ACCREU

Assessing Climate Change Risk in EUrope

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Advancing impacts and adaptation in IAM and CGE models

1. Changes with respect to the DoA

Due to some delays in the provision of data from WP2 and WP3 not all model developments are finalized at this point. The Deliverable therefore shows proof of concepts in particular for the already available sea level rise impacts from DIVA. However, all development is well planned to be finalized as soon as the data are available in the next 2-3 months, in particular the aggregate damage and adaptation cost functions. The new model code will be made available with the Deliverables describing the application.

2. Dissemination and uptake

This deliverable serves as the focal point for the finalization of the model development in WP4, paving the way to move on to application and analysis in Tasks 4.2-4.4. This Deliverable will be used for dissemination of model developments outside of the project.

3. Short Summary of results

This Deliverable describes the established linkages with WP2 and WP3 outputs and model developments. Building on Milestone 4.1 it demonstrates how planned developments are now implemented in WP4 models and how WP2 impacts are taken up. For that it summarizes the relevant scenario settings and outputs of WP2 models. It does not show results yet but focuses on model implementations.

4. Evidence of accomplishment

Proof of concepts for the models based on available finalized inputs, mostly from DIVA on sea level rise impacts, and from GLOBIOM on agricultural impacts.

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1. Introduction

A key focus of the ACCREU project is the improvement of the representation of climate change impacts and in particular adaptation options in integrated assessment, economic, and finance models. These improvements rely on model advancements together with the integration of new input data. These include data from impact models representing different adaptation scenarios in more detail, developed in WP2, and new data on adaptation costs compiled in WP3. Task 4.1 “Framing the integration between Adaptation, Mitigation, Residual Damage” facilitates these linkages across work packages and modeling approaches. Milestone 4.1 outlined the strategy and plans for this integration. This deliverable now reports on achieved objectives, focusing on the linkages built and on the model implementations. The key focus is the demonstration of use cases for each model for applications and analyses foreseen in Tasks 4.2-4.4.

Impacts are considered from WP2 models for sea-level rise, river floods, agriculture and forestry, energy, labor, and, newly, health, wildfires and ecosystems. A scenario framework was developed for impact models to assess impacts consistently under three different levels of adaptation (see Milestone 4.4). Output variables representing climate impacts were identified to be taken up in WP4 models, together with avenues to represent adaptation levels and costs. WP4 models are taking up these outputs either directly as sectoral impacts through a bottom-up approach, or through an aggregated approach, requiring the development of an aggregate damage function and adaptation cost function. This required an extensive effort of alignment of the data which was undertaken in close collaboration with Task 3.4. Not all impacts could be included in the global damage and adaptation functions as some (wildfire, health, ecosystems) are only available for Europe. The CGE models will take up the full suit in their European analysis, while global IAMs will be using the aggregated functions. The results of this will be made publicly available.

Short summary of model improvements

COIN-INT: COIN-INT implemented the available new data on impacts and adaptation costs/effectiveness along the ACCREU scenarios for all types of WP2 impacts. The implementation is described and illustrative results are provided.

ICES: The ICES model, in its Multi-Household version (ICES-MH), has been calibrated to reproduce the SSP2 scenario and RCP 7.0. All WP2 impacts are implemented in the model. The implementation is described and illustrative results are provided.

MIMOSA: MIMOSA updated the sea-level and non-sea level impacts based on ACCREU. It also included continuous adaptation and residual damages, based on the ACCREU adaptation cost functions.

WITCH: WITCH builds on its bottom-up representation of impacts and adaptation and includes new ACCREU outputs on sea level rise, energy demand and labor.

REMIND: The REMIND model updated its sea-level rise module, as well as the SLR and non-SLR damage function. It also developed the capability of representing adaptation through the adaptation cost function as provided in ACCREU.

DIFI: DIFI developed a new business-level insurance update module to advance the assessment of insurance as an adaptation option in CGE models. Through this the insurance coverage gap for flood risks can be assessed and tested against different options to increase insurance update.

CFR: The CFR model has been extended in order to integrate the levels of adaptation settings used in ACCREU and an application to impact data generated by WP2.

2. Overview: model linkages and scenarios

2.1 Models' implementations of the ACCREU scenario protocol

To align model output from WP2 models with WP4 models for integration, an ACCREU scenario protocol was developed (Annex A), covering 3 dimensions:

- Climate scenarios
- Climate and socioeconomic input data
- Adaptation specifications for three different levels of adaptation

Tables 1 and 2 provide an overview of the different scenario settings. Table 1 focuses on climate and socioeconomic scenarios and input data. Climate input data are coming from CMIP6, the climate model database underlying the IPCC 6th assessment report. Most models are using data provided through the ISIMIP project[1], which are bias corrected and cover a selection of 4 climate models (Frieler et al. 2025). Three main climate scenarios were chosen: RCP7.0 representing no mitigation, RCP4.5 as a low to medium mitigation scenario and RCP2.6 as a high mitigation scenario. Some models also provide data for the high emission scenario RCP8.5.

Socioeconomic input data (population and GDP) are based on the Shared Socioeconomic Scenarios (SSPs), using the "middle-of-the-road" pathway (SSP2) (Riahi et al. 2017)[2]. These data were first published in 2013 and updated in 2017. The most recent update from 2024 is a more substantial update, revising projections based on more recent trends in population and GDP including the COVID effect, as well as model improvements. Where possible, models were asked to use these updated data.

Model	**Climate data**	**Climate data source**	**RCP 2.6**	**RCP 4.5**	**RCP 7.0**	**RCP 8.5**	**SSP data**	**Coverage**
DIVA	CMIP6	IPCC	X	X	X		2024	Global
GLOFRIS	CMIP5	ISIMIP	X	X		X	2024	Global
LISFLOOD	EUROCORDEX							Europe
GLOBIOM	CMIP6	ISIMIP	X	X	X	X	2024	Global
CWaTM	CMIP6	ISIMIP	X	X	X	X	2024	Global
Labor	CMIP6		X	X	X			Global
Energy	CMIP6		X	X	X		2024	Global
Health	CMIP6		X	X	X	X	2024	Europe
IBIS	CMIP6	ISIMIP	X	X	X			Europe
ForeFire	CMIP6	ClimEx-II (RCM)	X	(X)	X		2024	Europe
OSeMOSYS-EU	CMIP6		X	X	X		2024	Europe

Table 1: Climate and socioeconomic scenario settings for WP2 models.

The alignment of adaptation assumptions across impact models is challenging given the variety of modeling approaches and their ability to represent different types of adaptation. A setup of three different levels of adaptation was chosen: reference/medium adaptation, low and high adaptation. Key dimensions of modeling are trade, technology and adaptive capacity. Each impact model specified these dimensions based on its specific abilities. Table 2 gives an overview of the

[1] https://www.isimip.org/

[2] https://iiasa.ac.at/models-tools-data/ssp

specifications. Not all dimensions are applicable to each model. Measures are a mix of planned and autonomous adaptation.

For this set of scenarios, WP2 models provide a set of damage and adaptation cost estimates. These are aligned and complemented with literature sources in WP3 to set up a comprehensive data set to be used in WP4 models. Table 3 gives an overview of the type of damages and adaptation costs estimated in WP2 or in WP3

Table 2: Overview of adaptation settings in WP2 impact models

Model		Reference/ medium adaptation	Low adaptation	High adaptation
DIVA	Trade	Does not apply		
	Technology	Seadikes – determined by adaptive capacity setting		
	Adaptive capacity	Constant protection level	Constant dike heights	Doubling and quadrupling of protection levels
GLOFRIS	Trade	Does not apply		
	Technology	Does not apply		
	Adaptive capacity	Constant protection standards	Constant dike heights	Optimal protection standards, zonal restriction, salt marshes
LISFLOOD	Trade	Does not apply		
	Technology	Does not apply		
	Adaptive capacity	Present protection standards	Incremental adaptation: flood proofing of buildings	Optimal adaptation: dykes strengthening and retention areas
GLOBIOM	Trade	Reference trade assumptions	Limited trade into EU	Expanded sustainable trade into EU
	Technology	Reference crop/livestock yield growth (0.7% p.a.) Medium improvement in irrigation efficiency (1.5% increase per decade)	Lower yield growth (0.5% p.a.) No improvement in irrigation efficiency	Higher yield growth (0.8% p.a.) High improvement in irrigation efficiency (3% increase per decade)
	Adaptive capacity	Sustainable irrigation expansion in equipped areas	Limited expansion of irrigation to already equipped areas	Sustainable expansion of irrigation in equipped areas and conversion of rainfed areas
CWaTM	Trade	Does not apply		
	Technology	Does not apply		
	Adaptive capacity	Does not apply (Water withdrawals reflect changes in economic growth from SSP2 assumptions and increasing water use efficiency based on from SSP2 assumptions)		
ForeFire	Trade	Does not apply	Does not apply	Does not apply
	Technology	Does not apply	Does not apply	Does not apply

	Adaptive capacity	Land-cover patterns based on a socioeconomic scenario with low adaptive capacity	Land-cover patterns based on a socioeconomic scenario with medium adaptive capacity	Land-cover patterns based on a socioeconomic scenario with high adaptive capacity
Labor supply	Trade	Does not apply	Does not apply	Does not apply
	Technology	Does not apply	Does not apply	Does not apply
	Adaptive capacity	Does not apply	Does not apply	Does not apply
Labor productivity	Trade	Does not apply	Does not apply	Does not apply
	Technology	Change in energy used by productive sectors (industry, services and agriculture) for cooling and other temperature-induced energy services.		
		AC adoption (indoor) is driven by climate changes	AC adoption (indoor) is assumed frozen at historical climate conditions	AC adoption (indoor) is driven by climate shifts and amplified by higher income
	Adaptive capacity	Does not apply	Does not apply	Does not apply
Energy	Trade	Does not apply		
	Technology	Does not apply	Current stock, intensive margin	Upgraded stock, extensive and intensive margin
	Adaptive capacity	Semi-elasticities of energy demand for cooling-heating at the baseline GDP/capita levels	Semi-elasticities of energy demand for cooling-heating low due to lower GDP/capita levels	Semi-elasticities of energy demand for cooling-heating high due to higher GDP/capita levels
Health	Trade	Does not apply	Does not apply	Does not apply
	Technology	AC adoption following Falchetta et al., 2024, differentiated only by SSPs and RCPs		
	Adaptive capacity	Does not apply	Does not apply	Does not apply
IBIS	Trade	Does not apply – adaptation levels set by input from GLOBIOM, ForeFire and DIVA (New: only agricultural adaptations from GLOBIOM included)		
	Technology			
	Adaptive capacity			
OSeMOSYS-EU	Trade	Reference electricity trade assumptions	Limited electricity trade	Expanded electricity trade

	Technology	Energy system development projections aligned with national and regional EU targets	Lower adoption rates of specific technologies or measures (e.g. building upgrades, a/c). Lower levels of electricity exchange potential within (and potentially beyond) EU. Lower flexibility in investment of alternative generation technologies that manage system shocks (e.g. storage technologies, flexible generation infrastructure)	Higher possible adoption rates of specific technologies or measures (e.g. building upgrades, a/c). Higher potential for electricity exchange potential within (and potentially beyond) EU. Higher flexibility in investment of alternative generation technologies that manage system shocks (e.g. storage technologies, flexible generation infrastructure)
	Adaptive capacity	- Investments in a/c adoption and building upgrades - Investments in generation and storage infrastructure - Increasing utilisation factor of alternative available technologies - Electricity trade potential limited to national outlook levels	- Investments in a/c adoption and building upgrades - Investments in generation and storage infrastructure - Increasing utilisation factor of alternative available generation technologies	- Investments in a/c adoption and building upgrades - Investments in generation and storage infrastructure - Increasing utilisation factor of alternative available generation technologies - Increased electricity trade potential

Table 3: Overview of damages and adaptation cost estimates provided and their uptake in the models

Impact type	**Model**	**Damages provided relevant for economic models**	**Adaptation cost estimates**	**Uptake in CGEs**	**Uptake in IAMs**
Sea level rise	DIVA	Expected annual damage, land loss, expected affected population	Seadike costs - maintenance costs + capital costs for new/raising existing dikes Migration costs (e.g. leaving behind capital)	Impact and adaptation: specific channels – see Tables 6 and 14	Impact: sea level rise damage function based on ICES results (all). Explicit cost from DIVA scenarios (WITCH). Adaptation: sea level rise adaptation cost function (all). Explicit dike cost from DIVA scenarios (WITCH)

Sea level rise and river floods	GLOFRIS	Expected annual damage with limited sectoral disaggregation (residential, commercial, industrial), Expected annual affected population	Investment + maintenance costs of raising dikes along coastlines and major rivers. Costs of preserving mangroves and saltmarshes aiming to reduce flood risk	Considering only river flood impacts and adaptation from GLOFRIS; specific channels mirror the implementation of sea level rise (DIVA) – see Tables 7 and 15	Not taken up as the investment structure of GLOFRIS does not lend itself to construct impact/adaptation functions
Agriculture	GLOBIOM	Crop yield changes, changes in land-use and land cover, prices	Costs for irrigation (operation & maintenance costs, capital costs, resource costs)	Impact and adaptation: specific channels – see Tables 8 and 19	Part of aggregate damage and adaptation cost functions
Water	CWaTM	Change in surface water available for economic use	Not explicitly included, costs for irrigation as modeled by GLOBIOM include the change in surface water available for economic use.	Used to provide input for GLOBIOM, not directly for WP4 models	
Labor	Empirical estimate	% change in labor supply % change in labor productivity For high and low exposure sectors	Change in AC electricity usage; AC costs	Impact and adaptation benefit: specific channels – see Tables 9 and 16	Part of aggregate damage and adaptation cost functions WITCH: explicit representation of impacts on labor productivity, with a direct link to adaptation through demand for air conditioning
Energy	Empirical estimate	Changes in energy demand (per fuel and sector), residential AC adoption and AC electricity use, effects of unplanned and planned power outages due to extreme weather events for thermal and renewable power energy	AC capital costs: new investments + replacement of existing units Costs for AC electricity use	Adaptation costs for investment in AC and AC electricity use: specific channels – see Table 9 for adaptation to the labour impact and Table 10 for adaptation to the health impact in COIN-INT See Table 18 for ICES-MH	Part of aggregate damage and adaptation cost functions WITCH: explicit representation of impact on energy consumption – endogenous adaptation response following 3 scenarios (low/medium/high)

	OSeMOSYS-EU	Impact on average cost of electricity generation from spikes in electricity demand (e.g. due to high cooling demand), thermal power plant outages and changes in renewable energy generation	Additional investments for A/C; associated increase in electricity price Investments in storage technologies and additional generation capacity Investments in energy efficiency measures in buildings		Not included
Health	Empirical estimates	Changes in health expenditure, heat-related mortality and morbidity costs	Benefits of adaptation: reduced mortality and morbidity due to AC penetration under SSP1_2.6, SSP2_4.5, SSP3_7.0, and SSP5_8.5. AC penetration rates were taken from Falchetta et al. (2024). According to the literature, heat-related mortality varies between 14 and 75% for an individual with AC relative to an individual without. We used the mean of these two values (44.5%).	Impact and adaptation benefit: specific channels – see Tables 10 and 17	Not included, only available for Europe
Ecosystems	IBIS	Combined climate and land-use impacts on European species habitat suitability.	Cost for protection and restoration not included	There is no direct entry point in the models for this output – it will be taken up in the final assessment through postprocessing in the welfare function	Not included as it cannot be included in the damage function from ICES and no adaptation costs are included

	CMCC	Biodiversity impacts due to pollination loss		Impact: specific channels – see Tables 11 and 20	
Wildfires	ForeFire	Burnt area under climate scenario - these outputs are used in G4M to assess change in biomass and harvested wood supply Burnt area under different climate and land use scenarios - the outputs will be used in selected CGE's	See under G4M/GLOBIOM Cost of GHG emissions from burnt areas; costs of technical adaptation/fire risk management solutions (surveillance, drones)	Impact: specific channels – see Tables 12 and 21	Not included, only available for Europe

2.2 Data transfer

Data is collected in excel sheets and exchanged through the IIASA Accelerator as a common portal for all project partners. They are provided on different levels of spatial (different NUTS levels, national) and temporal (annual or multiannual, sometimes only for specific years) resolution as well as in different currency units (MER vs PPP, different years), necessitating a harmonization step undertaken as part of Task 3.4 (see also Deliverable 3.4). Finally, data are provided on country and regional level, in 10 year time steps (2030-2100) and in three different monetary units (2023 USD or 2017 USD nominal, using country level inflation data, and 2017 USD nominal using USA inflation data. Annex 1 includes summary documents on these alignment and conversion steps.

2.3 Application in WP4 models

Milestone 4.1 developed the concept of data transfer from WP2 models to WP4 applications. This is illustrated in Figure 1 and guided the work which is now being reported on in this Deliverable. At the core are the two dimensions of impacts of climate change with different levels of adaptation (see Table 2) and the costs and effectiveness of adaptation for each sector. These can either be taken up on the sector level (by CGEs and selectively also by IAMs) or they are aggregated across sectors to be applied as aggregate GDP change in IAMs without sectoral detail (Table 3). For the latter, this is done for damages through the global CGE ICES and for an adaptation cost function linking costs to effectiveness (i.e. avoided damages) based on direct output of WP2 models. The derivation of the damage function follows the approach from COACCH (van der Wijst et al. 2023) and is described below in Section 5. The adaptation cost function derivation is described in Deliverable 3.4 and summarized below in Section 4. WP2 output is complemented by literature data where required and possible. Sections 6 and 7 describe in detail the methods of implementation in CGEs and IAMs, while sections 8 and 9 describe advancements in the DIFI and the CFR model. Results are shown only for proof of concept, a detailed scenario analysis will be provided in future Deliverables.

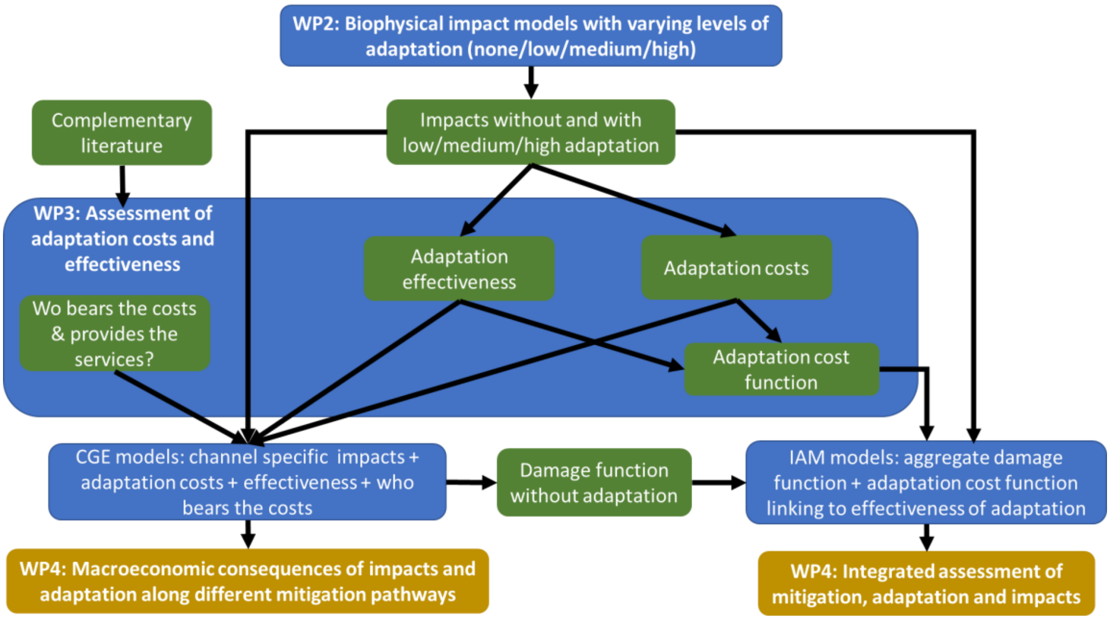

Figure 1: Data and information flow from WP2 and WP3 to CGE and IAM models in WP4.

3. Representation of new impact sectors

ACCREU operationalizes three new types of climate impacts for analysis in economic models: heat-related mortality and morbidity, wildfires and losses of pollination as a type of ecosystem impacts.

As they are available only on the European level, they are part of the comprehensive CGE-based analysis, but do not enter the global damage function used in the IAMs.

3.1 Heat-related mortality and morbidity

This is a brief summary of the estimation of these types of health impacts under ACCREU, more details can be found in Deliverable 2.3. For both the focus is on people aged 65 and older, the population most at risk from severe heat exposure. For mortality a temperature-mortality function (WHO 2014) was used to calculate baseline and future mortality under different climate impact and socioeconomic scenarios. The function relies on an optimum temperature (84^{th} percentile of daily maximum temperature) where mortality is lowest. Baseline mortality data (from Eurostat for 2013-2021 and 329 European regions) was then linked to deviations from this optimum at the higher end. Costs are estimated using a VSL of €1.3 million (2007) based on Szewczyk et al. (2018).

Morbidity estimates rest on mortality-morbidity relationships related to heat waves in France (Adélaide et al. 2022). They rely on data for excess morbidity based on different types of health services, including emergency department visits as well as outpatient visits with and without hospitalization, for the period 2015-2019. Morbidity costs combine medical costs and willingness to pay estimates also from Adélaid et al., but adjusted to European countries.

3.2 Wildfires

Macroeconomic impacts of wildfires are characterized by substantial complexity and uncertainty, affecting ecosystems, land productivity and capital stocks in both immediate and long-lasting ways. Unlike other climate-related impacts - such as flood damages or changes in labor productivity - for which established modeling approaches exist, there is currently no widely accepted best practice for representing wildfire impacts in macroeconomic (CGE) models. To address this challenge, the project adopts a twofold strategy to capture both broad, system-wide effects and more detailed, capital stock and multi-annual dynamics.

First, in ICES (see Table 21), expected annual wildfire impacts are incorporated at the EU scale through their impact on land productivity affecting agriculture and forestry. This ensures comparability with other climate damage channels. Second, COIN-INT (see Table 12) analyzes a more detailed case study for Spain to investigate the longer-term and lagged impacts of wildfires on perennial land uses. This focuses on the impact of fires on multi-annual crops (e.g., olive orchards, vineyards) and related capital. Unlike annual crops, these assets require multiple years to recover, implying persistent economic effects that extend beyond the immediate shock. Investigating the effect of a low-burn and high-burn year around 2050, this captures how wildfire damages can lead to a devaluation of capital tied to specific land uses. Together, these two approaches improve the representation of wildfire risks in economic modelling while advancing economic climate impact assessment into a largely unexplored dimension.

3.3 Biodiversity impacts based on pollination services

ACCREU develops one of the very first attempts to implement biodiversity loss impacts on the macro-economy. Impacts of global change on species habitat suitability from D2.4 are used to assess pollination services loss in a similar way as described in Section 5 of the deliverable. These are then fed into the ICES and COIN-INT models as productivity shocks to the agricultural sector.

Building on D2.4 data, we quantify changes in pollination ecosystem services across the European Union using observed long-term trends in wild pollinator populations and ecosystems degradation proxied by European biodiversity indicators, together with climate-driven projections derived from D2.4 data from IBIS species distribution models (SDM), covering up to 153 wild pollinator species across major taxonomic groups. The resulting spatially explicit ecological projections are matched with crop cultivation areas and crop-specific pollination dependency ratios for 129 European crops to estimate high resolution agricultural productivity impacts under multiple climate scenarios (RCP2.6, 4.5, 7.0, 8.5) and socioeconomic pathways up to 2070. These biophysical impacts are then translated into second-order macroeconomic shocks using a regionalized version of the ICES computable general equilibrium (CGE) model, enabling the assessment of economy-wide effects down to NUTS-2 regional resolution.

The methodology relies on the KIP-INCA framework (Vallecillo et al, 2018; MAES, 2020), where the service is provided by the functional match between pollination potential, defined as the ecosystem's ecological suitability to support wild insect pollinators, and pollination demand, defined as the spatial extent of pollinator-dependent crops (the use area). The spatial co-occurrence of pollination potential and pollination demand is used to quantify the actual flow of the service. To build the pollination potential baseline (2020-2070), the initial level of Pollination Potential relies on data from the INCA (2018) potential (Vallecillo et al., 2018), normalized to a 0–1 scale. The assessment is based on an indicator of the environmental suitability to support wild insect pollinators which integrates land use, land cover and on the distance to semi-natural areas, being the most important drivers, while current climate is included as well. Future changes are modelled by reducing the 2020 potential up to 2050 to meet expected pollination losses based on historical trends. The broad literature analysed suggested that a -1% annual decline is a robust assumption and in line with analysis carried out for EU Science and Technology for Pollinating Insects (STING) project (Potts et al., 2024). This annual decline in pollination potential is applied until 2035, assuming that the historical negative trend persists throughout the present decade and the degradation reaches its peak around that year. After 2035, the decline is assumed to gradually lessen, decreasing linearly to reach a 0% change rate by 2050. Consequently, no further decline is projected between 2050 and 2070 if climate change is not taken into account.

Projected declines in pollination potential due to changing climate are provided by D2.4 at a level of granularity comparable to that of the INCA datasets, capturing both increases and decreases in pollinator distributions due to habitat suitability as driven by projected regional climate conditions. Consequently, some regions are expected to experience gains in pollination potential, while others will face substantial declines. This spatial heterogeneity reflects the inherently local nature of climate impacts: current evidence suggests that many wild pollinator species may shift towards northern ranges, whereas most bumblebee species are projected to undergo substantial range contractions (Potts et al., 2015). By imposing the projected, spatially explicit climate-induced changes in habitat suitability onto the baseline potential, we estimate future pollination potential percentage change relative to 2020 at a high spatial resolution of 1 km × 1 km.

The ibis.iSDM provides species-specific habitat availability indices, represented as a fraction of suitable habitat per 10 km 2 grid cell across Europe for different climate and adaptation scenarios from 2015 to 2095 in 10-year intervals. From these, they calculated species-weighted habitat availability across all pollinator species for each 10 km 2 grid cell, providing a measure of overall pollinator potential (0-1). The analysis captured the combined impact of future climate and land use on individual species distributions by coupling a species distribution modelling approach with the ibis.iSDM modelling tool (Jung, 2023a) and refinement of suitable habitat (Brooks et al., 2019; Pereira et al., 2024; Visconti et al., 2024, 2016). By refining a species distribution by its species-specific habitat requirements, they capture the availability of natural and modified land directly available to the species. This enables to capture both climatically driven shifts in the distribution of European species and their attributed LULUCF impacts in terms of land-use change. This integrated approach allows for a better understanding of how land-use changes and management practices affect species habitat suitability beyond what climate-only SDMs can provide. Accordingly, we provided two different scenario sets based on SDMs assumptions.

The IIASA-CLIM scenarios are based on on the ‘climate_only_mean_suitability’ experiment which relies on the 2015/2025 baseline land use data and future modelled GCMs projections from ISIMIP3b climate forcing data (DOI: https://zenodo.org/records/13259644). These account for climate impacts on species distribution without including adaptation-induced land use shifts. In the IIASA-2 scenarios, land use projections from the downscaled GLOBIOM land use maps of the ACCREU scenarios (Deliverable 2.2) are also used. Including also the effects of autonomous land-use change resulting from the adaptation scenario.

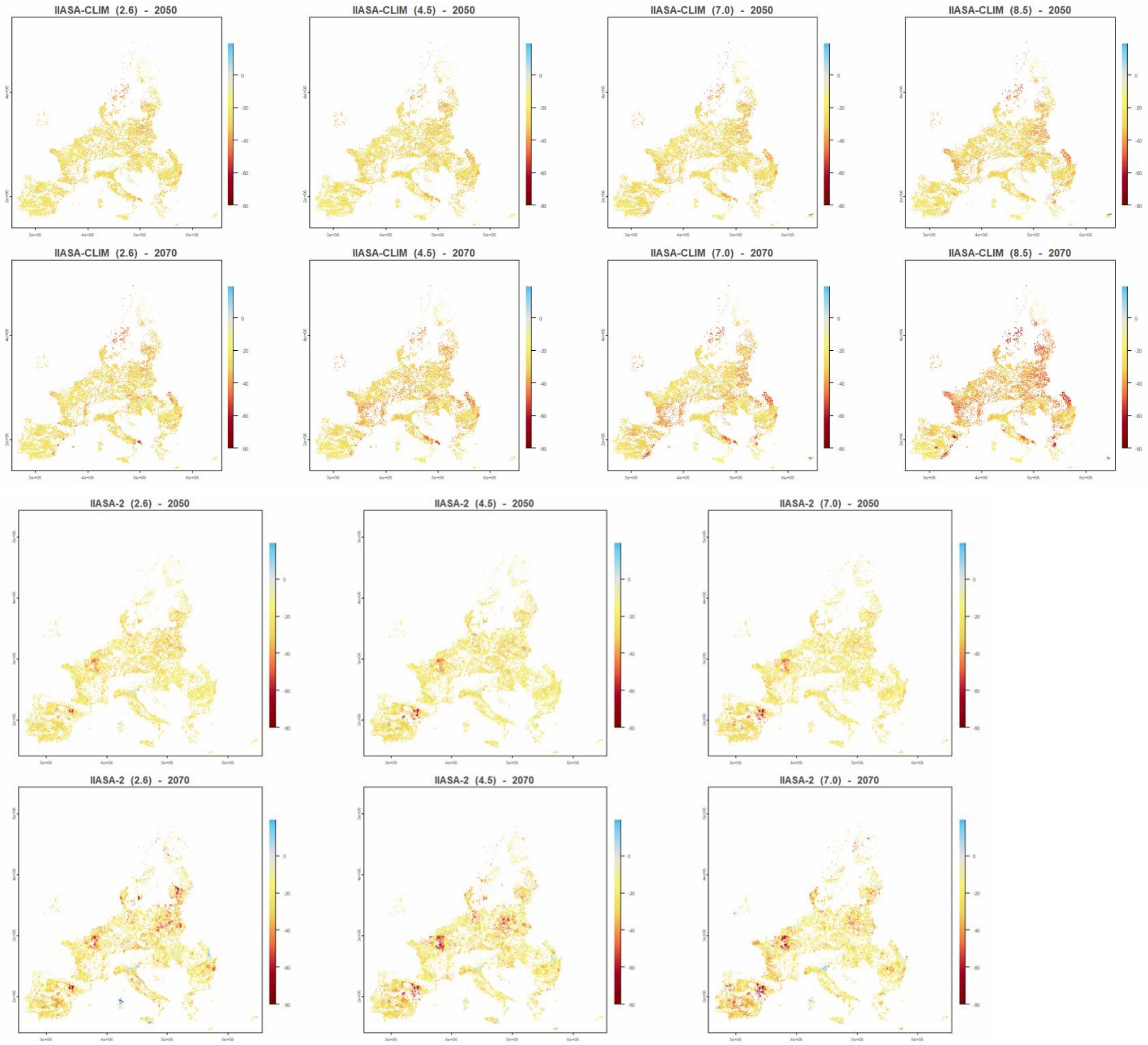

Figure 2: Each panel shows the average projected pollination potential percentage change in 2050 and 2070 with respect to 2020 under IIASA-CLIM and IIASA-2 scenarios.

We assess the agricultural impacts due to yield reduction for specific crop in a similar way as (Gallai et al., 2009; Grammatikopoulou et al 2014, 2024 ; Bauer, 2016), based on the dependency of specific crops to pollination and on the expected reduction of pollination potential in the cultivation area. Following a well established methodology (MAES, 2020), the overlap between the pollination potential and demand for pollination is used to quantify the area generating the actual flow of service (i.e. the use area). This can be defined as the number of hectares of pollinator-dependent crops covered by areas with different pollination potential levels. Consequently, changes in crop areas (service demand) or declines in pollination (service supply) translate into variations in agricultural output. Accordingly, the impact of pollination decline is modelled as a decrease in cropland productivity for specific crops, based on each crop's dependency on pollination and its cultivated area. Agricultural impacts are then represented as the percentage change in crop yield (crop-specific cropland productivity) relative to the no-impact-scenario.

To determine use areas at the highest possible spatial resolution, agricultural land (cultivated hectares) for 129 crops and crop categories from FAO CROPGRIDS (2020) is first mapped at the grid level and then overlapped with raster layers representing projected percentage changes in pollination potential. This enables us to quantify the extent to which the 2020 cultivation areas of specific crops in the EU are affected by pollination decline.

The impact of pollination changes is modelled as decreased cropland productivity based on the dependency of specific crops on pollination, which measures the fractional reduction in crop yield associated with a loss of animal pollination (Klein,2007; Bugin et al., 2022). For example, a pollination dependency of 0.05, means that a 100% decrease in pollination results in a 5% decrease in crop yield. The impact on production for a specific crop in a given area is therefore determined by the projected change in pollination service in the area where the crop is cultivated and by that crop's dependency on animal pollination.

$$yield_{c,n,t_1} = yield_{c,n,t_0} \cdot (1 + dependency\_p_c \cdot \Delta p_{n,t_1})$$

where:

- *c* the specific crop;
- *n* the specific spatial unit of production area (grid cell);
- Δp the absolute variation (t0 − t1) of pollination potential in n;

The projected gridded percentage changes in yield for each crop and climate scenario are mapped and aggregated at NUTS levels (0 to 2) and then used as land-productivity shocks in the macroeconomic model.

Since the agricultural sector in ICES is relatively aggregated, we averaged the projected yield percentage changes based on the relative weight of each crop cultivated in each region, aligning them with the crop categories used in the model. To do this, we compute a weighted average in which the weight of crops in each grid cell within a NUTS region is proportional to the number of hectares cultivated in that cell based on constant 2020 land use. These results are then further aggregated to match the crop categories used in the economic model, taking into account the relative contribution of each crop within the NUTS region of interest.

In this way, the resulting changes in cropland productivity fully embed spatial information on habitat-specific suitability shifts, crop-specific pollination dependency, and the spatial distribution of crop areas.

4. Modelling adaptation costs and effectiveness in CGEs

CGE models capture macroeconomic, second-order impacts, and cross-sectoral feedback effects, as they model the interactions among different economic sectors and agents. Their sectoral granularity also enables the implementation of climate impacts and adaptation in sectoral detail, making it possible to differentiate not only between different types of adaptation (e.g. reactive versus proactive), but also between different actors bearing the implementation costs (e.g. government, households, firms) and different beneficiaries from the reduction in impacts. While this level of detail allows for an improved representation of adaptation costs and effectiveness in models and thereby enhances the understanding of initiated indirect mechanisms, its adequacy relies on a thorough understanding of the considered adaptation actions. To ensure a meaningful translation of impact and adaptation effects from biophysical or process-based models into macroeconomic models, particularly CGE models, a common understanding of adaptation across modeling communities is essential for consistent and comparable assessments of climate change adaptation. The exchange of information is structured around five key guiding questions, which help economic modellers to understand key characteristics of adaptation measures.

(1) What is the main adaptation objective and how does it influence quantifiable climate impacts?

The most basic question concerns the central adaptation objective regarding the interaction between adaptation measures and climate impacts. For example, adaptation in the context of sea level rise reduces economic damages (measured in terms of expected annual damages), but also protects people from being flooded. The installation of air conditioning and the more intensive use of energy for cooling can counteract several health implications (e.g., labour productivity losses, mortality, subclinical outcomes, such as fatigue, troubles at sleeping, irritability), but only a subset thereof can be quantified and thus implemented in a modelling framework.

(2) What type of adaptation is being assessed (e.g., infrastructural, nature-based, soft adaptation (behavioral or institutional); incremental vs. transformational)?

Adaptation types assessed include infrastructural ("grey") measures such as seawalls and flood defenses, nature-based ("green") solutions like ecosystem restoration, and "soft" adaptations involving policies, regulations, or behavioral changes.These distinctions shape how adaptation is modeled, influencing assumptions about the type of costs. For instance, upfront investment cost is the most relevant cost category for infrastructural measures and also many nature-based solutions while maintenance or recurring costs dominate for other types such as information systems (personnel costs) and campaigns.

(3) How is adaptation implemented or realized within the economic system (e.g., investments in construction of new infrastructure, changes in production or consumption structures)?

Adaptation can be realized through a variety of implementation pathways within the economic system. It can involve investments in physical infrastructure such as building or upgrading flood defenses. Simultaneously, adaptation can occur through shifts in production and consumption structures, including changes in agricultural practices, adoption of climate-resilient crops, or alterations in energy use patterns.

(4) Who bears the costs and reaps the benefits of implemented adaptation measures?

Planned adaptation is often undertaken by public entities, when public actors are either the owner of the infrastructure (e.g. sea level rise) or when coordination is required (e.g. irrigation, trade policies, risk financing schemes, insurance) or when the provision of information is entailed (e.g. public campaigns) (Eakin and Patt, 2011). However, several adaptation measures are also undertaken at the private level, by either households (e.g. change in energy consumption, migration) or firms (e.g. flood proofing of buildings, heating and cooling systems, insurance, change in production methods). While sectoral (biophysical) models often do not distinguish between these agents as they are not represented in the model, there are underlying, implicit assumptions about who initiates and finances these adaptation measures. In some cases, the allocation of costs can also be country specific. For example, irrigation or water management are matters that might be subject to governance systems in some countries, but privately managed in other countries.

(5) What is the temporal relationship between climate impacts, adaptation measures, and their benefits?

A further consideration includes the temporal dimension of adaptation costs and benefits—whether these follow a linear relationship or display non-linear dynamics often driven by impact model structures. Specifically, this means, whether the benefits of an implemented adaptation measure are delayed compared to the costs or whether they appear simultaneously. Proactive adaptation actions have a longer time lag between the investment actions, which might take up to decades, and the manifestation of the benefits of adaptation. Reactive adaptation and coping measures, such as changes in expenditure patterns co-occur with the manifestations of the impacts.

By understanding the characteristics of the considered adaptation action, CGE models can translate the information from WP2 and WP3 into changes in model parameters according to Table 4. The first column categorizes the adaptation type according to its general approach or characteristics, such as infrastructural ("grey"), nature-based ("green"), or soft (policy, behavioral, planning-related) adaptation. It serves as a high-level classification of the adaptation being considered. The adaptation mechanism is captured in the second column. It specifies the operational means through which adaptation is achieved—for example, through building physical infrastructure, implementing ecosystem restoration, changing land use, or introducing regulatory changes. It clarifies the pathways or tools that realize the adaptation. The third column identifies the main actor responsible for initiating, financing or implementing the adaptation mechanism. These may include government bodies (public sector), private production sectors, or private households. A concrete illustration of WP2 adaptation measures is given for each adaptation type and mechanism in the example column. The second to last column indicates how the adaptation mechanism enters or is represented in the CGE model. It references the economic variable or sector affected, such as public investment, capital endowment, or changes in productivity or factor supply, thereby linking the adaptation measure to economic modeling structures. The final column flags important aspects that require special consideration when integrating the adaptation into models.

Table 4: Modelling adaptation in CGE models: illustrative examples of implementation

Key characteristics of adaptation measure based on WP2 models				**Modelling approach in CGE models (WP4)**	
Adaptation type	**Adaptation mechanism**	**Agency**	**Example**	**Targeted channel in CGE models**	**To be considered**
Infrastructural/ grey	Investments in new or updated infrastructure	Public agent	Building flood defense structure, irrigation infrastructure	Increase public investment	How does adaptation investment contribute to the accumulation of capital stock?
Infrastructural/ grey	Recurring expenditures to maintain infrastructure	Public agent	Maintaining flood defense structure	Increase public consumption from the construction sector	Depending on the public budget closure, public adaptation consumption (i) crowds out other consumption (unaltered government expenditure); (ii) implies transfers cut or tax increase (unaltered primary deficit); (iii) determines deficit and debt rise
Infrastructural/ grey	Change of production technology	Private production sector	Increased water use in the agricultural production for irrigation	Change composition of intermediate goods in the respective sector	
Soft/planning	Implementing new regulation	Public agent	Zoning	No adaptation costs, only benefits expressed as reduced expected annual damages	
Soft/planning	Migration of people and assets	Private household	Internal migration due to sea level rise	Labour supply shocks; migration costs (include leaving behind infrastructure)	Does the public agent compensate for incurred costs?

Green/nature-based solutions	Restoration of land or changing land dedication	Public agent	Coastal wetlands	No adaptation costs, only benefits expressed as reduced expected annual damages	
Soft/behavioral changes	Change of production technology	Private production sector	Increased insurance uptake	Change composition of intermediate goods in the respective sector	
Soft/behavioral changes	Change of demand structure	Private household	Increased energy use for air conditioning; increased insurance uptake	Change in households' expenditure structure	Do expenditure changes affect private savings?

5. Adaptation cost functions for application in IAMs

Task 3.4 of the project developed a set of adaptation cost functions for the IAMs, which are described in Deliverable 3.4.

In summary, the analysis took the sector model results from WP2, updating them to a common price year and equivalent units. This data was uploaded for the direct use by the CGE models in WP4. It was also used to produce functional relationships for the IAMs, to allow analysis of the trade-off between impacts and adaptation in a cost-benefit framework. This requires a function that links adaptation benefit to adaptation cost (avoided damage versus adaptation costs).

Following discussion with the IAMs, it was agreed that two functions would be generated. The first was an explicit sea-level-rise (SLR) function, reflecting that all the IAMs model this impact separately. The second was an aggregate function for other damages, which compiled the results from the various sector analyses (e.g., for river floods, agriculture, etc.). These functions were initially generated at the global level, but were further refined with regional breakdowns aligned to the specific regional aggregation in each IAM model.

5.1 Adaptation to sea level rise

The global results from the DIVA model were used to develop the SLR function. The analysis was focused on the data runs for:

- 1S = Constant protection standards
- 2S = Doubling of constant protection standards
- 4S = Quadrupling of constant protection standards

This was undertaken for different RCP scenarios and over time. The costs of inaction (residual damage) are reduced significantly in the 2S and 4S scenarios relative to the 1S baseline. Average annual damages between 2030 and 2100 are reduced by 25-26% in the 2S scenario and by 43-44% in the 4S scenario, depending on the RCP. The doubling and quadrupling of constant protection standards leads to a moderate increase in adaptation costs over time. Average annual costs between 2030 and 2100 are 5% higher in the doubling scenario and 10% higher in the quadrupling scenario. Note that in this analysis, migration was included as a damage cost, rather than an adaptation cost.

A global function was derived from this data, using the following functional form:

$$EAD_{avoided} = L\left(1 - e^{-\beta\, AC}\right)$$

where AC is the additional adaptation cost relative to the no adaptation scenario, $EAD_{avoided}$ is the expected annual damage avoided relative to the no adaptation scenario. L is a limit to adaptation and β is the curvature parameter, both estimated by the regression.

The function is shown below, with L=87.5% and β=0.30752.

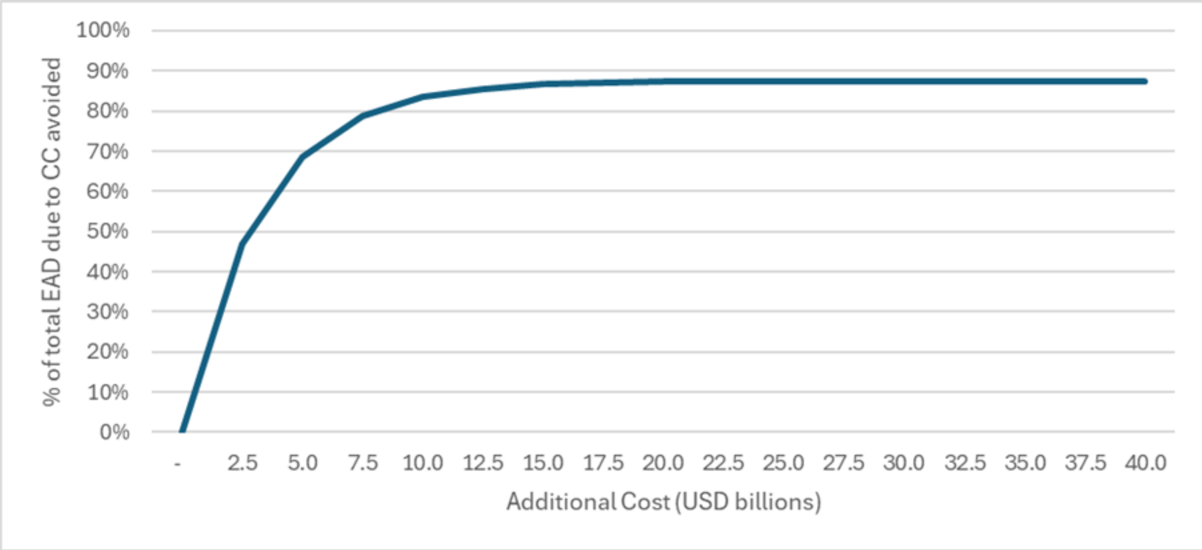

Figure 3: **Expected annual damage avoided vs additional adaptation costs for sea level rise.**

5.2 Adaptation to other impacts

At the global level, WP2 included three sectors that produced adaptation costs, river flooding from the GLOFRIS model, agricultural adaptation from the GLOBIOM model, and air conditioning from the energy modelling as an adaptation option to reduced labour productivity impacts.

As detailed in D3.4, the approach to adaptation differs structurally in each of these models, and while all models consider three alternative RCPs, for agriculture and river floods there was not the same level of sensitivity testing around different levels of adaptation, limiting the number of data points for the non-SLR function. GLOFRIS (river floods) works with an upfront adaptation cost (over the first 30 years) to define future protection levels (end of century), rather than an annual adaptation cost and benefit as for the DIVA model above. For the functional analysis in D3.4, it was possible to get around this by looking at total present values to derive a function (see Figure 4 top left panel), but this does not work for a composite non SLR function where other sectors are based on annual cost. Thus an assumption has to be made on how these river flood adaptation costs are spread over time to work in a global adaptation effectiveness function.

Similarly, for agriculture, adaptation in GLOBIOM shows relatively little variation over time and between RCPs, due to the modelling set up in GLOBIOM, which optimises for economic surplus. In this case, the optimal strategy is to frontload investment costs. This means costs in a given year are not determined by expected damage in that year but rather by the curve of expected damage over the 50-year period. To reflect this and avoid an unreasonable function costs and benefits are aggregated over the whole time period, leading to only three data points (for 3 RCPs) available for fitting a function (Figure 4, top right panel).

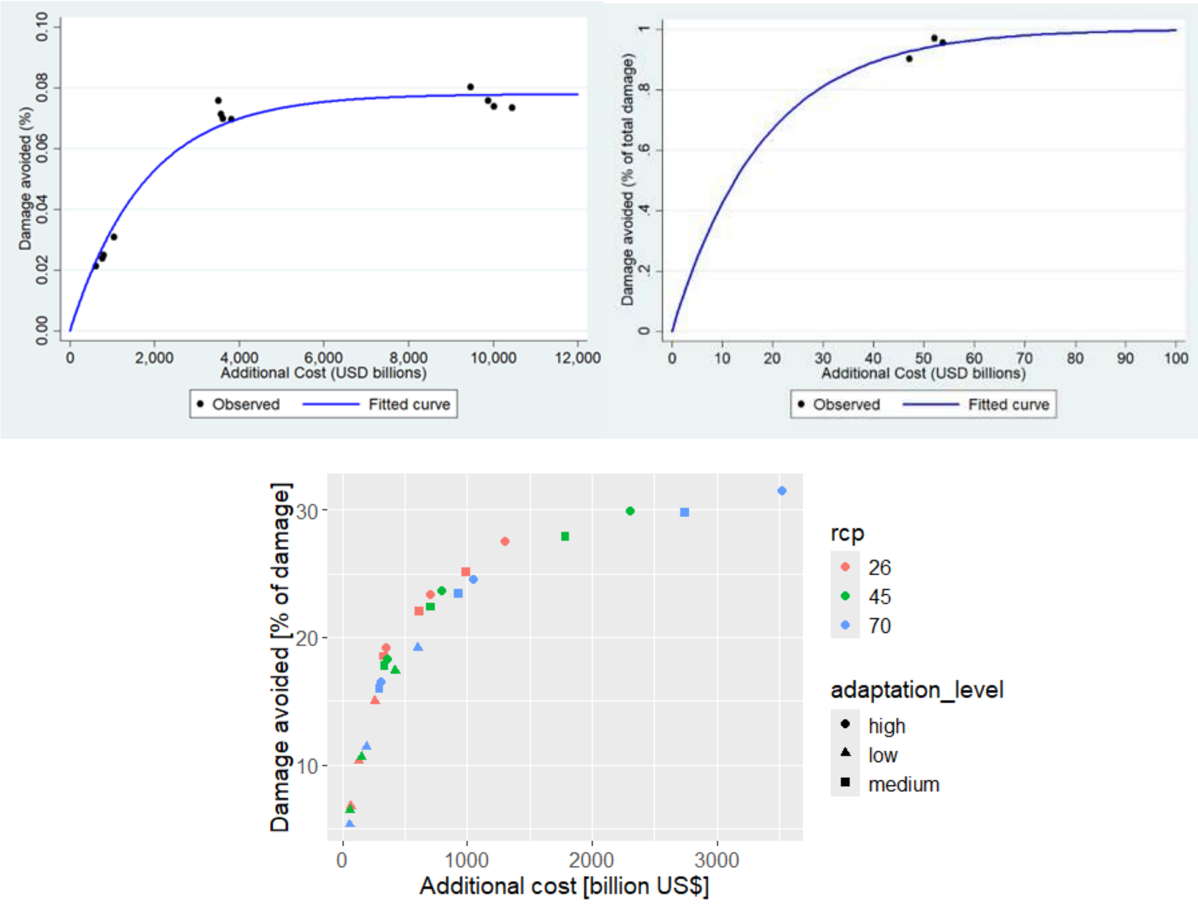

Figure 4: Expected annual damage avoided vs additional adaptation costs for river flood (PV values) (top left), agriculture (top right) and labour productivity-cooling (bottom).

Aggregation can only be done after harmonization of the data to a common framework. This was done by aggregating all over time and then adding up both costs and benefits across sectors. This provides the aggregate function shown in Figure 5, left panel.

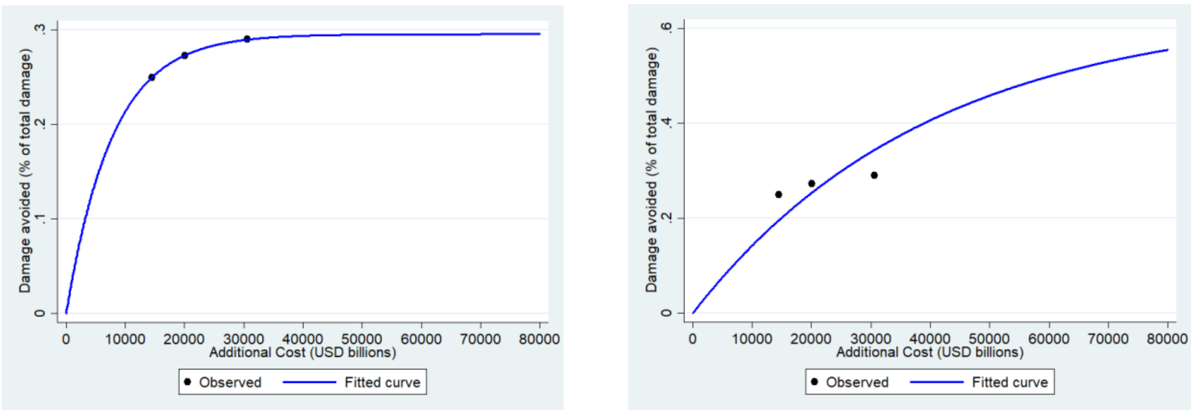

Figure 5: Aggregate non-SLR adaptation cost function with high (left) and low (right) effectiveness.

As can be seen in Figure 4 the level of adaptation effectiveness varies significantly between the different models, with coastal protection the highest. However, the values derived from the models are considered a high effectiveness scenario, especially for coastal, river floods and agriculture. This is not necessarily realistic, as the modelling analysis is ex ante and assumes perfect foresight (with respect to future climate change), and thus removes uncertainty. These estimates also assume high implementation efficiency, correct management regimes, etc. and thus have a degree of optimism bias. There is relatively little ex post adaptation literature, but a recent review (Greene et al., 2025) does indicate that effectiveness is lower in practice than in the ex-ante models.

Trying to reconcile these outcomes and aiming for more realistic effectiveness we looked at two recent studies which have collated information on effectiveness. Rexer and Shamra (2024) undertook a systematic review of the literature on adaptation to climate change, and conducted a quantitative meta-analysis of the effectiveness of climate adaptation. This meta-analysis indicates that observed adaptations offset 46% of climate losses on average. There is a significant range around this (38–72%).The percent varies with adaptation action. Public goods (including infrastructure) were higher at 64%, but effectiveness was lower for climate smart agriculture (42%). Rising et al (2026) review a smaller number of studies, which include ex and ex post (26 studies) for effectiveness. They find a bimodal distribution, with one portion of the literature reporting estimates showing similar reductions in damages to Rexer and Sharma (50%), while another reports estimates showing larger benefits (90%), the latter primarily being ex ante coastal studies.

It is therefore considered important to have a low effectiveness variation of our adaptation cost functions, reflecting these more real world outcomes. For this, we keep the same curve shape, but limit adaptation to the level indicated by Rexer and Sharma (64%) for public goods, assuming the same cost profile (Figure 5, right panel).

Overall, the translation of sectoral models to derive IAM adaptation function proved much more challenging than anticipated. At the start of the project, it was considered that using different models with harmonised climate and RCP data would allow derivation of functions, but the key lesson is impact-adaptation modelling harmonisation is far more important. This may mean restructuring models (or model outputs) to allow more comparability on adaptation for IAM use.

6. Derivation of damage function

The climate change impact data from WP2 models has been used as an input to the regionalized CGE model ICES-REG to produce economy-wide damages as the GDP loss derived from the interaction of the impact-specific drivers with the rest of the economy following Bosello et al. (2020), Bosello & Parrado (2021) and Standardi et al. (2023). Table 5 presents a summary of the climate impacts included for the estimation of the reduced-form climate change damage functions (CCDFs) with the corresponding impact driver and the mapping for three ACCREU IAMs (MIMOSA, REMIND and WITCH). It is worth noting that Table 5 shows only impacts where climate change impact data is available for all regions in the world, allowing for a consistent estimation of the CCDFs. The rest of climate change impacts studied in ACCREU (energy supply, wild fires, health and biodiversity) are restricted to Europe and, while they are not included in the CCDFs, they are assessed with an EU focus considering the fiscal and financial dimensions (Deliverable 4.3) and a distributive analysis (Deliverable 4.2).

The main climatic driver for sea-level rise damages is the change in sea-level, while for the rest of the impacts it is the change in temperature. For this reason, we derive two damage functions for each IAM. For the case of the sea-level rise damage functions, the GDP losses are a function of changes in sea-level rise, while for the non-sea-level rise aggregated damage function, GDP losses are a function of changes in global mean surface temperature.

The mean values of both sea level rise and temperature have been taken from the IPCC AR6 data available in Fyfe et al. (2021) and IPCC (2021) corresponding to each RCP.

Impact category	Impact drivers	Main associated climatic driver	REMIND	MIMOSA	WITCH
Sea Level Rise	-Land loss -Capital loss -Labour productivity loss	Global mean sea-level rise (m)	Yes, as a standalone SLR damage function	Yes, as a standalone SLR damage function	Yes + direct damages from DIVA (alternative option)
River floods	- Capital loss -Labour productivity loss	Global mean surface temperature change (°C)	Yes, as part of a non-SLR damage function	Yes, as part of a non-SLR damage function	Yes + direct impacts from GLOFRIS (alternative option)
Energy demand	Changes in energy demand for electricity and fossil fuels in residential, agriculture, commercial, industrial activities	Global mean surface temperature change (°C)	Yes, as part of a non-SLR damage function	Yes, as part of a non-SLR damage function	No (direct impacts on energy demand from WP2)
Agriculture	Land productivity	Global mean surface temperature change (°C)	Yes, as part of a non-SLR damage function	Yes, as part of a non-SLR damage function	Yes, in aggregated damage function
Forestry	Natural resource productivity	Global mean surface temperature change (°C)	Yes, as part of a non-SLR damage function	Yes, as part of a non-SLR damage function	Yes, in aggregated damage function
Labour productivity	Labour productivity	Global mean surface temperature change (°C)	Yes, as part of a non-SLR damage function	Yes, as part of a non-SLR damage function	No (direct impacts on energy demand from WP2)

Table 5: Mapping of damage functions from ICES-Reg CGE model to IAMs

The CCDFs estimation follows the methodology described in van der Wijst et al. (2023) and van der Wijst et al. (2021). The main input for damages is the GDP loss produced with the ICES-REG CGE model for 5-year time intervals over the period 2025-2070 for the climate impacts analysed in ACCREU for three scenarios, namely SSP2-RCP2.6, SSP2-RCP4.5, and SSP2-RCP7.0. To include uncertainty on impacts, three levels were used: low, medium and high. This provides 10 observations for each scenario simulation for 9 scenarios giving a total of 90 data points. These GDP losses are paired with the corresponding driving climatic variables with respect to the same reference period (1995-2014).

We focus on two functional forms. The first is a linear CCDF as in equation 1 while the second is a quadratic function. In both cases the independent variable *x* could be either sea-level rise or the change in temperature depending on the CCDF.

These equations are estimated with a quantile regression model for the 50th percentile.

$$D = \hat{\beta}_1 x \quad (1)$$

$$D = \hat{\beta}_1 x + \hat{\beta}_2 x^2 \quad (2)$$

where D = GDP loss as a percentage of the baseline level

x = climatic variable (sea-level rise or change in temperature)

$\hat{\beta}$ = estimated coefficient

To account for uncertainty we rely on the 5th and 95th percentiles of GDP losses by using a quantile regression based on the estimated damages ($\widehat{D}$) in equations 1 and 2 against the actual damages (D). First, we calculate predicted damages using the CCDF ($\widehat{D}$) as in equations 3 and 4:

$$\widehat{D} = \hat{\beta}_1 x \quad (3)$$

$$\widehat{D} = \hat{\beta}_1 x + \hat{\beta}_2 x^2 \quad (4)$$

Then we proceed to estimate a quantile regression for each one of the percentiles 0.05, 0.50 and 0.95 using the following function that fits the actual damages against the predicted damages as in equation 5:

$$D = \alpha \widehat{D} \quad (5)$$

where the coefficient α is the scaling factor for the corresponding percentile. Note that α=1 for the 0.50 percentile meaning it coincides with the value of the corresponding $\hat{\beta}$ parameters estimated in equations 1 and 2.

The final CCDF coefficients for each percentile are given by multiplying α with the corresponding $\hat{\beta}$, as in equations 6 to 8:

For the linear case: $$\beta_1 = \alpha \hat{\beta}_1 \quad (6)$$

For the quadratic case: $$\beta_1 = \alpha \hat{\beta}_1 \quad (7)$$

$$\beta_2 = \alpha \hat{\beta}_2 \quad (8)$$

Therefore, the final CCDFs are:

$$D = \alpha\left(\hat{\beta}_1 x\right) \quad (9)$$

$$D = \alpha\left(\hat{\beta}_1 x + \hat{\beta}_2 x^2\right) \quad (10)$$

The methodology has been applied on a regional level for the three IAMs of ACCREU (REMIND, MIMOSA, WITCH) following the mapping in Table 5. All estimations have been produced with the robust linear quantile regression (lqr) package (Galarza et al. 2024) using the R software (R Core Team 2025).

5.1 Sea-level rise damage function

The CCDF for sea-level rise is derived under the assumption of constant dike height as a low adaptation case using the Diva model inputs as impact drivers, namely: capital loss, land loss and labour productivity based on affected population as detailed in Table 5. Figure 6 shows the GDP losses derived from sea-level rise as a function of changes in global mean sea-level rise for the world and the EU27+UK regions as two specific examples of the SLR damage functions both relative to the period 1995-2014.

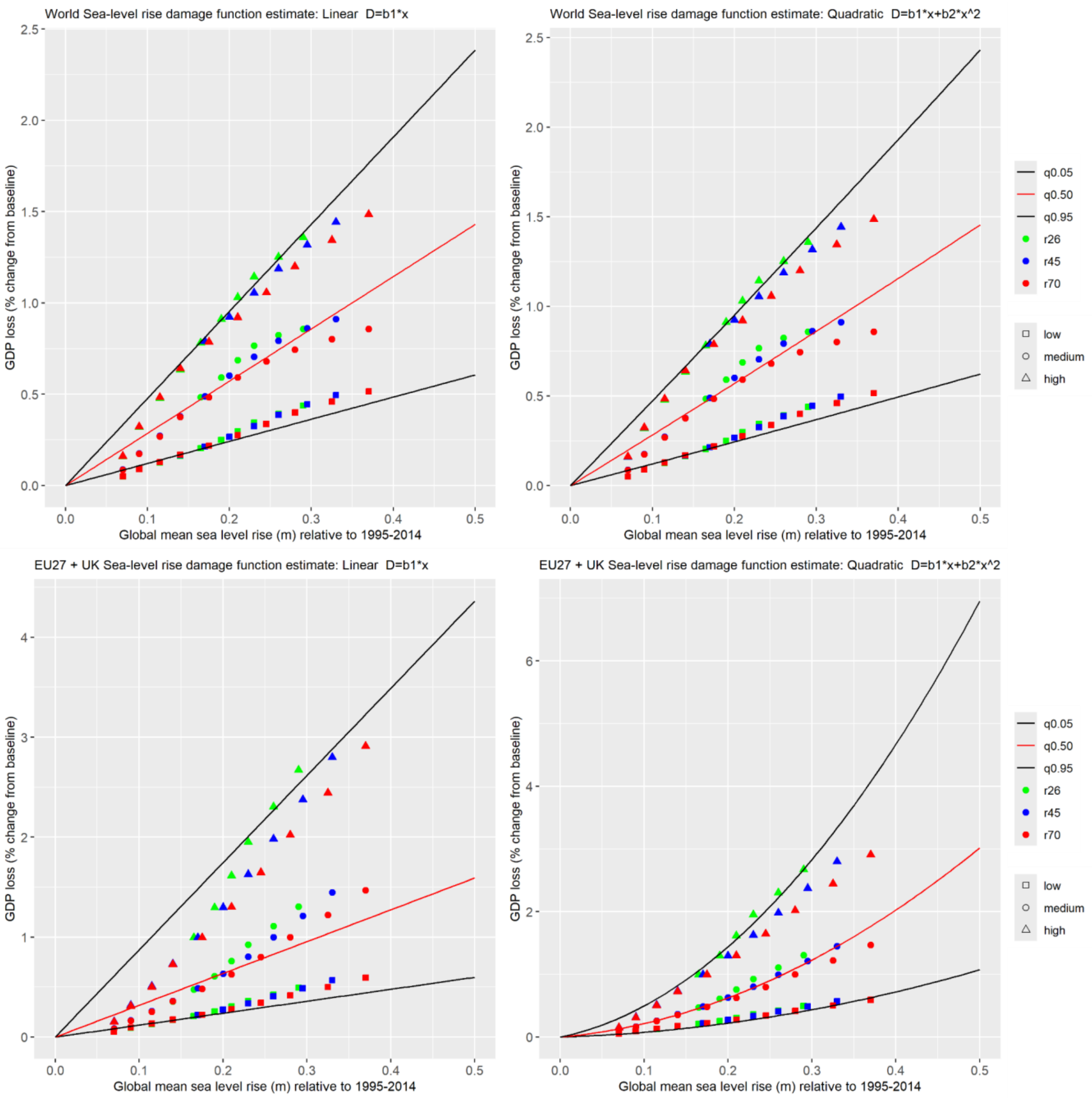

Figure 6: Climate change damage for sea-level rise for the World and the EU27+UK regions: GDP loss as a function of global mean sea-level rise relative to 1995-2014

5.2 Aggregate non-SLR damage function

The aggregate non-sea-level rise CCDF is estimated using the impact drivers detailed in the second column of Table 5, and shown in Figure 7 with the GDP losses derived from non-sea-level rise impacts as an aggregate function of changes in global mean surface temperature for the world relative to the period 1995-2014 (not pre-industrial). It considers five impacts with data available at the global level: riverine floods, energy demand, agriculture, forestry, and labour productivity. The result is shown in Figure 7 for the global function. For RCP2.6 and 4.5 temperatures stabilize and even decline over time. In combination with the general equilibrium effects in ICES in response to the damage, e.g. trade or relocation of investment, this can lead to the leveling or even declining damage observed there. This poses a challenge for fitting a reasonable damage function

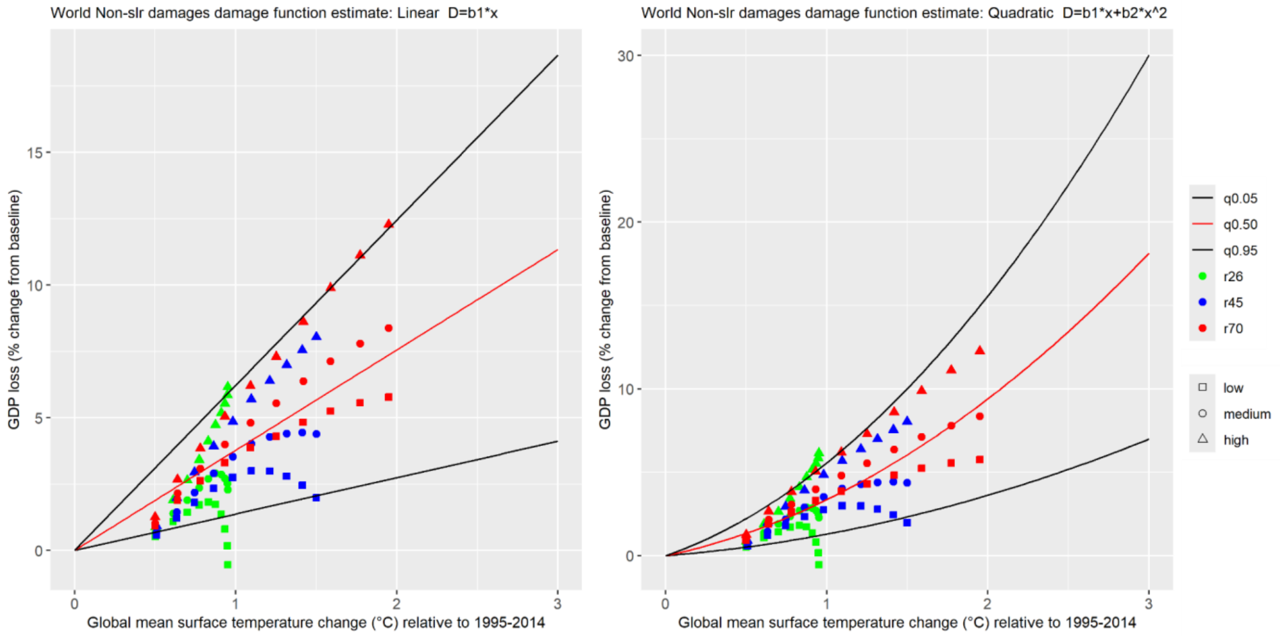

Figure 7: Climate change damage for non-sea-level rise for the World and the EU27+UK regions: GDP loss as a function of global mean surface temperature change relative to 1995-2014, not pre-industrial. Symbols refer to the quantiles of the distribution.

5.3 Caveats and limitations

The CCDF is estimated using the results of simulations with a regionalized CGE model at the end of a climate change impact assessment modelling chain. This process has some caveats and limitations that should be considered when used in integrated assessment models.

First, as mentioned before, the CCDFs encompass only a subset of all climate change impacts that will affect the economic activity, not covering either climate change impacts for which data was available only for Europe, nor extreme or catastrophic events. Second, the simulation horizon of the ICES-REG models is 2070, limiting the range of sea-level rise and temperature change projected to that time span. Third, the scenarios considered do not include extreme cases either of sea-level rise or temperature increase which could provide additional data to address uncertainty of extreme cases. Fourth, the economic interplay resulting from the general equilibrium framework provides a built-in adaptive capacity or market-driven adaptation that could reduce the final economic impacts and/or transfer climate change impacts to other regions thanks to intra/inter-regional trade flows and investment mobility. In addition, the projected economic growth, which for specific regions shows a rapidly growing economy, could reduce the economic importance of a specific impact, leading to CCDFs with non-linear reduced-form shapes, different from the quadratic reduced-form. For this reason we explore the possibility of logistic CCDFs as shown in Figure 8.

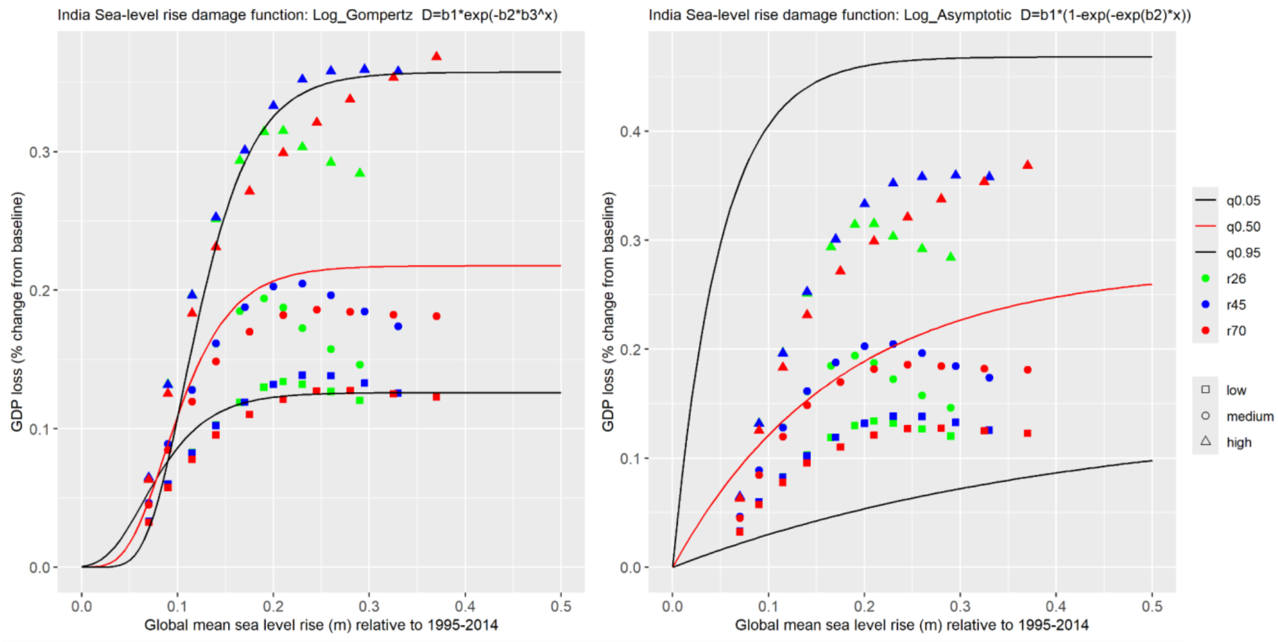

Figure 8: Climate change damage for sea-level rise for India: GDP loss as a function of global mean sea-level rise relative to 1995-2014

Considering the abovementioned limitations, IAMs are advised to assess the data directly and choose the best CCDF to be used in their assessment or also explore additional alternatives to fit the CCDFs.

7. Model-specific descriptions of impact and adaptation applications

This section covers the specific advances and implementations made in each of the core models in WP4 as part of ACCREU. It focuses in particular on how the data from WP2 and WP3 on impacts and adaptation costs and effectiveness are used in the modeling framework of CGEs and IAMs. For each of the two sections on the CGE models (sections 6.1. and 6.2.), we first describe the implementation of all impact and adaptation data into the CGE models, specifying the targeted model parameters and then summarize the results across all impact sectors. The IAMs describe their approaches separately. While MIMOSA and REMIND take a similar approach using aggregate functions from Sections 4 and 5 WITCH uses a hybrid approach of sectoral and aggregate inputs. This section also includes a description of updates in the financial models CFR and DIFI.

7.1 COIN-INT

7.1.1 Technical description of translating impact and adaptation data into the COIN-INT model for all impact sectors

Sea level rise impacts and adaptation based on DIVA

The assessment of climate impacts and adaptation to reduce adverse impacts from rising sea levels considers a combination of expected annual damages, migration of people living in a floodplain that is on average flooded every year and built infrastructure, namely sea dikes. The extent to which adaptation is performed is determined in the DIVA model following adaptation rules for three scenarios (low, reference and high adaptation levels). The three scenarios differ with respect to the costs of investment and maintenance as well as the residual damages, which creates differences in the macroeconomic outcomes. Since we are interested in the effect of varying adaptation efforts, we compare high and low adaptation levels to the reference scenario, rather than comparing three adaptation scenarios to a scenario with only climate change impacts in the absence of adaptation. The specific adaptation assumptions are described in Table 2 for each impact sector.

In the following, we describe how impacts and adaptation are implemented in the COIN-INT CGE model. For each impact or adaptation category, Table 6 lists the relevant DIVA variable, which is then translated into a CGE parameter, and finally, how that parameter changes are modeled and interpreted.

Impact/ adaptation	DIVA variable	Parameter	COIN-INT implementation
Impact	Expected Annual Damages (EAD)	Capital stock	Reduced capital stock □ reduced capital stock accumulation with lower capital availability for production (i.e., a lower capital endowment in the economy)
	Land loss	Land endowment	Reduction of land endowment (lower cropland availability for agricultural crop production)
	Expected number of people flooded annually	Labour endowment	Labour supply loss in the amount of two weeks, following Parrado et al (2020) and Bachner et al (2022)
	Migration costs	Capital endowment (Private capital loss) and endowment change for government transfers	Negative private capital endowment compensated by public transfers, only in European regions, in Rest of the World, there is only on regional household, that loses capital
	Number of people migrating	Labour income	Labour income loss in the amount of 24% according to estimates by Athey et al. (2023)
Adaptation	Sea dikes cost investment	Government investment demand	Forced investment crowding out public consumption. Sea dikes are not considered in the accumulation of capital stock.
	Sea dikes cost maintenance	Government demand for construction	Consumption-neutral shift of public consumption towards construction

Table 6: Implementation of impacts and adaptation for sea level rise from DIVA

River flood impacts and adaptation based on GLOFRIS

The assessment of river flooding using the GLOFRIS model includes consequences in terms of expected annual damages and involves adaptation through infrastructural measures that include investment and maintenance costs, as well as zoning as a budget-neutral adaptation measure.

While adaptation costs associated with zoning are not quantified, we implement the associated benefits— the reduction in damages—in the CGE model.
There are three adaptation scenarios considered. The reference adaptation scenario refers to an adaptation profile that maintains current protection levels, with or without zoning. In the model, adaptation costs arise in the form of investment and maintenance costs. The low adaptation scenario refers to an adaptation profile where existing dike heights are maintained without investments in new or raised dike infrastructure, with or without zoning. Adaptation costs arise in the form of maintenance costs. The high adaptation scenario refers to a profile that optimises the protection level in 2080, while investments and construction are implemented between 2020 and 2050. Adaptation costs arise in the form of investment and maintenance costs.

Impact/ adaptation	Parameter	GLOFRIS variable(s)	COIN-INT implementation
Impact	Increased construction demand	EAD	Increased demand for construction goods by private households
	Labour endowment	EAAP	Labour supply loss in the amount of two weeks (following Parrado et al (2020) and Bachner et al (2022))
Adaptation	i. Government investment demand	Costs	Forced investment demand (financed by shifting public consumption in the budget neutral scenario)
	ii. Government demand for construction	Maintenance	Consumption-neutral shift of public consumption towards construction

Table 7: Implementation of impacts and adaptation for river flooding from GLOFRIS

Agricultural changes and adaptation based on GLOBIOM and CWaTM

The adaptation action considered to reduce productivity losses in the agricultural crop and livestock sector due to climate change is the implementation of irrigation infrastructure. Thereby, three adaptation scenarios are considered: i) reference adaptation, ii) high adaptation and iii) low adaptation which, in terms of the implementation in the CGE model, differ with respect to their cost for irrigation (investment into new irrigation capital and depreciation of the existing irrigation capital stock) and corresponding water demand. The consequential effect of adaptation is considered via the effect on crop and livestock productivity, as well as through different rates of agricultural land abandonment. For a more detailed rationale of the parametrization of each adaptation scenario, see D2.2. The three scenarios differ with respect to the costs of implementing the two adaptation options as well as the residual damages, which creates differences in the macroeconomic outcomes. The translation and implementation of impacts and adaptation is described in Table 8.

Again, our interest lies in understanding the macroeconomic implications of different adaptation levels. Thus, we compare high (sustainable irrigation, expansion and conversion of rainfed areas) and low (limited irrigation expansion) adaptation levels to the reference (sustainable irrigation expansion) adaptation scenario.

Impact/ adaptation	Parameter	GLOBIOM variable	COIN-INT implementation

Impact	Change productivity of agricultural production (crop)	Agricultural Production|Non-Energy|Crops	Change in TFP of crop sector
	Change productivity of agricultural production (livestock)	Agricultural Production|Non-Energy|Livestock	Change in TFP of livestock sector
Adaptation	Public sector funds investment for irrigation expansion	Investment Costs| Total Irrigation Cost (Efficiency improvement Cost + Expansion Cost + Upgrade Cost)	Government investment demand to crowd out public consumption. Irrigation capital is not considered in capital accumulation.
	Production cost structure of crop sector	Water withdrawal|Irrigation	Change in intermediate demand for utility (includes water) by the crop sector

Table 8: Implementation of impacts and adaptation based on GLOBIOM

Labour supply and productivity (CMCC) impacts and energy-related adaptation (CMCC)
In contrast to the impact sectors described above, labour-related impacts and adaptation are estimated using empirical approaches and therefore do not have model names. Instead, we add the institution of ACCREU partners, who provided the input for clarity and transparency. Climate impacts on labour supply and labour productivity can be addressed by adaptation in the form of heating and cooling as an input into sectoral production. The benefits of the adaptation costs are depicted via lower impacts on labour productivity, while labour supply remains unchanged.

In the following, we describe how impacts and adaptation are implemented in the COIN-INT CGE model. For each impact or adaptation category, Table 9 lists the relevant variable, which is then translated into a CGE parameter, and finally, how that parameter changes are modeled and interpreted.

Impact/ adaptation	Labour/ energy variable	Parameter	COIN-INT implementation
Impact: labour (CMCC)	Labour productivity	Labour input in sectoral production	Adjustment of labour input differentiated for agricultural, industrial and commercial sectors mimicking high and low exposure sectors.
	Labour supply	Labour endowment	Adjustment of regional labour endowment, reducing labour income and thereby consumption possibilities.
Adaptation: energy (CMCC)	Sectoral energy demand estimated for agricultural, industrial and commercial sectors (for heating and cooling)	Sectoral production	Increased energy demand in sectoral production split for fossil fuels and electricity and differentiated for agricultural, industrial and commercial sectors

Table 9: Implementation of labour supply and productivity impacts and energy-related adaptation

Health (BC3) impacts and energy-related adaptation (CMCC)
Climate impacts on health can be addressed by adaptation in the form of air conditioning (AC), which requires upfront investment for new infrastructure, investment for retrofitting existing and new infrastructure and recurring costs for more intense use of installed AC. Depending on the level of adaptation, energy demand for cooling is increased based on the change in the number of cooling

degree days and combined with increasing the stock of air condition appliances. The benefits of the higher adaptation costs are depicted via lower impacts on health.

In the following, we describe how impacts and adaptation are implemented in the COIN-INT CGE model. For each impact or adaptation category, Table 10 lists the relevant variable, which is then translated into a CGE parameter, and finally, how that parameter changes are modeled and interpreted.

Impact/ adaptation	**Labour/ energy variable**	**Parameter**	**COIN-INT implementation**
Impact: health (BC3)	Morbidity costs	Heat related annual morbidity medical costs estimations	Expenditure-neutral shift of government expenditures towards health services, reducing all other public expenditures, except for transfers, which scales with tax income.
	Mortality costs	Heat-related annual deaths monetized via the VSL	Ex-post consideration of mortality in terms of welfare costs.
Adaptation: energy (CMCC)	Energy demand for adaptation (only for cooling) estimated for the residential sector	Private consumption	Consumption-neutral shift of private consumption towards energy split for fossil fuels and electricity
	Investment costs for new installation of air condition appliances and retrofitting existing infrastructure	Private investment demand	Forced investment crowding out generic private investment

Table 10: Implementation of health impacts and energy-related adaptation

For the two impact sectors biodiversity and forest fires, which have been newly developed in ACCREU, there are only impact data available without adaptation. Thus, the following two Tables describe the implementation of the impact channels, which are then assessed compared to the baseline scenario without climate change.

Biodiversity impacts based on pollination loss (CMCC)

COIN-INT implements biodiversity impacts in terms of the regulating service of pollination and the role for agricultural crop yields under different RCP scenarios under the assumption of constant land use.

Impact/ adaptation	**Biodiversity impact variable**	**Parameter**	**COIN-INT implementation**
Impact	Consequences of pollination loss on crop yields	Projected yield shocks (%). Up to 2070 relative to 2020.	Relative change in total factor productivity of crop sector.

Table 11: Implementation of biodiversity impacts on agricultural productivity

Forest fire impacts based on ForeFire

Wildfire impacts are implemented through a land-use specific assessment that links burned area to sectoral capital and productivity effects. Burned area projections from ForeFire are spatially matched to CORINE land cover classes, allowing wildfire exposure to be differentiated across agricultural and forest land uses and annual and perennial plantations. The resulting data provide, for each land-use type, the share of area affected by fire relative to the total extent of land in the respective category. This normalized metric ensures consistency with the COIN-INT model. To translate physical damages into economic impacts, the burned area shares are combined with sector specific capital stock information from FAO statistics. This allows the identification of capital at risk that is tied to specific land uses, such capital needed to cultivate fruit orchards or timber plantations. In contrast to annual crops, these assets are tied to multi-year growth cycles. Accordingly, this assessment considers wildfire impacts in two ways: i) immediate output losses are captured as relative reductions in total factor productivity in the affected sectors, and ii) devaluation of sector-specific capital, reflecting the destruction of perennial assets and resulting decline in returns to land-based capital. This enables the model to capture both short-term, but also longer-term economic impacts arising from increasing wildfire occurrence.

Impact/ adaptation	ForeFire variable	Parameter	COIN-INT implementation
Impact	i) Burnt area on ALL agricultural land and commercially used forests	% land burnt in high/low fire hazard year	Loss of total factor productivity from destroyed harvest in the year of the burn
	ii) Burnt area - forest	% land burnt in high/low fire hazard year	Multi-annual effect on the return on capital tied to this land
	ii) Burnt area - multiannual crops:olive groves, fruit trees & berry plantations		

Table 12: Implementation of burnt area from forest fire and impacts on agriculture & forestry

7.1.2 COIN-INT: Results overview

This section gives an overview of the results obtained with the COIN-INT CGE model. Table 13 summarizes real GDP effects for all impact sectors, implemented as described in the previous section. Presented results are given relative to GDP in the reference adaptation scenario. Therefore, GDP effects show losses (negative values) or gains (positive values) for high versus reference adaptation and low versus reference adaptation. The adaptation scenarios for each impact model are specified in Table 2. The exceptions are biodiversity and forest fire impacts, which are compared to a baseline without climate change, but including socioeconomic change. According to the ACCREU scenario protocol, all simulations are based on the SSP2 baseline scenario development. Regarding the emission pathway, results summarized here are depicted for the high warming scenario, RCP7.0, and are shown for 2070, where impacts and adaptation benefits tend to be strongest. The table shows all EU countries as well as the United Kingdom (UKD), Switzerland (CHE) and Norway (NOR). However, for two impacts there is only data for the EU available: agricultural impact and adaptation and health data (mortality and morbidity). And for the forest fire impacts, there is only data for Spain.

Table 13: Overview of results for European countries in 2070 under SSP2-RCP7.0: assessing high and low adaptation levels relative to reference adaptation levels for sea level rise, river flood, agriculture, health and energy, as well as labour and energy, and assessing an impact scenario relative to a reference scenario without climate change for the two impact sectors without adaptation biodiversity and forest fires. n.a. indicates, where no data was available for the macroeconomic assessment.

	sea level rise (DIVA)		river flood (GLOFRIS*)		agriculture (GLOBIOM)		health (BC3) and energy (CMCC)		labour and energy (CMCC)		biodiversity loss (CMCC)	forest fires (ForeFire) (low/high burn year)
region/ scenario	low vs ref	high vs ref	low vs ref	high vs ref	low vs ref	high vs ref	low vs ref	high vs ref	low vs ref	high vs ref	impact vs noCC	impact vs noCC
aut	-0.03%	0.00%	-0.02%	0.00%	-0.76%	0.06%	0.000%	0.000%	-0.22%	0.00%	-0.10%	n.a.
bgr	-0.07%	0.00%	0.00%	0.00%	-3.66%	3.17%	0.007%	0.000%	-0.82%	0.02%	-0.46%	n.a.
hrv	-1.01%	0.02%	-0.03%	-0.01%	-4.44%	0.43%	-0.004%	-0.001%	-0.64%	0.02%	-0.18%	n.a.
cze	-0.05%	0.01%	0.00%	0.00%	-2.46%	0.56%	0.001%	0.001%	-0.38%	0.00%	-0.26%	n.a.
dnk	-1.60%	0.05%	-0.01%	0.01%	-0.18%	-0.54%	0.001%	0.000%	-0.07%	0.01%	-0.16%	n.a.

fin	-0.19%	0.02%	-0.02%	0.00%	-0.31%	0.19%	0.000%	0.000%	-0.01%	0.00%	-0.01%	n.a.
fra	-0.68%	0.04%	0.00%	0.00%	-0.74%	0.16%	-0.001%	-0.001%	-0.25%	0.01%	-0.18%	n.a.
deu	-0.40%	0.08%	0.00%	0.00%	-0.60%	0.05%	-0.001%	-0.001%	-0.57%	0.00%	-0.08%	n.a.
grc	-0.39%	0.02%	0.00%	0.00%	-3.88%	0.54%	0.007%	-0.001%	-0.27%	0.01%	-0.62%	n.a.
hun	-0.05%	0.01%	-0.04%	0.01%	-4.19%	4.52%	-0.004%	-0.002%	-0.46%	0.02%	-0.30%	n.a.
irl	-0.49%	0.02%	-0.03%	0.01%	-0.51%	-0.85%	0.001%	0.000%	-0.02%	-0.01%	-0.04%	n.a.
ita	-1.06%	0.03%	-0.03%	0.01%	-2.46%	0.55%	0.004%	-0.001%	-0.18%	0.00%	-0.21%	n.a.
nld	-0.36%	0.03%	0.00%	0.00%	-1.09%	0.34%	0.001%	-0.001%	-0.09%	0.00%	-0.10%	n.a.
pol	-0.44%	0.01%	-0.01%	0.00%	-1.88%	-0.33%	0.000%	0.001%	-0.28%	0.01%	-0.18%	n.a.
prt	-0.24%	0.01%	0.00%	0.00%	-1.40%	1.08%	0.005%	-0.002%	-0.39%	0.00%	-0.30%	n.a.

rou	-0.06%	0.00%	-0.01%	0.01%	-6.73%	1.43%	0.000%	0.000%	-0.62%	0.03%	-0.46%	n.a.
svk	-0.04%	0.00%	-0.02%	0.00%	-1.75%	0.16%	-0.001%	-0.001%	-0.47%	0.01%	-0.18%	n.a.
svn	-0.46%	0.02%	-0.02%	0.00%	-2.44%	0.00%	0.002%	0.000%	-0.33%	0.01%	-0.15%	n.a.
esp	-0.56%	0.01%	0.00%	0.00%	-0.32%	0.51%	0.00%	0.00%	-0.22%	0.01%	-0.25%	-0.02%/ -0.004%
swe	-0.35%	0.02%	-0.11%	0.01%	-0.25%	0.10%	0.00%	0.00%	-0.03%	0.00%	-0.05%	n.a.
BLU (bel&lux)	-1.97%	0.22%	0.00%	0.00%	-1.39%	-0.60%	0.00%	0.00%	-0.18%	0.00%	-0.13%	n.a.
BAL (est,ltu,lva)	-0.22%	0.02%	0.00%	0.02%	-5.51%	0.79%	0.00%	0.00%	-0.14%	0.01%	-0.51%	n.a.
UKD	-1.29%	0.11%	0.00%	0.00%	n.a.	n.a.	n.a.	n.a.	-0.03%	0.00%	-0.02%	n.a.
che	-0.06%	0.01%	0.00%	0.00%	n.a.	n.a.	n.a.	n.a.	-0.36%	0.01%	-0.03%	n.a.
nor	-1.31%	0.07%	0.00%	0.00%	n.a.	n.a.	n.a.	n.a.	-0.06%	0.01%	-0.03%	n.a.

* The high emission scenario in GLOFRIS follows the RCP8.5 pathway (instead of the RCP7.0).

In summary, the results suggest that higher adaptation levels generally improve GDP outcomes relative to lower adaptation, but the efficacy of these measures varies significantly by country and impact sector. In many cases, high adaptation reduces losses or even turns them into small gains, particularly in agriculture, while sectors such as health and energy exhibit more muted GDP responses. The observed pattern reveals that the disparity between low-adaptation levels and the reference scenario is consistently larger than that between the reference and high-adaptation scenarios. This implies that the reference adaptation level already incorporates a substantial degree of protection, suggesting that a significant portion of climate damage is mitigated under existing frameworks. Consequently, if the reference adaptation level is neglected in current impact assessments, the true costs of inaction may be systematically underestimated, obscuring both the benefits and the costs of the adaptive measures already in progress.

For agriculture, the table shows clearly that low adaptation leads to substantially larger GDP losses, with sizable effects in several countries. This highlights the importance of maintaining existing irrigation infrastructure and related adaptation measures through 2070, even if those measures come with higher costs. Countries such as Romania, Croatia, Hungary, Greece, the Baltic States and Bulgaria show particularly noticeable agricultural losses under low adaptation, while high adaptation often softens those effects.

For sea level rise, the differences are generally smaller than in agriculture, and country patterns differ. Coastal and low-lying countries such as Denmark, the Netherlands, Croatia, Italy, Belgium/Luxembourg (BLU), the UK and Norway stand out in the sea-level-rise column, suggesting that the reference adaptation is important to avoid GDP losses. This reinforces the idea that the reference adaptation scenario is not “no adaptation,” but rather a case with some protection already in place. In contrast, higher adaptation levels only show marginal improvements.

River flood impacts show a different dynamic, where GDP differences between the reference and other adaptation levels remain very small, often nearing zero for most countries. This indicates that, under the current model setup, the specified river flood adaptation measures contribute minimally to macroeconomic GDP changes relative to the reference path.

In health and energy, the GDP-relevant effects are limited because mortality is not counted in GDP and is instead captured in welfare measures. What remains in GDP mainly reflects residential energy demand and investment costs, so the table does not show the full benefit of adaptation in this impact sector. Hence, differences across adaptation levels are negligible.

Labour and energy show slightly more variation than health and energy, with low adaptation resulting in stronger GDP losses across many regions, most notably in Bulgaria, Croatia, Romania and Germany. These results indicate that energy demand for heating and cooling in economic sectors provide distinct benefits for labour productivity resulting in macroeconomic improvements. Moving toward high adaptation only shows marginal additional improvements.

For the two impacts, where no adaptation is considered, we see negative GDP effects across all regions. Biodiversity losses are strongest in Greece, the Baltic States, Romania and Bulgaria. Forest fires are shown for Spain only, with GDP impacts of -0.02% in a high burn year and -0.004% in a low burn year. These estimates mainly capture immediate effects, while longer-run impacts on perennial crops and timber are not included in this single-year snapshot. A fuller assessment would need a more detailed sectoral and capital-focused approach to capture those delayed effects.

Assessing the potential of adaptation to mitigate macroeconomic losses from climate impacts, the summary of results indicates two groups of regions with distinct vulnerabilities. Regarding temperature-related vulnerabilities, encompassing agriculture, health, labour, and energy, the potential for adaptation to secure macroeconomic gains is concentrated within Southeast and Central Europe. Countries such as Croatia, Bulgaria, Hungary, and Romania exhibit the most substantial GDP losses under low adaptation scenarios and highest improvements with high adaptation levels, suggesting that these regions are more sensitive to variations in adaptation levels. In this context, transitions toward higher adaptation levels substantially lower losses or even reverse

them, which indicates that adaptation is a relevant factor for their long-term economic performance. Conversely, flood-related impacts, which span both sea-level rise and river flooding, demonstrate the greatest sensitivity in Northern and Southern European coastal corridors. Countries such as Denmark, Italy, Belgium, Luxembourg, and the United Kingdom represent the primary regions, where the maintenance of current protection infrastructure serves as a fundamental economic imperative to prevent GDP loss. While the agricultural hotspots are defined by the prospective gains from enhanced adaptation, these coastal regions highlight the critical role of the reference adaptation scenario itself. In these areas, the baseline protection level functions as a necessary buffer against substantial climate-induced damages.
Ultimately, there are only a few instances where higher adaptation levels fail to moderate GDP losses. It is important to note that the presented GDP effects represent net outcomes, balancing the costs of implementing higher adaptation measures against the value of reduced climate-related damages.

7.2 ICES

7.2.1 Technical description of translating impact and adaptation data into the ICES model for all impact sectors

Climate-change impacts associated with RCP7 are evaluated under three adaptation levels (high, medium, and low) to assess the cost-effectiveness of adaptation strategies in a high-warming context. The ICES-MH model is employed to capture the macroeconomic effects of climate impacts and adaptation policies across countries, sectors, and economic agents. Results are summarised in terms of GDP losses.

Sea level rise impacts based on DIVA results
As described in Table 14, the DIVA model provides country-specific estimates of sea-level-rise-related impacts, including Expected Annual Damages (EAD), Expected Affected Population (EAP), and land loss. In addition, the model reports the number of relocated people and the associated relocation costs.

These impacts are translated into the ICES-MH model through different shock channels. EAD and relocation costs are combined with estimated asset values to construct shocks to the capital stock. Labour impacts are introduced as labour-productivity shocks, combining EAP and relocated population figures with country-specific population data. Following the literature, we assume that recovery from sea-level-rise events implies an average annual productivity loss equivalent to two weeks (Parrado et al., 2020; Bachner et al., 2022), while population relocation entails a longer disruption of approximately thirteen weeks (Athey et al., 2023). Land-loss impacts are modelled as shocks to the land endowment, computed relative to the available land in each country.

Regarding adaptation investments and maintenance costs, relative shocks are calibrated using country-specific public investment levels observed under the no-climate-change scenario, as well as public expenditure in construction and public services. As anticipated above, we also explore a scenario in which increased public expenditure partially crowds out private expenditure.

In ICES-Reg, SLR impacts are implemented following the same methodology as ICES-MH, except for maintenance costs, which are modeled as additional capital stock losses.

Impact/ adaptation	DIVA Variable	ICES-MH Variable	ICES-MH implementation
Impact	Expected Annual Damages	Shock on capital stock	Combined with annual asset value to compute annual shock on capital
	Expected People Flooded	Shock on labour productivity	Combined with population of the year to compute the annual shock on affected population; converted into labour productivity shock assuming that the SLR recovery takes on average 2 weeks (Parrado et al. 2020 and Bachner et al. 2022)
	Land loss	Shock on land stock	Reduction of the available land (in ICES model land is only agricultural land) Land shock
	Displaced population	Shock on labour productivity	Combined with population of the year to compute the annual shock on migrating population; converted into labour productivity shock assuming that the SLR recovery takes on average 13/52 weeks according to estimates by Athey et al. (2023)
	Migration costs	Shock on capital stock	Combined with annual asset value to compute annual shock on capital
Adaptation	Sea dikes cost investment	Shock on government investment	Shock on government investment
	Sea dikes cost maintenance	Shock on government expenditure in construction	Shock on government expenditure in construction (and coherent shock on total government expenditure)

Table 14: SLR impact and adaptation in ICES-MH model

Floods impacts based on GLOFRIS results

The flood impact assessment considers two main impact channels: one affecting the capital stock and the other affecting labour productivity. In addition, it includes two adaptation channels. The first consists of investment costs, which are modelled as a shift in public investment, while the second captures maintenance costs, represented through public expenditure in the construction sector.

The derivation of the shocks closely follows the approach adopted in the SLR case, with the main difference concerning the treatment of sectoral capital stocks. The analysis starts from sectoral Expected Annual Damages (EAD) produced by GLOFRIS, which are then combined with capital asset stocks from the ICES model. In ICES, however, the total capital stock is not differentiated by sector. To obtain sector-specific capital assets, we therefore relied on capital service shares to allocate total capital across sectors.

This approach revealed a well-known limitation concerning the residential sector. In the GTAP database and the associated Social Accounting Matrices, residential capital is represented through imputed rents and housing services, which are systematically underestimated, particularly in regions with high owner-occupation rates, regulated rental markets, or large informal housing sectors. As a result, the flow of housing services recorded in GTAP does not scale proportionally with the underlying housing stock. When capital stocks are inferred from capital services using these shares,

the residential sector therefore appears unrealistically small relative to its true economic and physical importance.
This underestimation is structural rather than methodological: GTAP is designed to represent market-based production flows, whereas residential capital largely generates non-market or imputed services that are imperfectly captured in national accounts and even more so in globally harmonised databases.
To overcome this issue we adopted a three steps adjustment:

1. Derivation of sectoral capital assets from capital services

For non-residential sectors, sectoral capital stocks are derived by allocating total capital in proportion to observed capital service payments, assuming that capital services provide a reliable proxy for the relative importance of capital across productive activities. This approach is standard in CGE calibration and is appropriate for market-based sectors where capital services are directly remunerated.
In the case of the residential sector, capital does not generate market output, but instead provides housing services, which are recorded in GTAP as imputed rents. Residential capital is therefore inferred from housing service flows using a standard user-cost relationship, which links capital services to the underlying capital stock K_r^{res}:

$$K_r^{res} = \frac{KServ_r^{res}}{u_{res,r}}$$

Where $KServ_r^{res}$ denotes residential capital services (imputed housing rents) in region r, and $u_{res,r}$ is the user cost of residential capital. The user cost is the cost of holding one unit of residential capital and is defined following standard capital theory as: $u_{res,r} = r_r + \tau_r + \mu_r + \pi_r$ where r_r is the real rate of return required by investors in region r, τ_r is the property taxes and insurance, μ_r is maintenance and repair, and π_r represents expected real capital gains (e.g. housing price appreciation). Operationally, $u_{res,r}$ converts a flow variable (housing services) into a stock variable (residential capital). The user cost of residential capital, $u_{res,r}$, is differentiated across regions to reflect systematic differences in financing conditions, housing market risks, and operating costs. A lower user cost of 0.035 is assigned to EU countries and other advanced economies (United States, Canada, Japan–Korea, and Australia–New Zealand), where real interest rates are relatively low, housing markets are mature, maintenance practices are well established, and long-run house-price appreciation partially offsets ownership costs. A higher value of 0.045 is applied to upper-middle-income and emerging regions (Brazil, China, Rest of East Asia, and Latin America), reflecting higher financing costs, greater market volatility, and less stable capital gains. For transition and lower-middle-income regions (Former Soviet Union, India, Rest of South Asia, South Africa, and MENA), the user cost is set to 0.050, capturing higher risk premia, higher maintenance requirements, and weaker housing market institutions. Finally, the highest user cost of 0.060 is assigned to Sub-Saharan Africa, where housing markets are characterized by high informality, limited access to finance, elevated maintenance burdens, and low or uncertain capital gains.

2. Application of the β residential to total capital threshold

To tackle the still underestimated capital services, the initial residential capital stock derived in Step 1 is still sometimes unrealistically small. To correct for this bias, we impose a β-based lower bound on residential capital, defined as a minimum share of total capital stock:

$$K_r^{res} = max(K_r^{res,raw}, \beta\, K_r^{tot})$$

where $K_r^{res,raw}$ is the residential capital stock inferred from capital services in the previous step, β threshold is defined as a minimum share of residential capital in total regional capital stock, and K_r^{tot} is the total capital stock in the country. When the raw estimate falls below the threshold, residential capital is scaled up to meet the minimum β share. We adopt region-specific β thresholds reflecting differences in capital composition: β = 0.35 for advanced economies, β = 0.30 for emerging and transition economies, and β = 0.25 for Sub-Saharan Africa.

3. Capital rebalancing

This step guarantees that the correction affects only the composition of capital, not its aggregate level. We recomputed sectoral capital shares after step 1 and 2, and we applied them to the original total capital stock to obtain consistent sector-specific capital assets.

A few minor clarifications are needed regarding the implementation of the different adaptation scenarios. Low adaptation is represented by the constant dyke scenario and includes only maintenance costs. The reference adaptation corresponds to the constant protection scenario and includes both time-specific investment and maintenance costs. Finally, high adaptation corresponds to the optimal adaptation scenario, in which total investment and maintenance costs are discounted and evenly distributed in the period 2020-2050.

In summary, Expected Annual Damages (EAD) are translated into shocks to the sectoral capital stock, while the Expected Affected Population (EAP) is translated into a shock to labour productivity. Adaptation is modelled as an increase in public investment and a reallocation of public expenditure towards the construction and public services sectors, representing maintenance costs.

In ICES-REG, flood impacts are implemented following the same modelling approach. In the low-adaptation scenario, adaptation expenditures are limited to maintenance costs only. However, since maintenance costs are not available at the sub-national level, they cannot be represented explicitly in the model and are therefore excluded from the analysis.

Impact/ adaptation	GLOFRIS Variable	ICES-MH Variable	ICES-MH implementation
Impact	Expected Annual Damages (EAD), sectoral	Sectoral capital stock	EAD is combined with sectoral capital asset values form the ICES model to compute the shock on capital stock
	Expected Affected Population (EAP)	Labour productivity	Expected Affected Population is combined with population of the year to compute the annual shock on affected population; this is converted into labour productivity shock assuming that the recovery takes on average 2 weeks (Parrado et al.,2020; Bachner et al., 2022)
Adaptation	Sea dikes cost investment	Government investment	The shock is computed by adding the investment costs associated with adaptation measures to baseline public investment.
	Sea dikes cost maintenance	Government expenditure in construction	The shock is computed by adding the maintenance costs associated with adaptation measures to baseline public expenditure in the construction sector, with a consistent shock applied to both construction-specific and total government expenditure.

Table 15: Flood impact and adaptation in ICES-MH model

Labour impacts and energy adaptation based on CMCC econometric results

Labour impacts are represented through a composite shock to effective labour, decomposable into a labour-supply component and a labour-demand component. The labour-supply shock is applied at the country level and affects total employment. The sectoral reallocation of employment is then determined endogenously within the model. Due to constraints in the empirical module, the labour-supply shock is RCP-specific and does not respond to adaptation measures.

Labour-productivity shocks are modelled at the sectoral level, capturing the differentiated impacts between outdoor-exposed sectors (agriculture and construction) and less exposed sectors (manufacturing and services). Adaptation through air-conditioning is explicitly incorporated in the econometric specification, clearly only for the less exposed sectors; no adaptation measures are considered for the most exposed sectors.

As anticipated, adaptation in the labour sector is implemented through increased energy use aimed at improving workers' thermal comfort. The resulting energy shifts are modelled by fuel type (fossil fuels and electricity), by service (heating and cooling), by sector (industrial and commercial), and by adaptation level (low, reference and high adaptation). These energy demand shifts in the productive sectors are incorporated into the modelling framework as energy-efficiency shocks, capturing the impact of adaptation measures on energy use per unit of output.

ICES-Reg follows the same approach for impact modelling.

Impact/ adaptation	Econometric variable	ICES-MH Variable	ICES-MH implementation
Impact	Shock on labor supply	Labour supply	Shock on labour stock
	Labour productivity shock (exposed and non-exposed sectors)	Labour productivity	Shock on labour productivity (exposed and non-exposed sectors)
Adaptation	Electricity/fossil energy demand for cooling by Agriculture / Industry / Service sectors	Demand shift	Shock on efficiency in using electricity/fossil energy for heating and cooling

Table 16: Labour impacts and energy related adaptation in ICES-MH model

Health impacts and energy adaptation based on CMCC and BC3 econometric results

Among the inputs provided by the BC3 empirical model, ICES-MH uses estimates of heat-related annual deaths among individuals aged over 65, rather than monetary estimates of mortality based on the Value of a Statistical Life (VSL). However, VSL-based death costs are employed to quantify avoidable mortality attributable to air-conditioning (AC) adaptation, as the available information on adaptation effects is provided exclusively in terms of avoided death costs due to AC. With respect to morbidity, we consider all relevant categories of health-related expenditures, including emergency visits, outpatient visits, outpatient hospital visits, emergency hospital visits, and hospitalisation costs. Mortality and morbidity costs are further adjusted to account for the fact that the underlying empirical estimates correspond to specific SSP–RCP combinations, namely SSP1–RCP2.6, SSP2–RCP4.5, and SSP3–RCP7.0. Since the ACCREU exercise focuses on an SSP2 socioeconomic framework, mortality and morbidity impacts are rescaled to ensure consistency with SSP2 conditions. This rescaling is performed using differences in GDP per capita assumptions across SSP1, SSP2, and SSP3, reflecting variations in income levels, adaptive capacity, and baseline health conditions.

In ICES-MH, health impacts are represented through two main channels: increased mortality and higher public expenditures associated with morbidity. Morbidity-related impacts are incorporated into the model as increases in public health expenditure.

Adaptation responses are modelled through higher energy use, capturing intensive-margin adjustments aimed at improving thermal comfort, and through additional investments in air-conditioning infrastructure, representing adaptation along the extensive margin. The intensive-margin adjustment accounts for changes in energy demand for both cooling and heating services.

ICES-Reg considers only impacts on population.

Impact/ adaptation	Econometric variable	ICES-MH Variable	ICES-MH implementation
Impact	Mortality	Population	Shock on population growth
	Morbidity costs	Public expenditure	Shock on government expenditure in health (and coherent shock on total government expenditure)
Adaptation	Residential electricity/fossil energy demand for cooling and for heating	Demand shift	Shift on residential electricity/fossil energy demand for cooling and for heating
	AC investment by residential	Private investment	Shift of private investment

Table 17: health impacts and energy related adaptation in ICES-MH model

Energy supply impact based on CMCC econometric results

Energy-supply shocks are captured as reductions in output in renewable energy sectors. These impacts are modelled in ICES-MH through sector-specific total factor productivity shocks, reflecting temporary or persistent reductions in production efficiency.

ICES-Reg follows the same approach for impact modelling.

Impact/ adaptation	Econometric variable	ICES-MH Variable	ICES-MH implementation
Impact	Output loss of renewable (wind, solar, hydro) power	TFP	Percentage change of primary factor TFP in the renewable sectors

Table 18: energy supply impact in ICES-MH model

Agriculture and forestry impacts based on GLOBIOM results

The ICES-MH model features a level of detail in the agricultural sector that is closely aligned with the GLOBIOM model. It represents four crop sectors, i.e. cereals, oilseeds, sugar crops, and other crops, as well as livestock. For specific crops, we directly compute crop-specific yield shocks, while the aggregate crop yield is used to shock the “other crops” sector. Crop-specific cropland data are

employed to aggregate and weigh the information consistently. For livestock productivity shocks, we rely on production data and pastureland, ensuring coherence between yield, land use, and livestock dynamics. The agriculture related shocks are implemented as land productivity shocks in the respective sectors.
Regarding forestry, we consider roundwood production together with forest land area, acknowledging that roundwood is harvested from both managed and unmanaged forests. This information is used to derive a productivity measure for forest products, which is then translated into a shock to forest natural resources in the ICES-MH model. This approach reflects the fact that, in ICES-MH, the timber sector does not directly use forest land as an input, but rather relies on forest natural resources.
Adaptation in the agricultural sector is modelled through increased public investment in irrigation infrastructure. In addition, we account for the effect of new irrigation infrastructure on agricultural water demand. The current version of the model does not explicitly represent a dedicated water sector; instead, water-related activities are embedded within the market services sector. For this reason, the water-withdrawal shock is weighted by the average share of agricultural water demand relative to total market services demand differentiated by crop type.

ICES-REG adopts the same impact-modelling approach; however, shocks affecting livestock and forestry are computed based on sectoral production levels and do not consider the corresponding land inputs.

Impact/ adaptation	Econometric variable	ICES-MH Variable	ICES-MH implementation
Impact	Crop specific yield	Land productivity	Percentage change of land productivity across different crops
	Livestock production and pastureland	Land productivity	Percentage change of land productivity in livestock sector
	Forest production of roundwood and forest land	Natural resource productivity	Percentage change of forest natural resource productivity in timber sector
Adaptation	Public investment costs: Expansion Cost + investment costs+ Efficiency Improvement Cost	Government investment	Shock on government investment
	Water withdrawal for irrigation (crop specific)	Efficiency shift in using water in crop production	Shock on water demand by agriculture

Table 19: agriculture and forest impacts and adaptation in ICES-MH model

Biodiversity loss impacts based on pollination loss (CMCC)
Biodiversity loss leads to reduced pollination potential and lower pollinator availability, which negatively affect crop production. In ICES-MH, these effects are captured through a land-productivity shock in the corresponding agricultural sectors.
ICES-Reg follows the same impact modelling.

Impact/ adaptation	Econometric variable	ICES-MH Variable	ICES-MH implementation
Impact	Yield loss due to lower pollination potential and pollinator availability	Land productivity	Percentage change of land productivity

Table 20: biodiversity loss (pollination) impact in ICES-MH model

Wildfire impacts based on econometric results

Wildfire impacts are computed as the share of sector-specific burned area, covering crops, livestock, and forestry, relative to the corresponding sectoral land availability over each five-year simulation step. For crops and livestock, these impacts are implemented as land-productivity shocks, reflecting the assumption that land becomes fully available again in subsequent simulation periods and that no permanent land loss occurs. The same assumption applies to the forestry sector, where wildfire impacts are modelled as shocks to forest resource productivity rather than as permanent reductions in land endowments.

ICES-Reg follows the same impact modelling.

Impact/ adaptation	Econometric variable	ICES-MH Variable	ICES-MH implementation
Impact	Cropland and livestock burnt area	Land productivity	Percentage change of land productivity loss
	Forest burnt area	Natural resource productivity	Percentage change of natural resource productivity

Table 21: wildfire impact impact in ICES-MH model

7.2.2 ICES-MH: Results overview

This section provides a synthetic overview of climate-related economic impacts and adaptation outcomes across EU Member States and the United Kingdom in 2070 under the SSP2 and RCP7.0 scenario. The analysis focuses on GDP losses and on the extent to which different adaptation levels mitigate these impacts. Most adaptation measures rely on public expenditure and investment.

Table 22 uses the reference adaptation as a benchmark and compares the effects of both lower and higher adaptation levels relative to this baseline. Across the different risk components, the reference adaptation, accounting for both current public expenditure and investment, represents the level of response that either maintains risk at current levels, as in the case of sea level rise and riverine flooding, or reflects adaptation consistent with available resources as in the case of energy for adaptation. By contrast, the low-adaptation scenario represents a situation in which no additional adaptation investments are undertaken beyond those currently in place, implying limited capacity to mitigate climate-related risks relative to the reference case. The high-adaptation scenario assumes substantial additional investments, which for some risk components approach optimal adaptation levels, as in the case of flood risk. In other sectors, such as energy, adaptation reflects the evolution of income and the increasing affordability of adaptation options over time. Two risk components, namely biodiversity and wildfire losses, fall outside this comparative framework of alternative adaptation levels. For these impacts, no explicit adaptation options are modelled; therefore, the reported results refer exclusively to the estimated effects under climate change conditions compared to the no climate change scenario.

The main conclusion that emerges from Table 22 is that maintaining adaptation measures at their current levels leads to GDP losses across nearly all risk categories and Member States when compared with the reference adaptation scenario. The high-adaptation scenario leads to clear GDP gains relative to the reference adaptation case, particularly for risk components such as sea level rise and riverine flooding. By contrast, the effects are more heterogeneous in sectors such as agriculture and labour, where, for some countries, increasing adaptation efforts beyond the reference level does not yield additional economic benefits and may even prove inefficient.

The largest GDP losses are observed when moving from the reference adaptation scenario to lower adaptation levels, particularly in the case of labour impacts and adaptation through air-conditioning. The largest negative impacts are observed in Bulgaria (-4.9%) and Estonia (-4.5%). Increasing adaptation levels is beneficial for the majority of EU Member States, with Estonia representing the most notable exception. Health impact and adaption scenarios are the ones with lowest impact on GDP.

Reducing adaptation effort from the reference to the low-adaptation scenario is particularly detrimental in the case of sea level rise, with the largest GDP losses observed in Belgium (−3.64%), Denmark (−2.20%), and Italy (−2.06%) compared to the reference adaptation scenario. By contrast, increasing investment in adaptation is beneficial for all countries, with particularly strong gains in Belgium (+0.3%) relative to the reference scenario. Regarding agriculture, the effects of adaptation are more heterogeneous, with outcomes varying significantly across countries. Lower adaptation effort in the agricultural sector results in consistent GDP losses for Romania (−3.65%), Latvia (−3.88%), Lithuania (−2.82%), and Croatia (−2.72%) relative to the reference adaptation level. While higher adaptation levels reduce losses in some regions, they do not uniformly translate into additional benefits, and in certain cases the gains remain limited or even negative compared to the reference adaptation level. GDP losses associated with a reduction in adaptation efforts to address riverine flood risks are relatively small overall; Hungary is the most affected country, with a loss of −0.79% compared to the reference adaptation scenario.

As anticipated, the last two columns of the table report GDP losses associated with biodiversity impacts—specifically the effects of pollination losses on agricultural productivity—and with wildfire damages, both measured relative to a no-climate-change baseline. In the case of biodiversity loss, the overall GDP impact is relatively small, reaching at most −0.32% in Bulgaria and -0.30 in Greece. Finland registers a small GDP gain. The impact of wildfires on GDP is considerably larger in magnitude, reaching as much as −5.25% in Greece, −1.91% in Portugal, and −1.19% in Bulgaria.

	sea level rise (DIVA)		river flood (GLOFRIS)		agriculture (GLOBIOM)		health (BC3) and energy (CMCC)*		labour and energy (CMCC)		biodiversity loss (CMCC)*	wildfires (ForeFire)
region	low vs ref	high vs ref	low vs ref	high vs ref	low vs ref	high vs ref	low vs ref	high vs ref	low vs ref	high vs ref	impact vs noCC	impact vs noCC
aut	-0.75	0.07	-0.21	0.80	-0.03	0.06	0.000	0.000	-1.61	0.01	-0.09	-0.08
bel	-3.64	0.34	-0.14	1.24	-1.24	-1.37	0.001	-0.001	-1.62	0.24	-0.12	-0.12
bgr	-0.50	0.04	-0.06	0.74	-1.75	-2.39	0.001	-0.001	-4.91	0.12	-0.32	-1.19
cyp	-0.64	0.06	-0.09	0.91	-0.05	0.39	0.001	0.000	-2.58	0.45	-0.25	-0.17
cze	-0.85	0.07	-0.02	0.87	-1.52	0.10	0.001	0.000	-1.74	-0.01	-0.18	-0.15
deu	-1.29	0.16	-0.10	0.96	-0.23	-0.08	0.000	0.000	-1.73	0.10	-0.04	-0.05
dnk	-2.20	0.09	-0.09	0.79	-0.23	0.10	0.000	0.000	-0.88	-0.05	-0.07	-0.06
esp	-0.93	0.06	-0.07	0.84	-0.30	-0.03	0.001	0.000	-2.12	0.18	-0.15	-0.51
est	-0.43	0.04	-0.10	0.64	-1.04	0.05	0.000	0.000	-4.49	-2.17	-0.08	-0.08
fin	-0.70	0.07	-0.08	0.71	-0.05	-0.08	0.000	0.000	-1.73	-0.15	0.03	0.07
fra	-1.24	0.08	-0.09	0.87	-0.70	0.04	0.001	0.000	-1.33	0.07	-0.13	-0.11
gbr	-1.57	0.12	-0.09	0.75	0.12	-0.02	0.001	0.000	-0.38	0.00	-0.03	-0.03
grc	-0.72	0.06	-0.10	0.85	-1.16	-0.15	0.001	-0.001	-3.15	0.75	-0.31	-5.25
hrv	-1.27	0.06	-0.24	0.32	-2.72	-0.35	0.001	0.000	-2.47	0.10	-0.18	-0.65
hun	-0.67	0.06	-0.79	0.83	-1.25	0.66	0.001	0.000	-2.20	0.22	-0.32	-0.47
irl	-1.00	0.05	-0.05	0.68	-0.14	-1.33	0.000	0.000	-0.36	-0.19	-0.06	-0.10

ita	-2.06	0.11	-0.16	1.15	-0.46	0.36	0.000	0.000	-2.55	0.27	-0.10	-0.64
ltu	-0.68	0.06	-0.07	0.87	-2.82	0.09	0.000	0.000	-1.85	0.16	-0.18	0.00
lux	-0.93	0.09	-0.12	1.20	-0.21	0.10	0.000	0.000	-1.32	0.06	-0.04	-0.05
lva	-1.16	0.08	-0.02	0.53	-3.88	0.08	0.000	-0.001	-3.05	-0.60	-0.20	-0.15
mlt	-0.36	0.03	-0.04	0.48	0.10	0.25	0.000	0.000	-1.01	0.45	-0.02	-0.04
nld	-1.46	0.11	-0.14	0.72	-1.00	-0.04	0.000	-0.001	-1.43	0.34	-0.10	-0.11
pol	-1.08	0.05	-0.10	0.69	-0.50	1.65	0.000	-0.001	-1.71	-0.14	-0.16	-0.11
prt	-0.66	0.05	-0.10	0.56	-0.15	0.68	0.001	0.000	-1.71	0.19	-0.25	-1.91
rou	-0.83	0.07	-0.09	1.13	-3.65	-0.41	0.001	-0.001	-2.78	0.26	-0.48	-0.30
svk	-0.80	0.07	-0.25	1.16	-0.20	0.12	0.001	0.000	-1.40	0.53	-0.18	-0.17
svn	-1.13	0.07	-0.19	0.96	-0.86	-1.05	0.001	0.000	-2.23	-0.30	-0.12	-0.08
swe	-0.95	0.07	-0.08	0.90	0.15	0.08	0.000	0.000	-0.93	-0.12	-0.02	-0.02

Table 22: Overview of results for 2070 under SSP2-RCP7.0 for the EU27 countries: assessing high and low adaptation levels relative to reference adaptation levels for all impact sectors (%).

7.3 WITCH

The adaptation module

In the WITCH model, climate impacts are represented either as exogenous shocks or through endogenous damage functions that reduce the productivity of production factors (physical capital, labor, energy demand, and energy supply). Adaptation services mitigate these impacts and are modeled using a production-based approach. Adaptation can be either reactive or anticipatory, both of which are modeled as explicit endogenous choice variables selected by the decision maker. In WITCH, the decision maker is a social planner acting on behalf of consumers and producers. As a result, adaptation cannot be assigned to specific actors; instead, what matters is whether the action takes the form of a reactive flow of expenditures, similar to consumption, or a proactive investment that generates a stock of capital, which accumulates and depreciates over time.

The effectiveness of adaptation strategies depends on adaptive capacity, which in turn is influenced by proactive investments in institutional capacity, technology, and human capital. Figure 9 illustrates the adaptation CES tree, which has three levels: the top level represents aggregated adaptation; the second level includes capacity building and adaptation strategies; and the lower levels specify choices governed by substitution elasticities that determine trade-offs across the tree.

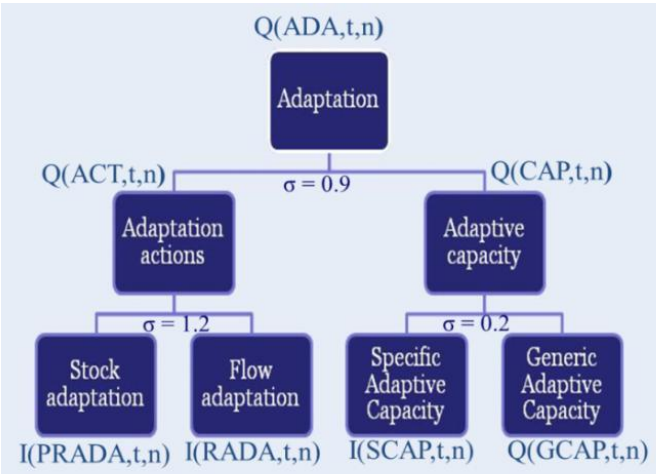

Figure 9: The CES tree of adaptation in the WITCH model.

While the adaptation module in WITCH provides a generic representation, it aggregates impacts across different sectors and types of climate change damages. This design ensures that adaptation is only represented for sectors that are not explicitly modeled elsewhere, thereby avoiding double counting of impacts and responses. We expect to draw on the outputs of WP2 for the calibration of the explicit (for some sectors) as well as of the generic, implicit adaptation module with the associated damage functions. In what follows, we provide a description of the explicit representation of damages and the corresponding level of adaptation for sea level rise, labour productivity and energy.

Sea-level rise

Sea-level rise, or SLR, damages and adaptation costs are represented in WITCH using country-level and global datasets from the DIVA framework. The country data provide information on expected annual damages, migration costs, and protection expenditures under different adaptation strategies, while the global files supply consistent trajectories of global sea-level rise by SSP-RCP scenario and uncertainty quantile. These global trajectories are first harmonized to ensure consistency across confidence levels, adaptation assumptions, and migration settings, and then merged with the country panel to provide a common driver, denoted as *gslr(t).*

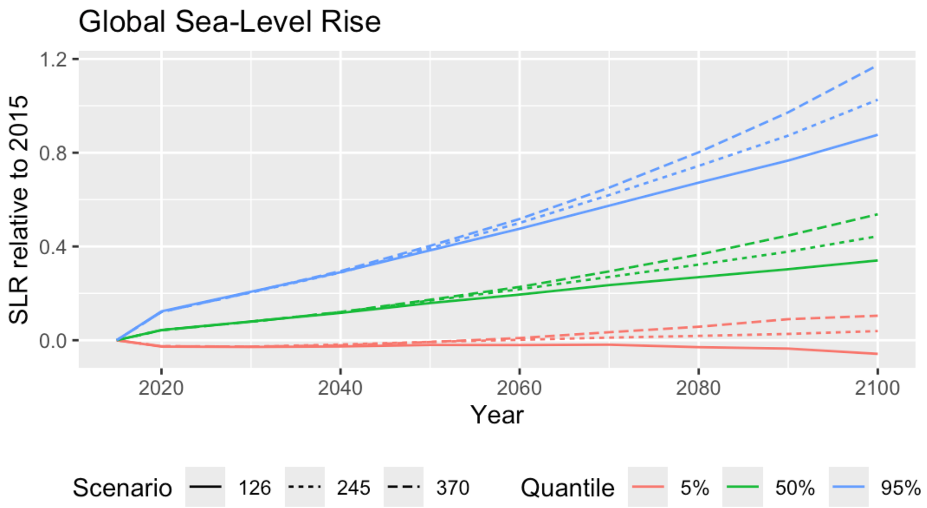

Figure 10: GLSR from the DIVA dataset

Adaptation costs are derived from DIVA's representation of sea-dike investments and maintenance. Two paradigms of adaptation scenarios are considered. The first paradigm seeks to understand the adaptation potential. In this case, a reference level of adaptation ("Ref"), where the dikes' height remains at current levels, is compared with the optimal level of protection/height ("OptAdapt"), where dikes' height is defined based on the most cost-effective level of protection. The second paradigm seeks to represent selection of the level of adaptation, by choosing the level of protection, as defined by the DIVA model. Three adaptation scenarios are distinguished in this case: constant flood protection standards ("ConstProt"), and scenarios doubling ("DoubProt") and quadrupling ("QuadProt") the level of protection. For each country,adaptation, and migration scenarios, annual protection costs come from the residual damages, the sum of investment and maintenance expenditures, and potential migration costs..

Linear cost curves are then built for (1) the total costs for SLR, including (residual) damages, migration costs and dike construction (investment and maintenance), and (2) dike construction costs, using country level data from DIVA. For a given country i and a given adaptation scenario i, in a given year t, the costs are represented as a linear function of the form

$$cost(t, i, a) = \alpha(i, a) + \beta(i, a)\, gslr(t)$$

where the slopes ($\beta(.)$) and the intercepts ($\alpha(.)$) coefficients are estimated based on its goodness of fit and its theoretical and ordering consistency between adaptation scenarios. The resulting country-level parameters are subsequently aggregated to the regional resolution of WITCH, ensuring consistency with model regions.

Table 23 presents the characterization of the slope and intercept coefficients, depending on the cost variables (column) and the adaptation paradigm and scenarios (rows). To satisfy theoretical consistency and ordering across the scenarios, we implement different restrictions on the regressions. The restrictions, although not necessarily minimize errors in the data, are more robust to extreme behaviors in the DIVA data. Nevertheless, the final set of constraints were defined also based on the behavior of the data under unconstrained regressions, and it was set as the preferred fitting when consistency could be guaranteed. Two examples of the adjustments are presented in Figures 11 and 12.

<table>
<tr><th rowspan="2">Adaptation Scenarios</th><th colspan="2">cost</th></tr>
<tr><th>Total Cost of SLR</th><th>Dike's construction cost</th></tr>
<tr><td colspan="3"><u>Paradigm 1</u></td></tr>
<tr><td rowspan="2">Reference</td><td>α: Same as in the Optimal scenario</td><td>α: Average for 2030-2060</td></tr>
<tr><td>β: Pass through the right extreme point</td><td>β: Slope of zero</td></tr>
<tr><td rowspan="2">Optimal</td><td>α: Non-negative number of the regressions on the extreme points. If not, set to zero</td><td>α: Intercept OLS with 2030-2100 data</td></tr>
<tr><td>β: Non-negative number of the regressions on the extreme points. If not, set to zero</td><td>β: Non, negative slope of OLS with 2030-2100 data. If not, set to zero.</td></tr>
<tr><td colspan="3"><u>Paradigm 2</u></td></tr>
<tr><td rowspan="2">Constant Protection</td><td>α: Same as in Quadruple Protection</td><td>α: Intercept OLS regression with fix effects for protection scenarios</td></tr>
<tr><td>β: Pass through the right extreme point but higher than DoubProt</td><td>β: Non-negative slope of the OLS regression with fixed effects for protection scenarios.</td></tr>
<tr><td rowspan="2">Double Protection</td><td>α: Same as in Quadruple Protection</td><td>α: Intercept OLS regression with fix effects for protection scenarios, but greater than intercept of Constant Protection</td></tr>
<tr><td>β: Pass through the right extreme point but higher than QuadProt</td><td>β: Non-negative slope of the OLS regression with fixed effects for protection scenarios.</td></tr>
<tr><td rowspan="2">Quadruple Protection</td><td>α: Non-negative number of the regressions on the extreme points. If not, set to zero</td><td>α: Intercept OLS regression with fix effects for protection scenarios, but greater than intercept of Double Protection</td></tr>
<tr><td>β: Non-negative number of the regressions on the extreme points. If not, set to zero</td><td>β: Non-negative slope of the OLS regression with fixed effects for protection scenarios.</td></tr>
</table>

Table 23: Slope and Intercept definitions under linear fit of the costs of adaptation to SLR in WITCH

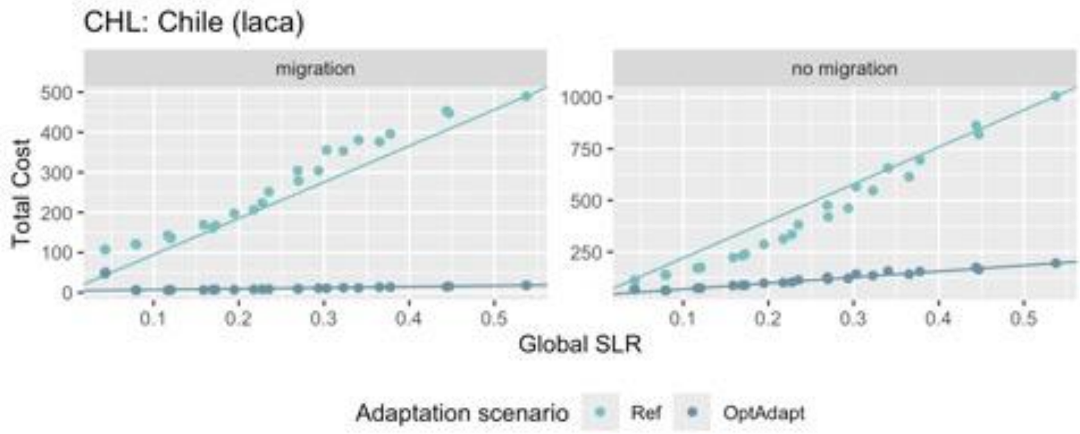

Figure 11: Total SLR costs [MPPP$2011/year] from DIVA dataset and fit imputed, here for Chile. Reference and Optimal Adaptation Scenarios

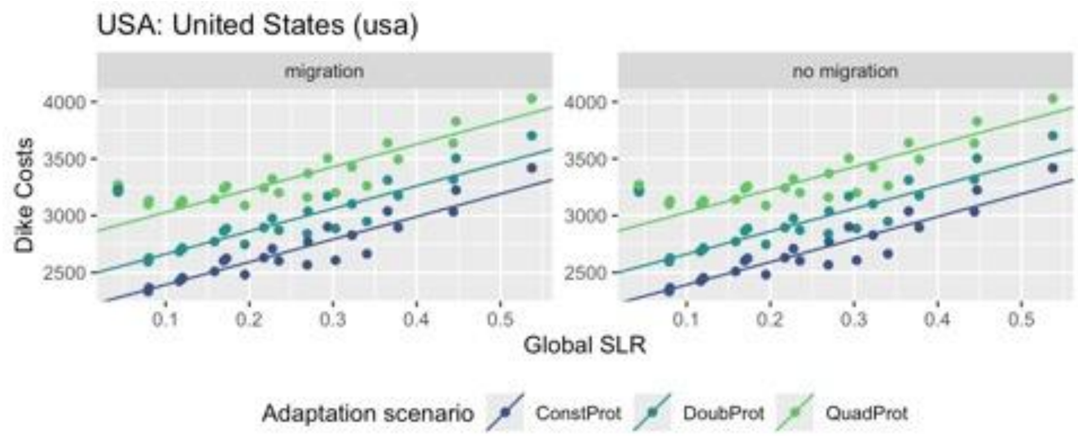

Figure 12: Dike constructions/maintenance costs [MPPP$2011/year] from DIVA dataset and fit imputed, here for the United States. Constant, Double and Quadruple Protection Levels

This methodology ensures that coastal protection and residual damages are represented consistently with global climate scenarios and without double counting. The DIVA-based functions provide exogenous cost and damage schedules that can be combined with the generic adaptation module in WITCH. In this way, coastal adaptation is explicitly represented as a sectoral application, while residual damages from sea-level rise enter the model as part of the calibrated regional damage functions. The approach is aligned with the COACCH project's calibration and can be extended with alternative quantiles for uncertainty analysis or with explicit representation of displaced populations.

Energy Demand

For ACCREU, the WITCH model is expanded to represent the impact of climate change on aggregated energy consumption in *residential, commercial, industrial* and *agriculture* sectors. Accordingly, the existing aggregated impact functions for energy demand in the model will be updated with new data from the econometric estimates produced in Deliverable D2.2. (1.2.4.1. and 1.3.1. Sectoral final energy demand).

To estimate how changes in both hot and cold exposure result in additional energy consumption across sectors, a panel dataset of annual observations across 134 countries and 50 years (1970-2019) was used. It comprises *i)* historical per capita energy consumption in four sectors (residential, commercial, industrial, agriculture) and for two energy carriers (electricity and fossil fuels), is derived from IEA statistics; and *ii)* the population-weighted annual temperature exposures in the form of

Cooling Degree Days (CDD) and Heating Degree Days (HDD) from ERA5 data. These are defined as the cumulative number of days in a year when daily temperatures exceed 24 °C or fall below 15 °C. Economy-wide per capita GDP and total capital stock per capita from the OECD dataset is accounted for as well. These data were used to empirically model associations between final demands for electricity and fossil fuels in economic sectors and high-frequency temperature anomalies versus low-frequency trends.

Three exploratory scenarios accounting for different adaptation levels (Low, Med, High) are evaluated from Deliverable D2.2. (Table 2, *Representation of adaptation in the energy sector impact estimations*). These reflect the changes in energy demand as a consequence of different forms of autonomous adaptation across households and firms, particularly through the more intensive use of adaptive appliances, and on planned adaptation, in terms of increased adoption of technologies. First, people and firms respond to temperature shocks by adjusting their usage of energy-consuming goods like air conditioners. This immediate response, called the "intensive margin," reflects changes in the utilization of a fixed technology stock requiring increased energy. Over longer periods, agents perceive repeated temperature regimes as climatic shifts, prompting more significant adjustments, such as households without air conditioning purchasing one, which can also be classified as a planned adaptation response ("extensive margin").

The resulting adaptation scenarios are:

- Low adaptation: No additional technology is adopted with respect to the baseline level without climate change. Energy responses are restricted to the intensive margin alone, i.e. existing technologies are assumed frozen at historical climate conditions.
- Medium, reference adaptation: Long-term technological adoption is driven by climate changes alone, allowing more flexible responses and increased additional energy demand with respect to the low case. The increase of the extensive margin is bounded by income levels, i.e. assuming income does not amplify the energy use response.
- High adaptation: Additional, long-term technology adoption is driven by climate shifts and amplified by higher income, reflecting an enhanced adaptive capacity to future climate risks. Intensive use changes due to the variation in per capita income, affecting energy-intensive capital stock on top of future climate.

The implementation of these scenarios in the WITCH model relies on two steps.

First, a statistical emulator is implemented that connects the endogenous variable of projected global and regional near surface average temperature with the expected regional temperature extremes (CDD24s, HDD15s) used in the econometric analysis. The calibration relies on estimated coefficients linking mean and extreme local temperatures. Second, the total shock on final energy consumption (including adaptation) due to climate is implemented based on the empirical semi-elasticities of energy demand over climate extremes (CDD24s, HDD15s) variations from D.2.2. estimates.

Energy used in the economy is a combination of electricity (EL) and non-electric (NEL) energy [1], which includes coal, gas, and oil aggregated through a CES function, where each factor is further decomposed into several sub-components.

$$EN(t,n) = (\alpha_{EN}(n)EL(t,n)^{\rho_{EN}} + (1-\alpha_{EN}(n))NEL(t,n)^{\rho_{EN}})^{\frac{1}{\rho_{EN}}} \qquad [1]$$

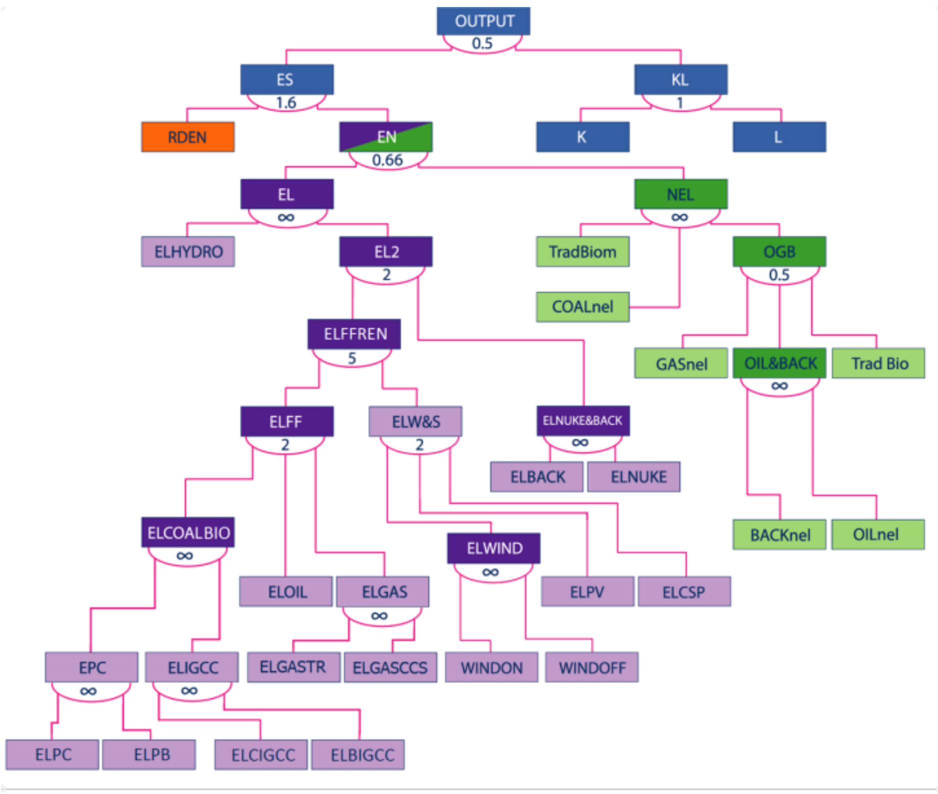

Figure 13: WITCH CES Production Function Tree. The numbers under the boxes represent the production elasticities (α) used in the energy production CES functions

Following the methodology established in Colelli et al. (2022), projected climate-related increases in energy demand are modelled in WITCH as technological retrogression, requiring more inputs to generate a given output. This is done by modifying production function shares ($\alpha_{j,t,n}$), for each fuel type (*j*) electricity (EL), oil (OILnel) and gas (GASnel) in the CES sub-functions for energy composition in the model. These are re-calibrated according to the empirical climate-induced total shock on final energy consumption including adaptation ($\Phi_{j,t,n}$) -consistent with the LOW, MED and HIGH adaptation scenarios evaluated- and the estimated relationship (median) on how a % change in alpha translates into final energy change (Θ_j). In this formulation, the productivities of electricity and nonelectricity are endogenous functions of climate shocks [2].

$$\alpha(j, t_2, n) = \alpha(j, t_1, n) \cdot \left(1 + \frac{\Phi(j, t_2, n)}{\Theta(j)}\right) \qquad [2]$$

The composition of energy EN in the model (combination of electricity EL and nonelectric energy NEL), is therefore re-calibrated to match the additional expected share of energy used per fuel type (el, gas, oil) as a response to climate change, reflecting the loss of productivity of Energy Services. This assesses the response of endogenous energy demand to extreme temperature increase (CDDs, HDDs) projected by the model, also capturing the increased energy use for indoor cooling (AC) as a form of adaptation.

In the energy sector, adaptation will therefore occur endogenously during the re-optimization of consumption and energy investments by the model, following the implementation of the impact functions for energy demand and shocks for energy supply. The new energy demand can be accounted for as a proxy of sectoral adaptation due to climate extremes, reducing the climate change impact on labour in those sectors (see below).

Labour impact

The WITCH model is expanded to also account for the impact of increasing temperature on labour productivity. For the first time, a new global damage function is implemented, linking labour and meteorological variables while explicitly accounting for the protective effect of adaptation. Adaptation is approximated by the additional projected energy demand for cooling under the different adaptation scenarios described in D2.2 (Table 2 *Representation of adaptation in the energy sector impact estimations*). These scenarios reflect varying levels of energy use and the cumulative stock of air-conditioning units needed to respond to projected shifts in the frequency of extreme-temperature days, encompassing both upper and lower thresholds.

The new damage-response functions are calibrated on results from a new econometric model derived from the empirical evidence described in Deliverable D2.3. Section *2.5.2 A macro approach with adaptation*.

The empirical model identifies the impact of inter-annual variation in Cooling Degree Days (CDD, threshold used 24°C) on interannual variations in labour productivity, defined as the annual gross value added divided by the number of employed persons. The model accounts for: country-fixed effects (μ_i), which capture all time-invariant country-specific unobservable factors; Time-fixed effects (δ_t), which control for global shocks affecting all countries in a given year; Quadratic regional time trends ($\phi_{r(it)}$), where *r(i)* indexes the regional group to which country *i* belongs, capturing region-specific trends over time. Sectoral labour productivity is aggregated into *high exposure* (i.e. work that takes place mostly outdoors, agricultural, construction, mining and quarrying) and *low exposure sectors* (i.e. work that takes place mostly inside buildings, manufacturing, services and utilities).

The econometric specification is:

$$y_{it} = \text{CDD}_{it}\left(\alpha + \beta\,\text{Energy Adapt}_{it}\right) + \mu_i + \delta_t + \phi_{r(i),t} + \varepsilon_{it} \qquad [3]$$

Where:

- y_{it} is the logarithm of labour productivity in country *i* at time *t*,
- CDD_{it} is the number of cooling degree days above 24°C,
- Energy Adapt_{it} is the logarithm of per capita energy used for adaptation in productive sectors,
- ε_{it} is the idiosyncratic error term.

This specification allows us to isolate the effect of thermal stress on productivity while controlling for unobserved heterogeneity across countries, global shocks, and regional trends.

Empirical results reveal that the negative effects of increases in CDDs on labour productivity depends on the aggregate level of adaptation.

Results show that high-exposure sectors experience a significant decline in productivity with rising temperatures. When interactions between CDD24 and energy for adaptation are included in the analysis, a statistically significant relation is found only as for low-exposure sectors, indicating that higher energy use mitigates the negative impact of heat on productivity. On the other hand, the role of energy for adaptation is not statistically significant in the high-exposure sectors, suggesting as expected that energy for cooling is not an effective adaptation strategy for improving outdoor working conditions. Note that energy for adaptation considers energy used in productive sectors only (commerce, industry, agriculture).

Effect of CDD24 on Labour Productivity: selected models			
Dependent Variables:	Total	High Exposure	Low Exposure
Model:	(1)	(2)	(3)
Variables			
cdd24	-0.0001*	-0.0002*	-0.0002**
	(7.26×10^{-5})	(8.74×10^{-5})	(8.66×10^{-5})
cdd24 × log_energy			3.21×10^{-5}**
			(1.34×10^{-5})
cdd24 × log_energy ^{2}			-4×10^{-6}**
			(1.9×10^{-6})
Controls (HDDs, Capital stock)	Yes	Yes	Yes
Regional time trends	Yes	Yes	Yes
Fixed-effects			
iso3	Yes	Yes	Yes
time	Yes	Yes	Yes
Fit statistics			
Observations	2,554	2,554	2,551
R^2	0.98127	0.98669	0.95023
Within R^2	0.29989	0.34354	0.29753

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 24: CDD24 and Energy for Adaptation in Productive Sectors (i.e. Excluding Residential)

Importantly, the estimated relationship between CDDs, energy use, and low-exposure sector productivity shows a clear saturation effect (Figure 14 below). The marginal mitigation of CDD-induced productivity losses diminishes at higher levels of per capita energy use for adaptation, with most of the effect plateauing beyond 5–10 GJ per capita. This non-linear pattern reflects diminishing returns to additional energy consumption in reducing heat-related productivity losses and varies widely across countries depending on the initial consumption level, giving a measure of the **effectiveness of additional adaptation** and the **limits of adaptation to mitigate negative climate impacts**. The heterogeneity implies that while additional adaptation energy could substantially reduce productivity losses in regions with low historical energy use, countries already above the 5–10 GJ threshold experience limited additional benefits.

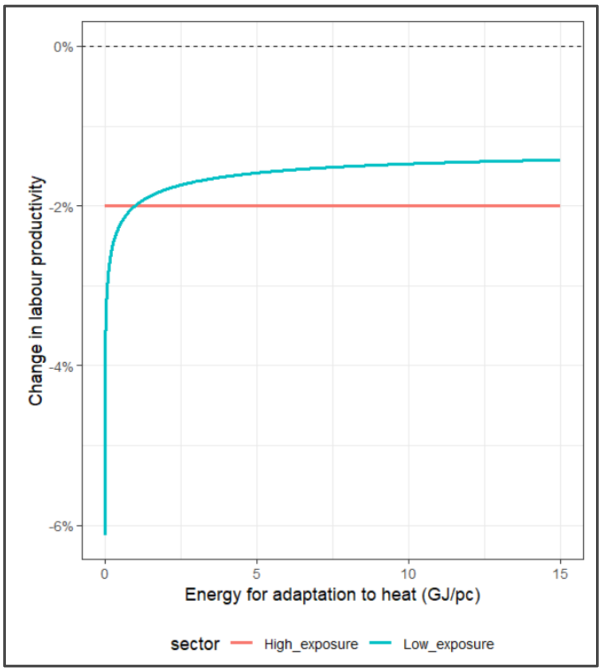

Figure 14: Marginal change in labour productivity from an increase of 100 CDDs, by level of per capita energy use.

Some exploratory, ex-ante projections of labour productivity shocks are produced by combining country-level CDD projections (ISO3 level) with projected changes in energy demand for cooling under the three adaptation scenarios (Figure 15). These show heterogeneous shocks between countries, with projected labour productivity losses reaching up to −20% by 2050 and −30% by 2100 in the absence of adaptation. When the mitigating effects of adaptation energy are included, these losses are nearly halved under the "high" adaptation scenario, highlighting the substantial potential of productive-sector energy use to reduce heat-induced productivity shocks.

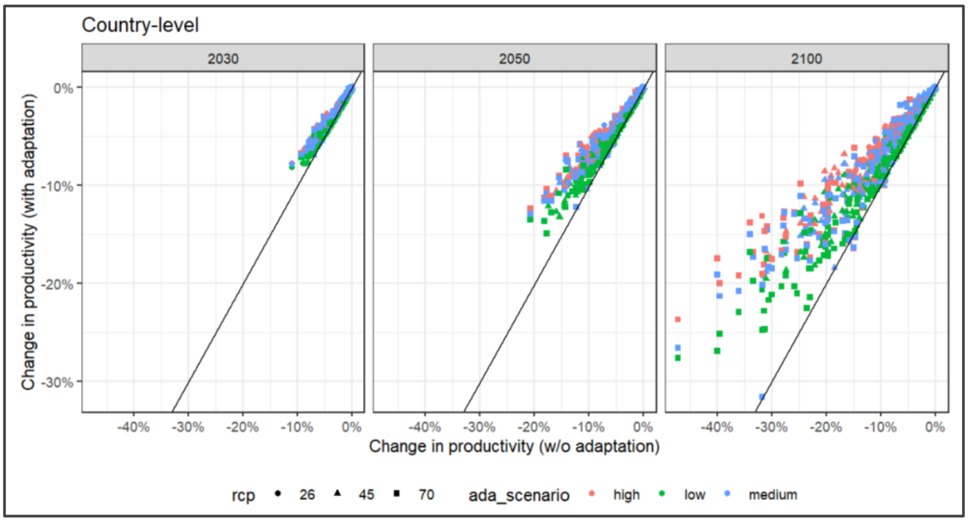

Figure 15: Ex-ante change in Low-Exposure labour productivity based on CDDs changes and energy adaptation projections.

Simulated ex-ante changes in productivity of high- and low-exposure sectors in Europe in 2100 and RCP 4.5 are shown in Figure 16. Low-exposure shocks are presented in two cases: without and with adaptation. Decreases in high-exposure labour productivity range from -2% to -6%, while in the low-exposure sector they range between 2% and 4% in the no adaptation case and are roughly 20%-40% lower (less negative), depending on the country, when adaptation is accounted for.

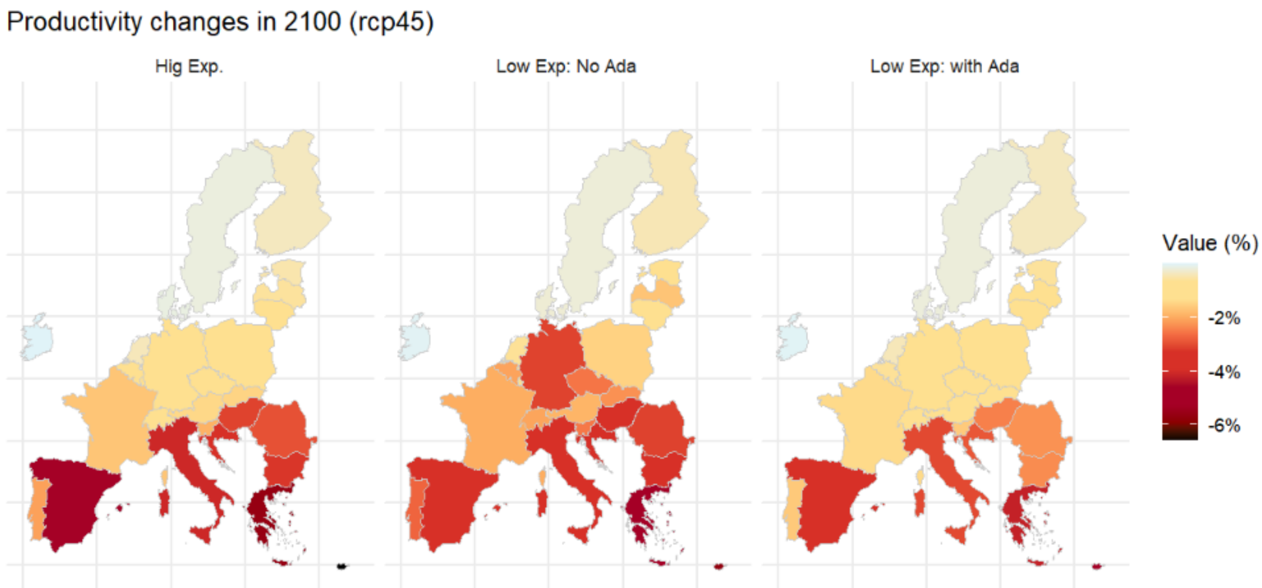

Figure 16: Ex-ante change in High- and Low-Exposure labour productivity in Europe, based on CDDs changes and energy adaptation projections.

The implementation in WITCH relies on the dynamic calibration of the Total Factor Productivity (*tfpy*) in each time step in the model.

The production in the model is described by the Constant Elasticity of Production function [4] that aggregates energy services *(ES)* and a Cobb-Douglas bundle combining labor and capital with an elasticity of substitution equal to 1. The (tfpy) increases the productivity of the K-L aggregate and is dynamically calibrated in the baseline run, evolving with time.

$$Y(t,n) \;=\; \left[\alpha(n)\left(tfpy(t,n)\;\left(K(t,n)^{\beta(n)}\;L(t,n)^{1-\beta(n)}\right)\right)^{\rho}\;+\;\left(1-\alpha(n)\right)\;ES(t,n)^{\rho}\right]^{1\rho}$$

[4]

For ACCREU, a new impact-adaptation module enables further calibration of Total Factor Productivity (tfpy) based on projected temperature extremes and the increased energy use for adaptation described above. This makes it possible to capture both the impact of climate change on labour productivity and the autonomous adaptation feedback from increased energy consumption. It also allows the execution of multiple scenarios, with and without different levels of adaptation feedback, calibrated to match the expected share of *High* vs in *Low exposure* sectors across countries.

The (*tfpy*) is re-calibrated according to new endogenous energy levels by using results from the empirical model described above (Table 24), and the increase in thermal stress relative to the no climate change conditions ($\Delta\_CEI\ t,n$). This is the difference between historical and projected CDD24 in a year, as the number of days by which the projected daily temperatures in the model exceed the threshold of 24°C. These are endogenously assessed by the model as a function of the projected regional mean temperature, following estimates produced in Deliverable D2.2. and described here above in section *Energy Demand*. In this way, a direct feedback is established between temperature, energy use and labour, allowing to explicitly account for the protective effect of adaptation on labour productivity.

The resulting function [5] is:

$$\text{tfpy(t,n)} = \text{tfpy(t-}1,n)$$

$$\cdot\left[1+\left(tfpy\_CEI^{\text{low}}(t,n)\cdot exp\_share_{\text{low}}(n)+tfpy\_CEI^{\text{high}}(t,n)\cdot\left(1-exp\_share_{\text{low}}(n)\right)\right)\right]$$

With:

$$\text{tfpy\_CEI}^{\text{low}}(t,n)=\Big(-\sigma+\gamma\cdot\log\big(ena\_AC(t,n)\big)-\eta\cdot\big[\log\big(ena\_AC(t,n)\big)\big]^2\Big)\cdot\left(\Delta CEI_{\text{CDD24},t,n}\right)$$

$$\text{tfpy\_CEI}^{\text{high}}(t,n)=-\sigma\cdot\left(\Delta CEI_{\text{CDD24},t,n}\right)-\theta\cdot\left(\Delta CEI_{\text{HDD18},t,n}\right)$$

Where:

- exp_share_low is the share of indoor labour on the total workforce in region (n),
- tfpy_CEI is the shock on indoor/outdoor sectors total factor productivity due to climate extremes (CDD24,HDD18) impacts,
- σ is the expected negative shock on labour productivity for any increased CDD24,
- θ is the expected positive shock on labour productivity for any reduction in HDD18,
- γ, η are the linear and quadratic specifications for the protection effect of energy in LOW exposures sectors,
- *ena_AC* is the endogenous projected energy increase for AC for additional CDD24 respect to the historical level in the reference period (1990-2019) (Gjoule/person),
- *Δ-CEI* is the endogenous projected difference of CDD24/HDD18 with respect to the historic period.

Negative and positive effects of changing temperature extremes on labour productivity are therefore implemented as an endogenously determined shock on the baseline Total Factor Productivity in the model, weighted for the country-specific share of High versus Low exposure sectors' contribution to GDP and the increased energy demand for adaptation.

Moreover, the additional cumulative stock of air-conditioning equipment at the country level is also endogenously determined, which provides an estimate of the capital stock required to achieve thermal comfort both in the working environment and at home. This quantification provides the additional stock of air-conditioning equipment needed to provide the flow of energy for adaptation simulated in the model, with respect to the historical level of AC stock in the reference period (1990-2019). The temperature-driven energy demand and the resulting AC stock investments also include residential energy use, and follow the Low, Med and High adaptation scenarios of energy demand. This is meant to capture a form of autonomous adaptation (e.g., adjustments by households and firms through more or less intensive use of energy-consuming appliances) when considering energy use, and the consequent increased adoption of energy-using appliances such as air conditioning machines. The adaptation response is, however, fully endogenous in the model -driven by projected CDD-HDDs- and reflects both empirical estimates and their effectiveness. In this specification, direct costs to households from heat stress (e.g., hospitalization costs) are not explicitly modelled, while indirect costs associated with morbidity are partially captured through the empirical estimates used to assess labour productivity shocks.

7.4 MIMOSA

Introduction

In MIMOSA, we differentiate between climate damage resulting from sea level rise (SLR) and damage caused by other factors. We use the latest empirical estimates provided by partners within the ACCREU consortium as direct input for determining damage. Below, we describe the structure of the MIMOSA model, the improvements made compared to an earlier version, and how we use the ACCREU data.

Improvements

Two significant enhancements have been incorporated into this version of MIMOSA, both shown in Figure 17, which set it apart from its predecessor. Firstly, the amount of **adaptation is now a continuous variable** rather than a binary choice (present or absent). Consequently, the model can choose to invest greater or lesser amounts in adaptation, depending on regional circumstances.[3] This is a more realistic approach compared to expecting governments to either not adapt at all or implement optimal adaptation plans. It acknowledges that governments will always weigh adaptation against mitigation and against the practical constraints they face. Furthermore, adopting a continuous approach to adaptation provides modellers with greater flexibility regarding its application within the model. This allows the adaptation level to be optimised, set at extremes or intermediate levels, or made dependent on scenarios.

A second improvement in the current version of MIMOSA is that it **distinguishes between gross climate damage and residual damage in all sectors**. Residual damage is the actual damage experienced as a result of climate change, taking into account the effects that have been mitigated by adaptation. Gross damage is the damage that would have been experienced if no adaptation measures had been implemented in the event of the same level of climate warming. This distinction

[3] The model can do this autonomously, as an endogenous element of the optimizing-exercise, or the modeler can exogenously determine certain conditions of adaptation.

was not made in the previous version because there was no explicit data on adaptation costs and benefits before.

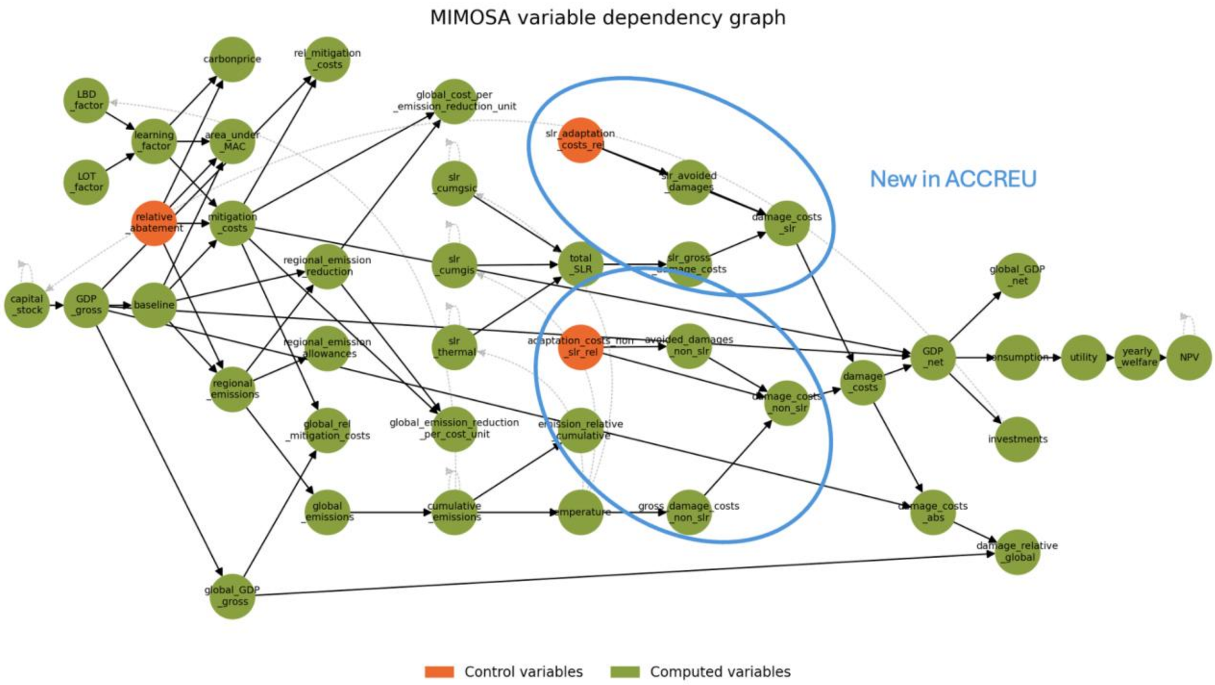

Figure 17: Architecture of MIMOSA. Changes to the previous version of the model are highlighted: the adaptation and damage modules of both SLR and non-SLR (temperature dependent) damages are updated.

Cost curves

In what follows, we illustrate the structure of MIMOSA using one sector (SLR), which was chosen because of the earlier availability of preliminary data. However, the architecture of the model outlined below is the same for both SLR and the non-SLR sector.

In MIMOSA, we express adaptation costs in dollars but express damage in percentage of GDP.[1] [Mv1] [Mv2] We make this choice because the costs of building a dyke depend more on the height of the dyke, than on the size of GDP. However, the value of the economic activity in the protected region and, consequentially, the value of the potential (avoided) damage varies much more depending on economic growth.

Functions used in the model to calculate damage:

The model calculates the total economic damage caused by climate change for each region. This variable encompasses all financial losses resulting from climate change, including actual damage and expenditure on adaptation measures that would not have been necessary in the absence of climate change.

(1) Gross damages in the absence of policy:

$$Gross\ damage_{SLR} = a * (b_1 * SLR + b_2 * SLR^2) - [a * (b_1 * SLR_{intial} + b_2 * SLR_{initial}^2)]$$

- Gross damage is the amount of climate damage that would be suffered if no measures were taken. It is determined on the basis of regionally differentiated parameters derived from empirical data.

- Expressed as a percentage of GDP.
- b1 and b2 are regional parameters.
- The damage already incurred at the start year of the model is not taken into account, as this is already factored into the GDP figures. We only calculate the *additional* damage by *additional* climate change.

(2) Avoided damages as a result of policy:

$$Avoided\ damage_{SLR} = L * (1 - e^{-\beta * adaptation\ costs})$$

- Expressed as a percentage of GDP.
- L = The limit to adaptation, estimated by best fit through the DIVA-data made in WP2.
- β=Curvature parameter, estimated by best fit through the DIVA-data made in WP2.
- Adaptation costs are a control variable, meaning the model endogenously optimizes its value in function of the welfare function. As such, its effectiveness and costs are weighted against those of mitigation in the basic CBA-run. The modeler can also impose exogenous constraints or limits to explore different adaptation-scenario's.

(3) Residual damages which cannot be avoided through policy:

$$Residual\ damage_{SLR} = Gross\ damage_{SLR} * (1 - Avoided\ damage_{SLR})$$

- Expressed as a percentage of GDP

The non-SLR-effects of climate change are handled analogously, as shown in Fig. 14.

<u>Illustrative model results</u>

In Figures 18 and 19 we show the model output for a cost-benefit analysis (CBA) for two regions: Western-Europe and India. Note that for this illustration, we have only chosen adaptation in the SLR sector.

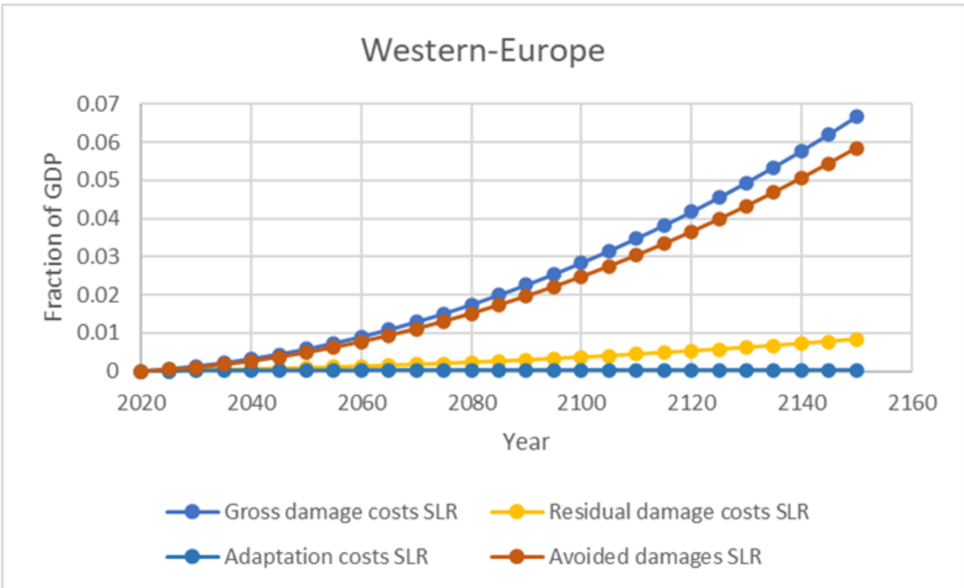

Figure 18: Damage and adaptation costs in Western Europe. MIMOSA-output.

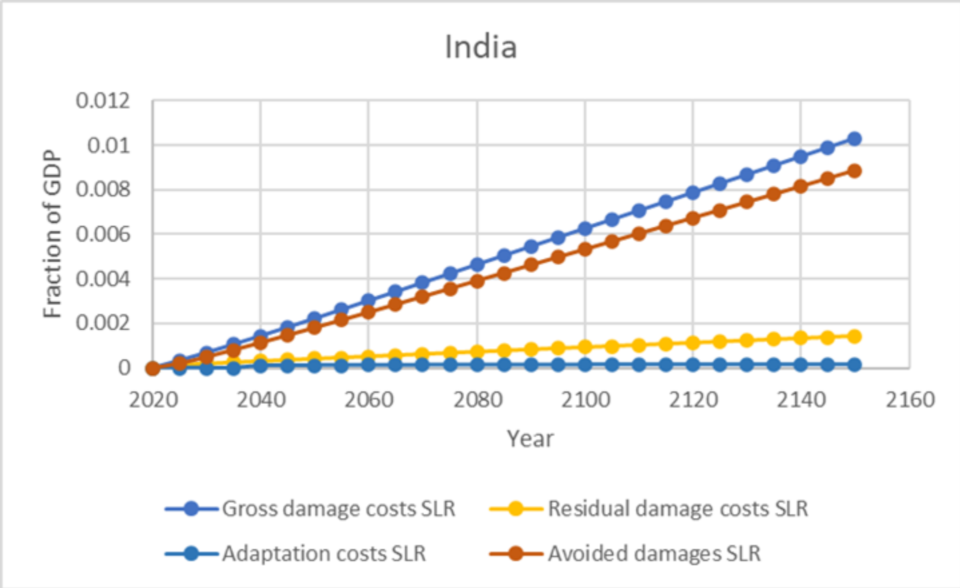

Figure 19: Damage and adaptation costs in India. MIMOSA-output.

Two things stand out immediately: (a) the consequences of sea-level rise are potentially much worse in Western Europe than in India, (b) in both regions, a large proportion of the potential damage caused by sea-level rise can be prevented provided that adaptation measures are implemented. The latter is a logical consequence of the enormous effectiveness of adaptation policies in DIVA. In Figure 20, we illustrate this using the ratio of $\frac{Avoided\ damages}{Adaptation\ costs}$ for both regions. Every euro spent on adaptation policy generates considerable returns in terms of avoided damage. As a result, in a KBA analysis, the model very quickly opts to move towards the predefined adaptation limit β, which in this case is 87.9%, as shown in Figure 20. While this demonstrates the value of such policies, it also highlights the need for modeling-simulations to investigate potential pitfalls relating to the effectiveness of adaptation (as discussed in Milestone 4.4).

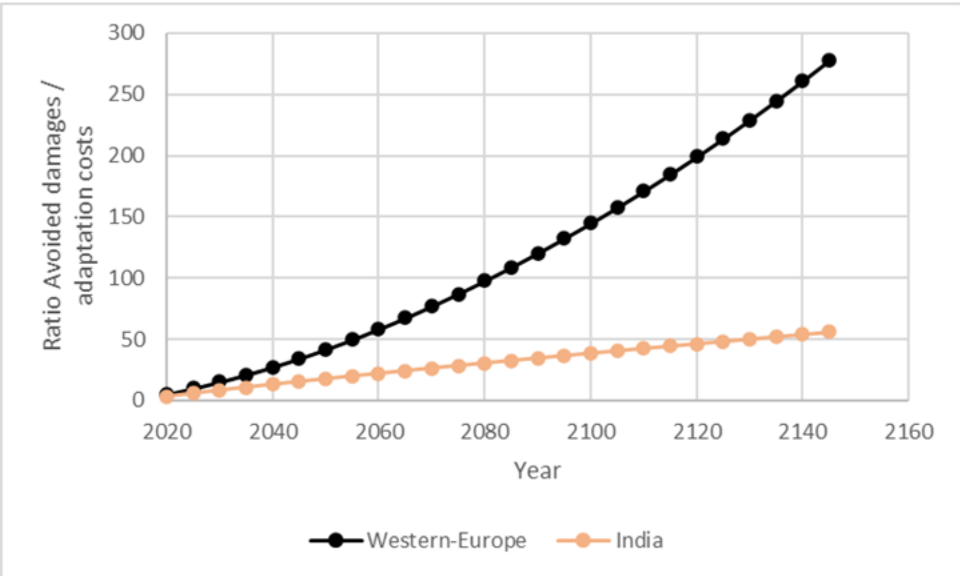

Figure 18: Effectiveness of adaptation policy: euros saved per euro spent on adaptation..

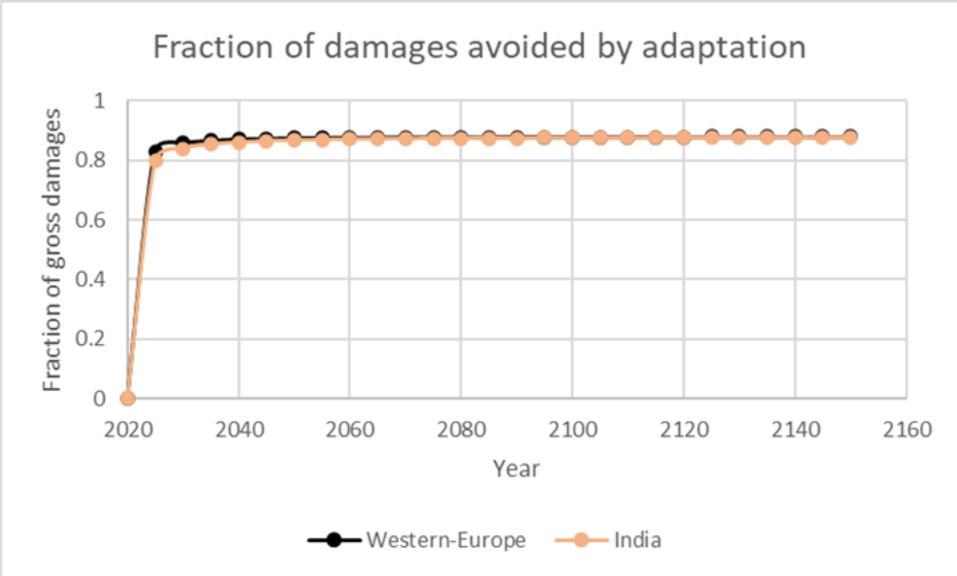

Figure 20: Effectiveness of adaptation policy: fraction of gross damages avoided through adaptation. MIMOSA-output.

7.5 REMIND

REMIND includes climate change damages through aggregate damage functions linking temperature change to GDP loss. These are applied on the level of REMIND regions. Developments in ACCREU build directly on the COACCH damage function implementation which separates out sea level rise from other damages. Below we describe the implementation, the new developments to include adaptation, and how we will use the ACCREU inputs.

Implementation of climate change damages

Figure 22 illustrates how climate change damages are included in REMIND's modeling framework. It uses an iterative soft-coupling approach with a damage module (Schultes et al. 2021). Based on REMIND emission projections global mean temperature pathways using the MAGICC model. The associated sea level rise, which was computed from a simple emulator in COACCH, is now calculated consistently in MAGICC through the use of an updated MAGICC version based on Nauels et al. (2025). This improves consistency and updates the sea level rise to be in line with CMIP6-based projections. Figure 23 illustrates the range of sea level rise for a current policy scenario with a temperature outcome of 2.9° above preindustrial in 2100. Mean 2100 sea level rise in this scenario is 0.725 m.

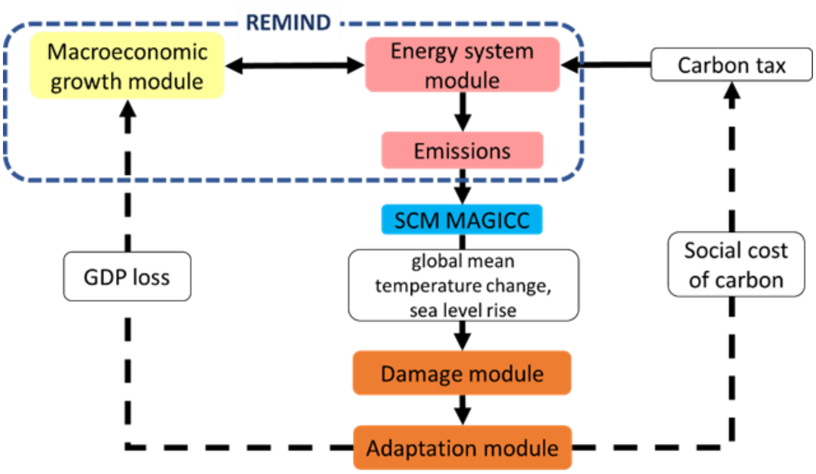

Figure 22: Modeling framework for damages and adaptation in REMIND

The damage module applies damage functions to calculate gross GDP reductions. We use the SLR and non-SLR damage functions from Section 5, driven by global mean temperature change and sea level rise, respectively, on a regional level. Total damages are the sum of both. As the model assumes historic GDP data until 2025, where impacts are included already, we rebase the damage function to be aligned with that. The final damage function then looks as follows:

$$D_{r,t}^{tot} = D_{r,t}^{nSLR} + D_{r,t}^{SLR} = \alpha_r^{nSLR}\left[(\beta_{1,r}^{nSLR}T_t + \beta_{2,r}^{nSLR}T_t^2) - (\beta_{1,r}^{nSLR}T_{2025} + \beta_{2,r}^{nSLR}T_{2025}^2)\right] + \alpha_r^{SLR}\left[(\beta_{1,r}^{SLR}SLR_t + \beta_{2,r}^{SLR}SLR_t^2) - (\beta_{1,r}^{SLR}SLR_{2025} + \beta_{2,r}^{SLR}SLR_{2025}^2)\right]$$

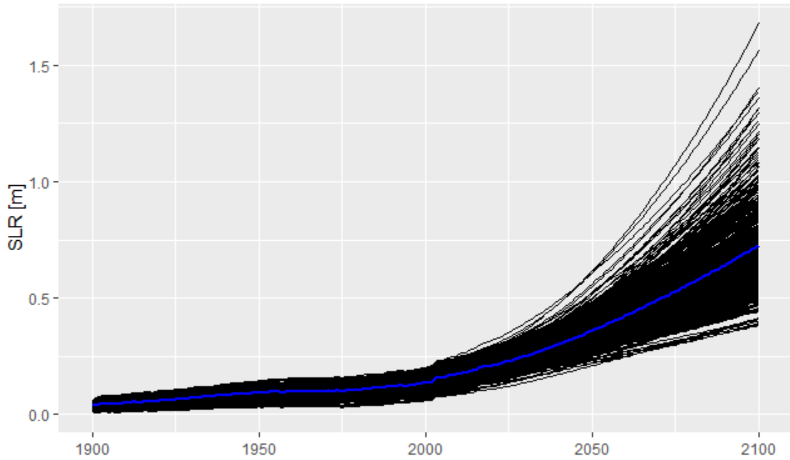

Figure 23: Sea level rise projections from the MAGICC ensemble for a current policy run. The blue line indicates the mean.

Implementation of adaptation

A key innovation in ACCREU is the explicit inclusion of adaptation in REMIND as an endogenous response option to damages. We follow the literature (de Bruin et al. 2009) and separate damages into residual damages and adaptation costs:

$$D_{r,t}^{ada} = D_{r,t}^{res} + AC_{r,t}.$$

The level of adaptation can be optimized based on the respective SLR and non-SLR adaptation cost functions from Section 4, linking the costs of adaptation to the achieved protection level.

For SLR, as shown in Section 4, adaptation is very efficient, rising steeply and then reaching a maximum level of protection. For REMIND we use a function with costs in % of GDP and avoided damages in % of the gross damages. We use a logistic fit:

$$P_{r,t}^{SLR} = \gamma_1/(1 + exp(\gamma_2 - AC_{rt}/\gamma_3)).$$

The protection level is linked to the avoided damages through

$$D_{r,t}^{SLR,res} = D_{r,t}^{SLR,gross}(1 - P_{r,t}^{SLR}).$$

The link is similar for non-SLR damages. Instead of optimizing adaptation within REMIND we can also use exogenous projections of residual damages and adaptation costs along given emission pathways (RCPs) as provided by WP2 and WP3.

7.6 DIFI

The Dynamic Integrated Flood Insurance (DIFI) model is a partial equilibrium model of the flood insurance market in Europe, that combines a spatially explicit flood risk module with an insurance sector and consumer behavior module. The model was first introduced by Hudson et al. (2019), and applied in Tesselaar et al. (2020a), Tesselaar et al. (2020b), Tesselaar et al. (2022), and Tesselaar et al. (2023). The DIFI model can be used to assess various societal consequences of increasing flood risk and socio-economic development for flood insurance arrangements in the EU, and evaluate policy options to improve the functioning of flood insurance markets under the aforementioned increasing pressures. More specifically, the model projects changes in insurance prices, insurance affordability, and market penetration. Moreover, the DIFI model can be used to assess disaster risk reduction (DRR) efforts by policyholders. Whereas earlier versions of the DIFI model focus solely on flood insurance for households, recent developments aim to include insurance for businesses. This section will describe the current state of the DIFI model including the development of a business-level insurance uptake module which is designed to be applied in the ACCREU WP4 CGEs.

The DIFI model is subdivided into three modules: module 1 concerns estimating the risk based on a catastrophe model, module 2 concerns calculating the insurance premium based on various stylized insurance market forms, module 3 concerns simulating the consumer demand for insurance and hence the uptake.

Module 1: risk simulation

Module 1 starts with simulating the flood risk. Risk can be subdivided into three components: hazard, exposure and vulnerability.

Hazard is defined as the frequency and intensity of a climatic disaster. Currently, flood hazard is calculated using the GLOFRIS model. Riverine flooding and coastal flooding are simulated separately.

The GLOFRIS model simulates water levels that occur with 9 different return periods: 1/2, 1/5, 1/10, 1/25, 1/50, 1/100, 1/250, 1/500, 1/1000. Here 1/2 indicates that a flood of a given magnitude occurs once every 2 years, therefore, these return periods can be seen as probabilities. The simulations are carried out for four time periods (2010, 2030, 2050 and 2080). These four time periods are chosen to reduce the variability in climate data and instead capture sufficient variation in the future trend of climate change. Each of these years represent the mean of a 40-year time series where the GLOFRIS cascade (i.e., hydrological, hydrodynamic, and risk modules) is run using various meteorological input fields (i.e., rainfall, snowfall). For 2010, the mean is taken over the period 1960-1999, for which climatic data is obtained from the EU-WATCH project (Weedon et al., 2011). For future estimations the mean is taken from 40-year periods around the specific years, for which climatic data is obtained from the ISIMIP project (Hempel et al., 2013), which uses meteorological simulations from the CMIP5 global circulation models (GCMs). The GCMs are forced using Representative Concentration Pathways (RCPs) 2.6, 4.5, 6.0 and 8.5, in order to capture a range of possible greenhouse gas concentrations for future periods. By using CMIP5 models this method deviates from the agreed upon ACCREU-scenarios, which use CMIP6-models. Although we aimed to be able to use the agreed upon scenarios, implementing these scenarios in the hazard module of GLOFRIS has encountered such delays that it is no longer realistic in the timespan of the project. Although implementing CMIP6-scenarios is done by researchers outside the ACCREU-consortium, and is not a registered task or deliverable in the project proposal, it is nonetheless unfortunate that this innovation cannot be used in the project. The most important difference between the two ensembles is that CMIP5 uses RCP8.5 as an upper bound scenario, which is RCP7.0 for CMIP6. The "optimistic" and "middle-of-the-road" scenarios remain the same.

The simulations lead to hazard maps with a 30''x 30'' (arcseconds) resolution for each return period. Riverine flooding and coastal flooding have a separate set of hazard maps.

To simulate the **exposure**, defined as the value and quantity of assets exposed to the climatic disaster, urban density maps are used. For 2010, this map is obtained from the HYDE database (Klein Goldewijk et al., 2011), while for future periods the urban density and population growth is derived from the 2UP-model (van Huijstee et al., 2018), which uses Shared Socio-economic Pathways (SSP) scenarios for socio-economic forecasting. The economic value of exposed assets is determined based on national GDP per capita in 2010 (van Vuuren et al., 2007), which is also adjusted for future periods based on the SSP scenarios to allow for five alternative socio-economic developments. To distinguish between damages to households, commercial sector, and industrial sector, each cell with built-up area has a fixed percentage of buildings belonging to the three aforementioned categories. The percentages of buildings belonging to the aforementioned categories are retrieved from Economidou et al. (2011) and an analysis of the CORINE Land Cover data by Tiggeloven et al. (2020) for each of the cells with built-up area.

Vulnerability is defined as the predisposition to be negatively affected by a climatic disaster. The vulnerability is operationalized using depth-damage curves from Huizinga et al. (2017). Depth-damage curves relate inundation depth to a percentage damage of the total value of the inundated asset. These depth-damage curves exist on a country basis and differentiate between, among others, residential buildings, commercial buildings and industrial buildings.

To account for protection standards, the FLOPROS database is used (Scussolini et al., 2016). The FLOPROS database provides regional protection standards that are assumed to remain constant through time. The protection standards follow the same return-period scheme as in the inundation simulation. This means that an area which has a protection standard of 1/100 will not experience inundation of floodings with a probability of 1/100 or higher. To achieve this, a damage probability curve is fitted based on a power-law function, which takes the form: $L = \tau_1 + \tau_2 p^{\tau_3}$ (Hudson et al., 2019). Using a Monte-Carlo approach, random return-periods are drawn per region and compared to the protection standards in place.

The three components of risk are coupled together to calculate the expected annual damage (EAD) and volatility of the losses, taking the protection standards into account and aggregated at NUTS3 level. Between the four time points (2010, 2030, 2050 and 2080) the damages and corresponding volatilities are linearly interpolated. The EAD is disaggregated into damages to households, the commercial sector, and the industrial sector, based on the aforementioned urban density maps.

A major update of the model is that, besides the direct damages to businesses, it will also assess business interruption damages. For the Netherlands, the business interruption has been calculated using the Slachtoffer en Schade Module (Slager and Wagenaar, 2017), while this is currently only available for the Netherlands only, a relationship between water depth, direct damage and business interruption can be established for other countries.

In terms of adaptation, the GLOFRIS model uses three different options. The first adaptation scenario concerns constant dike-heights, which means that the protection standards will decrease over time. The second adaptation scenario concerns constant protection standards, which means that the dike-height will grow in tandem with the rising flood risk, guaranteeing the protection standards. The final adaptation scenario concerns optimal protection standards, which means that the protection standards are updated in a cost-effective manner where the dikes grow more in highly exposed areas and less in areas with a lower exposure.

Module 2: insurance premium calculation

For households, based on the risk calculated in module 2, the insurance premium is calculated for six stylized insurance market forms that are representable for European countries. These market forms range from fully voluntary risk-based insurance to a solidarity structure with mandatory uptake and a public-private partnership market form. The market forms differ in the extent to which premiums are risk-based, whether or not insurance is mandatory, and what reinsurance mechanisms are in place.

All market structures make use of a deductible of 15%, based on Paudel et al. (2013). Furthermore, it is assumed that 99.8% of the damages are insurable, following Paudel et al. (2015).

For the solidarity structure, the risk per NUTS3 region is divided by the number of households in the respective NUTS3 region. This average risk is aggregated on a national level. The solidarity premium is calculated by taking the mean of the average risk of all NUTS3 regions.

The voluntary and semi-voluntary market structures are fully risk-based, meaning that the premium reflects the risk. Therefore, the EAD calculated in module 1 divided by the number of households exposed to flooding, serves as the basis for the voluntary premium market form. On top of this EAD, the premium has a primary insurer loading factor and a reinsurance loading factor. For the primary insurance loading factor, Bertrand competition is assumed, meaning that there is no profit-loading. However, a cost-loading factor is used on a country-level based on OECD insurance statistics (Hudson et al. 2019). For private reinsurers, a cost-loading factor is fixed at 0.5.

The public-private partnership makes use of risk-based premiums up to a certain extent. The premiums are capped at 1.8% of median income per region, following Hudson et al. (2019), to increase affordability. If in a region the fully risk-based premium exceeds the 1.8% median income cap, the capped premium is charged, otherwise the fully risk-based premium is charged.

The market structures for businesses are divided into risk-based and solidarity, which is consistent with the current situation in Europe. The premium-setting rules for these insurance structures are computationally similar to the household structures.

Module 3: policyholder behavior

Module 3 simulates the demand for flood insurance, which allows an analysis of the insurance penetration rate and the level of insurance unaffordability.

For households, the behavior module is centered around a subjective expected utility framework, where each actor makes a decision by comparing the expected utility of insuring with the expected utility of not insuring in a way which accounts for risk-misperception and affordability. An actor purchases insurance if the expected utility of insuring is higher than the expected utility of not insuring. The framework for households is illustrated in the following formula:

$$U = \begin{cases} insure & if \quad E(U)_{1,i,j,t,s} < E(U)_{2,i,j,t,s} \quad s.t.\ \pi_{i,j,t,s} \leq Income_{i,j,t} - Poverty\ Line_{c,t} \\ not\ insure & if \quad E(U)_{1,i,j,t,s} \geq E(U)_{2,i,j,t,s} \quad or \quad \pi_{i,j,t,s} > Income_{i,j,t} - Poverty\ Line_{c,t} \end{cases} \tag{1}$$

The modeled decision process of purchasing insurance for a household is illustrated in formula (1), with i being household, j being region, t is the time period, s indicates the market structure and c indicates the country. A household will insure against flood risk if its expected utility of insuring $(E(U)_{2,i,j,t,s})$ is greater than not insuring $(E(U)_{1,i,j,t,s})$, as long as the premium $(\pi_{i,j,t,s})$ is equal to or smaller than the poverty adjusted income $(Income_{i,j,t})$ minus the national poverty line $(Poverty\ Line_{c,t})$, which is set at 60% of median income. If this is not the case, the household will not insure.
The expected utility of insuring $E(U_{2,i,j,t,s})$ and not insuring $E(U_{1,i,j,t,s})\}$ for household i is determined following equation (2). The expected utility function shows a logarithmic relationship, which is often used to depict risk averse behavior (Wakker, 2008). The expected utility is calculated over income $(W_{i,j,t})$ subtracted by the subjective risk of flood damage $(\gamma_{i,j}L_{i,j,t}(p))$, where $(\gamma_{i,j})$ represents a flood risk misperception parameter, which is randomly drawn from a distribution that is based on survey data. For more details on this procedure, we refer to Hudson et al. (2019). The expected utility of insuring is calculated over the income $(W_{i,j,t})$ minus the deductible in case of flood damage $(0.15\gamma_{i,j}L_{i,j,t}(p))$ and subtracted by the insurance premium $(\pi_{i,j,t,s})$.

$$E(U) = \begin{cases} E(U_{1,i,j,t,s}) = \int_0^{p=\widehat{PS}_{i,j}} p ln\left(W_{i,j,t} - \gamma_{i,j}L_{i,j,t}(p)\right) dp \\ E(U_{2,i,j,t,s}) = \int_0^{p=\widehat{PS}_{i,j}} p ln(W_{i,j,t} - 0.15\gamma_{i,j}L_{i,j,t}(p) - \pi_{i,j,t,s}) dp \end{cases} \quad \textbf{(2)}$$

Business-level uptake

For businesses, the insurance uptake module is based on a subjective-cost benefit analysis on a company level (Figure 24). First of all, each business is assigned a balance sheet which is used to calculate three financial ratios that give an indicator of the business' financial health: the current ratio, debt-equity ratio, and working capital ratio. If these ratios fail, the company is deemed financially unfit to purchase an insurance policy or to invest in adaptation measures.
After the initial affordability check, the business-level uptake simulation follows three stages: the initial adaptation decision, the insurance decision, and the incentivized adaptation decision (if applicable).
This way, module 3 can also be used to analyze adaptation effort and the effect of incentivizing adaptation via premium discounts. This is done by offering insured companies a discount on the insurance premium if an investment in adaptation is made. The adaptation measure is assumed to cost €37 per square meter and a lifespan of 75 years following (Aerts 2018; Kreibich et al. 2011), and is assumed to reduce the EAD by 35% (Aerts et al. 2013; Kreibich et al. 2015).
Stage 1: Initial adaptation decision

$$Subjective\ benefit\ adaptation - cost\_adaptation = \sum_{t=1}^{75} \frac{\left((1-\epsilon) * \bar{L}\right) * X_1}{(1+r)^t} - I \quad \textbf{(3)}$$

Where ϵ is the adaptation effectiveness, $\bar{L}$ is the EAD, r is the discount rate, X_1 is the benefit misperception factor for stage 1, and I is the adaptation investment cost
Stage 2a: insurance decision (if chosen adaptation in stage 1)

$$Subjective\ benefit\ insurance = \left((1-D) * \bar{L}\right) * X_2 \quad \textbf{(4)}$$

$$Cost\ insurance = \pi \quad \textbf{(5)}$$

Where D is the deductible, X_2 is the benefit misperception factor for stage 2a, and π is the premium.
Stage 2b: insurance decision (if chosen no adaptation in stage 1)

$$Subjective\ benefit\ insurance = \left((1-D) * \left(\epsilon * \bar{L}\right)\right) * X_3 \quad \textbf{(6)}$$

$$Cost\ insurance = \pi \quad \textbf{(7)}$$

Where X_3 is the benefit misperception factor for stage 3a.
Stage 3: subsequent adaptation decision (if chosen no adaptation in stage 1 and chosen insurance in stage 2b)

$$Subjective\ benefit\ adaptation = \sum_{t=1}^{75} \frac{((1-\epsilon) * (D * \bar{L}) * X_1) + ((1-\iota) * \pi)}{(1+r)^t} \quad \textbf{(8)}$$

Where ι is the insurance discount.

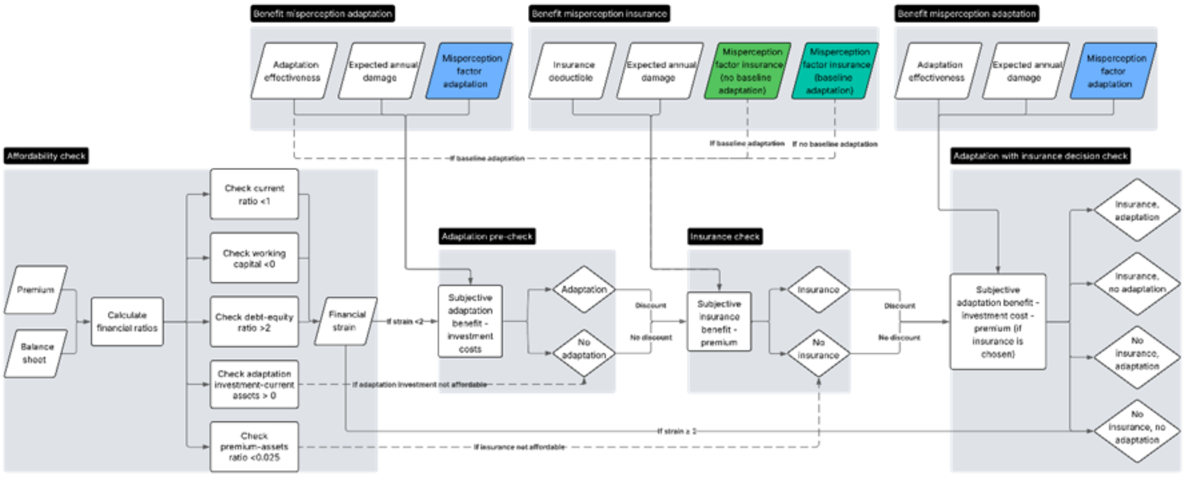

Figure 24: Business-insurance uptake schematic DIFI model.

Figure 24 shows the business-insurance uptake schematic in the DIFI model. It is first checked whether the investment in either adaptation or insurance is viable based on the company's simulated balance sheet. If the investment is viable, it is checked whether an investment in adaptation is (subjectively) cost-effective. Next, it is checked whether an insurance policy is (subjectively) cost-effective given the decision to invest in adaptation or not. If an insurance incentive is applied and the company has not invested in adaptation in the first stage, the third stage is activated in which it is checked whether the insurance incentive makes the adaptation investment (subjectively) cost-effective. Each company has a benefit misperception factor drawn from a gamma distribution that is calibrated on survey data.

Output

Using the DIFI model, several insurance related markers can be obtained. Using the EAD, insurance premiums for various insurance market forms can be calculated, as well as how these insurance premiums develop over time under different climate change and socioeconomic development scenarios. The insurance premiums are used to estimate the insurance penetration rate on a NUTS3 level, allowing to analyse which NUTS3 regions have a higher coverage gap. Furthermore, applying different insurance market structures reveals how varying insurance premiums influence insurance uptake and, consequently, the coverage gap.

7.7 CFR - Climate Financial Risk model

In line with the objectives of Task 4.3, the UNIVE team has been working on estimating the impact of climate-related extreme events on EU financial institutions' portfolios, using data and scenarios that are consistent with those used throughout ACCREU activities.

In particular, this work aims to provide insights that can be relevant for EU financial authorities in order to inform the debate on climate adaptation finance. We make use of the class of models called Climate Financial Risk models (CFR), building specifically on CLIMACRED-PHYS by Mandel et al. (2025). CLIMACRED-PHYS is a reference model in the field of climate-related risk. Indeed it has been selected by the international platform of financial authorities of the Network for Greening the Financial Sector (NGFS) to be used to develop the NGFS Short Term Scenarios[4] released in 2025. This model can be used also to study climate financial risk on a longer time horizon. It is well-suited for the purpose of Task 4.3 because: 1) it belongs to the class of *structural models of credit risk*, which is the one used by finance practitioners and authorities; 2) it provides in output metrics that are directly relevant for financial risk management and regulation (such as default probability of individual firms and Value-at-Risk at the portfolio level); 3) it is specifically designed to incorporate climate extremes in terms of Return Periods and not just expected annual impacts.

In the context of financial risk management, assessing financial risk requires to characterize the tail of the distribution of losses and not just the average loss. In particular, the notion of Value-at-Risk (VaR), used in banking and insurance, is the financial equivalent (under some technical but mild assumptions) of Return Periods magnitude in the context of climate impact extremes. For instance, a VaR at the 99th percentile confidence level is equivalent to a loss with Return Period 100. For this reason, in order to provide results that are relevant for the intended audience of finance practitioners, we need to go beyond the analysis of Expected Annual Impacts and focus on a range of Return Periods.

Accordingly, in this task, we extend the CLIMACRED-PHYS model in order to incorporate the climate scenarios and adaptation levels used in ACCREU.

The CLIMACRED-PHYS model takes in input data on projections of climate impacts, depending on the selected RCP scenario and data on geolocalized economic activities to estimate the economic losses for the firm and from that derive the losses on the financial instruments related to the firm (e.g. loans, bonds, equity). The CLIMACRED-PHYS model is designed in particular for analysing the impact of hazards in the tail of the distribution of magnitudes (tail risk). The application of the model involves four steps. The steps are summarised here, while more detailed are provided further below for the first three.

Step 1. Construction of climate risk maps. Geospatial matrices of Return Periods (5, 10, 25, 50, 100, 200, 250, 1000) for a given hazard and time horizon, are computed from trajectories over time of climate variables. <u>This step is aligned within ACCREU as follows</u>.

- Climate variables are obtained from the same set of models (ISIMIP3) used by ACCREU partners, under two of the three climate scenarios adopted by ACCREU, i.e. RCP2.6 and RCP7.0, using 2050 as time horizon.

- In particular, for riverine flood, the water depth data comes from the same set of runoff hydrological models that feeds the model GLOFRIS used in ACCREU by the partners Deltares and VU.
- For coastal flood, we use data from the same set of physical models (i.e. combination of hydraulic models and flood protection standards that feeds the model DIVA used in ACCREU by the partner GCF.
- Moreover, in one case study application, we will use the set of dike-breaching scenarios for NL produced in WP2 by the partner Deltares in order to estimate the financial impacts on

[4] NGFS Short Term scenarios, https://www.ngfs.net/en/publications-and-statistics/publications/ngfs-short-term-climate-scenarios-central-banks-and-supervisors

selected EU investors having assets in the NL with the transmission channels and their function for adaptation levels.

Step 2. Cross-matching climate impacts with firms' economic activities.
We cross-match the geolocation of firms' production units with climate risk maps from Step 1. In order to attribute production units to firms and eventually to financial securities, datasets are reconciled with a database of firms and parent companies using text mining techniques.

Step 3. Computation of firms' economic losses. We consider three transmission channels from climate related hazards to economic losses: capital loss, output loss and labour productivity loss. This is the step in which ACCREU adaptation levels are incorporated.

Step 4. Computation of financial losses.
Using the financial valuation model, CLIMACRED-PHYS, we carry out the financial valuation of securities having firms as issuers or counterparties, under each scenario. To assess the effect of climate change, we compute the relative difference with respect to the case of absence of climate impacts.

Final output and relevance. The results of this work are estimates of financial impacts on a portfolio of interest, depending on hazard, time horizon and RCP scenario. This analysis enables investors and financial authorities to address several relevant question, including: whether a given financial portfolio can withstand a scenarios of climate impacts, what is the effect of adaptation on financial losses

Further details the workflow steps

Step 1. Construction of climate risk maps.

In this step, geospatial matrices of return periods for a given hazard and time horizon are gathered from ISIMIP3 when available, or computed using ISIMIP3 trajectories of climate variables. In particular we use GCM trajectories for future projections and reanalysis data for historical trajectories. This step is aligned within ACCREU as follows.

We focus on two of the three climate scenarios adopted by ACCREU: RCP 2.6 and RCP 7.0, under the socio-economic pathway SSP2, and on the time horizon of 2050 in line with the scenario selection used in ACCREU (see Section 2.1).

Climate variables come from the same set of models (ISIMIP3) used by ACCREU partners, as described more in detail below. In particular, task T4.3, the UNIVE team uses risk maps computed or gathered from ISIMIP3 data for the hazards: floods (riverine and coastal), heatwaves and droughts.

Riverine floods.
The water depth data comes from the same set of runoff hydrological models (e.g. PCR-GLOBWB) that feeds the model GLOFRIS used in ACCREU by the partners Deltares and VU. The data are used, for the same scenarios, and return periods as input to compute economic losses and then financial losses.

Coastal floods.

We use data from the same set of physical models (i.e. combination of hydraulic models and flood protection standards that feeds the model DIVA used in ACCREU by the partner GCF. Data of coastal floods are expressed in maximum depth of water per year, for a given scenario. ISIMIP3b data already takes into account flood protection level (such as dykes or nature based solutions) to limit the water damages, based on the FLOPROS model.

Application to dike-breaching scenarios.
In this case study we apply our model to a selection of scenarios of dike-breaching events prepared by Deltares. Maps of flood risk in the Netherlands have been produced by LIWO (the Dutch national service for flood and inundation). Based on a further downscaling with the SSM model, Deltares has selected 32 dykes and the related flooded areas together with their riskiness expressed as return periods. We aim to illustrate the added value of this type of extreme scenarios for financial risk assessment. By using a geolocalized database of production units in the Netherlands, we will assess the impact of these extreme events on financial investors exposed to these economic activities (see more, in details for Step 3).

Heatwaves.
Heatwaves data are obtained from ISIMIP3 and processed as follows. Time series of temperature (daily max) and humidity are combined in a measure known as Web Bulb Temperature, an index that takes into account the effects of moisture on the ability of the human body to exchange heat with evaporation, a process that depends also on the water content of the atmosphere. The impact on productivity, which is linear within an interval between 25 and 39.5°, in moist conditions, is applied to outdoor production labour activities and does not take into account the usage of Air Conditioning.

Droughts.
Following an established approach, we use a combination of data on precipitation and temperature. Higher temperatures accelerate the effects of droughts. An index of evapotranspiration known as SPEI (Standardized Precipitation Evapotranspiration Index) is calculated for accumulation periods of potential moisture deficit from 1 to 18 months, with a monthly frequency allowing for the analysis of different drought durations. Usually a deficit over 12 months is considered valid to describe yearly impact, and to get the “fraction of months” where moisture level, and water deficit is below the value of -2 (drought condition). We focus on the fraction of months in the year with drought conditions (available for the series 2040–2079 and 2060–2099 with scenarios 2.6, 7.0), defined in the domain [0-1]. We use a Beta distribution to fit the empirical data and from that we obtain the set of desired return periods by computing the corresponding quantiles of the fitted distribution.

Step 2. Cross-matching climate impacts with firms’ economic activities.
In the second step, risk maps of climate impacts expressed in terms of Return Period magnitude (e.g. one-in-100 year event) are cross-matched with the location of economic activities of firms.

We focus on the following economic sectors: *agriculture, manufacturing* and *commercial services*. These are the sectors for which data on economic activities of firms is available to us from public and commercial data providers. We do not consider:

- real estate: this would require to cross match climate impacts with granular data on the location and value of real estate assets, which we do not have at the EU scale.
- health: health services (private or public) are impacted primarily indirectly by climate-related hazards and these indirect impacts are outside the scope of our model.

Given a portfolio of financial securities we identify the firms that are counterparties of each security based on the ISIN code of the security. For instance, for an equity instrument (stock) we identify the firm issuing the stock. For each firm we have gathered data on the geolocation of its production units within the jurisdiction of EU27. If we do not have data on production units, we use its NACE sector of economic activity and its country of incorporation.

Each production unit of a firm is assigned a RP magnitude for each hazard, time horizon and RP. For instance, for a unit located in position x, the cross-matching results in the following association.

Firm	Production unit location	Hazard	Time horizon	RP100 magnitude
Firm1	x1	riverine flood	2050	0.7 meters
Firm1	x2	riverine flood	2050	0.4 meters

Table 25. Example of association of RP magnitude to the locations of production units of a firm.

When geolocalised data of production units is not available, then construct a synthetic representation of the firm in which for each grid cell of the geographical map of the country of incorporation we assign a weight based on the local GDP intensity and an RP magnitude based on the centroid of the cell. In this case, downscaled GDP data at 0.25°x 0.25° granularity is used from Wang and Sun (2022) to estimate the distribution of exposed economic capital within countries. The geographical distribution is assumed to be the same across sectors.

In the case of floods, realisations of flood events are generated at the country scale assuming full correlation below grid-cell granularity (0.25°x 0.25°, i.e. approximately 25x 25km2 at the equator) and independence across cells. This is a first-order approximation that neglects correlation beyond the grid scale and can thus potentially underestimate impacts.

Step 3. Computation of firms' economic losses.

Economic impacts are modelled via three transmission channels:

- **Capital loss:** represents the share of fixed capital destroyed per sector and country.
- **Output loss**: represents the share of yearly production lost due to business interruptions following the destruction of capital.
- **Labour productivity loss:** represents the yearly reduction in supply of productive labour units.

Levels of impact as a function of the hazard magnitude are obtained via hazard-specific and where possible sector-specific vulnerability functions. The following table illustrates which hazards trigger each transmission channels

Transmission channel	**Channel description**	**Relevant sector and hazard type**
Capital loss	Direct biophysical impacts on physical assets including **buildings, production plants, machines, and logistics**.	Manufacturing (impact of flood on equipment)

Output loss	Loss of production volume resulting from **downtime or operational interruption days** due to a hazard event. It focuses on the time needed to restore operations after asset damage.	Manufacturing and services (impact of flood on business interruption); Agriculture (impact of flood on harvest)
Labour productivity loss	Losses in output per worker caused by exposure to hazards like heatwaves or floods. It is estimated using **vulnerability curves** linking hazard intensity (e.g., WBGT) to productivity declines.	Manufacturing, services and agriculture (impact of heatwaves on outdoor work)

Table 26. Description transmission channels triggered by various hazards

The following list provides some details on each transmission channel by hazard and sector.

- **Capital loss from flood**: country-sector specific damage functions are used from the widely used reference of the JRC review by Huizinga et al. (2017), used also by ACCREU partner VU in the DIFI model.
- **Output loss from floods on manufacturing and services**: we proxy this quantity as the fraction of days of the year for which business has been interrupted for each production facility. In turn, this is estimated from the variable $nd_{country,sector}$ representing the fraction of days of the year of business interruption following the complete destruction of the capital stock of a productive facility in a given sector and country. These coefficients are obtained from the Federal Emergency Management Agency (FEMA 2013). We assume that interruption for partial destruction increases proportionally, i.e. that the fraction of business interruption days over one year at one facility is proportional to the product of the share of capital loss times the fraction of business interruption days over one year in case of complete capital loss at the facility.
- **Output loss from floods on agriculture**: we follow the estimates provided in Brémond et al. (2013).
- **Labour productivity loss**: we infer location-specific trajectories for labour productivity with a daily resolution following the approach of Dasgupta et al. (2021). In detail, we build on the parametric relation established in Stull (2011) to derive wet bulb globe temperature (WBGT) from ISIMIP data on daily maximum temperature and mean relative humidity. We then use the linear approximation proposed in Dasgupta et al. (2021) for the effect of WBGT on labour productivity assuming a linear decrease between 25.0° and 39.5°. We further assume, following Kjellstrom (2014), that WBGT is increased by 3° for outdoor activities in the sun. To obtain consistent measures of vulnerability, we transform linearly productivity losses in business-day interruptions. Overall, this approach is consistent with the WITCH model that explicitly accounts for the impact of increasing temperature on labour productivity. Differently from WITCH, we do not model the effect of AC cooling as we focus on outdoor labour activities.

Impact Category	Metric	RCP 2.6, 2020	RCP 7.0, 2050
Loss on Fixed Capital	Productive Capital Destroyed (% per year)	**Mean:** 1.90% **RP100:** 3.34%	**Mean:** 2.22% **RP100**: 3.80%

Loss of Production & Labour Productivity	Business Interruption (Days per year)	**Mean:** 2.68 days **RP100:** 4.89 days	**Mean:** 3.27 days **RP100:** 5.43 days

Table 27 Example estimate of economic impacts obtained in Step 3.

Integrating ACCREU adaptation levels into Step 3

In line with the adaptation settings adopted by ACCREU (see D4.1 Table 2), we introduce in the model two adaptation levels.

- **Low adaptation.** Adaptation efforts are proportional but only reactive: protection strength is raised ex-post in response to the maximum level of hazards observed previously.
- **High adaptation.** Adaptation efforts raise the protection strength so as to withstand future hazards up to a given equivalent level of RP magnitude. Consider for example a protection, in a given location, designed to withstand flood events with magnitude RP100. In this setting, the protection strength is raised so that it can withstand an RP100 magnitude in 2050. However, a hazard of magnitude larger than the protection level (e.g. RP200) comes with larger effects compared to the RP200 of today.

We integrate these levels of adaptation by means of adjusting the damage functions
Where possible we integrated the work of other ACCREU partners by using the adaptation functions they use while rescaling the damages by factors or formulas[5].

Application to the ACCREU set of dike-breaches scenarios under several RCP-SSP paths.
This case study application will make use of data and models produced by ACCREU partners as follows. We will adapt the model to conduct an analysis of the financial impact of the set of flood extreme events for the Netherlands based on WP2 output. In D2.5, DELTARES has elaborated a set of 32 dike-breaches scenarios, representing large impact flood events, illustrated in D2.5, Figure 3. We will proceed as follows.

1. The output data from WP2 includes the flooded area and estimates of the impact on capital, considered valid until 2050.
2. We focus the analysis on a set of firms operating in NL. We collect information on the firms' economic activities located in each flooded area and we compute the capital loss taking into account the adaptation level.
3. We apply the CLIMACRED-PHYS model on the set of firms to estimate the loss on financial valuation of the firms that have economic activities in those areas.

Where data on geolocalised production facilities of firms is not available, we resort to applying our model to representative firms with activities in the regions, as estimated on the basis of the NUTS3 downscaled Gross-Value-Added, in line with what is done by other ACCREU partners.

8. Lessons learnt

ACCREU brings together a diverse group of modeling approaches with the common goal of providing a coherent assessment of climate change impacts, adaptation costs and effectiveness, to

[5] For instance, in the DIVA model, the adaptation function EAD_avoided=L(1-e^(-βAC)) (a saturation exponential) helps mitigate the impact of the sea level rise at various scenario levels.

be used in aggregate economic models within ACCREU, but also in applications outside of the project. A key lesson learnt in the process of preparing WP2 data for WP3 and WP4 applications is the need for early and continuous alignment. This refers in particular to the formats data are provided in, as well as units. It is essential that there is a dedicated and diligent plausibility check of results conducted by sectoral modelers before providing results data to macroeconomic modelers.
Especially when detailed, process-based models are involved, the exchange process needs to start as soon as possible, and sufficient time needs to be allocated to these types of interface tasks. Possibly, a mock dataset should be tested to identify mismatches and harmonization challenges earlier and avoid delays in data provision for subsequent modeling steps. ACCREU managed the process through a combination of monthly group calls of the modeling teams and detailed bilateral exchanges, which was much more time intensive than anticipated.
ACCREU also faced the challenge to integrate results from different impact modeling approaches, for example in the case of sea level rise with multiple process-based models (e.g. DIVA and GLOBIOM); in the case of flood and energy with different methodological approaches, bottom-up (DIFI, energy system models) versus econometrics (PIK, D2.5, CMCC, D2.2); in the case of labour productivity with models using different definitions of labour. In some cases, the availability of multiple methods and models could be used to characterize some degree of modeling uncertainty since models take different approaches to address a similar question, e.g. the different treatment of adaptation investment between GLOFRIS and DIVA. In some other cases, models complement one another (e.g. energy).
As discussed in Section 5, the use of optimizing models to assess adaptation costs results in outcomes difficult to align with the need for an adaptation cost function. Aggregation across different types resulted in a loss of detail. The functions provided here should always be seen in this context.
ACCREU strives to include impacts and adaptation in the health and biodiversity sectors in the macroeconomic assessment. This continues to prove challenging especially regarding the quantification of adaptation effectiveness. Quite some advances were made on the impact side, for example on labor, mortality and morbidity from a range of sources, pollination and wetland services. However, those are only available for Europe and therefore cannot be part of the global damage damage function. In the CGE-specific analyses ICES and COIN-INT are including mortality and morbidity impacts as well as related health expenditures costs and cost and benefits of AC to reduce health impact. They account for the channel of biodiversity loss affecting pollination and agricultural yield and the preservation costs. In addition, impacts and adaptation benefits that cannot be implemented directly into the modelling framework will be considered in the ex-post analysis of the COIN-INT model in a consistent scenario framework. Thereby the economic indicator of welfare provides a broader measure for the impact assessment. This certainly remains an important area for future research.

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