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# Climate change economics in Vietnam: Redefining economic impact

Christian Otto [a], Christoph Schult [b,*], Thomas Vogt [a]

[a] Transformation Pathways, Potsdam Institute for Climate Impact Research (PIK), PO Box 6012 03, Potsdam, 14412, Brandenburg, Germany
[b] Macroeconomics, Halle Institute for Economic Research (IWH), Kleine Maerkerstrasse 8, Halle, 06108, Saxony-Anhalt, Germany

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A B S T R A C T

Vietnam, a low middle-income economy, grapples with considerable climate impacts, primarily driven by heat waves, sea level rise, and tropical cyclones. Under ongoing global warming, these extreme weather events are projected to further intensify. We use a dynamic general equilibrium model to study economic transition dynamics from 2015 to 2100, accounting for heat-induced labor productivity losses, agricultural land loss from sea level rise, and residential property damage from tropical cyclones. We compare a Paris-compatible strong mitigation scenario where global warming is limited to well below 2 °C above preindustrial levels to a strong emission scenario where warming reaches 4–5 °C. We find that the impacts of climate change on output and investment are highly uncertain, with differences between the two emission scenarios remaining statistically insignificant until the end of the century, despite substantially higher climate forcing in the latter. By contrast, consumption losses are significantly larger under the high emission scenario. These negative impacts are primarily driven by heat-induced labor productivity losses, while TCs are the main source of uncertainty. Our findings highlight the need for analytical frameworks to capture the different channels through which climate and climate change affect economic development, rather than focusing mainly on output-related damage, as done in many existing studies.

## 1. Introduction

Extreme weather events, such as tropical cyclones (TC) and droughts, as well as regular fluctuations in temperature and precipitation, have been increasingly recognized as significant determinants of economic activity, with effects that may persist for several years (Linsenmeier, 2023). While numerous empirical studies document the economic consequences of these climate-related shocks (Krichene et al., 2023; Berlemann and Wenzel, 2018, 2016; Loayza et al., 2012; Kotz et al., 2021, 2022; Kalkuhl and Wenz, 2020; Burke et al., 2015; Tol, 2019; Havranek et al., 2015; Bilal and Känzig, 2026; Harding et al., 2025), the heterogeneity in their findings highlights the need for a more structured approach to disentangling the underlying impact mechanisms. State-of-the-art climate integrated assessment models often assume a top-down approach that only accounts for the aggregate impacts of global mean temperature change on output (Liu et al., 2019). This approach is convenient because impacts can be described solely as a function of global mean temperature, which is calculated endogenously in these models. However, bottom-up modeling approaches, such as computable general equilibrium models, which explicitly resolve different impact channels demonstrate that the economic consequences of climate variability and change critically depend on the transmission mechanisms considered. Depending on the dominant channels, climate impacts can trigger markedly different macroeconomic responses in terms of capital accumulation, economic growth, and distributional effects (Dellink et al., 2019; Piontek et al., 2019; Dellink et al., 2014). These can amplify but also partially offset direct damage (Bachner et al., 2022; Eboli et al., 2010). All these response dynamics remain hidden when only aggregate impacts are considered, which can lead to an underestimation of the impacts of climate change on economic development and non-optimal policy responses (Casey et al., 2024). Furthermore, in a recent integrated assessment model inter-comparison exercise, it was shown that temperature damage functions built on bottom-up modeling result in substantially higher end-of-century damage than the established temperature damage functions (van der Wijst et al., 2023).

In this study, we contribute to the literature by employing a dynamic general equilibrium model specifically calibrated for Vietnam, a lower-middle-income economy highly exposed to climate risks (Raitzer et al., 2015). Our analysis extends beyond the conventional focus on GDP impacts by examining how climate-induced economic disruptions alter structural transformation dynamics and consumption patterns. Our model explicitly captures sector-specific heterogeneity in climate impacts by distinguishing agriculture, industry, and services while

* Corresponding author.
*E-mail address:* christoph.schult@iwh-halle.de (C. Schult).

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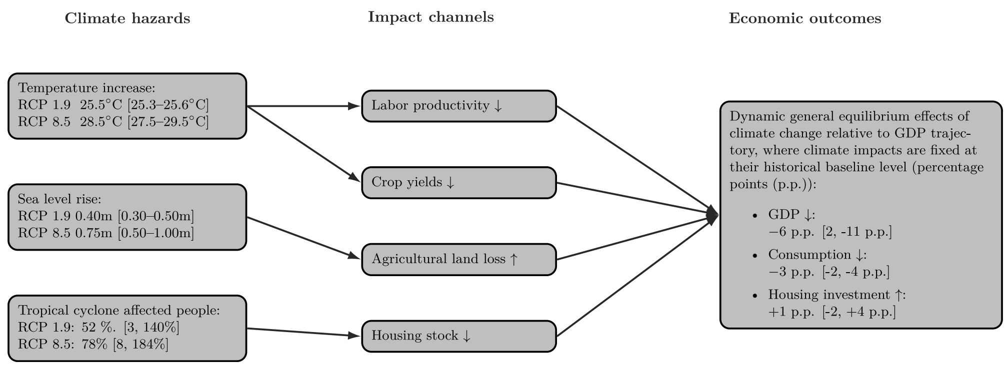


**Fig. 1. Overview of climate change impact analysis.** Graphic illustrating the transmission of key climate-related hazards – namely rising temperatures, sea-level rise, and heightened exposure to tropical cyclones – into economic impacts via several intermediate channels, including reductions in labor productivity, declines in crop yields, loss of agricultural land, and damage to residential structures. Upward- and downward-oriented arrows indicate the direction of causal influence, and the numerical values in brackets correspond to 95% confidence intervals. Collectively, these impact channels generate adverse general equilibrium effects, characterized by reductions in GDP and aggregate consumption, alongside a pronounced increase in required housing investment for reconstruction and climate adaptation.

incorporating their interdependence through sectoral supply chains derived from input–output tables. We incorporate multiple key transmission channels: (i) heat-induced reductions in labor productivity, which vary across sectors; (ii) sea level rise, which diminishes arable land and affects agricultural productivity. We thereby extend the existing computable general equilibrium literature by introducing TC-induced damage to a durable consumption good – specifically, the housing stock – as a novel impact channel. Within Vietnam's aggregate capital stock, housing represents the predominant asset class. It functions, on the one hand, as a durable consumption good for households and, on the other hand, as a source of income for the financial sector via mortgage claims. In addition, by incorporating large ensembles of synthetic TCs, we are able to robustly characterize the uncertainty associated with changes in TC landfall frequency and intensity under global warming (see Fig. 1).

By explicitly modeling these channels and their interactions, we provide novel insights into the long-term economic consequences of climate change, offering a more comprehensive understanding of the underlying mechanisms that drive climate-related economic disruptions.

We simulate economic transition dynamics from 2015 to 2100 under two distinct emission scenarios: a strong global mitigation scenario, where, consistent with the Paris Agreement, global mean temperature increase is limited to well below +2°C above pre-industrial levels and a high emission scenario leading to +4°C to +5°C of warming by the end of the 21st century (van Vuuren et al., 2011). Additionally, we incorporate two socioeconomic development pathways to account for possible trajectories of population growth and economic development (O'Neill et al., 2020; Riahi et al., 2017).

Due to the stark differences in direct climate damage, the economic transition dynamics differ substantially between the two scenarios. Most notably, higher TC damage under the high-emission scenario requires greater reconstruction investments, resulting in substantially higher consumption losses. Nevertheless, aggregate economic growth trajectories do not differ statistically significantly across both scenarios throughout the century. This suggests that key climate-induced transition dynamics may be obscured when focusing solely on GDP impacts, as done in much of the climate econometrics literature.

Importantly, this suggests that key transitional dynamics are overlooked when climate impacts are represented solely through aggregate temperature – i.e., functions that relate (global) mean temperature change to aggregate damage on output – as is common in most climate integrated assessment models (Barrage and Nordhaus, 2024; Wahba and Hope, 2006; Ricke et al., 2018; Dennig et al., 2015).[1] To demonstrate this, we compare results from our full model to those obtained using the temperature damage function from the 2023 version of Nordhaus' seminal Dynamic Integrated Climate-Economy (DICE) model (Barrage and Nordhaus, 2024). This comparison underscores the importance of accounting for sector-specific and structural impacts, rather than relying exclusively on aggregate GDP measures, and highlights the need to capture dynamic feedbacks between climate shocks, investment decisions, and long-term economic development, consistent with recent findings that interaction effects among damage significantly amplify aggregate costs (Bretschger and Komarov, 2024). While discount rates and equity weights critically shape the social cost of carbon (Hope, 2008), it is equally important to capture diverse climate impact channels – such as productivity, health, and capital damage – to avoid biased welfare estimates.

The remainder of this paper is structured as follows: Section 2 presents the macroeconomic model. Section 3 details the climate change and socioeconomic scenarios. In Section 4, we analyze the relative importance of different impact channels. Section 5 explores the economic response dynamics under different transition pathways. Section 6 discusses our findings and situates them within the broader literature, and Section 7 concludes with policy implications.

## 2. Model

We apply a dynamic general equilibrium model that has been calibrated specifically for the context of Vietnam (Großmann et al., 2023). The simulation of transitions within the model extends from the base year of 2015 all the way to the year 2100, allowing for a comprehensive analysis of long-term economic dynamics and climate change-induced structural change. The initial conditions of the model are chosen so that they represent the steady state at the beginning of the simulation period. In the following, the main model blocks are briefly explained. Further, Fig. 2 provides an overview of the model's structure, and Section A of the Online Appendix provides an in-depth model description. Our approach parallels recent efforts to regionalize integrated assessment models (Cantelmo et al., 2023).

### 2.1. Household

A representative household derives utility $U$ from consumption $C_t$, housing $H_{t+1}$, and disutility for hours worked $N_{s,t}$ in period $t$ and sector

[1] Keppo et al. (2021) provide an overview of climate integrated assessment modeling exercises during the first two decades of the 21st century.

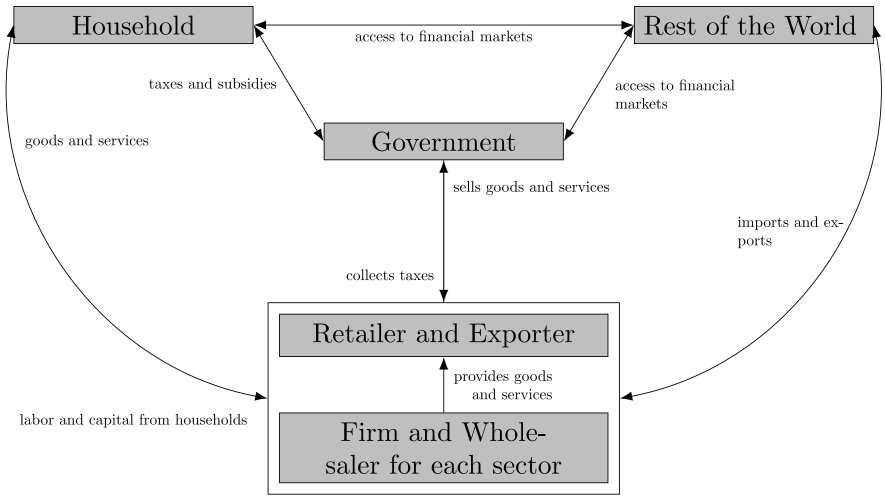


**Fig. 2.** Model overview.

$s \in \{1, \ldots, S\}$,

$$U(C_t, H_{t+1}, N_{s,t}) = \frac{\left(C_t^{1-\gamma} H_{t+1}^{\gamma}\right)^{1-\sigma^C}}{1-\sigma^C} - \sum_{s=1}^{S} A_{s,t}^L \phi_s^L \frac{N_{s,t}^{1+\sigma^L}}{1+\sigma^L},$$

where $\gamma$ is the preference parameter for housing. Furthermore, the intertemporal elasticity of substitution $\sigma^C$ determines the responsiveness of the household's consumption to a change in the real interest rate, and $S$ is the total number of sectors. Similarly, the response of labor supply to changes in real wages is governed by the inverse Frisch elasticity $\sigma^L$. The disutility of labor is directly proportional to labor productivity $A_{s,t}^L$, assuming that higher labor productivity requires more accumulation of human capital, which in turn implies a reduction in leisure time (Schultz, 1961; Stantcheva, 2015). Finally, sector-specific disutility coefficients $\phi_s^L$ ensure that the allocation between sectors represents the actual observed labor share for given sector real wages in the long term.

The household decides on its optimal consumption level $C_t$, labor supply $N_{s,t}$, investments $I_{s,t}$, capital stock $K_{s,t+1}$, housing $H_{t+1}$, and net foreign asset holdings $B_{t+1}$ by intertemporally maximizing instantaneous utility $U(C_t, H_{t+1}, N_{s,t})$ over an infinite time horizon, discounting future utility with the discount factor $\beta$,

$$\max_{\substack{C_t, I_{s,t}, N_{s,t},\\ H_{t+1}, K_{s,t+1}, B_{t+1}}} \sum_{t=0}^{\infty} \beta^t U(C_t, H_{t+1}, N_{s,t}) \tag{1a}$$

subject to:

$$\text{Income}_t = \text{Expenditures}_t, \tag{1b}$$

$$K_{s,t+1} = (1-\delta)K_{s,t} + I_{s,t}\Gamma_{s,t} - D_{s,t}^K \ \forall s, \tag{1c}$$

$$H_{t+1} = H_t\left(1-\delta^H\right) + I_t^H - D_t^H. \tag{1d}$$

The household faces a budget constraint, such that its total expenditures must equal its income (Eq. (1b)). They own capital stocks $K_{s,t+1}$ specific to each sector. During the process of capital accumulation (Eq. (1c)), these grow due to sector-specific effective investments $I_{s,t}\Gamma_{s,t}$ and depreciate at a fixed rate $\delta$. Effective investment depends on the amount of investment $I_{s,t}$ and the investment adjustment costs $\Gamma_{s,t}$. In addition, the household owns a housing stock $H_{t+1}$, which increases with equity based investments in housing $I_t^H$ and depreciates over time at a constant rate $\delta^H$ (Eq. (1d)). Thus, household spending includes consumption, investment in sector-specific capital and housing, and the purchase of international bonds. Both capital and housing stocks are susceptible to impacts from climate change, manifested as damage to sector-specific capital $D_{s,t}^K$ and housing $D_t^H$. The representative household is assumed to own the entire physical stock of residential structures. Housing wealth is given by the resale value of the housing stock net of outstanding mortgage liabilities and therefore corresponds to the household's net housing equity. Residential investment, $I_t^H$, represents the equity-financed component of housing accumulation and augments the physical stock of dwellings. Mortgage financing modifies the household's liability position but does not affect ownership of the underlying physical asset.

The services sector – which encompasses financial intermediation – holds mortgage claims that are collateralized by housing. In the present version of the model, these claims are recorded as part of the services sector's capital stock. Consequently, a fraction of the resale value of the housing stock is represented in the services-sector capital through financial claims, while the entire physical housing stock remains on the household's balance sheet.

Under this structure, climate-induced damage to housing is modeled as negative shocks to household wealth that reduce net housing equity. Reconstruction is financed through additional equity-based residential investment rather than through adjustments in mortgage claims. This constitutes a reduced-form treatment that deliberately abstracts from a more detailed representation of the financial accounts and balance-sheet interactions.

Household income consists of several components: revenue from lending capital, labor income, and returns from previously purchased foreign bonds. Furthermore, households earn a world interest rate from foreign bonds if their net foreign asset position is positive. If the household is a net debtor, which means it owes more to foreign lenders, the interest payments increase with the debt level. By contrast, higher levels of net foreign assets reduce the interest rates on net foreign assets.

## 2.2. Firm

The representative firm sells its goods $Q_{s,t}$ at prices $P_{s,t}^Q$. Further, the firm pays sector-specific wages per hour worked $W_{s,t}$.[2] A representative firm in each sector maximizes profits using optimal production factors. These factors include labor $L_{s,t} \equiv N_{s,t} LF_t$, where $N_{s,t}$ and $LF_t$ are the number of hours worked and the labor force, respectively, and rented capital $K_{s,t}$ provided by the representative household. In addition to the primary production factors, the firm also uses intermediate goods $Q_{s,k,t}^I$ produced by a representative wholesaler using products from different

[2] Only a portion of the population works, represented by the ratio of the labor force to the total population, which reflects the share of the working age population.

sectors $k \in \{1,\dots,S\}$ at prices $P^D_{k,t}$. Beneath the wages $W_{s,t}$, costs associated with production factors include payments for rented capital $P^K_{s,t}$, taxes related to both labor $\tau^{N,F}_{s,t}$, capital expenditure $\tau^{K,F}_{s,t}$, and purchases of intermediate goods $\sum_k P^D_{k,t} Q^I_{s,k,t}$. Here, $P^I_{s,t} = \frac{\sum_{k=1}^S P^D_{k,t} Q^I_{s,k,t}}{Q^I_{s,t}}$ represents the average cost of the intermediate good bundle. The firm's gross prices for labor and capital read $\tilde{W}_{s,t} \equiv (1+\tau^{N,F}_{s,t})W_{s,t}$ and $P^K_{s,t} \equiv (1+\tau^{K,F}_{s,t})P_{s,t} r_{s,t}$, respectively. Here, $P_{s,t}$ represents the value-added deflator or the dual price of the firms cost minimization problem in subsector $s$ and $r_{s,t}$ the sector specific price-adjusted rental rate on capital. All production factors are combined according to a three-layer production function with constant elasticities of substitution. The elasticities of substitution between labor and capital $\eta^{NK}_s$, intermediates and value added $\eta^I_s$, and intermediates from different subsectors $\eta^{IA}_s$ determine the degrees of substitution $\rho^{NK} \equiv \frac{\eta^{NK}-1}{\eta^{NK}}$, $\rho^I \equiv \frac{\eta^I-1}{\eta^I}$ and $\rho^{IA} \equiv \frac{\eta^{IA}-1}{\eta^{IA}}$. This function allows the firm to combine production factors to produce goods and services. The firm's profit maximization problem then reads:

$$\max_{\substack{Q^I_{s,k,t}, L_{s,t},\\ K_{s,t}}} P^Q_{s,t} Q_{s,t} - \tilde{W}_{s,t} L_{s,t} - P^K_{s,t} K_{s,t} - \sum_{k=1}^{S} P^D_{k,t} Q^I_{s,k,t}$$

where

$$Q_{s,t} = \begin{cases} \left[ \omega^I_s{}^{\frac{1}{\eta^I_s}} \left(Q^I_{s,t}\right)^{\rho^I_s} + (\omega^Y_s)^{\frac{1}{\eta^I_s}} \left(Y_{s,t}\right)^{\rho^I_s} \right]^{\frac{1}{\rho^I_s}} & \text{if } \eta^I_s \neq 1, \\ \left(A^I_{s,t} Q^I_{s,t}\right)^{\omega^I_s} \left(Y_{s,t}\right)^{\omega^Y_s} & \text{if } \eta^I_s = 1, \end{cases}$$

$$Y_{s,t} = A_{s,t} \begin{cases} \left[ \alpha^L_s{}^{\frac{1}{\eta^{NK}_s}} \left(\tilde{A}^L_{s,t} L_{s,t}\right)^{\rho^{NK}_s} + \alpha^K_s{}^{\frac{1}{\eta^{NK}_s}} \left(K_{s,t}\right)^{\rho^{NK}_s} \right]^{\frac{1}{\rho^{NK}_s}} & \text{if } \eta^{NK}_s \neq 1, \\ \left(\tilde{A}^L_{s,t} L_{s,t}\right)^{\alpha^L_s} \left(K_{s,t}\right)^{\alpha^K_s} & \text{if } \eta^{NK}_s = 1, \end{cases}$$

and

$$Q^I_{s,t} = \begin{cases} \left[ \sum_{k=1}^S \omega^Q_{s,k}{}^{\frac{1}{\eta^{IA}_s}} \left(Q^I_{s,k,t}\right)^{\rho^{IA}_s} \right]^{\frac{1}{\rho^{IA}_s}} & \text{if } \eta^{IA}_s \neq 1, \\ \prod_{k=1}^S \left(Q^I_{s,k,t}\right)^{\omega^Q_{s,k}} & \text{if } \eta^{IA}_s = 1. \end{cases}$$

The share parameters for labor $\alpha^L_s$, capital $\alpha^K_s$, primary production factors $\omega^Y_s$, intermediate goods $\omega^I_s$, and intermediates from different sectors $k$ are invariant in time. The productivity of capital and labor within a firm depends on the total productivity factor $A_{s,t}$, while the productivity of intermediate use depends on $A^I_{s,t}$. These factors reflect the overall efficiency and technological advancements within the region and sector. Overall labor productivity $\tilde{A}^L_{s,t}$ reflects sector-specific technology and human capital $A^L_{s,t}$ and depends on damage caused by climate change $D^L_{s,t}$. The firm sells products to the domestic wholesaler $Q^D_{s,t}$ and the exporter $X_{s,t}$ at the same price $P^Q_{s,t}$.

### 2.3. Wholesaler

The representative wholesaler for each subsector combines domestic products with imports from the same subsector to provide intermediates to the representative firm $Q^I_{s,t}$ and final products to retailers $Q^F_{s,t}$. The wholesaler operates under perfect competition. Its profit maximization problem reads:

$$\max_{Q^D_{s,t}, M^I_{s,t}} P^D_{s,t} Q^{D,U}_{s,t} - P^Q_{s,t} Q^D_{s,t} - P^M_{s,t} M^I_{s,t},$$

where

$$Q^{D,U}_{s,t} = \begin{cases} \left( (\omega^Q_s)^{\frac{1}{\eta^Q_s}} (Q^D_{s,t})^{\frac{\eta^Q_s-1}{\eta^Q_s}} + (\omega^M_s)^{\frac{1}{\eta^Q_s}} (M^I_{s,t})^{\frac{\eta^Q_s-1}{\eta^Q_s}} \right)^{\frac{\eta^Q_s}{\eta^Q_s-1}} & \text{if } \eta^Q_s \neq 1, \\ \left(Q^D_{s,t}\right)^{\omega^Q_s} (M^I_{s,t})^{\omega^M_s} & \text{if } \eta^Q_s = 1. \end{cases}$$

Domestically used sector products $Q^{D,U}_{s,t} \equiv Q^I_{s,t} + Q^F_{s,t}$ are a combination of domestic $Q^D_{s,t}$ and imported intermediate products $M^I_{s,t}$. The degree of substitution $\eta^Q_s$ between imports and domestic production is sector-specific. The distribution parameters $\omega^{Q,M}_s$ determine the home bias for each subsector.

In general, the wholesaler acts as an intermediary, ensuring that the right mix of products is available to meet the demands of the regional retailer.

### 2.4. Retailer

A representative retailer provides goods and services to households and the government. This retailer is a price taker, which means that it does not have the power to influence prices and simply provides various goods to meet the final demand of consumers.

The retailer satisfies the final demand for goods and services $D^F_t$ used for three distinct purposes by households and the government: investment goods $I_t$, consumption goods $C_t$, and government expenditure $G_t \equiv I^G_t + C^G_t$, including public investment $I^G_t$ and consumption $C^G_t$. The primary objective of the retailer is to maximize profit, which is calculated as the difference between the revenue generated by selling the products at the price $P_t$ and the costs associated with acquiring or producing them.

To provide these goods, the retailer combines two types of input: imports from the subsector for final use $M^F_{s,t}$ and domestic goods for final use $Q^{D,F}_{s,t}$. We explicitly distinguish between imports used for final consumption ($M^F_{s,t}$) and those used as intermediate inputs ($M^I_{s,t}$). This reflects the empirical observation (according to national input–output tables) that imports are substantially used in both firms' production processes and for final demand. Additionally, this distinction allows us to better capture firms' capacity to adapt to climate change by adjusting their mix of production factors and their sourcing. The retailer's profit maximization problem can be expressed as follows:

$$\max_{\substack{Q^{D,F}_{1,t},\dots,Q^{D,F}_{S,t},\\ M^F_{1,t},\dots,M^F_{S,t}}} \left[ P_t D^F_t - \sum_{s=1}^S P^M_{s,t} M^F_{s,t} - \sum_{s=1}^S P^D_{s,t} Q^{D,F}_{s,t} \right] \tag{2}$$

where

$$D^F_t = \begin{cases} \left( (\omega^F)^{\frac{1}{\eta^F}} (M^F_t)^{\rho^F} + (1-\omega^F)^{\frac{1}{\eta^F}} (Q^U_t)^{\rho^F} \right)^{\frac{1}{\rho^F}}, & \text{if } \eta^F \neq 1, \\ (M^F_t)^{\omega^F} (Q^U_t)^{1-\omega^F} & \text{if } \eta^F = 1, \end{cases}$$

$$M^F_t = \begin{cases} \left( \sum_{s=1}^S (\omega^{M,F}_s)^{\frac{1}{\eta^Q}} (M^F_{s,t})^{\frac{\eta^Q-1}{\eta^Q}} \right)^{\frac{\eta^Q}{\eta^Q-1}} & \text{if } \eta^Q \neq 1, \\ \left( \prod_{s=1}^S (M^F_{s,t})^{\omega^{M,F}_s} \right) & \text{if } \eta^Q = 1, \end{cases}$$

and (3)

$$Q^U_t = \begin{cases} \left( \sum_{s=1}^S (\omega^{D,F}_s)^{\frac{1}{\eta^Q}} (Q^{D,F}_{s,t})^{\frac{\eta^Q-1}{\eta^Q}} \right)^{\frac{\eta^Q}{\eta^Q-1}} & \text{if } \eta^Q \neq 1, \\ \left( \prod_{s=1}^S (Q^{D,F}_{s,t})^{\omega^{D,F}_s} \right) & \text{if } \eta^Q = 1. \end{cases}$$

The degree of substitution for final use between final use imports and domestic production not exported is represented by $\rho^F = \frac{\eta^F-1}{\eta^F}$. Imports and domestic production from different sectors exhibit identical substitution elasticity for final use $\eta^Q$. The substitution elasticity between imports and domestic production $\eta^F$ indicates the degree to which domestic and foreign goods can replace each other. The distribution parameters $\omega^{M,F}_s$, $\omega^{D,F}_s$, and $\omega^F$ specify the allocation shares at identical prices between domestic and foreign goods and services.

Eq. (2) determines how foreign and domestic goods are combined and transformed into final products, taking into account various elasticity parameters that influence the substitution between these goods. The demand for different products is derived from these equations, which determine how consumers and the government respond to changes in prices and available goods.

### 2.5. Exporter

Similarly to the retailer, the exporter bundles products from different subsectors $X_{s,t}$ into one final product $X_t$ purchased by the rest of the world at the same price $P_t^Q$; it encounters the substitution elasticity between exports from different subsectors $\eta^X$ and combines exports according to distribution parameters $\omega_s^X$. This can be formulated as the following profit maximization problem:

$$\max_{X_{1,t},\dots,X_{S,t}} \left[ P_t^Q X_t - \sum_s P_{s,t}^Q X_{s,t} \right]$$

where

$$X_t = \begin{cases} \left( \sum_{s=1}^S (\omega_s^X)^{\frac{1}{\eta^X}} (X_{s,t})^{\frac{\eta^X-1}{\eta^X}} \right)^{\frac{\eta^X}{\eta^X-1}} & \text{if } \eta^X \neq 1, \\ \left( \prod_{s=1}^S (X_{s,t})^{\omega_s^X} \right) & \text{if } \eta^X = 1, \end{cases}$$

Consequently, the exporter serves as the retailer in the global market, irrespective of production in the rest of the world.

### 2.6. Government

We follow previous work specifying fiscal policy by simple rules for tax rates and government borrowing, while government expenditure is determined by a budget constraint (Christiano et al., 2014; Drygalla et al., 2020; Leeper et al., 2010; Kliem and Kriwoluzky, 2014). The government collects taxes on consumption $\tau_t^C C_t$, labor income $\sum_s^S (\tau_t^{N,H} + \tau_{s,t}^{N,F}) W_{s,t} N_{s,t} LF_t$, and capital income $\sum_s^S (\tau^{K,H} + \tau_{s,t}^{K,F}) P_{s,t} r_{s,t} K_{s,t}$. Tax rates on household labor income ($\tau_t^{N,H}$) and employer labor costs ($\tau_{s,t}^{N,F}$). To finance its activities, the government can borrow loans from the rest of the world $B_{t+1}^G < 0$ and has to repay the loans and interest ($r_t^f$) from the previous period denominated in foreign currency $(1 + r_t^f)\pi_t^S$ identical to the interest rates paid by households. The government budget constraint can be written as

$$\begin{aligned} G_t + Tr_t + B_{t+1}^G = \sum_s^S \Big\{ & (\tau_t^{K,H} + \tau_{s,t}^{K,F}) P_{s,t} r_{s,t} K_{s,t} \\ & + (\tau_t^{N,H} + \tau_{s,t}^{N,F}) W_{s,t} N_{s,t} LF_t \Big\} \\ & + (1 + r_t^f) \pi_t^S \phi_t^B B_t^G + \tau_t^C C_t. \end{aligned}$$

In contrast to Kliem and Kriwoluzky (2014), we set the tax rates on capital, labor, and consumption constant. Therefore, we do not consider changes in government financing as a reaction to climate change or other economic conditions.

The model also incorporates predictable exchange rate effects $\pi_t^S$, debt-sensitive interest rates $\phi_t^B$, transaction costs $adj_t^B$,[3] and unexpected valuation effects $\Delta_t^B$ (Atkeson et al., 2022; Eugeni, 2024).

## 3. Climate change and socioeconomic scenarios

Our objective is to project the impacts of climate change on Vietnam's economy until the end of the 21st century. It is clear that such long-term projections come with substantial uncertainties regarding (i) global future emissions and (ii) future developments of Vietnam's population and economy. We use a scenario analysis, which is a well-established way to address such compounding climate and socioeconomic uncertainties (Pörtner et al., 2022). In our analysis, we identify and capture four key uncertainty dimensions, which are discussed in the following.

First, to capture uncertainties regarding future global emissions, the climate impact and climate mitigation modeling communities have agreed on the concept of Representative Concentration Pathways (RCPs) (van Vuuren et al., 2011) within the United Nations' Intergovernmental Panel on Climate Change process. To account for the full range of available emission futures, we account for RCP 1.9, a low-emission scenario that allows limiting warming well below 2°C above pre-industrial levels (in Vietnam) according to the employed climate models. At the other end of the scale, we account for RCP 8.5 which is a strong emission scenario that results in 4°C to 6°C of warming in Vietnam until the end of the century compared to pre-industrial levels.

Second, to account for uncertainties with regard to future socioeconomic developments, the community of climate scientists agreed on different shared socioeconomic pathways (SSPs) (Riahi et al., 2017; O'Neill et al., 2020). These are alternative, global story lines for future societal development (e.g. demographics, economic growth, governance, policy orientations) at the level of world regions. In addition, key development indicators such as population and economic growth are provided as country-specific quantitative projections. The SSPs span a range of futures with respect to the implied challenge for climate change mitigation and adaptation. In particular, here, we account for SSP 1 "Sustainability" which describes a world that continuously shifts towards sustainable development. This includes a reorientation of consumption toward low material growth and lower resource and energy growth. That is why economic growth is comparable to that at the global level. By contrast, SSP 5 "Fossil Fuel Development" assumes strong fossil-driven economic growth globally. In both SSPs, the global population first peaks around 2060 and then declines toward the end of the century. SSP 1 is typically combined with a low emission RCP scenario (e.g., RCP 1.9 or 2.6), while SSP 5 is often combined with one of the high emission scenarios (RCP 7.0 and 8.5), which is why here we consider SSP 1-RCP 1.9 (SSP 119) and SSP 5-RCP 8.5 (SSP 585) as our main specifications. However, by design, RCP and SSP are independent, which is why the opposite combinations (SSP 185 and SSP 519) are also possible. This enables us to separate the impact of climate change on economic development from confounding socioeconomic factors.

Third, we address uncertainties in the regional warming response to additional emissions using daily mean temperature data (tas) from two global climate models included in the sixth phase of the Coupled Model Intercomparison Project (CMIP6) (Eyring et al., 2016). Specifically, we employ the Geophysical Fluid Dynamics Laboratory Earth System Model 4 (GFDL-ESM4) and the Institut Pierre-Simon Laplace Climate Model 6A-Low Resolution (IPSL-CM6A-LR). Here, we use temperature data provided within the third modeling round of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) which were downscaled to 0.5° resolution (about 50 × 50 km at the equator) and bias corrected for reanalysis data based on the European Centre for Medium-Range Weather Forecasts's fifth generation atmospheric reanalysis of the global climate (ERA5) produced by the Copernicus Climate Change Service (C3S) (Frieler et al., 2024). This setup aligns with Dietz et al. (2021), showing that integrated assessment models cannot reproduce the same temperature response as climate models. Furthermore, Gillingham et al. (2018) highlight significant parameter uncertainty in integrated assessment models with respect to temperature changes for a given level of radiative forcing.

Fourth, we capture uncertainties with regard to (i) changes in TC climatology with climate change (e.g., with respect to their location, timing, intensity, and frequency distributions of landfall) and (ii) sea level rise.

[3] Transaction costs for foreign assets depend on the change in net foreign asset holdings: $adj_t^B \equiv \phi^{adj,B} \left( B_{t+1} - B_t + \epsilon_t^{adj,B} \right)^2$.

### 3.1. Socioeconomic scenarios

In our analysis, we consider socioeconomic development scenarios that span from 2015 through 2100. For the historical period 2015–2021, we use trajectories for GDP growth (3c), population growth (3d), and labor force growth (age 15–69) (3e) as provided by the ISIMIP project within the current ISIMIP3a modeling round (see the protocol document for details Frieler et al., 2024). From 2022 onward, we use SSP-based trajectories of these quantities provided within ISIMIP. In these trajectories, the transition to the SSPs starts in 2022 and stretches for about a decade to avoid jumps (Koch and Leimbach, 2023). For the model runs, we need projections of gross value added (GVA) and employment shares until the year 2100, which are not explicitly included in the SSPs. To do this, we analyze the changes in GVA and employment shares between 2002 and 2023 and project these trends forward through the rest of the century. (3a and b) (see Section C in the Online Appendix for details). For example, agriculture exhibits relatively low growth rates compared to industry and services. This results in a significant decline in the relative importance of the agriculture sector, with its GVA and employment shares falling from 16% and 42% in 2015 to 1% and 2% in 2100, respectively.

### 3.2. Labor productivity damage

In Vietnam, annual mean temperatures are projected to increase by about 0.5°C to 1°C above the current level (+1.1°C above the preindustrial level) until the end of the 21st century for the strong mitigation scenario RCP 1.9 and by about 2°C to 3°C for the strong emission scenario RCP 8.5 (4a). There is strong empirical evidence that high temperatures have a negative impact on labor productivity (Dasgupta et al., 2021), which is higher in the agricultural sector than in the industry and service sectors due to the comparably higher exposure of workers to high temperatures (Szewczyk et al., 2021; Zander et al., 2015; Kjellstrom et al., 2009). Following Sun et al. (2024) we use exposure response functions for labor productivity reductions. These functions, originally derived by Kjellstrom et al. (2018) from epidemiological data for three different classes of work intensity levels, classified by their metabolic rates in Watt (W) as 200 W, 300 W, and 400 W have been widely adopted in recent literature. They are of sigmoidal shape and describe the heat-induced labor productivity reductions in dependence on the wet bulb globe temperature $\mathrm{WBGT}_t$ as

$$\tilde{D}_s^L(\mathrm{WBGT}_t) = \frac{1}{2}\left[1 + \mathrm{erf}\left(\frac{\mathrm{WBGT}_t - \mu_s}{\sqrt{2}\,\sigma_s}\right)\right], \tag{4}$$

where $s \in \{200\,\mathrm{W}, 300\,\mathrm{W}, 400\,\mathrm{W}\}$ is the metabolic rate and erf denotes the error function. Furthermore, $\mu_s$ and $\sigma_s$ are the mean and standard deviation of the corresponding normal distribution, respectively (see Table C.1 in the appendix for their numerical values).

The WBGT is a composite index designed to assess the heat stress on the human body during work activities, incorporating temperature, humidity, wind speed, and solar radiation (Kjellstrom et al., 2018). Following Kjellstrom et al. (2009) and Sun et al. (2024), we use a simplified version of WBGT. Assuming moderately high levels of heat radiation in light wind conditions, it can be calculated from the near-surface temperature (tas, measured in °C) and relative humidity (huss, measured in %) as,

$$\mathrm{WBGT}_t = 0.567\,\mathrm{tas}_t + 3.94\,^{\circ}\mathrm{C} + 0.393\,^{\circ}\mathrm{C}\,E_t, \tag{5}$$
$$\text{where } E_t = \frac{\mathrm{huss}}{100}\,6.105\,\exp\left(17.27\,\frac{\mathrm{tas}_t}{237.7^{\circ}\mathrm{C} + \mathrm{tas}_t}\right).$$

Indoor or full-shade WBGT (excluding solar radiation) is approximated by $\mathrm{WBGT}_{\mathrm{in},t} = WBGT_t - 4^{\circ}\mathrm{C}$. This simplified version of the WBGT has the advantage that it can directly be derived from the biased-corrected climate variables provided by ISIMIP (Frieler et al., 2025), which are used throughout this study. Originally, Eq. (4) was derived for hourly WBGTs. Since ISIMIP currently provides only daily data, we use the "4+4+4"-method introduced by Kjellstrom et al. (2018) to estimate hourly labor productivity losses from these daily data. It assumes a 12-hour working day from which workers are exposed for four hours to the daily maximum WBGT, for four hours to the daily mean WBGT, and for four hours to a WBGT which is the arithmetic mean of the daily maximum and mean WBGT.

As common in the literature (Sun et al., 2024; Zhao et al., 2022; Kjellstrom et al., 2018), we make the assumption that agricultural workers have the highest metabolic rate of 400 W and are exposed to the outdoors WBGT, while labor in the service and industrial sectors is associated with metabolic rates of 200 W and 300 W, respectively. Further, we make the (conservative) assumption that workers in the latter sectors are either working indoors or can work in the shade such that they are only exposed to $\mathrm{WBGT}_{\mathrm{in}}$. In addition, in our main specification of the model, we follow (Sun et al., 2024; Cai et al., 2024) and consider only reductions in labor productivity induced by heat stress in the summer months from June 1 to September 30 to avoid a potential overestimation of labor productivity losses in moderate WBGT, which can be relatively easy to adapt to.

Sectoral annual labor productivity losses are calculated by weighing the labor productivity losses by the 2015 population distribution and aggregating them across all summer days and grid cells. As we focus on climate change-induced additional productivity losses, we compute differences relative to the historical reference period (2015–2024). The sector-specific damage functions are thus defined as

$$D^L_{\mathrm{Agriculture},t} = \tilde{D}^L_{400\mathrm{W}}(\mathrm{WBGT}_t) - \tilde{D}^L_{400\mathrm{W}}(\mathrm{WBGT}_{\mathrm{ref}}), \tag{6a}$$
$$D^L_{\mathrm{Industry},t} = \tilde{D}^L_{300\mathrm{W}}(\mathrm{WBGT}_{\mathrm{in},t}) - \tilde{D}^L_{300\mathrm{W}}(\mathrm{WBGT}_{\mathrm{in,ref}}), \tag{6b}$$
$$D^L_{\mathrm{Services},t} = \tilde{D}^L_{200\mathrm{W}}(\mathrm{WBGT}_{\mathrm{in},t}) - \tilde{D}^L_{200\mathrm{W}}(\mathrm{WBGT}_{\mathrm{in,ref}}), \tag{6c}$$

where $\mathrm{WBGT}_{\mathrm{ref}}$ and $\mathrm{WBGT}_{\mathrm{in,ref}}$ denote the average summer outdoor and indoor WBGT during the reference period, respectively.

### 3.3. Agricultural damage

We account for two mechanisms through which climate variability and change directly impact agricultural productivity. First, the rise in sea level is projected to reduce the available arable land. Here, we use novel regional-specific station-level estimates for the rise of sea level by Perrette and Mengel (2025). For Vietnam, this global data set contains station-level data for Hanoi, which we use as a basis for our projections of rising sea levels. According to these estimates, median sea levels will increase by 0.4 m (2.5–97.5 percentile range: 0.3–0.5 m) above present-day levels even under the strong mitigation scenario RCP 1.9 and by 0.75 m under the strong emission scenario RCP 8.5. In particular, not only does the median value for the expected increase in sea level at the end of the century nearly double from RCP 1.9 to RCP 8.5, but the uncertainty of the projection also increases substantially (Fig. 4**(b)**). Rising sea levels reduce available agricultural land, which we model as a permanent decline in effective land input in agriculture. We assume that inundated land cannot be replaced elsewhere. Estimated land loss in terms of sea level rise is derived from unpublished administrative data provided by the Ministry of Natural Resources and Environment of Vietnam to the authors and the authors' own calculations (Table C.2).

Second, there is empirical evidence that high temperatures are damaging to crops (Zhao et al., 2017; Kawasaki, 2023). In the Vietnamese context, Trinh (2018) provides microeconomic evidence that temperature and precipitation variability significantly reduce agricultural net revenues, underscoring the country's vulnerability to climate shocks. The yield losses of the three main staple crops rice, maize and soybeans grown in Vietnam are likely to decrease with each 1°C increase in annual mean temperature by 3.5%, 8.0% and 3.1%, respectively (Zhao et al., 2017). The meta-study summarizes results from global grid-based and local point-based models, statistical regressions, and field-warming experiments. To factor in these anticipated yield reductions, we apply weighted adjustments based on value-added shares of rice, maize, and soybean within the broader agricultural, forestry and fishing sector, assuming that these will stay constant throughout the century. Specifically, we calculate a weighted average of these losses, resulting in an approximate value of $0.83\frac{\%}{°\mathrm{C}}$ yield reduction. This figure is derived by first multiplying the value added shares of rice (0.18), maize (0.025), and soybeans (0.002) with the respective marginal decreases (rice: 0.035, maize: 0.080, and soybeans: 0.031) and then adding the three crops.

Combining both contributions, the damage function for agricultural damage reads,

$$D_{\mathrm{Agriculture},t}(\mathrm{tas}_t) = \sum_b \mathrm{ll}_b\, \delta_{\mathrm{SL}_t \in \mathrm{SL}_b} + 0.0083\,(\mathrm{tas}_t - \mathrm{tas}_{ref}). \tag{7}$$

The indicator function ($\delta_{\mathrm{SL}_t \in \mathrm{SL}_b}$) takes the value of one if the observed rise in sea level at time $t$ falls within the bin $b$. For each bin, a portion of agricultural land is lost as a result of sea level rise. The associated land loss for a given bin is cumulative, which means that it also includes the losses from all previous bins.

### 3.4. Tropical cyclone damage

As an indicator for damage estimates, we use annual national shares of people affected by strong TC winds. Using wind-based indicators for TC impacts is very common in the literature because they are typically easier to calculate than indicators for storm surge or pluvial flooding. In the earlier literature, non-spatially resolved indicators such as wind speed at landfall have been used, whereas, in recent studies, spatially resolved wind field indicators (e.g. affected areas) are used since these better capture the land exposure to TCs. Following Krichene et al. (2023), we here use national shares of affected people, arguing that these should be a better proxy for the effects on economic activity than affected areas. To project TC activity along climate change scenarios, we use the TC emulator of Geiger et al. (2021). The emulator is calibrated using basin-specific frequency and intensity statistics for synthetic TC tracks with landfall from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) during the period 1861–2100 according to the CMIP5-GCMs participating in ISIMIP2b (Frieler et al., 2017; Emanuel, 2013). After calibration, the emulator can project the TC activity along a specified trajectory of global mean temperature (GMT). For this study, we used GMT trajectories extracted from two CMIP6 GCM (IPSL-CM6A-LR, GFDL-ESM4) for four scenarios (SSP 119, SSP 519, SSP 185 and SSP 585). For each GCM-SSP combination, we generate 100 probabilistic time series of TC events for the period 1980 to 2100. The CLIMADA impact assessment tool (Bresch and Aznar-Siguan, 2020) is used to generate wind footprints for each (synthetic) TC track. The share of the Vietnamese population exposed to the derived 1-minute sustained winds of at least 34 knots is aggregated by year. The population exposure for the future period is generated by extending the historical HYDEv3.2.1 population data set (Klein Goldewijk et al., 2017) for each SSP over the period 2010–2100 (Jones and O'Neill, 2016). The data were downscaled to 300 arcsec from the original 450 arcsec resolution and linearly merged to the historical data starting from 2005. Since physical impacts have been calibrated at the basin level of TC, a bias correction is applied to the Vietnam-specific time series of TC-affected people by comparing the simulated estimates with the numbers in the global historical data set of TC exposure (TCE-DAT) (Geiger et al., 2018) over the observational period 1950–2015 (see above). Following Krichene et al. (2023), we multiply the simulated time series of affected people by a correction factor so that the simulated average over 1980–2015 agrees with the respective historical average for Vietnam according to TCE-DAT.

Since TCs in Vietnam are rather rare but extreme events, within each realization, the shares of affected people vary strongly from year to year and between realizations, leading to comparably large uncertainty ranges (Fig. 4**(c)**). Under the strong mitigation scenario RCP 1.9 there is no significant trend in the median share of the Vietnamese population affected annually that varies around its value in the historical period of about 50%, with no observable trend throughout the 21st century. By contrast, under the strong warming scenario, the median share of affected people increases to about 75% toward the end of the century.

The primary impact of these TCs is the destruction of houses (Zhang et al., 2009). Buildings account for more than 50% of the total capital stock (Feenstra et al., 2015), with residential structures constituting the single most significant component of this asset category. Data from the Emergency Event Database (Delforge et al., 2025) indicate that, between 1985 and 2015, 1.5% of Vietnam's population was affected by TCs each year. Further, according to this database, the damage per affected individual, adjusted for GDP per capita, equates to 200% of the GDP. However, simulations with the TC emulator show that more than 45% of the population was affected by storms exceeding 34 knots during the same period. To reconcile this discrepancy, we rescale the damage by the ratio reported to simulated affected people, $\frac{1.5}{45.6}$. Therefore, if the entire population was affected by storms exceeding 34 knots, the resulting annual damage would be approximately 5% ($\approx \frac{1.5}{45.6}\times 200\%$) of GDP. This magnitude is consistent with empirical evidence showing that, if normalized by GDP, TC damage did not exhibit a significant long-run trend over the period 1983–2006 (e.g., Zhang et al. (2009)). In particular, normalized damage remained broadly constant over time despite rising absolute damage and adaptation measures, reflecting growing exposure due to economic development. Since the housing stock in the model is measured in physical units, while empirical damage estimates are reported as a share of GDP, we convert output damage into units of housing by dividing by the housing price,

$$D_t^H(P_t^{\mathrm{TC}}) = 0.05\,\frac{Y_t}{P_t^H}\,\left(P_t^{\mathrm{TC}} - P_{ref}^{\mathrm{TC}}\right), \tag{8}$$

where $P_t^{\mathrm{TC}}$ and $P_t^H$ denote the share of the population affected by strong TC winds exceeding 34 knots and the average price of housing in period $t$, expressed net of outstanding mortgage debt, respectively.[4] Damage to the value of the housing stock is expressed relative to GDP $Y_t$ and depends on the average price of housing $P_t^H$ in each period.

In conclusion, for each RCP scenario, we consider uncertainties with regard to (i) regional warming by accounting for temperature projections provided by two global climate models, (ii) rises in sea level by considering the 2.5, 50, and 97.5 percentiles of the sea level rise projections provided by Perrette and Mengel (2025), and (iii) changes in TC impacts with global warming, which are taken into account by considering 100 different TC trajectories that lead to different shares of affected people for each combination of RCP-SSP scenarios and climate model. As a result, we end up with 600 distinct simulations for each RCP-SSP combination, accounting for two climate models, three sea level rise trajectories, and 100 TC scenarios.

### 3.5. Comparison with DICE damage function

In many integrated assessment models, climate impacts are accounted for by a single aggregate damage function that uniformly reduces total economic output in all sectors. For comparison with this standard approach, we apply the damage functions of Nordhaus's scholarly DICE model in its latest re-calibration (Barrage and Nordhaus, 2024). The Nordhaus damage function estimates the reduction in economic output resulting from global temperature increases relative to

[4] Between 2015 and 2024 45 percent of the population in Vietnam was exposed to TCs exceeding 34 knots in each year ($P_{ref}^{\mathrm{TC}} = 0.45$).

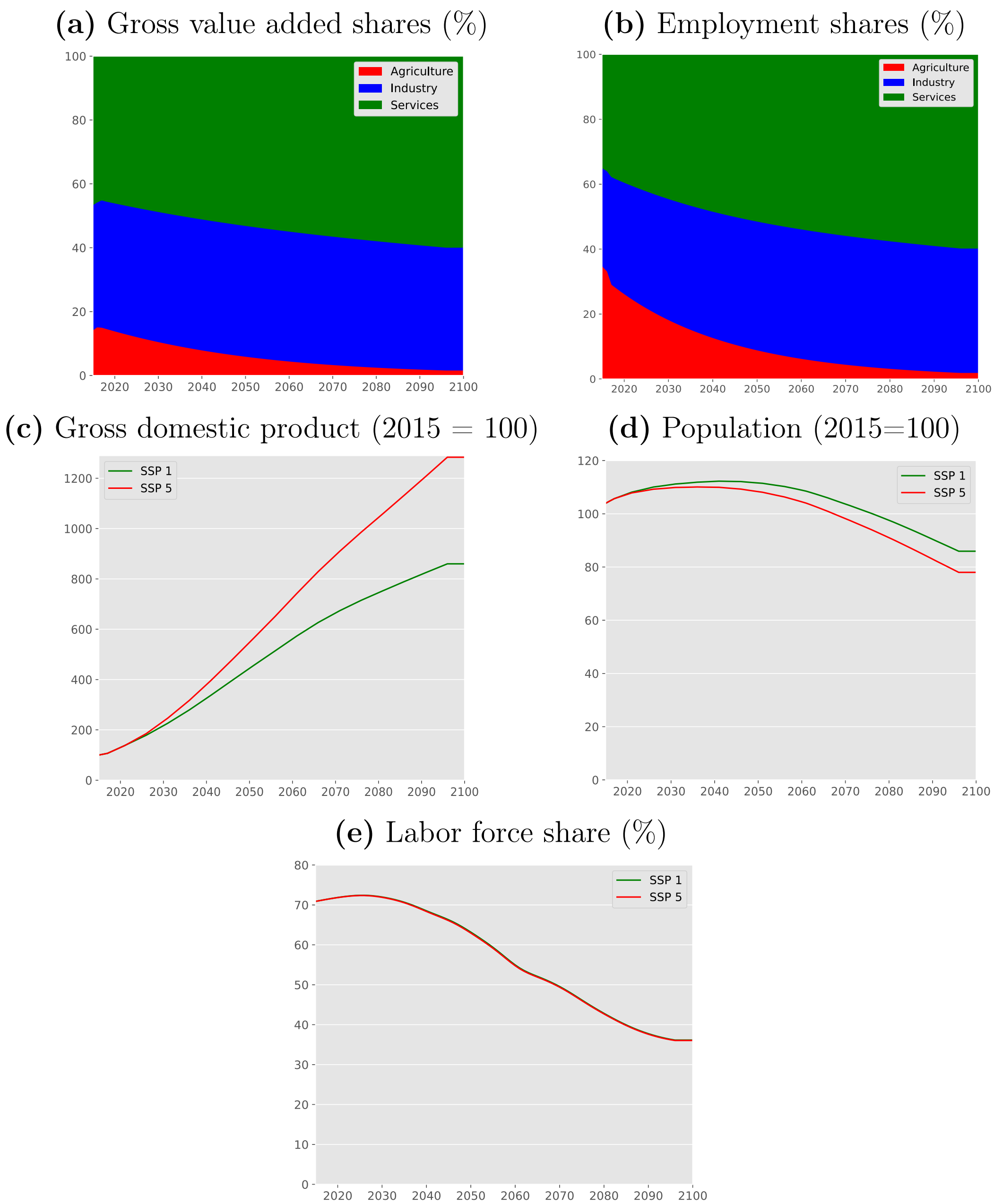


**Fig. 3. Socioeconomic projections for Vietnam.** Projected changes of (**a**) Gross value added, (**b**) Employment shares for the agriculture (red), industry (blue), and service (green) sectors, (**c**) GDP growth rate, (**d**) Population, and (**e**) Labor force share from 2020 through 2100 for SSP 1 (green) and SSP 5 (red). All changes are relative to 2015 values. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

pre-industrial levels,

$$D_t^{\text{DICE,orig}}(\text{tas}_t) = \underbrace{\pi_1}_{=0}(\text{tas}_t - \text{tas}_{\text{pre}}) + \underbrace{\pi_2}_{=0.003467}(\text{tas}_t - \text{tas}_{\text{pre}})^2, \quad (9)$$

where $D_t^{\text{DICE}}$ denotes the proportional loss in GDP due to climate damage in sector $s$ at time $t$, which is the same for all sectors. Furthermore, $\text{tas}_{\text{pre}}$ is the preindustrial temperature baseline, and $tas_t$ represents the mean temperature across the two climate models. Parameters $\pi_1$ and $\pi_2$ are empirically calibrated. The linear term is typically set to zero, and the quadratic term captures the increasing marginal damage of warming (Barrage and Nordhaus, 2024). This specification allows for a tractable, yet non-linear representation of climate impacts to the economy.

Since our channel-based damage assessment is calibrated to the historical reference period 2015–2024, we align the DICE damage function with this baseline by subtracting the damage already realized between preindustrial times and this reference period,

$$D_t^{\text{DICE}}(\text{tas}_t) = D_{\text{tas}_t}^{\text{DICE,orig}} - \underbrace{D_t^{N,\text{orig}}(\text{tas}_{\text{ref}})}_{\approx 0.04}. \quad (10)$$

In Vietnam, the annual mean surface temperature has increased by approximately 1°C between preindustrial times and our reference period. According to Nordhaus's specification, this corresponds to an estimated annual GDP loss of about 0.04%.

Unlike Nordhaus, we use Vietnam's annual mean surface temperature rather than global annual mean surface temperature to calculate aggregate damage to production. This choice ensures consistency between our sector-specific damage estimates. Since these are based on annual mean temperatures for Vietnam, they are subject to greater year-to-year variability than damage estimates based on changes in

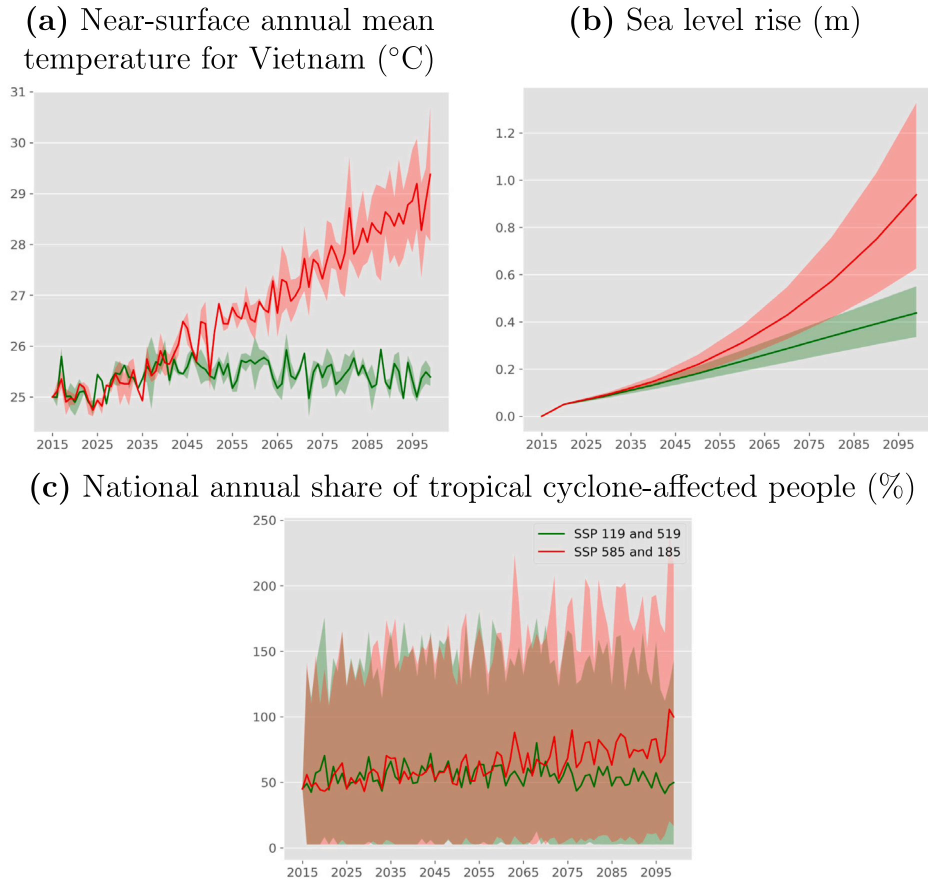


**Fig. 4. Change in climate and climate impact indicators for the two studied emission pathways from 2020 through 2100. (a):** Change in annual mean temperatures for Vietnam for two global climate models that were bias-corrected towards reanalysis data, **(b):** Sea level rise projections for Hanoi as provided by Perrette and Mengel (2025), **(c):** National annual shares of people affected by strong tropical cyclone winds as obtained from 100 realizations of synthetic tropical cyclones for each of the two climate models for the period 2020–2100 under a strong mitigation scenario (RCP 1.9, green) and a strong emission scenario (RCP 8.5, red). Solid lines and shaded areas denote means and 2.5%–97.5% percentile ranges, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

global mean temperature. However, we do not expect this change to significantly affect the magnitude of damage, as the increase in Vietnam's annual mean temperature from the reference period to preindustrial times closely mirrors the corresponding increase in global mean temperature.

Importantly, the DICE damage function is based on top-down estimates of total economic damage reported in the literature (Barrage and Nordhaus, 2024). As a result, it implicitly incorporates climate impacts that our method does not capture, such as damage arising from climate tipping points. In addition, it includes a "judgement adjustment" factor to capture damage that is hard to measure, such as the economic value of biodiversity losses. For this reason, we would expect the DICE damage estimates to be higher than the damage derived from our bottom-up method, which explicitly models separate impact channels.

## 4. Channels through which climate variability and change impact the economy

The various damage functions already indicate that the impacts of climate on the Vietnamese economy are heterogeneous, since (i) vulnerability differs between sectors and (ii) climate variability and change affect the economy through different *impact channels*. To understand the relative importance of these channels, we calculate the resulting direct damage for the different SSP–RCP combinations, assuming the same sectoral allocation of capital and labor as in the underlying SSP baseline, where climate impacts are fixed at their historical baseline level. In doing so, we visualize our applied impact channels from the previous section without any general-equilibrium effects.

The direct damage estimates represent the loss in value added by economic activity, evaluated at constant relative prices and baseline production-factor allocations (including intermediates) as well as the loss of housing. Their main purpose is to quantify economic damage across economic activities and impact channels. To this end, we translate labor-productivity losses, total-factor-productivity losses, and housing destruction into monetary values. Otherwise, the direct magnitudes of the different impact channels would not be comparable (see Appendix A for details).

Absolute direct climate damage depends on the underlying SSP pathways that determine population and economic development; however, if measured relative to the baseline GDP trajectories, where climate impacts are fixed at their historical baseline level, damage becomes independent of the underlying SSP. Fig. 5 shows the relative damage induced by climate change through the different impact channels for the periods 2015 to 2019, 2020 to 2039, 2040 to 2059, 2060 to 2079 and 2080 to 2099. Columns labeled 'L', 'M' and 'H' denote the 2.5th, 50th, and 97.5th percentiles of damage (relative to baseline GDP) across all realizations for each RCP. Here, we only consider one impact channel at a time. This allows for comparing the relative importance of the impact channels, but neglects potential general equilibrium effects such as changes in relative prices or wages, as well as changes in the

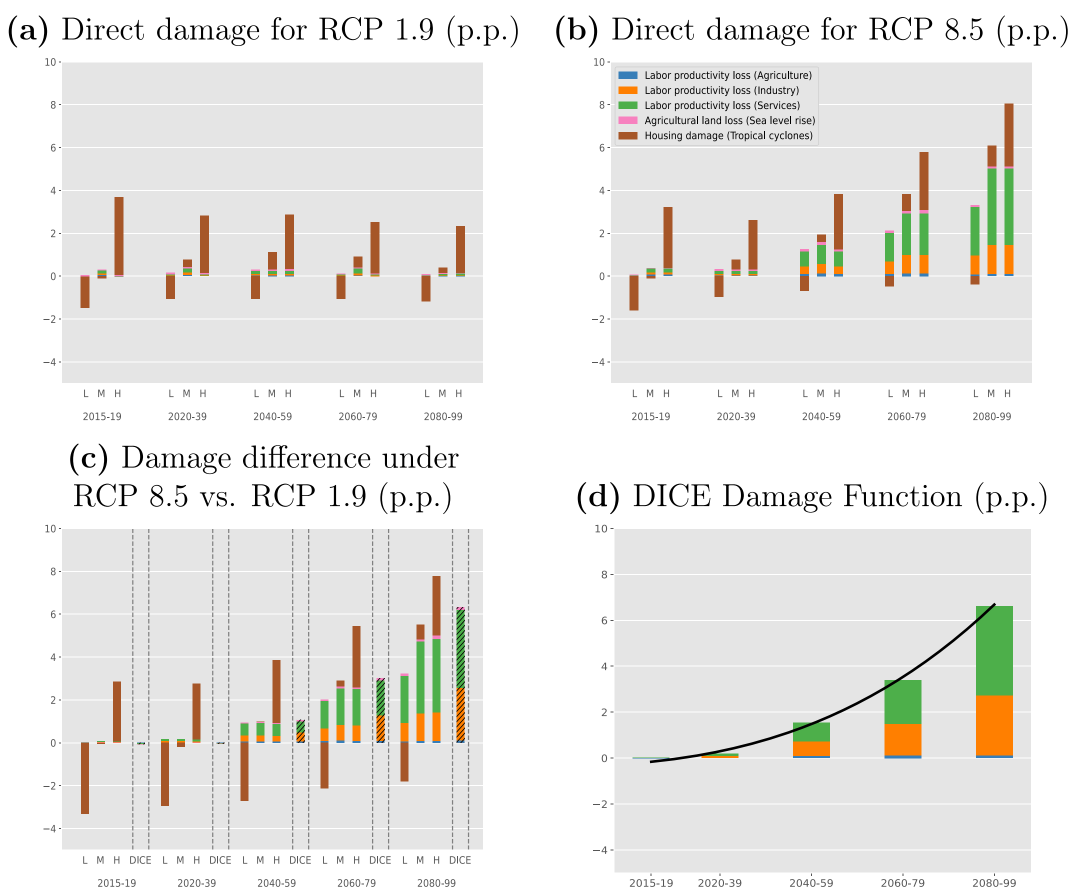


**Fig. 5. Decomposition of climate impact channels for the two emission scenarios**. Percentage-point (p.p.) deviation in GDP (relative to GDP in the SSP baseline, where climate impacts are fixed at their historical baseline level) induced through the various impact channels under the strong mitigation scenario (RCP 1.9, **(a)**) and the strong emission scenario (RCP 8.5, **(b)**). **(c):** Difference in GDP (in p.p. of the GDP of SSP baseline) induced through the various impact channels under RCP 8.5 relative to RCP 1.9. Columns labeled 'L', 'M' and 'H' refer to the 2.5 (low-damage outcome), 50 (medium-damage outcome) and 97.5 percentile (high-damage outcome) across all 600 realizations for each RCP. Further, the column 'DICE' depicts the results as obtained with the quadratic temperature damage function of Nordhaus's DICE model from annual temperature changes averaged across both climate models (see Appendix A for details). **(d):** Total damage to output (in p.p. of the GDP of SSP baseline) as obtained from the quadratic DICE damage function in the calibration of Barrage and Nordhaus (2024) (black solid line) and sectoral decomposition of damage (stacked bars). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

allocation of labor and other production factors (see Appendix A for details).

By contrast, Barrage and Nordhaus (2024) use a single aggregate damage function that uniformly reduces total economic output in all sectors. For comparison, with this standard approach, we apply this damage function to each sector. Climate damage remains minimal until around 2040, after which it increases nonlinearly in the second half of the 21st century (Fig. 5**c**). Notably, incorporating the labor productivity channel through the WBGT-approach allows us to capture the non-linear damage patterns described by Barrage and Nordhaus (2024). To better quantify the difference in damage between the two emission scenarios, we additionally consider relative changes in damage (in percentage points (p.p.)) between the strong mitigation scenario RCP 1.9 and the strong warming scenario RCP 8.5 (Fig. 5**c**).

Due to the substantially higher warming under RCP 8.5 (cf. Fig. 4**a**), climate damage is much higher in the high emission scenario RCP 8.5 compared to the strong mitigation scenario RCP 1.9, especially in the second half of the 21st century (Figs. 5**(a)–(c)**); while median damage remains at a few tenths of a percentage point of baseline GDP throughout the century under RCP 1.9 (cf. Fig. 5**a**), it reaches 6 p.p. (2.5–97.5% CI: [+3.0 p.p., 8.0 p.p.]) of baseline GDP at the end of the century (Fig. 5**b**).

The main difference between the two warming pathways is that under RCP 8.5 labor productivity losses increase substantially and make up the largest share of direct damage in the 2nd half of the century (median 5.0 p.p., 2.5–97.5% CI: [3.2 p.p., 5.0 p.p.] at the end of the century) (Fig. 5**b**). At the end of the century, the largest single damage contribution arises from labor productivity losses in the service sector (median 3.4 p.p., 2.5–97.5% CI: [2.2 p.p., 3.5 p.p.]). The contribution of losses in labor productivity in the agricultural and industry sectors to the increase in aggregate GDP damage is substantially smaller (industry (agricultural) median 1.4 p.p. (0.09 p.p.), 2.5–97.5% CI: [0.9 p.p., 1.4 p.p.] ([0.07 p.p., 0.09 p.p.]). Productivity in the agricultural sector is reduced through two processes: heat-induced reductions in labor productivity and productivity reduction through the loss of arable land due to sea level rise. Since agricultural labor is more vulnerable to heat than labor in the industry and service sectors (cf. Section 3.2), this renders the agricultural sector the most vulnerable sector. However, because the share of agricultural value added in aggregate GDP is relatively small and declines over the course of the century from approximately 20% to about 1% (cf. Fig. 3), both agricultural impact channels exert only a relatively limited influence on aggregate GDP.

For both RCPs, damage caused by TCs is by far the most uncertain because the year-to-year variability in damage is large compared to the increase of TC damage with temperature rise (cf. Fig. 5**c**). Under RCP 1.9, the relative TC damage remains nearly constant throughout the century due to the leveling of the warming signal around 2040 (cf. Fig. 4**a**). The median impact on GDP is negligible, but there is a risk of GDP losses. For example, in the worst 2.5% of the realizations, the damage reaches over 2 p.p. (2.5–97.5% confidence interval (CI): [−1.8 p.p., 2.7 p.p.]) (cf. Fig. 5**c**). Negative values, as in the case of TCs, indicate that the proportion of affected individuals can be lower under RCP 8.5 than the mean number of affected people in the historical study period. Consequently, fewer residential structures are destroyed, which implies reduced reconstruction requirements and lower direct economic damage compared to the historical average.

The standard approach to model damage as a fraction of GDP, assuming equal impacts across economic activity, hides the heterogeneous effects across sectors and impact channels (cf. Fig. 5**d**). The 20-year average of damage according to the DICE damage function (leading to identical losses in relative productivity across sectors) closely follows the underlying quadratic damage function obtained using the projected temperature trends.

## 5. Economic response dynamics to climate change impacts

Next, we study the dynamic economic response to the climatic forcing, including general equilibrium effects, by analyzing the trajectories of key economic aggregates. The baseline trajectories (where climate impacts are fixed at their historical baseline level) of real GDP, consumption, investment, and the real value of the housing stock show all positive growth trajectories from 2015 through 2100 in both the low-emission SSP 1–1.9 and high-emission SSP 5–8.5 scenarios (Fig. 6). Consistent with the strong fossil-fuel-driven growth assumptions underlying SSP 5, the high-emission pathway (SSP 5–8.5, solid red lines with dots) projects a higher absolute level of growth for all four variables compared to the ambitious mitigation, moderate-growth pathway (SSP 1–1.9, solid green lines with dots). Under climate change impacts, the median growth of all components is reduced (solid red and green lines for SSP 5–8.5 and SSP 1–1.9, respectively), but climate forcing is not strong enough to revert growth trends. Furthermore, comparably larger direct impacts (cf. Fig. 5) under the strong emission pathway RCP 8.5, result in a stronger reduction of the growth of all components, but the forcing is not strong enough to reduce the SSP 5–8.5 growth trajectories under the corresponding trajectory under SSP 1–1.9. Neglecting TC impacts reduces investment and GDP growth because post-TC reconstruction of the housing stock, which otherwise stimulates economic activity, is no longer required but has minor effects on consumption and the real value of the housing stock (solid orange and cyan lines for SSP 5–8.5 and SSP 1–1.9, respectively).

We next compare changes in aggregate GDP and its expenditure components (consumption, investment, and housing expenditure) under the strong emission scenario (RCP 8.5) with those under the strong mitigation scenario (RCP 1.9) throughout the 21st century for SSP 5 (Fig. 7). We find that median GDP (relative to its SSP baseline value, where climate impacts are fixed at their historical baseline level) initially increases under RCP 8.5 compared to RCP 1.9 by up to 0.24 p.p. in 2020–39 before declining by 6 p.p. in 2080–2099 (red crosses in Fig. 7**(a)**). Consumption remains broadly similar under both RCP scenarios until 2020–2039, after which it declines more strongly under RCP 8.5, contributing more than 3 p.p. to GDP reductions by 2080–2099 (red crosses in Fig. 7**(b)**). Median private investment rises moderately in 2020–2039 under RCP 8.5 relative to RCP 1.9, before declining superlinearly by almost 2 p.p. (red crosses in Fig. 7**(c)**). The early increases reflect slightly lower temperatures under RCP 8.5 than under RCP 1.9 over 2020–2039 (cf. Fig. 4**(a)**), implying more favorable climatic conditions. In the second half of the 21st century, however, the stronger temperature rise under RCP 8.5 results in substantially larger heat-induced labor productivity losses. These losses drive the comparatively larger declines in aggregate GDP, investment, and consumption under RCP 8.5, despite the greater housing reconstruction needs resulting from TC strikes under RCP 8.5 (red crosses in Fig. 7**(d)**; see discussion below). These relative differences between RCP 8.5 and RCP 1.9 are largely independent of the underlying SSP (for SSP 1 see Fig. B.10). Further, the simulations without TC impacts reveal that post-TC reconstruction demand for housing increases median investment and median aggregate GDP at the expense of consumption (cf. red crosses and triangles in Fig. 7**(a)**–**(c)**).

The year-to-year variability of TC impacts is the main source of uncertainty, which can be seen by comparing the simulations with and without the TC impact channels in Figs. 6 and 7. This finding is robust to alternative specifications of TC damage channels, where damage affects only household housing expenditures or additionally destroys productive capital in the service sector (Fig. B.11). With a constant 70% loan-to-value ratio, housing losses are shared through mortgage contracts: lenders (service sector) bear 70% of losses and households 30%. Since the housing capital stock is directly affected by these storms (cf. Section 3.4), the necessary expenditures for rebuilding are subject to the largest uncertainties. In the end-of-century period 2080–2099, housing expenditure can increase by up to 4 p.p. relative to GDP without climate change impacts, but it can also decrease by up to 2 p.p. under the strong emission scenario RCP 8.5 compared to the strong mitigation scenario RCP 1.9. These uncertainties are substantially dampened during their spillover to consumption, private investments, and aggregate GDP. Nevertheless, changes in GDP and private investment remain statistically insignificant throughout the century at 95%-level. For example, depending on the realization, GDP can be almost identical under both emission pathways but also more than 11 p.p. lower under RCP 8.5 than under RCP 1.9 in the end-of-century period 2080–2099. By contrast, the effect on consumption is consistently negative in all realizations (statistically significant at the 95% level), and consumption can be between 2 p.p. and 4 p.p. lower relative to GDP without climate change impacts in 2080–2099 under RCP 8.5 than under RCP 1.9.

Using the DICE damage function, median aggregate GDP, consumption, and investment decline similarly under RCP 8.5 relative to RCP 1.9 from 2040 onwards, both in terms of magnitude and degree of nonlinearity (Fig. 7**(a)**–**(c)**). The reason is that labor productivity reductions are the dominant damage channel, and these increase superlinearly with annual mean temperature (cf. Fig. 5**(d)**), mimicking quite closely the quadratic increase of the DICE damage (cf. Fig. 5**(c)**). The reductions obtained with the DICE damage function are somewhat larger than those obtained with our channel-resolving approach. This is expected because the DICE damage function accounts for additional categories of catastrophic events, climate tipping points, and biodiversity loss, at least implicitly, which are not resolved in our approach. However, when labor productivity losses are assumed to occur year-round rather than only during the summer months (as done in several previous studies Kjellstrom et al., 2018; Zhao et al., 2022), we obtain larger losses in aggregate GDP, consumption, and investment in the second half of the 21st century (Fig. B.13), despite still omitting several additional impact channels. Furthermore, by not explicitly accounting for TC impacts, the DICE damage function not only omits the main source of climate impact uncertainty but also fails to capture the reconstruction dynamics of the housing stock and its general equilibrium effects, in particular, its tradeoff on consumption. In consequence, the end-of-century reduction in GDP is about 20% higher using DICE damage than with the channel-resolving approach (main specification), but the reduction in consumption is only marginally higher. These findings indicate that using the DICE damage function may underestimate the consumption and thus welfare effects of climate change.

Although the evolution of each variable shows how climate change will impact the components of GDP, it does not directly show the contribution to overall GDP change. Decomposing GDP change – one time by expenditure components and the other by sector – reveals a complex interplay between different economic components (Fig. 8). In particular, we find that the changes in TC risk impact the transition dynamics by altering savings and investment dynamics, supporting findings by Bakkensen and Barrage (2018). Cyclone-induced housing

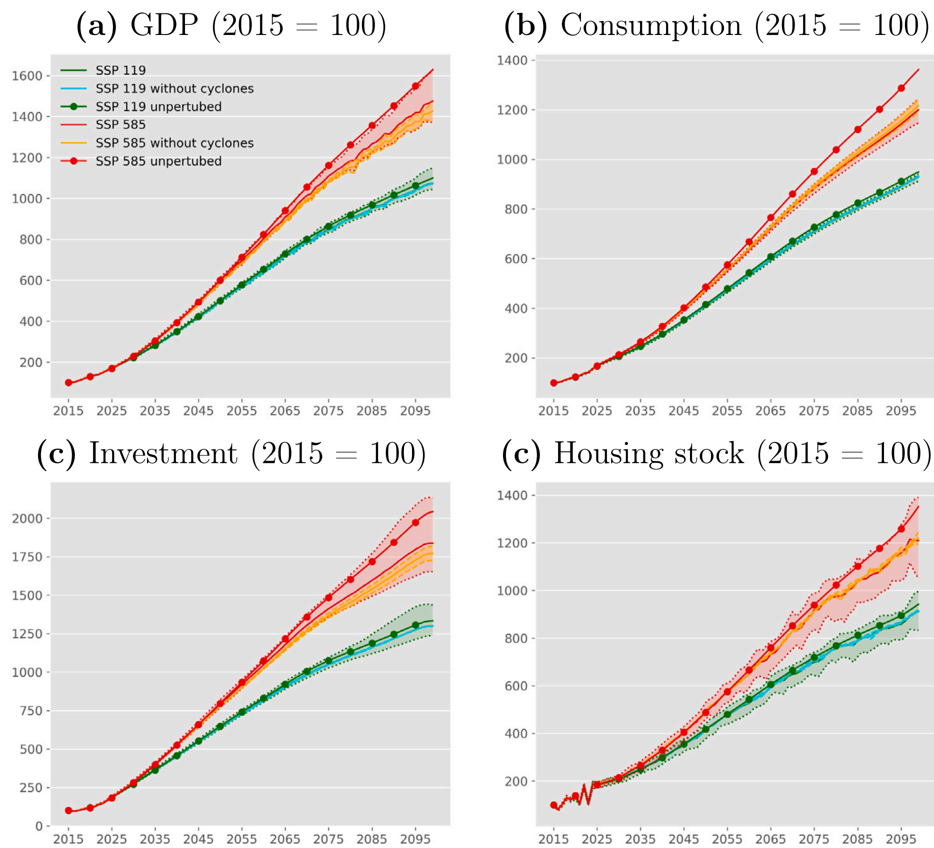


**Fig. 6. Impacts of climate change on GDP components and housing stock (2015–2100) under the two emission pathways.** Real value trajectories for key economic aggregates **(a)** GDP, **(b)** Consumption, **(c)** Investment, and **(d)** Housing stock, indexed to 2015 = 100 for the ambitious mitigation scenario (SSP 1–1.9, green/cyan) and the high-emission scenario (SSP 5–8.5, red/orange). Solid lines with dots, solid lines, and dashed lines indicate the SSP baseline (where climate impacts are fixed at their historical level), mean trajectories of the model with and without tropical cyclone impacts, respectively. Shaded areas represent the 2.5th–97.5th percentile uncertainty ranges. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

expenditures and private investment compensate for lower consumption under RCP 8.5 compared to RCP 1.9 (Fig. 8**(a)**). This mechanism also explains why the realizations with the largest TC damage relative to baseline GDP are associated with the highest aggregate GDP outcomes. Larger housing destruction mechanically induces stronger reconstruction investment, which boosts GDP. This pattern becomes evident when comparing realizations with large (L, 2.5th percentile), medium (M, 50th percentile), and small (H, 97.5th percentile) GDP losses relative to the baseline, where climate impacts are fixed at their historical baseline level, in Fig. 8**(a)** and **(b)**. Importantly, the corresponding direct damage (in terms of GDP) shown in Fig. B.9 does not align with the damage-based sorting in Fig. 5, underscoring that higher damage does not necessarily translate into lower GDP. Generally, in realizations with high TC damage (labeled 'H' in Fig. 8), GDP losses are lower than in realizations with low TC damage (labeled 'L' in Fig. 8), because the reconstruction of the housing stock after TC impacts raises the demand for industrial goods, which mitigates overall GDP losses. The service and industry sectors exhibit falling quantities and relative prices. By contrast, the agriculture sector experiences increasing relative prices while quantities fall. These differences reflect the heterogeneous exposure of sectors to climate impacts, as illustrated in Fig. 8**(b)**.

In particular, the stronger climate change impacts under RCP 8.5 have only very minor effects on the trade balance of Vietnam compared to the strong mitigation scenario RCP 1.9. Productivity losses in agriculture and industry increase relative prices of Vietnamese products, leading to lower foreign demand. However, the effects of demand and price almost counteract each other. In general, the contribution of the trade balance to the change in GDP is negligible.

## 6. Discussion

We have studied the impact of climate change on the Vietnamese economy under a strong emission scenario leading to 4–5°C of warming above pre-industrial levels compared with a strong mitigation scenario, where warming can be kept within the limits of the Paris Agreement. To this end, we combined a newly developed multi-sector growth model, which allows us to explicitly describe structural change in the economy for the industry, service, and agricultural sectors with process-based modeling of temperature increases, sea level rise, and intensification of TC impacts. In our analysis, we account for different channels through which these changes in climate hazards translate into direct economic impacts: while TCs impact the housing stock, heat and sea level rise reduce sectoral labor productivities, with the highly exposed agricultural sector being the most vulnerable. Our results indicate that heat-induced labor productivity losses are the main damage channel in the 2nd half of the 21st century under the strong emission scenarios, whereas TC damage is the dominant source of uncertainty in both scenarios throughout the 21st century.

The decomposition of GDP reveals that through the different impact channels, climate variability and change trigger a complex interplay between different economic components. Under the strong emission scenario, the reconstruction needs for housing are higher than under the strong mitigation scenario due to more damaging TCs, resulting in a statistically significant decline in consumption. Furthermore, sectoral

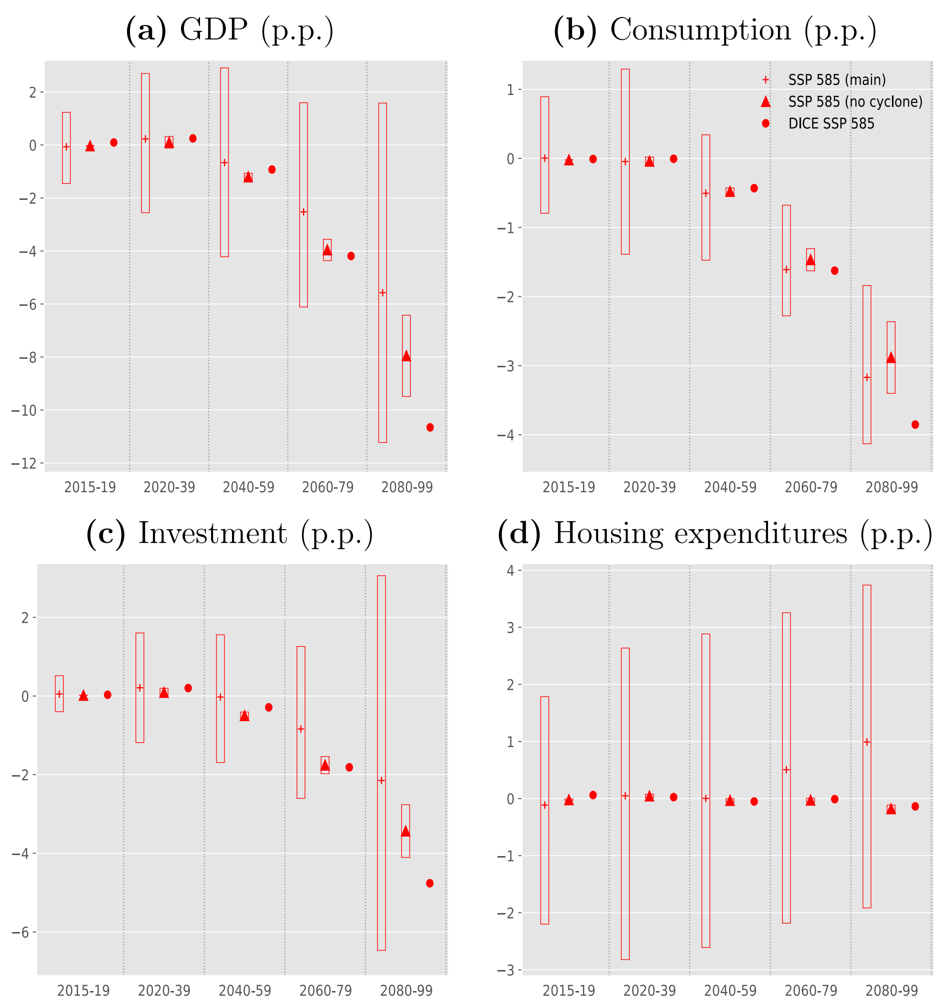


**Fig. 7. Climate change impact on GDP, consumption, investment, and housing expenditures.** Percentage-point (p.p.) deviations of aggregate **(a)** GDP, **(b)** Consumption, **(c)** Investment, and **(d)** Housing expenditures relative to the GDP of the SSP 5 baseline, where climate impacts are fixed at their historical baseline level, comparing the high-emissions scenario (RCP 8.5) with the corresponding outcomes under the strong mitigation scenario (RCP 1.9) over the 21st century. Crosses, boxes, and triangles indicate median impacts, 2.5–97.5% confidence intervals, and median impacts excluding housing destruction from tropical cyclones, respectively. Dots depict results from the DICE model, computed using Nordhaus's temperature-based damage function and annual temperature changes averaged across both climate models (see Appendix A for details).

decomposition reveals that increased investment in housing reconstruction stimulates the industrial sector, leading to relative price pressures due to increased demand and lower labor productivity. By contrast, the effects of the relative price for services and agricultural goods do not depend on the realization of the TC impacts.

In line with several global, bottom-up climate change impact assessments (Dellink et al., 2019, 2014; Eboli et al., 2010), we find that the various economic dynamics partially offset each other. In consequence, the net effect of climate change on GDP remains unclear. There are no statistically significant differences in GDP between the two emission scenarios, even though the stronger emission scenario results in much stronger climate impacts. By contrast, the reduction in consumption becomes significant and sizable in the second half of the century. Together with substantially higher housing reconstruction needs, this is a clear indication of higher welfare losses under the strong-emission scenario. These would remain hidden for studies focusing only on GDP effects, which is the case for much of the rapidly growing climate econometric literature (Burke et al., 2015; Kalkuhl and Wenz, 2020; Kotz et al., 2021, 2022). Our results suggest that future climate impact assessments should go beyond aggregate GDP as the main indicator and instead place greater emphasis on consumption, which is in line with a recent study by Casey et al. (2024). While GDP components help identify the distinct transmission channels through which climate change affects the economy, consumption more directly captures the resulting welfare implications. Focusing on consumption, therefore, allows for a more robust estimate of the welfare costs of climate change.

The focus of our analysis was on the dynamics of the economic response to climate variability and change. To this end, we did not develop new damage functions but used estimates derived from the existing body of literature for climate impacts in Vietnam. Further, we would consider it likely that our analysis does not cover all channels through which climate variability and change impact the economy. In evaluating the consequences of sea level rise, our analysis is restricted to the direct impacts on agricultural systems. It is thus very likely that it underestimates socioeconomic costs of sea level rise since major channels such as damage to physical capital, critical infrastructure (ADB, 2023) and forced coastal migration are excluded (Bachner et al., 2022). In particular, in the literature, TC impacts are often described as physical capital damage (Eberenz et al., 2021). Since most physical capital in Vietnam is housing, we take a different approach and focus on damage to the housing stock as a durable consumption good. In this regard, we would consider our impact estimates conservative since TC damage to sectoral capital stocks is not considered in our main specification. Moreover, at the case study level, TCs have been

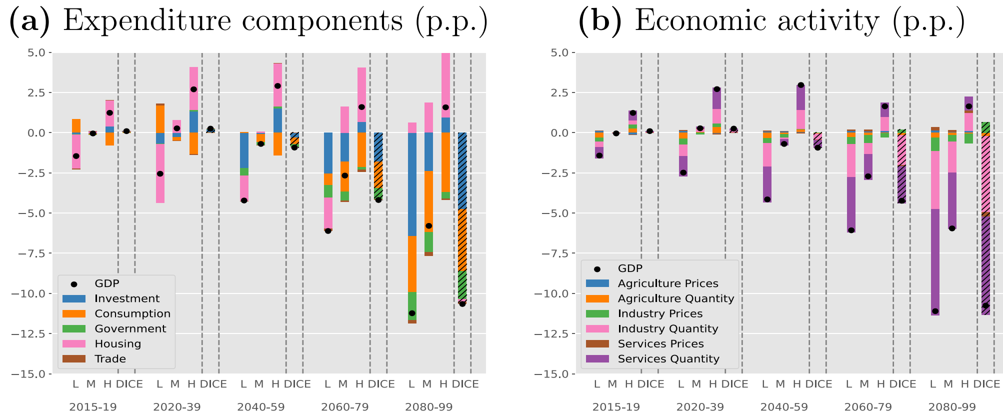


**Fig. 8. Decomposition of climate change impact on GDP by expenditure component and economic activity. (a):** Percentage-point (p.p.) differences in the expenditure components of the GDP (private investment (blue), consumption (orange), government expenditure (green), housing expenditure (pink), and trade (brown) under the strong emission scenario RCP 8.5 to the strong mitigation scenario RCP 1.9 relative to the SSP baseline, where climate impacts are fixed at their historical baseline level. Changes in overall GDP are marked by black dots. **(b):** same as **(a)** but for changes in sectoral components (agricultural prices (blue), agricultural quantity (orange), industry prices (green), industry quantity (pink), services prices (brown), and services quantity (purple)). Columns labeled 'L', 'M' and 'H' refer to the 2.5 (large GDP loss), 50 (medium GDP loss) and 97.5 percentile (low GDP loss) with regard to the aggregate GDP of the SSP baseline across all 600 realizations for each RCP. Columns 'DICE' depict the results as obtained with the temperature damage function of Nordhaus's DICE model from annual temperature changes averaged across both climate models (see Appendix A for details). Damage sorted by GDP loss is depicted in Fig. B.9. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

shown to affect employment (Wu et al., 2019; Chaganti and Waddell, 2015) and the availability of (skilled) labor (Zissimopoulos and Karoly, 2007). In addition, we neglect the impact of TCs through higher post-disaster mortality and hospitalization (Huang et al., 2024). Perhaps even more importantly, we do not account for the impacts of TC-induced storm surges and rainfall, which are projected to increase under global warming (Knutson et al., 2020).

Second, our results are subject to several dimensions of uncertainty. We showed that the uncertainties related to the climate models are rather small. Further, the relative changes considered for economic components under strong emission compared to strong mitigation scenarios only marginally depend on the underlying socioeconomic development scenario. However, this by no means implies that the absolute impacts of climate change on the economy are also similar across these scenarios, since these describe quite different growth futures. Further, the uncertainty with regard to TC impacts is large due to the high year-to-year variability of these storms. This uncertainty induced by TCs is one main reason why the observed changes in private investment and housing expenditures are not statistically significant at the 95% level. The other main reason is the potential to adapt to heat stress, reducing the potential impact of an increase in the wet bulb globe temperature. If we do not restrict the effect of wet bulb globe temperatures on labor productivity to the summer season as done, we observe statistically significant negative effects on GDP between −5% to −22% (Figs. B.13 and B.14) due to stronger heat-induced labor productivity losses (Fig. B.12).

However, we would not expect that these limitations challenge the robustness of our main finding that studying the impacts of climate change on aggregate GDP can be misleading and – in general – does not allow estimating the welfare implications of climate change impacts for the following two reasons: First, adding additional impact channels may lead to a more pronounced relative decline in GDP, but it would likely not result in a more positive development of consumption. In this sense, our results can be considered conservative estimates of the economic impacts of climate change. Second, while accounting for additional impact channels may add additional layers of uncertainty, it appears unlikely that these uncertainties would render the consumption response to the climate impacts ambiguous. Rather, we would expect additional channels to lead to greater consumption losses. For example, we do not account for climate change-induced housing demand through migration, which can drive housing prices up and reduce disposable income for other forms of consumption (Fan et al., 2018; Wrenn, 2024).

Our findings have significant implications for estimating the costs of climate change for societies, making them highly relevant for both national and international climate policy. One of the most important metrics in climate negotiations and national mitigation strategies is the Social Cost of Carbon (SCC), which quantifies the estimated economic damage caused by emitting an additional metric tonne of $CO_2$. This metric helps weigh the costs of mitigation against the benefits of avoiding climate-related damage. However, many current methods for estimating SCC focus on its impact on aggregate GDP, as seen in recent studies (e.g. Ricke et al. (2018), Rennert et al. (2022) and Krichene et al. (2023)). Our results suggest that this approach can be misleading. For the standard approach pioneered by Nordhaus (1993) using one damage function that reduces overall output, direct damage without general equilibrium effects and with general equilibrium effects coincide. However, if one differentiates between capital stock destruction and productivity losses, direct damage and general equilibrium effects on GDP can differ not only quantitatively but also qualitatively.

In line with the global computational general equilibrium literature (Bachner et al., 2022; Dellink et al., 2019, 2014; Eboli et al., 2010), we find that GDP-based methods overlook crucial factors, such as substantial reconstruction needs and consumption losses in high-emission scenarios. As a result, relying solely on GDP to estimate the SCC underestimates the broader welfare losses and, thus, the true costs of climate change (for Vietnam). Although our study focuses on Vietnam, these insights are likely to be applied more broadly. If current GDP-based SCC estimates underestimate climate-related damage globally, this could result in insufficient ambition in mitigation efforts.

At the national level, downplaying the welfare impacts of climate change risks leading to insufficient national adaptation plans and too few adaptation efforts. Evidence from OECD countries shows that climate shocks affect economies differently, reinforcing the need for country-specific policy mixes to balance growth and climate objectives (Ciccarelli and Marotta, 2024). Our analysis underscores that country-specific policy mixes are essential to balance growth and climate goals. Our study highlights the political importance of gaining a deeper understanding of how climate change affects economies and societies to enable more comprehensive and effective policy responses. As Cantelmo et al. (2023) concluded, addressing macroeconomic vulnerabilities in disaster-prone economies requires a comprehensive understanding of disaster impacts, which is crucial for Vietnam.

## 7. Conclusion

In its seminal work, Nordhaus (1993) introduced a single damage function to represent the economic impacts of climate change, a framework that remains central to many contemporary impact assessment models (Cai et al., 2023; Nordhaus and Yang, 1996; Nordhaus, 2014, 2019). This damage function aggregates various impact channels, including effects such as sea level rise, natural disasters, loss of agriculture, labor productivity, and mortality (Fankhauser, 1994).

Our national analysis complements the growing body of global studies highlighting the importance of impact disaggregation (van der Wijst et al., 2023; Dellink et al., 2019, 2014; Eboli et al., 2010), as different channels trigger distinct economic response dynamics. For example, while productivity losses directly reduce GDP, damage to physical capital stock can lead to increased investment, resulting in ambiguous effects on GDP. Importantly, although all impacts negatively affect consumption, the effects on GDP depend on the relative weight of damage stemming from capital stock destruction versus productivity decline. Our analysis shows that heat stress is the main driver of negative GDP responses. At the same time, it is likely the impact channel with the lowest-cost adaptation opportunities (Sun et al., 2024).

The results of our Vietnam case study are likely to be representative of other TC-affected low- and middle-income countries that are highly vulnerable to climate change. These findings underscore the critical need for targeted adaptation strategies tailored to the specific vulnerabilities of different sectors. In addition, they emphasize the need to evaluate a broader set of economic indicators, beyond GDP, to comprehensively assess the welfare implications of climate change.

### CRediT authorship contribution statement

**Christian Otto:** Writing – review & editing, Writing – original draft, Visualization, Resources, Conceptualization. **Christoph Schult:** Writing – review & editing, Writing – original draft, Visualization, Software, Formal analysis, Data curation, Conceptualization. **Thomas Vogt:** Writing – original draft, Visualization, Methodology, Investigation.

### Materials and/or code availability

Model code is available in Zenodo at https://doi.org/10.5281/zenodo.16729785.

### Use of AI tools

During the preparation of this work, the authors used OpenAI's ChatGPT to improve wording, check consistency, and assist with formatting. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the final version of the manuscript.

### Funding

No funding was received for conducting this study.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Table C.1**
Parameters for heat-induced productivity loss functions.

| Metabolic rate (W) | Mean $\mu$ (°C) | Standard deviation $\sigma$ (°C) |
|---|---|---|
| 200 | 35.53 | 3.94 |
| 300 | 33.49 | 3.94 |
| 400 | 32.47 | 4.16 |

Note: Parameters are according to Kjellstrom et al. (2018).

### Appendix A. Computation of direct damage

We aim to measure the direct impact of different climate impact channels (one at a time), without considering potential general equilibrium effects or interdependence of impact channels (Fig. 5). To this end, we fix all other variables such as relative prices, real wages, and the allocation of labor to their respective values of the underlying SSP baseline, where climate impacts are fixed at their historical baseline level, and only account for the impacts introduced by the considered channels. In the model, the value added in each sector is a function of its production factors (A.1),

$$Y_{s,t} \equiv Y_s(A_{s,t}, A^L_{s,t}, D_{s,t}, D^L_{s,t}, K_{s,t}, L_{s,t}), \tag{A.1}$$
$$= \tilde{A}_{s,t} \begin{cases} \left[ \alpha_s^{L\,\frac{1}{\eta_s^{NK}}} \left( \tilde{A}^L_{s,t} L_{s,t} \right)^{\rho_s^{NK}} + \alpha_s^{K\,\frac{1}{\eta_s^{NK}}} \left( K_{s,t} \right)^{\rho_s^{NK}} \right]^{\frac{1}{\rho_s^{NK}}} & \text{if } \eta_s^{NK} \neq 1, \\ \left( \tilde{A}^L_{s,t} L_{s,t} \right)^{\alpha_s^L} \left( K_{s,t} \right)^{\alpha_s^K} & \text{if } \eta_s^{NK} = 1, \end{cases}$$
$$\text{where } \tilde{A}_{s,t} \equiv A_{s,t}(1 - D_{s,t}), \text{ and } \tilde{A}^L_{s,t} \equiv A^L_{s,t}(1 - D^L_{s,t}).$$

This allows calculating the damage to labor productivity relative to GDP, $\Delta DAM^{L,SCE}_{s,t}$, for each SSP–RCP scenario combination ($SCE$) as the difference in added value caused solely by reductions in labor productivity,

$$\Delta DAM^{L,SCE}_{s,t} \equiv \frac{P_{s,t} \Delta Y^{SCE}_{s,t}}{P^{SSP}_t Y^{SSP}_t},$$
$$\text{with } \Delta Y^{SCE}_{s,t} = Y^{SSP}_{s,t} - Y_s(A^{SSP}_{s,t}, A^{L,SSP}_{s,t}, D^{SSP}_{s,t}, D^{L,SCE}_{s,t}, K^{SSP}_{s,t}, L^{SSP}_{s,t}). \tag{A.2}$$

The same procedure is applied for damage caused by the rise in sea level and temperature on crop yields in agriculture. TCs impact the economy only through the destruction of the housing stock, which, in contrast to labor, is not a production factor. This is why damage from destruction of the housing stock, expressed relative to GDP, is computed differently:

$$\Delta DAM^{Cyclone,SCE}_t = \frac{P^{H,SSP}_t \left( H^{H,SSP}_t - H^{H,SCE}_t \left( D^{H,SCE}_t, I^{H,SSP}_t \right) \right)}{P^{SSP}_t Y^{SSP}_t}. \tag{A.3}$$

This methodology allows us to compare the various effects of different impact channels and assess their relative importance. However, the method does not include any general equilibrium effects, such as changes in relative prices and reallocation of production factors.

### Appendix B. Supplementary figures

See Figs. B.9–B.14.

### Appendix C. Tables

See Tables C.1 and C.2.

### Appendix D. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2026.109390.

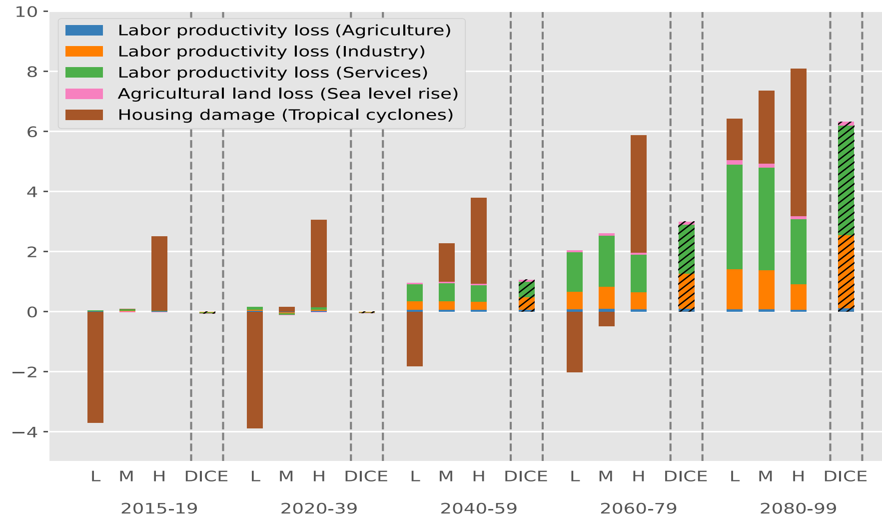


**Fig. B.9. Decomposition of climate change impact channels sorted by GDP deviations for RCP 8.5.** Damage by impact channel, expressed as percentage-point (p.p.) deviations in GDP (relative to GDP of the SSP baseline, where climate impacts are held constant at their historical baseline level), induced through the various impact channels under the strong emission scenario. The sorting corresponds to the GDP impacts in Fig. 8. Columns labeled 'L', 'M', and 'H' correspond to the 2.5th (large GDP losses), 50th (medium GDP losses), and 97.5th (low GDP losses) percentiles, respectively, across all 600 realizations for each RCP with respect to aggregate GDP in the SSP baseline. The column 'DICE' reports the results obtained using the temperature damage function of Nordhaus's DICE model, based on annual temperature changes averaged over both climate models (see Appendix A for details).

**Table C.2**
Agricultural land loss due to sea level rise.

| Sea level rise (cm) | Land loss $ll_b$ (percent) |
|---|---|
| 0 to 5 | 0.1 |
| 5 to 10 | 0.5 |
| 10 to 15 | 0.5 |
| 15 to 20 | 0.7 |
| 20 to 25 | 0.9 |
| 25 to 30 | 1.1 |
| 30 to 35 | 1.2 |
| 35 to 40 | 1.4 |
| 40 to 45 | 1.7 |
| 45 to 50 | 1.9 |
| 50 to 55 | 2.4 |
| 55 to 60 | 3.5 |
| 60 to 65 | 3.5 |
| 65 to 70 | 3.5 |
| 70 to 75 | 3.9 |
| 75 to 80 | 4.6 |
| 80 to 85 | 5.1 |
| 85 to 90 | 5.7 |
| 90 to 95 | 6.2 |
| 95 to 100 | 6.7 |

Note: Land loss estimates are based on unpublished administrative data provided by the Ministry of Natural Resources and Environment of Vietnam (private communication) and authors' own computations.

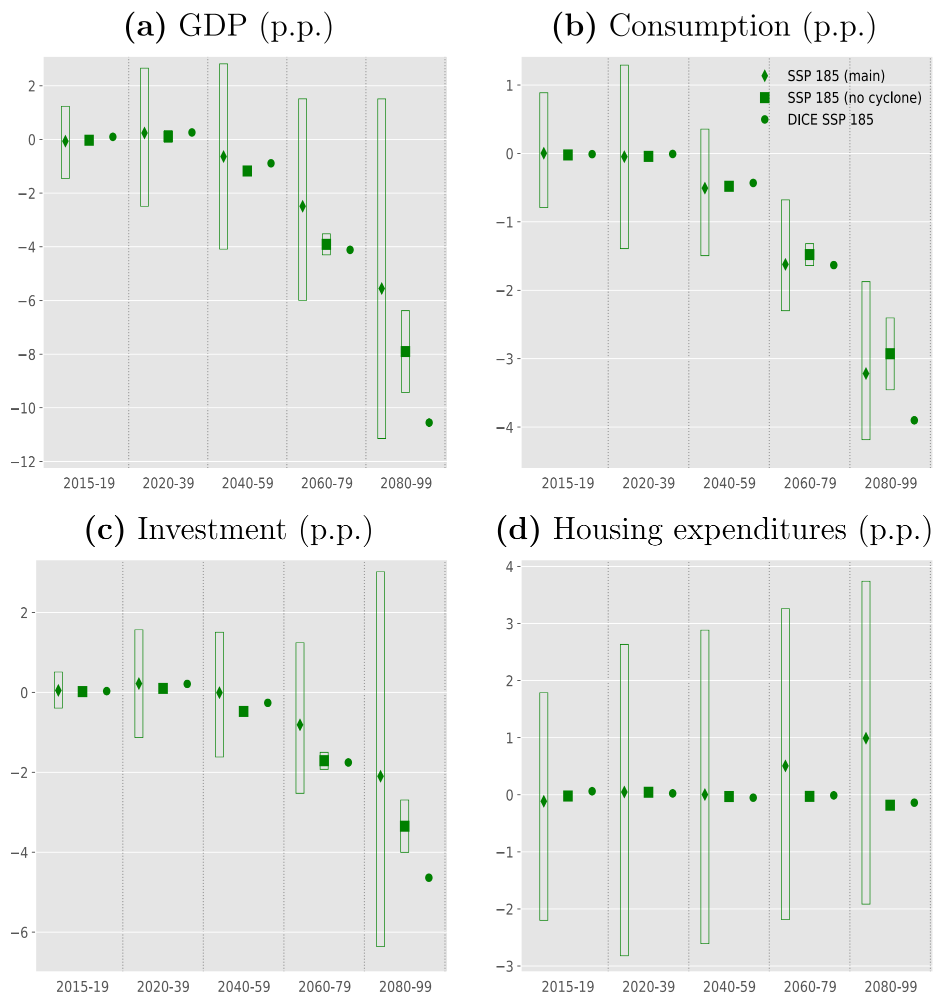


**Fig. B.10. Climate change impact on GDP, consumption, investment, and housing expenditures for SSP 1.** Percentage-point (p.p.) deviations of aggregate **(a)** GDP, **(b)** Consumption, **(c)** Investment, and **(d)** Housing expenditures relative to the GDP of the SSP 1 baseline, where climate impacts are fixed at their historical baseline level, comparing the high-emissions scenario (RCP 8.5) with the corresponding outcomes under the strong mitigation scenario (RCP 1.9) over the 21st century. Crosses, boxes, and triangles indicate median impacts, 2.5–97.5% confidence intervals, and median impacts excluding housing destruction from tropical cyclones, respectively. Dots depict results from the DICE model, computed using Nordhaus's temperature-based damage function and annual temperature changes averaged across both climate models (see Appendix A for details).

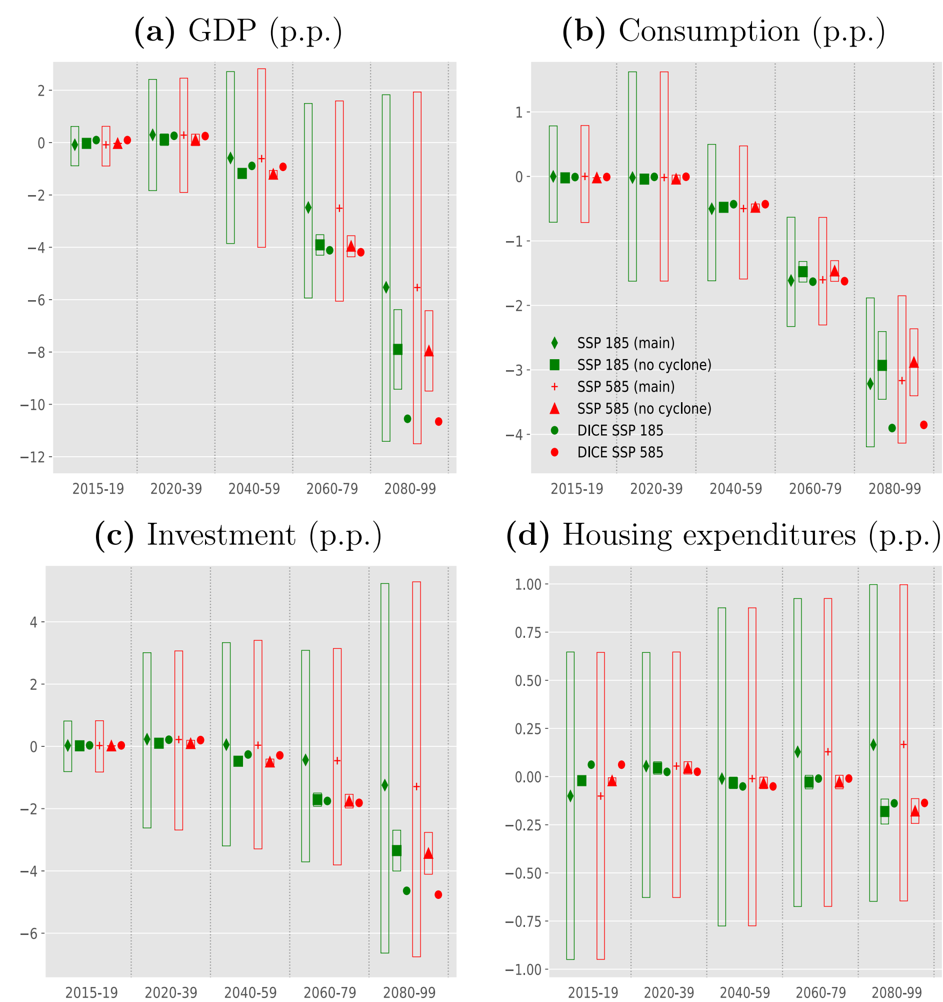


**Fig. B.11. Climate change impact on GDP, consumption, investment, and housing expenditures with mortgage risk sharing.** Percentage-point (p.p.) deviations of aggregate **(a)** GDP, **(b)** Consumption, **(c)** Investment, and **(d)** Housing expenditures relative to the GDP of the SSP baselines (SSP 1 (green) and SSP 5 (red)), where climate impacts are fixed to their historical baseline level, comparing the high-emissions scenario (RCP 8.5) with the corresponding outcomes under the strong mitigation scenario (RCP 1.9) over the 21st century. Crosses, boxes, and triangles indicate median impacts, 2.5–97.5% confidence intervals, and median impacts excluding housing destruction from tropical cyclones, respectively. Dots depict results from the DICE model, computed using Nordhaus's temperature-based damage function and annual temperature changes averaged across both climate models (see Appendix A for details).

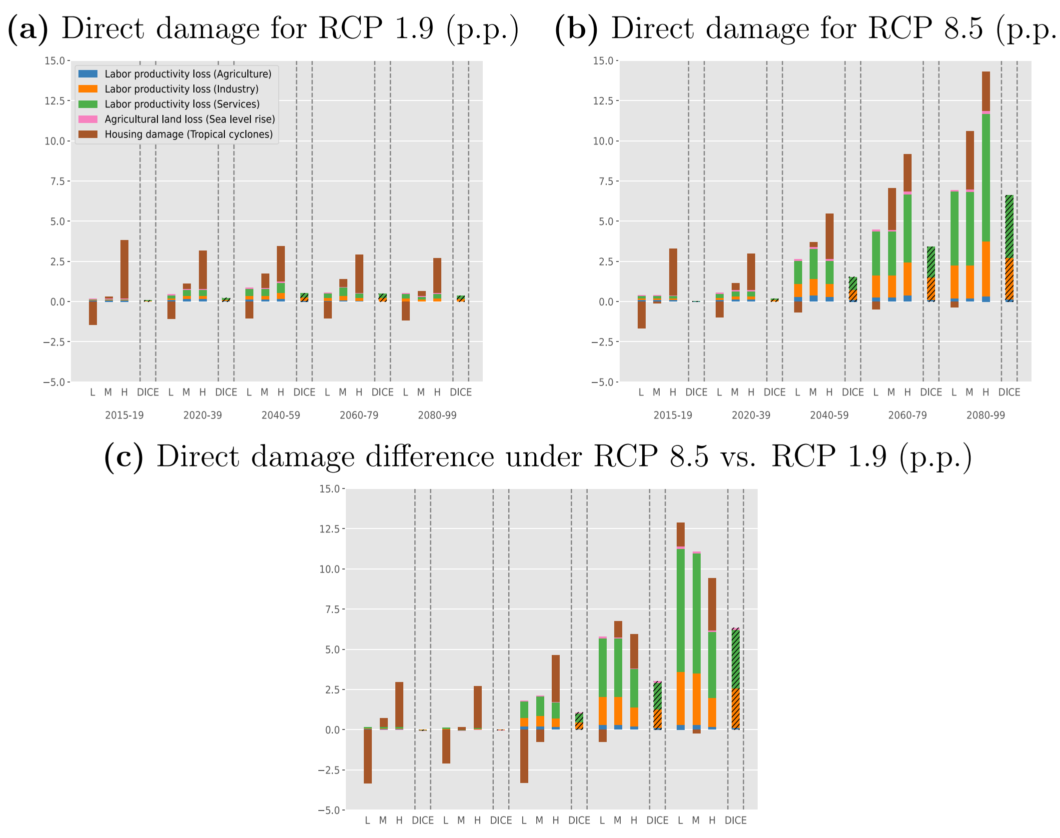


**Fig. B.12. Decomposition of climate change impact channels for year-round wet bulb globe temperature.** Percentage-point (p.p.) deviation in GDP (relative to GDP in the SSP baseline, where climate impacts are fixed at their historical baseline level) induced through the various impact channels under the strong mitigation scenario (RCP 1.9, **(a)**) and the strong emission scenario (RCP 8.5, **(b)**). **(c):** Difference in GDP (in p.p. of the GDP of SSP baseline) induced through the various impact channels under RCP 8.5 relative to RCP 1.9. Columns labeled ‘L’, ‘M’ and ‘H’ refer to the 2.5 (low-damage outcome), 50 (medium-damage outcome) and 97.5 percentile (high-damage outcome) across all 600 realizations for each RCP. Further, the column ‘DICE’ depicts the results as obtained with the quadratic temperature damage function of Nordhaus’s DICE model from annual temperature changes averaged across both climate models (see Appendix A for details).


**Fig. B.13. Climate change impact on GDP, consumption, investment, and housing expenditures for year-round wet bulb globe temperature.** Percentage-point (p.p.) deviations of aggregate **(a)** GDP, **(b)** Consumption, **(c)** Investment, and **(d)** Housing expenditures relative to the GDP of the SSP baselines (SSP 1 (green) and SSP 5 (red)), where climate impacts are fixed to their historical baseline level, comparing the high-emissions scenario (RCP 8.5) with the corresponding outcomes under the strong mitigation scenario (RCP 1.9) over the 21st century. Crosses, boxes, and triangles indicate median impacts, 2.5–97.5% confidence intervals, and median impacts excluding housing destruction from tropical cyclones, respectively. Dots depict results from the DICE model, computed using Nordhaus's temperature-based damage function and annual temperature changes averaged across both climate models (see Appendix A for details).

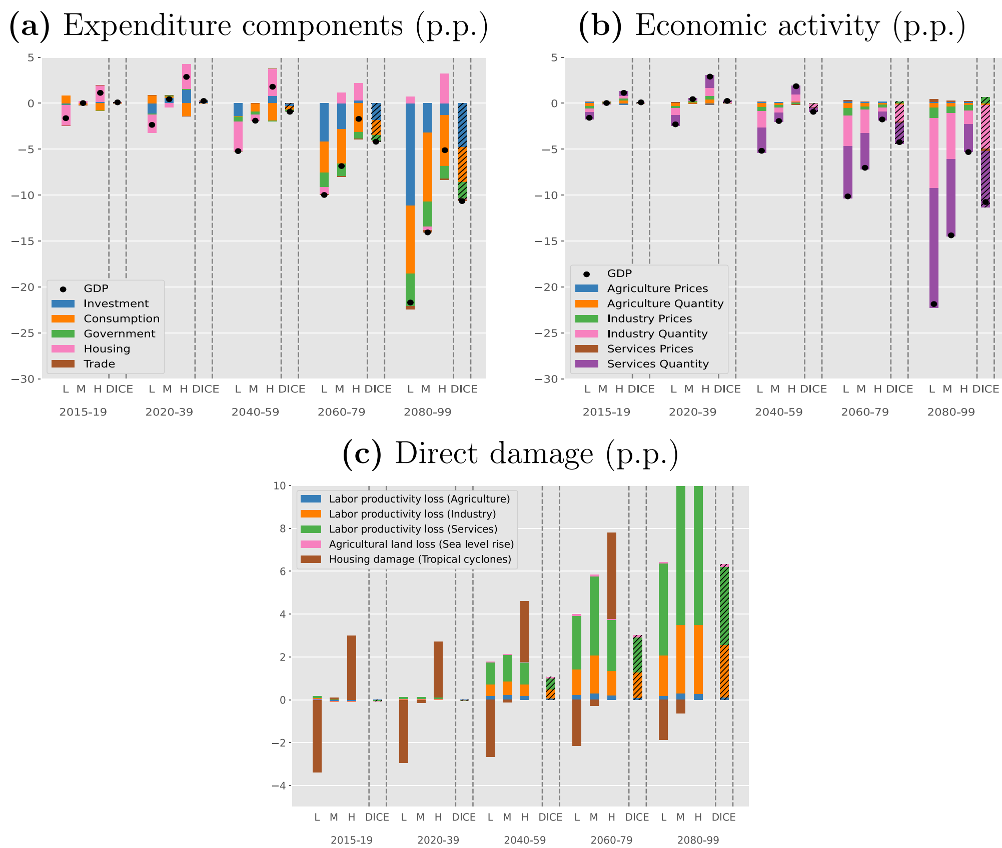


**Fig. B.14. Decomposition of climate change impact on GDP by expenditure component and economic activity for year-round wet bulb globe temperature. (a):** Percentage-point (p.p.) differences in the expenditure components of the GDP (private investment (blue), consumption (orange), government expenditure (green), housing expenditure (pink), and trade (brown) under the strong emission scenario RCP 8.5 to the strong mitigation scenario RCP 1.9 relative to the SSP baseline, where climate impacts are fixed at their historical baseline level. Changes in overall GDP are marked by black dots. **(b):** same as **(a)** but for changes in sectoral components (agricultural prices (blue), agricultural quantity (orange), industry prices (green), industry quantity (pink), services prices (brown), and services quantity (purple)). Columns labeled 'L', 'M' and 'H' refer to the 2.5 (large GDP loss), 50 (medium GDP loss) and 97.5 percentile (low GDP loss) with regard to the aggregate GDP of the SSP baseline across all 600 realizations for each RCP. Columns 'DICE' depict the results as obtained with the temperature damage function of Nordhaus's DICE model from annual temperature changes averaged across both climate models (see Appendix A for details). **(c)**: Direct damage differences under RCP 8.5 to RCP 1.9 (relative to GDP of the SSP baseline) across all 600 realizations. Columns 'DICE' depict the results as obtained with the temperature damage function of Nordhaus's DICE model from annual temperature changes averaged across both climate models (see Appendix A for details). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

## Data availability

The data supporting the findings of this study are openly available in Zenodo at https://doi.org/10.5281/zenodo.16729785.

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