize the fiscal value of resilience investments.

Data availability

The code and data needed to reproduce the analysis and figures in this paper can be found at https://github.com/mvbnffc/adaptation-smart-ratings

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Appendix

A1. Computing fluvial change factors

We derive change factors from the daily discharge simulations at each river basin. Two types of change factors are computed: (1) intensity multipliers for selected return periods and (2) adjusted return periods for baseline discharges under future climate conditions. We use daily river discharge from the JULES-W2 hydrological model for one historical period (1965–2014) and five overlapping future 50-year windows (2005–54, 2015–64, 2025–74, 2035–84, and 2045–94), which we refer to as the 2030s, 2040s, 2050s, 2060s, and 2070s, respectively.

A1.1 Peak-over-threshold (POT) modelling

For each grid cell and period (historical and each future window), we construct a POT sample as follows. Assume $\{Q_t\}_{t=1}^{n}$ represents a sequency of daily discharge levels simulated by the JULES-W2 hydrological model, then, for a sufficiently high value of u, we get that,

$$X_t = Q_t \ - u \mid Q_t \rangle \, u$$

converges to the generalized Pareto distribution (GPD). Then,

$$\Pr\left(X_t \leq x | Q_t > u\right) \approx G\left(x; \xi, \sigma\right) \ = \ \begin{cases} 1 - \left(1 + \frac{\xi x}{\sigma}\right)^{-1/\xi}, \ \xi \ \neq \ 0 \\ 1 - \exp\left(-\frac{x}{\sigma}\right), \ \xi \ = \ 0 \end{cases}$$

with ξ being the shape parameter and $\sigma \ > \ 0$ the scale parameter.

Because these raw discharge series Q_t can show short-term dependence, we perform a declustering procedure where only the maximum exceedance above threshold u within each contiguous run is kept.[1] This results in a sequence of cluster maxima $X_1, \ldots, X_{N_{exc}}$ that may be considered approximately independent realizations that can be used as inputs for the POT model.

Given our threshold u, for which we will discuss the calibration further, let z_i denote the declustered exceedances over u. We obtain the parameters for the GPD using the log-likelihood function where the location parameter is fixed to zero,

$$\updownarrow\left(\xi, \sigma | z_1, \ldots, z_m\right) = -m \log \sigma - \left(1 + \frac{1}{\xi}\right) \sum_{i=1}^{m} \log\left(1 + \frac{\xi z_i}{\sigma}\right), ,$$

The maximum likelihood estimates (MLE, $\hat{\sigma}, \hat{\xi}$) are obtained using numerical optimization with a log-scale parameterization for σ. To quantify estimation uncertainty, we compute the observed information matrix by finite difference approximation of the Hessian of the negative log-likelihood,

$I(\xi, \log \sigma) = -\nabla^2_{(\xi, \log \sigma)} \updownarrow.$

and obtain the covariance matrix of $(\hat{\sigma}, \ \hat{\xi})$ through inversion and the delta method. This provides us with an uncertainty measure for return levels.

The key parameter in the POT model is the threshold parameter u. Since this analysis is performed on a large set of grid points, an automated threshold selection procedure is used with potential thresholds equal to the 90th, 92nd, 94th, 96th, 97th, 98th, and 99th quantiles. The threshold for each grid point is determined based on three selection criteria. First, the number of exceedances of the threshold needs to be at least 50 observations to ensure that sufficient samples are available for the parameter estimation described above. Second, the Kolmogorov–Smirnov (KS) statistic is used to assess the fit of the GPD with the exceedances for each threshold. A significance level of 0.05 is used to discard any threshold leading to samples that do not align with the assumed GPD.

Lastly, we pick the final threshold based on the stability of the parameter estimates. For each threshold that meets the first two requirements, we compute the estimates for $\hat{\xi}$. We then start moving through the thresholds from lowest to highest and record the change in estimates for this parameter ξ. When the estimate changes substantially (we use a difference of 0.05 as a cut-off), then we assume that we

[1] A contiguous run is defined as each series where the values exceed the threshold with a separation of less than 3 days.

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moved from a stable region for estimating the POT to a less stable region. This follows the diagnostic principle that the tail index should stabilize once the threshold enters the domain where the asymptotic approximation holds. The selected threshold is the lowest u within the first stable region satisfying the KS constraints. This choice maximizes the use of available data while maintaining compatibility with the asymptotic theory.

The parameter estimates associated to the selected threshold are subsequently translated into a confidence interval of return levels. Let $\lambda = \frac{N_{exc}}{n}$ be the empirical exceedance rate associated with the chosen threshold u. The survival function under the POT model is approximated by

$$\Pr(Q > q) \approx \lambda\left(1 + \frac{\xi\,(q-u)}{\sigma}\right)^{-1/\xi}$$

leading to the T-year return-level Q_t defined by $\mathrm{P}(\mathrm{Q} > \mathrm{Q_T}) = \mathrm{T}^{-1}$. Solving for,

$$Q_T = \begin{cases} u + \frac{\sigma}{\xi}\left[(\lambda T)^{\xi} - 1\right], & \xi \neq 0 \\ u + \sigma\, log\,(\lambda T), & \xi = 0 \end{cases}$$

We then also obtain uncertainty bounds around the estimated values for Q_T using the multivariate delta method. Let $\theta = (\xi, \sigma)^T$ and $\hat{\theta}$ its MLE estimate with covariance $\widehat{\Sigma_\theta}$. Then, we have that,

$$Var\left(\hat{Q}_T\right) \approx \left(\nabla_\theta q_t\left(\hat{\theta}\right)\right)^T \widehat{\sum}_\theta \left(\nabla_\theta q_t\left(\hat{\theta}\right)\right)$$

A1.2 Computing intensity multipliers

To obtain intensity multipliers that represent the change in intensity of extreme discharge levels over time and scenarios, we first compute a baseline discharge for return periods (20, 50, 100, 250, 1,000 years) from the obtained parameter estimates for Q_T. For a given target non-exceedance probability level p (corresponding to a return period R), the baseline discharge is

$$Q^{hist}(p) = u^{hist} + Q_T\left(\xi^{\mathrm{hist}}, \sigma^{\mathrm{hist}}\right)$$

where u^{hist} refers to the historical baseline, Q_T is obtained using the survival function calibrated on samples that occur within our historical time window (see above).

For a future window, we compute the corresponding future discharge levels at the same return period:

$$Q^{fut}(p,\ t) = u^{fut} + Q_T\ \left(\xi_t^{fut},\ \sigma_t^{fut}\right)$$

The intensity multiplier for a given return period R at period t is then the ratio of future to historical design discharge:

$$M(R,\ t) = \frac{Q^{fut}(p_R,\ t)}{Q^{hist}(p_R)}$$

Confidence intervals for the intensity multipliers are derived using the estimate for $Var(\hat{Q}_{T,\,t})$,

$$95\%\, CI\, M(R,\ t) = \left[\frac{Q^{fut}(p_R,\ t) - 1.96\sqrt{Var\left(\hat{Q}_{T,\,t}\right)}}{Q^{hist}(p_R)},\ \frac{Q^{fut}(p_R,\ t) + 1.96\sqrt{Var\left(\hat{Q}_{T,\,t}\right)}}{Q^{hist}(p_R)}\right]$$

A1.3 Computing adjusted return period

The adjusted return periods express how often a current discharge level associated with a return period will occur in a future scenario. For example, a current discharge level at return period 500 years may occur once every 450 years in a high-emission scenario centred on the 2070 period. Using the obtained GPD with parameters $(\xi_t^{fut},\ \sigma_t^{fut})$, we can obtain a new quantile associated with the baseline discharge level $Q^{hist}(p_R)$.

Let $Q^{hist}(p_R)$ denote the historical discharge associated with return period R, obtained from the historical POT model as described above. For a given future time window t, the exceedance of discharge is modelled using the GPD with parameters $(\xi_t^{fut},\ \sigma_t^{fut})$, and threshold u_t^{fut}.

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Under the POT framework, the exceedance probability of a discharge level q is approximated by

$$\Pr(Q > q) \approx \lambda_t \left(1 + \frac{\xi_t^{fut}\left(q - u_t^{fut}\right)}{\sigma_t^{fut}}\right)^{-1/\xi_t^{fut}}$$

The subsequent adjusted return period is given by

$$RP_{adj}(p_R,\ t) = RP(p_R)\left(\frac{1 + \xi_t^{fut}\ \frac{Q^{hist}(p_R) - u_t^{fut}}{\sigma_t^{fut}}}{1 + \xi_t^{fut}\ \frac{Q^{fut}(p_R,\ t) - u_t^{fut}}{\sigma_t^{fut}}}\right)^{\frac{1}{\xi_t^{fut}}}$$

Similar to before, the confidence intervals can be obtained by substituting $Q^{fut}(p_R,\ t)$ with $Q^{fut}(p_R,\ t) \pm \sqrt{Var(\hat{Q}_{T,\ t})}$.

Table A1 DIGNAD calibration parameters for Thailand in 2022.

Parameter description	Parameter	Value
Public infrastructure investment to GDP ratio	iziy	0.031
Public adaptation infrastructure investment to GDP ratio	izay	0
Consumption tax rate (VAT)	ho	0.07
Labour income tax rate	hlo	0.2
Public domestic debt to GDP ratio	share_b	0.5219
Public concessional debt to GDP ratio	share_d	0.01
Public external commercial debt to GDP ratio	share_dc	0.0715
Private external debt to GDP ratio	share_bstar	0.3201
Real interest rate on public domestic debt	ro	0.005
Real interest rate on public external commercial debt	r_dco	0.035
Grants to GDP ratio	share_grants	0
Natural resources revenue to GDP ratio	oilro	0.01817
Remittances to GDP ratio	share_remit	0.0188
Imports to GDP ratio	imp2gdp	0.681
Government savings to GDP ratio (use only for contingency fund)	Savo	0
Trend per capita growth rate in absence of natural disasters	g	0.0196
Value added in NT sector	VA_n	0.366
Scaling parameter determining ability of adaptation capital to withstand natural disaster (see realism sheet)	ppi_nd_n	0
Cost ratio adaptation vs standard investment [adaptation is % expensive than standard]	a_za	0
Initial return on adaptation infrastructure investment	R_zao	0
Depreciation rate of public capital (adaptation)	delta_za	0

Note: Lists the DIGNAD parameters calibrated for Thailand. The full calibration sheet, together with the sources and rationale for the values reported here, is provided in the accompanying replication code.

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Table A2 Project percentage change in GDP annual average loss (AAL) and 100-year loss (RP100) relative to the historical baseline, with and without additional adaptation.

		AAL (mean)		RP100 (Q99)	
Scenario	**Epoch**	**Unadapted**	**Adapted**	**Unadapted**	**Adapted**
SSP126	2030	1.4 [−22.4, 50.6]	−43.2 [−48.5, −33.8]	1.8 [−12.8, 27.4]	−26 [−28.6, −19.8]
	2050	19.5 [−5.5, 83.6]	−39.7 [−45.5, −28.5]	9.6 [−2.2, 33]	−25.3 [−27.8, −19]
	2070	19.9 [−6.8, 83]	−38.9 [−44.5, −29.4]	9.9 [−4.6, 32.9]	−25 [−27.6, −18.9]
SSP370	2030	0 [−17.7, 32.9]	−44.3 [−48.4, −36.9]	3.5 [−9.7, 23.9]	−26.1 [−28.4, −19.2]
	2050	3.1 [−21.4, 63.6]	−43.6 [−49.1, −32]	3.1 [−11.8, 32.5]	−26.1 [−28.9, −19]
	2070	14.6 [−24.3, 135.4]	−40.7 [−49.5, −21.9]	8.4 [−13.8, 44.6]	−23.8 [−29.5, −17.1]
SSP585	2030	7.6 [−10.8, 43.5]	−41.9 [−46.2, −34.8]	4.9 [−4.5, 25.5]	−25.7 [−27.1, −20.6]
	2050	25.9 [−0.5, 109.3]	−38.6 [−44.7, −27]	16.1 [0, 40.9]	−23.2 [−26.5, −18.1]
	2070	35 [−9.7, 163.6]	−34.4 [−43.7, −15.3]	19.1 [−9.8, 46.9]	−22.1 [−28.3, −16.9]

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