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Multi-Dimensional Climate Change Impacts on Human Well-Being Under Past and Future Uncertainty

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Abstract

This thesis investigates the impacts of climate change on human well-being and economic systems through a multidimensional and uncertainty-aware framework. In contrast to most of the literature focusing on aggregate income effects from mean temperature, this thesis argues that such approaches underestimate the true costs of climate damages by neglecting broader dimensions of human development and the complex dynamics of climate variability, extremes and hazards.

The thesis advances the empirical literature in three key directions, which compose its chapters. First, it demonstrates that climate change significantly affects all components of human development, notably income, health, and education, revealing substantial and more widespread impacts than those identified by GDP-based assessments alone. Second, it highlights persistent and long-lasting consequences of climate overshoot for regional economic systems and human welfare. Third, it advances the literature on long-lasting climate hazards by providing a dynamical assessment of drought's effects on regional economies in Europe. Across all studies, it incorporates multiple layers of uncertainty, including socio-economic pathways and climate variability, to provide a comprehensive and policy-relevant assessment of future risks.

The findings indicate that a significant share of projected global human development gains may be eroded under unabated climate change, with adverse impacts observed across nearly all regions. If the global mean temperature were to overshoot and return to 1.5 or 2 degrees above preindustrial levels, only part of the lost development would be recovered. Finally, accounting for the dynamical and cumulative effects of multi-year events, such as droughts, highlights the risks of approaching 2 degrees of warming. For instance, in Europe, recent events could double their average impact.

By integrating multidimensional welfare metrics, extreme-event dynamics, and uncertainty analysis, this thesis contributes to a more complete and temporally realistic accounting of climate impacts. The results underscore the importance of moving beyond income- and mean-temperature-centric evaluations and provide a stronger empirical basis for climate policy aimed at safeguarding human development in a changing climate.

Keywords: climate change; human development; multidimensional impacts; climate extremes; climate hazards; future uncertainty

Abstract in Italiano

Questa tesi analizza gli impatti del cambiamento climatico sul benessere umano e sui sistemi economici attraverso un approccio multidimensionale, dinamico e attento all'incertezza. Mentre gran parte della letteratura esistente si concentra sugli effetti aggregati sul reddito, questo lavoro sostiene che tali approcci sottostimano la reale portata dei danni climatici, trascurando dimensioni più ampie dello sviluppo umano, le dinamiche persistenti e cumulative degli eventi estremi e l'incertezza che caratterizza sia le traiettorie climatiche sia le risposte socioeconomiche future.

In tre capitoli empirici, la tesi contribuisce alla letteratura in tre direzioni principali. In primo luogo, dimostra che il cambiamento climatico influisce in modo significativo su tutte le componenti dello sviluppo umano, ossia reddito, salute e istruzione, evidenziando, attraverso diverse proiezioni, danni sostanziali e più diffusi rispetto a quelli individuati dalle sole valutazioni basate sul PIL. Successivamente, mette in luce gli effetti persistenti e cumulativi dell'overshoot climatico, mostrando come possa generare conseguenze durature sui sistemi economici regionali e sul benessere umano. In terzo luogo, avanza la letteratura sui rischi climatici a lungo termine, con uno studio sugli effetti dinamici della siccità in Europa, trattata come un processo pluriennale e cumulativo. Un elemento trasversale dell'intera tesi è l'integrazione esplicita e sistematica di molteplici fonti di incertezza. In tutti i capitoli, le proiezioni e le stime vengono accompagnate da una decomposizione dell'incertezza legata ai modelli climatici, ai percorsi socioeconomici e alle stime empiriche, al fine di identificare quali risultati rimangano robusti rispetto a ipotesi, scenari e metodologie alternative. Questo approccio consente di fornire una valutazione più trasparente e rilevante sui rischi climatici futuri per le politiche pubbliche.

I risultati indicano che una quota significativa dei progressi previsti nello sviluppo umano a livello globale potrebbe essere compromessa in scenari ad emissioni elevate, con impatti negativi osservabili in quasi tutte le regioni. Se la temperatura media globale dovesse temporaneamente superare e poi tornare a livelli di 1,5 o 2 gradi sopra quelli preindustriali, solo una parte dello sviluppo perduto potrebbe essere recuperata. Infine, considerando gli effetti dinamici e cumulativi di eventi pluriennali, come le siccità, emerge il rischio concreto associato al raggiungimento dei 2 gradi, poiché eventi simili a quelli attuali potrebbero raddoppiare il loro impatto medio considerando la sola Europa.

Integrando indicatori multidimensionali di benessere, dinamiche degli eventi estremi e un'analisi esplicita dell'incertezza, questa tesi contribuisce a una valutazione più completa e realistica nel tempo degli impatti climatici. I risultati sottolineano l'importanza di superare le valutazioni

incentrate esclusivamente sul reddito e sulla temperatura media, fornendo una base empirica più solida per politiche climatiche volte a salvaguardare lo sviluppo umano in un contesto di cambiamento climatico.

Parole chiave: cambiamento climatico; sviluppo umano; impatti multidimensionali; estremi climatici; rischi climatici; incertezza futura

Summary

Climate change affects a wide range of economic and social outcomes, yet most impact assessments have focused on GDP (Gross Domestic Product) as the main metric and mean annual temperature as the primary indicator of climate exposure. This thesis addresses three key limitations of this dominant approach: the narrow representation of welfare beyond income, the inadequate treatment of persistence and compounding dynamics associated with climate extremes, and the limited characterization of uncertainty across climatic, socio-economic, and statistical dimensions. Building on an expanding empirical literature that incorporates sub-national data, extreme events, and non-income welfare indicators, it develops an integrated framework centered on multidimensional welfare assessment, dynamic impact modeling, and explicit uncertainty decomposition.

A substantial body of research has documented robust links between rising temperatures and reductions in economic output, particularly in warm and lower-income regions. Seminal studies identified nonlinear effects of temperature on GDP growth, persistent impacts in vulnerable economies, and the disproportionate exposure of tropical and developing countries. More recent contributions have extended this literature by incorporating precipitation variability, temperature extremes, and spatial heterogeneity, while also questioning assumptions of rapid post-shock recovery. The estimates of the magnitudes of the economic impacts of climate change have risen, but so have their uncertainties and the possibility of major economic threats induced by climate. In parallel, a separate literature has examined climate impacts on health and education, highlighting channels such as heat-related mortality, declines in labor productivity, and disruptions to schooling caused by extreme weather events. However, these strands of research have largely evolved independently. Empirical studies integrating income, health, and education within a unified framework remain limited. Likewise, although uncertainty decomposition has increasingly been applied to GDP projections, its extension to multidimensional human development outcomes is still underdeveloped. Additional gaps concern treating slow-onset hazards, such as drought, as cumulative multi-year processes rather than independent annual shocks, and evaluating the welfare consequences associated with temperature overshoot pathways. Figure 1 schematically reports the open challenges, the data employed in the thesis, the methodological framework, and an overview of the three thesis chapters.

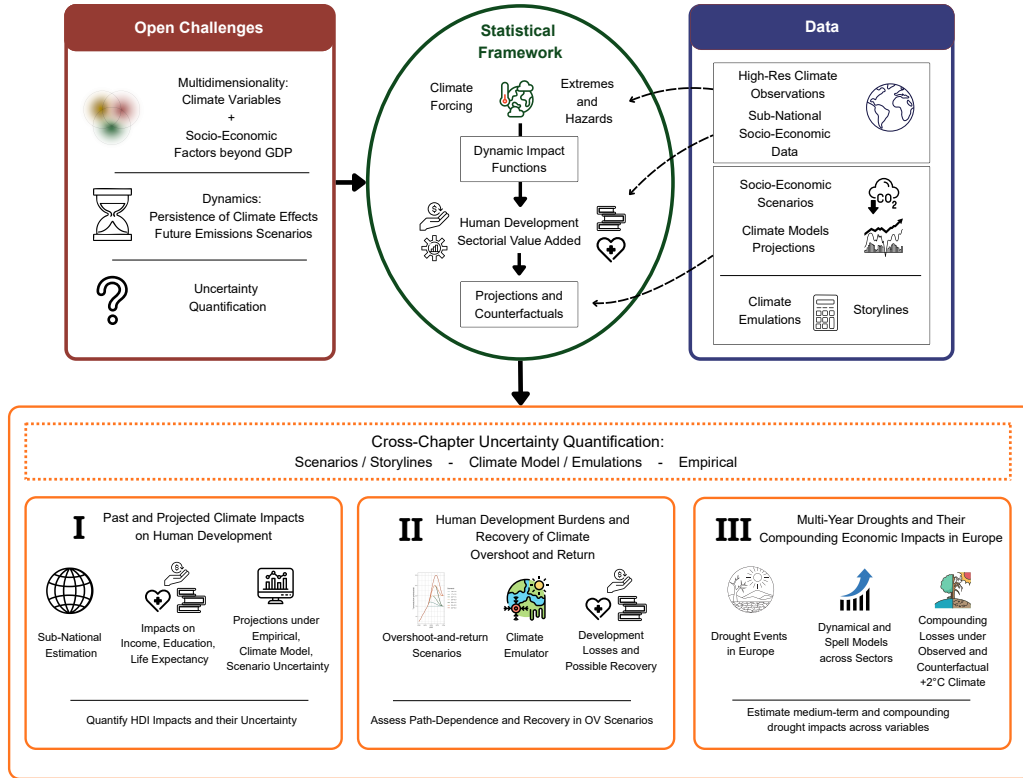


Figure 1: Thesis Pipeline. The red box (top left) outlines the main open challenges in the climate impact assessment literature. The blue box (top right) summarizes the datasets used throughout the thesis. The central green oval represents the statistical and empirical framework adopted in this work, spanning from the estimation of the impact function (first black box) to projections under alternative scenarios and counterfactual conditions (second black box). Together, these components form the basis of the three thesis chapters (orange box). Chapter 2 examines the effects of climate variables on Human Development Index components and projects their evolution under different emission and socio-economic scenarios. Chapter 3 investigates development recovery pathways in overshoot-and-return scenarios using climate emulations. Chapter 4 analyzes the local impacts of prolonged droughts on Gross Value Added components and assesses the implications of reaching +2°C warming above pre-industrial levels using a storyline approach. Across all chapters, uncertainty in statistical estimation, climate model outputs, and scenario design is explicitly addressed through formal decompositions and significance testing to ensure robust inference.

The first chapter contributes to this literature by providing a joint empirical assessment of climate impacts across all three dimensions of the Human Development Index—income, health, and education—within a self-contained framework. Instead of analyzing each outcome separately, the chapter identifies the distinct climatic channels and temporal scales through which mean climatic conditions and extreme events affect each dimension, and uses the estimated relationships to project future impacts under alternative climate and socio-economic scenarios. A central methodological contribution is the systematic decomposition of projection uncertainty across climate models, socio-economic pathways, and impact-function specifications, applied simultaneously to multiple dimensions of welfare.

The second chapter advances the literature on climate impact trajectories by developing a framework specifically designed to evaluate temperature overshoot-and-return pathways. Whereas most scenario-based assessments focus on outcomes at a particular future date or warming threshold, this chapter examines how the full temporal profile of warming shapes cumulative welfare losses, including both the magnitude and duration of overshoot above a target. To do so, it introduces a trajectory-sensitive climate emulator that preserves the temporal dynamics of overshoot scenarios and combines it with estimated impact functions to isolate the developmental burden associated with the pathway itself.

The third chapter contributes to the empirical literature on drought economics by conceptualizing drought as a slow-onset, multi-year hazard rather than a sequence of independent annual events. The chapter develops a dynamic estimation framework that captures how economic damages accumulate and compound across consecutive drought years, and complements this analysis with a climate storyline approach grounded in recent European drought events. In doing so, it advances the integration of econometric panel methods with physical climate attribution and extends the application of storyline techniques, traditionally used in the physical sciences, to the analysis of regional economic impacts.

The three chapters demonstrate that climate damages affect welfare beyond economic income alone when climate hazards are represented solely through annual averages and when temporal dynamics and path dependency are neglected. Across all chapters, the thesis systematically decomposes uncertainty into climatic, socio-economic, and empirical dimensions to identify which results remain robust across alternative assumptions, scenarios, and model specifications. The findings have direct implications for the allocation of adaptation finance, Loss and Damage negotiations, and regional hazard risk management. More broadly, the thesis points toward a new generation of climate impact research that integrates multidimensional welfare metrics, path-dependent scenario analysis, explicit uncertainty decomposition, and event-based climate storylines within a unified empirical framework.

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1 | Introduction

1.1. Motivation

Climate change is reshaping the conditions under which people live, work, and develop worldwide. Its consequences extend well beyond measurable economic losses: they include, among others, avoidable deaths and disruptions to children’s education during and after extreme events, or the erosion of productive capacity in regions with limited resources to adapt. These effects are already playing out, and their full extent remains poorly understood. The extent to which we quantify them shapes our ability to prevent and respond effectively, influencing which regions and populations receive adaptation support and whether the most exposed communities are adequately represented in the evidence base that informs policy.

The socio-economic and natural impacts of global warming have been widely studied (Carleton and Hsiang, 2016). Rising mean temperatures and consequently intensifying climate extremes alter the conditions under which societies sustain long-run improvements in living standards. These effects are uneven: they depend on different climate variables (Waidehlich et al., 2024), interact with existing socio-economic inequalities (Gilli et al., 2023), tend to concentrate among the most exposed and least protected populations (Burke et al., 2018), and unfold over timescales that extend beyond the immediate shock (Nath et al., 2024a). Capturing them adequately requires analytical frameworks that are correspondingly broad in scope, sensitive to dynamics and persistence, and explicit about multiple sources of uncertainty.

A substantial body of empirical literature has examined these questions using aggregate national GDP (Gross Domestic Product) as the primary welfare metric and mean annual temperature as the main measure of climate exposure. This work has established several robust patterns: higher temperatures are associated with decreased economic output, damages are concentrated in already warm and lower-income regions, and projected warming is expected to reduce global income relative to a counterfactual without climate change (Dell et al., 2012a; Burke et al., 2015; Moore and Diaz, 2015; Waidehlich et al., 2024; Howard and Sterner, 2025). At the same time, the magnitude and mechanisms of these losses remain uncertain, with estimates varying widely across empirical specifications, model assumptions, and adaptation representations (Diaz and Moore, 2017).

Recent work shows that mean temperature represents only one aspect of climate exposure. Incorporated sub-national data, precipitation, and measures of variability and extremes (Callahan

and Mankin, 2022a; Kotz et al., 2021, 2022a; Bellon et al., 2022b; Rising et al., 2022), consistently finding that analyses based on annual means alone understate damages relative to those accounting for short-term extremes and sustained anomalies (Waidelich et al., 2024; Estrada et al., 2025). Many of the most relevant mechanisms, including heatwaves, heavy precipitation episodes, and floods, operate through threshold exceedance and accumulation rather than shifts in long-run averages, plus their effects can be highly localized, with hundreds of billions in losses associated with individual events (European Environment Agency, 2024). Moreover, prolonged, complex hazards, such as drought, pose an additional challenge in identifying their potentially multifaceted effects. Higher spatial resolution further helps map these dynamics, as national averages tend to mask the concentrated exposure of sub-national regions.

Moreover, most studies still focus on single outcome variables, with relatively few integrating multiple dimensions of welfare within a unified empirical framework (Bressler et al., 2021; Prentice et al., 2024; Romanello et al., 2023). This remains a substantial limitation because the channels through which climate change affects human well-being extend far beyond what any single metric can capture. Gross Domestic Product (GDP) per capita, the dominant outcome measure in the empirical climate-economy literature, measures the market value of goods and services produced within an economy. Although it reflects many of the productivity channels through which climate influences economic activity, it only imperfectly captures welfare dimensions that respond to climate through partially independent and distinct mechanisms. For instance, investment may decline persistently in climate-exposed regions if elevated climate risk increases the cost of capital and discourages capital formation, potentially generating long-run reductions in productive capacity that are not fully reflected in contemporaneous output measures. Climate-induced displacement (Hauer et al., 2022) may generate persistent changes in labor allocation and demographic composition, implying welfare consequences that are only partially reflected in contemporaneous aggregate income statistics. At a more disaggregated level, the sectoral distribution of damages also matters: heterogeneous impacts across agriculture, manufacturing, construction, and services imply different degrees of persistence and recovery potential, yet these distinctions disappear in economy-wide aggregates (Fleming-Muñoz et al., 2023). Beyond these economic dimensions, non-market outcomes are often among the most directly affected by climate variability and extreme events (Hallegatte and Rozenberg, 2017; Menk et al., 2022). Life expectancy may deteriorate even as income rises (Carleton et al., 2022a). Climate-related disruptions to schooling accumulate into deficits in human capital that may appear in output statistics only after substantial delays, if at all (Goodman et al., 2018; Jacob, 2018). Mortality, morbidity, and educational attainment constitute independent dimensions of human welfare whose deterioration imposes persistent social costs regardless of their effects on measured output. A comprehensive assessment of climate damages, therefore, requires frameworks that are multidimensional in their outputs in two complementary respects: sufficiently broad to capture both market and non-market welfare outcomes, and sufficiently granular to identify heterogeneous responses across sectors. The Human Development Index (HDI; United Nations, 1990), developed by the United Nations Development Program, attempts to address the

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first requirement by combining income, life expectancy, and educational attainment into a theoretically grounded measure of welfare. In doing so, it operationalizes the capabilities approach to human development (Sen, 1999; Nussbaum, 2000) in a form that is empirically tractable and available at sub-national resolution through the Global Data Lab (Smits and Permanyer, 2019). Complementing this perspective, the analysis of sectoral and various macroeconomic outcomes addresses the second requirement by tracing the distributional and dynamic consequences of sustained climate shocks across regional economies. If the most severe impacts operate primarily through health, education, labor markets, and capital accumulation rather than aggregate output, GDP-based assessments will understate total welfare losses and misallocate their incidence across sectors, regions, and populations.

A related and equally important question concerns the persistence of climate damage over time. Impacts do not necessarily take the form of short-lived shocks followed by rapid recovery. Instead, extreme events can depress fiscal capacity, investment, and human capital accumulation for years beyond the initial shock (Bellon et al., 2022a; Huang and Dong, 2025; Jacob, 2018), while slow-onset hazards such as drought may generate cumulative losses that exceed the sum of independent annual shocks and propagate across sectors beyond those directly affected (Fleming-Muñoz et al., 2023; Kilimani et al., 2018). Whether climate shocks primarily affect output levels temporarily or growth trajectories persistently remains an open debate in the literature (Nath et al., 2024b; Moore and Diaz, 2015; Piontek et al., 2019; Kahn et al., 2021a), with important implications for how cumulative damage is measured and interpreted. This dynamic dimension enters the analysis at two distinct levels. At the level of empirical impact functions, a key question is whether the relationship between climate shocks and welfare outcomes is purely contemporaneous or unfolds over multiple years, and whether its magnitude and persistence vary across welfare dimensions and baseline climatic conditions. At the level of scenario trajectories, it is also important to consider whether warming levels alone are sufficient to characterize climate outcomes, or how much the pathway to those levels matters. If climate damages accumulate, persist, or trigger irreversible changes, scenarios converging on the same temperature target may nonetheless yield different welfare outcomes. In this case, exposure to higher temperatures during an overshoot period can leave lasting losses that are not fully reversed even after temperatures decline, making climate impacts path dependent rather than determined solely by the final warming level. If damages accumulate and persist, then two climate pathways that converge to the same end-of-century temperature may yield different welfare outcomes, as losses incurred during overshoot may only be partially reversible once temperatures decline (Schleussner et al., 2024; Schoengart et al., 2025).

A transversal layer of complexity is uncertainty. Future welfare outcomes depend not only on how much the planet warms but also on how societies develop, how adaptive capacity evolves, and how these forces interact. In many assessments, variation across socio-economic development scenarios is comparable to, or larger than, variation across climate models (Takakura et al., 2019), meaning that choices about which futures to consider matter as much as choices about which

physical climate to assume. Uncertainty in the empirical estimation of impact relationships adds a further layer. A comprehensive assessment must therefore be explicit not only about what damages are projected but about where that projection’s uncertainty comes from and which of its sources are most consequential for policy.

These considerations are not merely methodological. Each year without a clearer understanding of how climate change affects health, education, and long-term productive capacity is a year in which adaptation finance is allocated on the basis of incomplete evidence, Loss and Damage negotiations proceed without credible estimates of realized harm, and the populations most exposed to climate risk remain insufficiently reflected in the assessments meant to inform protection and response, even as climate impacts accumulate over time and contribute to growing disparities between more and less affected regions and populations.

Existing approaches still lack an integrated empirical framework capable of jointly estimating impacts across multiple dimensions of welfare, capturing a broad range of climate extremes, accounting for dynamic adjustment processes, and explicitly decomposing uncertainty arising from climate projections, socio-economic pathways, and impact-function specification.

In the three chapters, this thesis addresses these elements, providing a multidimensional, dynamic, and uncertainty-explicit assessment of climate impacts on human development and regional economic outcomes. It focuses, on the one hand, on how heat and wet extremes affect components of human development and, on the other, on how a complex, long-term hazard such as drought influences a range of regional economic outputs in Europe. A visual overview of the open challenges, empirical framework, and contributions is provided in Figure 1.1. As outlined above and summarised in the Figure’s red box (top left), we identify three interconnected gaps in the climate impacts literature: the limited dimensionality of commonly analyzed socio-economic and climate variables, the partial treatment of dynamic impacts and future trajectories, and the insufficient quantification of uncertainty. A detailed review of the relevant literature is provided in Section 1.2. To address these gaps, we develop a flexible statistical framework and construct dynamic impact functions for the three components of the Human Development Index, as well as for components of value added (green oval). The methodological framework is presented in Section 1.3. The estimation of the statistical impact functions combines subnational socio-economic data at both global and European scales with observed and reanalysis-based climate variables, including annual averages, heat and precipitation extremes, and drought indicators. We further explore future scenarios and counterfactual climate conditions using socio-economic projections, ensembles of climate model outputs, and an ad hoc emulator. These inputs are synthesized in the blue box (top right). Finally, the three chapters of the thesis are introduced in Section 1.4 and summarised in the orange box. A cross-cutting theme across the thesis’s chapters lies in its explicit treatment of uncertainty.

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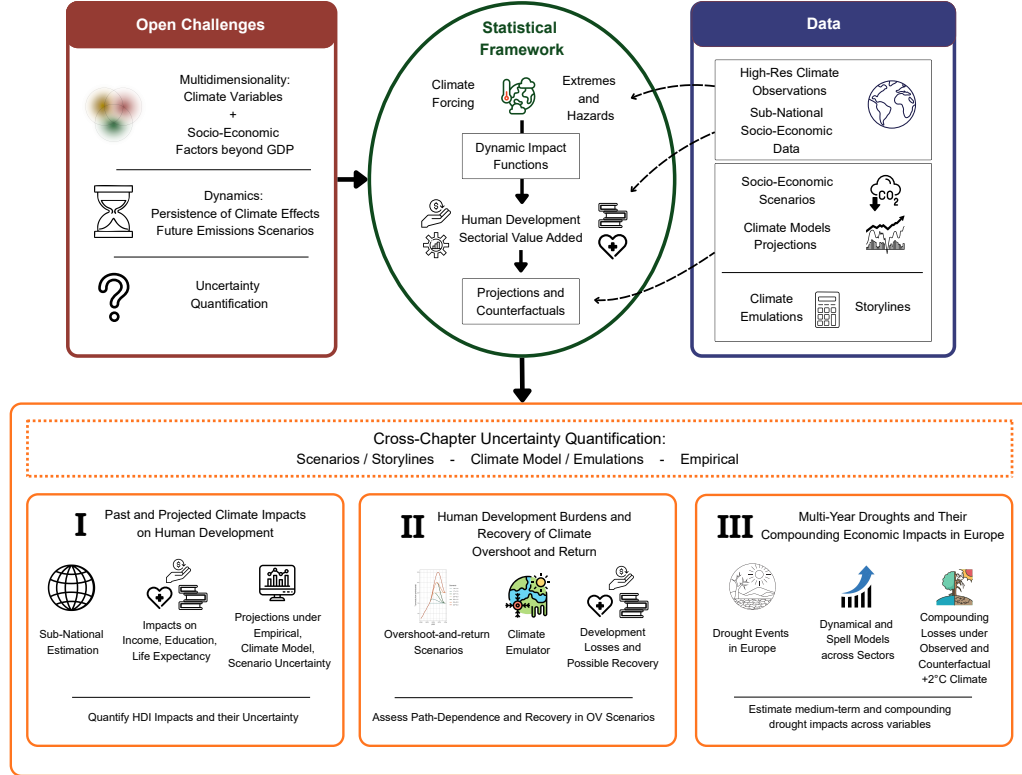


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1.2. Literature Background

1.2.1. Climate Impacts on Income, Health, and Education

Empirical research on climate impacts has expanded considerably over the past two decades, evolving from aggregate country-level analyses of the temperature-income relationship to a broader field encompassing health, education, migration, and multidimensional welfare at increasingly fine spatial scales. Several strands of this literature are directly relevant to the contributions of this thesis.

On the income side, Dell et al. (2012a) show that temperature shocks affect not only the level of economic output but also its growth rate, with potentially persistent long-run implications. Burke et al. (2015) estimate a non-linear relationship between GDP per capita and temperature across a global panel, finding an inverse-U-shaped response with damages concentrated in already warm, lower-income countries. Subsequent studies have extended this analysis to the sub-national level (Kalkuhl and Wenz, 2020), incorporated precipitation and rainfall variability (Kotz et al., 2022a; Damania et al., 2020), and shown that including temperature variability and rainfall metrics tends to increase estimated damages relative to specifications based on annual means alone (Kotz et al., 2021; Waidehlich et al., 2024). Overall, this literature points to economically significant, geographically heterogeneous climate damages, although the magnitude and persistence of these effects remain sensitive to specification choices and assumptions about adaptation, highlighting how empirical modeling decisions generate substantial uncertainty in policy-relevant damage estimates and shape the allocation of adaptation resources.

On the health side, the mortality consequences of extreme temperatures are among the most extensively studied climate impacts. A substantial share of global mortality is attributable to exposure to temperatures outside an optimal range, and future warming is projected to increase heat-related mortality, particularly in warmer and lower-income regions (Gasparrini et al., 2015, 2017a; Carleton et al., 2022a). Beyond direct temperature–mortality effects, climate change influences health through multiple additional channels. Extreme precipitation can increase the incidence of waterborne diseases, drought can generate food insecurity and nutritional stress with lasting developmental consequences and repeated exposure to climate extremes may contribute to chronic health burdens not fully captured by mortality statistics alone (Rocque et al., 2021b; Ebi et al., 2021). Aggregate indicators such as life expectancy could therefore be sensitive to a broad set of climate drivers.

On the education side, the empirical literature is less extensive but has grown rapidly in recent years. Evidence shows that exposure to extreme heat impairs cognitive performance and reduces exam outcomes (Goodman et al., 2018; Graff Zivin et al., 2018; Park et al., 2021). Climate-related disasters can disrupt schooling through infrastructure damage, school closures, and household income shocks, with disproportionately large effects on children from lower-income households (Jacob, 2018; Venegas Marin et al., 2024). These disruptions could translate into persistent human capital deficits with long-term consequences, although comprehensive global assessments remain limited (Prentice et al., 2024; Cappelli et al., 2021).

A consistent finding across these dimensions is that climate-related damage is unevenly distributed and tends to amplify existing inequalities. Impacts are generally found to be larger in lower-income and already warm regions with more limited adaptive capacity (Diffenbaugh and Burke, 2019; Hallegatte and Rozenberg, 2017). At finer spatial scales, sub-national regions most exposed to climate risks often combine higher physical vulnerability with lower incomes and weaker institutions, implying that aggregate country-level estimates may obscure substantial within-country heterogeneity (Kalkuhl and Wenz, 2020; Palagi et al., 2022; Gilli et al., 2023).

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1.2.2. Extremes, Persistence, and Multi-Year Hazards

A recurring theme in this literature is that annual mean temperature provides an incomplete summary of the climate conditions relevant for economic and social outcomes. Many transmission mechanisms involve threshold exceedance, short-term extremes, and sustained anomalies that are not well captured by annual averages. Studies incorporating temperature variability and extremes generally find larger damages than those based on mean temperature alone, particularly in regions frequently exposed to extreme conditions (Waidelich et al., 2024; Estrada et al., 2025).

A related and actively debated question is whether climate shocks generate temporary or persistent effects on economic output. This distinction is central: temporary effects imply recovery to a pre-shock growth path, whereas persistent growth-rate effects imply permanently diverging development trajectories and cumulative losses over time (Moore and Diaz, 2015; Piontek et al., 2019). Empirical evidence increasingly points to the possibility of persistent effects, including findings based on lower-frequency variation in temperature (Bastien-Olvera et al., 2022), long-lasting impacts of El Niño events (Callahan and Mankin, 2023b), and prolonged fiscal effects of extreme events (Bellon et al., 2022a). However, results remain sensitive to empirical design, and no consensus has fully emerged.

Among the different climate shocks, drought represents a distinct class of climate hazard characterized by slow onset, persistence, and multiple interacting transmission channels. Unlike short-lived shocks, drought affects economic activity through potentially prolonged reductions in water availability, agricultural productivity, hydropower generation, and ecosystem stability, with spillovers to food prices and trade (Fleming-Muñoz et al., 2023; Naumann et al., 2021). Its multi-year nature makes it particularly relevant for studying persistence and compounding effects, as standard approaches based on annual shocks may understate total economic impacts. While recent European droughts have highlighted the continent’s vulnerability (Pinke et al., 2024; European Commission. Joint Research Centre., 2020), the medium-term compounding dynamics of multi-year drought sequences remain insufficiently quantified.

1.2.3. Temperature Overshoot and socio-economic Reversibility

Temperature overshoot-and-return scenarios, in which global mean temperatures exceed a given warming target (e.g., 1.5°C or 2°C above pre-industrial levels) for several decades before gradually declining through emissions reductions and carbon removal, have become increasingly prominent in climate policy discussions as emissions trajectories diverge from Paris-consistent pathways (Reisinger et al., 2025; Intergovernmental Panel On Climate Change (IPCC), 2023). In these scenarios, societies experience a prolonged period of elevated temperatures before potentially returning below the target threshold later in the century. The welfare implications of such trajectories depend critically on the extent to which damages incurred during the overshoot period are reversible.

A central open question is whether socio-economic damages exhibit path dependence even if

underlying damage functions are symmetric. One mechanism through which this may arise is the temporal accumulation of welfare losses: populations exposed to elevated mortality, disrupted education, and reduced investment during peak warming may not recover these losses when temperatures decline, as affected cohorts can carry these deficits forward (Schoengart et al., 2025; Bauer et al., 2023; Kruczkiewicz et al., 2025). While this mechanism is increasingly discussed, its quantitative implications for multidimensional human development remain largely unexplored.

Schleussner et al. (2024) highlight that many policy frameworks implicitly assume reversibility of damages in overshoot scenarios, an assumption that is not strongly supported by existing evidence. To the best of our knowledge, no study has systematically quantified the joint implications of overshoot trajectories for income, health, and education.

1.2.4. Uncertainty in Projections and Scenario Frameworks

Climate impact projections are subject to multiple sources of uncertainty: the physical climate response to emissions, the trajectory of socio-economic development, and the empirical relationship between climate variables and welfare outcomes. Distinguishing these components is both analytically and policy relevant, as it informs where additional research and policy effort may yield the greatest reductions in uncertainty (Schwarzwald and Lenssen, 2022; Pretis et al., 2018).

Recent work suggests that socio-economic pathway uncertainty accounts for a substantial share of total projection variance, particularly at long time horizons. In many cases, variation across socio-economic pathways is comparable to, or even larger than, that across climate models (Takakura et al., 2019; Andrijevic et al., 2019). Impact function uncertainty also contributes significantly and may be particularly large for non-income outcomes where the empirical evidence base is more limited (Howard and Sterner, 2017; Morris et al., 2025). While variance decomposition approaches have been applied in climate impact assessment, they have not been extended to jointly evaluate uncertainty across multiple human development dimensions.

Alongside scenario-based projections, climate storyline methods offer a complementary approach to communicating uncertainty. Rather than estimating aggregate impacts across a range of possible futures, storylines use counterfactual reasoning to assess how specific observed events would have unfolded under alternative climate conditions (Callahan et al., 2026b; Grayson et al., 2026). By anchoring analysis to real-world events while varying the climatic background, this approach complements econometric frameworks and allows for more interpretable assessments of climate influence and risk. Chapter 4 applies this framework to recent European drought events to evaluate how their impacts would differ under a world reaching +2°C warming.

1.3. Methodological Framework

The empirical analysis developed in this thesis is organized around three central features of climate impacts we aim at capturing: their multidimensional nature, their temporal propagation,

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and their dependence on the trajectory of climate exposure over time.

As outlined above, climate damages affect multiple dimensions of welfare and economic activity. The framework adopted in this thesis combines multidimensional welfare indicators with disaggregated macroeconomic outcomes to capture both market and non-market climate impacts.

A central aspect of the framework concerns the dynamic nature of climate impacts. Climate shocks often have effects that extend beyond the year of exposure. Extreme heat, floods, and prolonged droughts can gradually alter investment patterns, labor productivity, educational attainment, migration, infrastructure quality, and fiscal capacity. Whether these effects are short-lived or persistent remains one of the main unresolved questions in the climate impacts literature, particularly in relation to long-run development trajectories.

To study these dynamics, given the lack of consensus in the literature, the empirical strategy we adopt in this thesis allows for flexible structures instead of imposing restrictive assumptions about temporal dynamics. Our empirical analysis relies on distributed lag models (DLMs), which relate current socio-economic outcomes not only to contemporaneous climate conditions but also to climate exposure observed in previous years. This approach allows the temporal structure of impacts to be estimated directly from the data rather than being imposed *ex ante*. Distributed lag specifications enable distinguishing immediate responses from delayed adjustments, identifying persistence in climate damages, and estimating cumulative effects over time. Their use is particularly relevant for slow-onset hazards such as drought, where impacts may accumulate across consecutive years and propagate through interconnected sectors of the economy. More generally, distributed lag models provide a framework for analyzing climate damages as evolving processes rather than isolated annual shocks.

This dynamic framework also emphasizes that welfare outcomes depend on the sequence and duration of climate exposure, rather than solely on the level of warming at a given point in time. Climate trajectories that converge on the same end-of-century temperature may nonetheless yield different cumulative damages if they differ in the timing, magnitude, or persistence of extreme events. This issue is especially relevant in temperature overshoot scenarios, where temporary exceedance of warming targets may produce losses in health, education, and productive capacity that are only partially reversible once temperatures decline. The analysis, therefore, considers climate impacts across entire warming pathways rather than treating damages as functions of global mean temperature levels alone. We carry out this analysis thanks to existing climate model outputs from CMIP6-ISIMIP (ISIMIP Repository, 2023), either by directly using the existing data in Chapter 2, or by constructing a climate emulator in Chapter 3. Chapter 4 applies a slightly different approach by reconstructing a historical multi-annual European drought under a $+2^{\circ}\text{C}$ climate, while preserving the estimated impact function dynamics, thereby allowing us to compute the cumulative long-term effect of the event.

These elements are integrated into a common empirical strategy that combines subnational socio-economic panel data, high-resolution climate observations, distributed lag estimation, and

scenario-based projections. Across the thesis, this framework is used to estimate dynamic impact functions for the components of the Human Development Index and for sectoral value added, and to project future outcomes under alternative climate and socio-economic pathways. Uncertainty is treated explicitly throughout by considering variation arising from climate model outputs, socio-economic scenarios, and statistical estimation of the impact functions.

The resulting perspective conceptualizes climate damage as a multidimensional, path-dependent process whose consequences evolve over time and differ across welfare dimensions, sectors, and regions. By integrating dynamic econometric methods with multidimensional welfare analysis and scenario-based climate projections, the thesis aims to provide a broader characterization of climate impacts than approaches centered exclusively on contemporaneous effects.

1.4. Overview of the Included Studies

Chapter 2: Past and projected climate impacts on human development. The second chapter provides the empirical foundation for the thesis by estimating the effects of climate conditions on the three components of human development—income, health, and education—using global sub-national panel data. It combines high-resolution climate data with distributed lag models to identify the temporal and cross-dimensional responses to both mean climate conditions and extremes. The estimated relationships are then used to project future impacts under alternative climate and socio-economic scenarios, with an explicit decomposition of uncertainty across climate models, development pathways, and impact-function specifications. The results indicate that climate change adversely affects all three dimensions through distinct channels, and that uncertainty in socio-economic pathways plays a central role in determining long-run outcomes. This work was coauthored by Jonathan Spinoni and Massimo Tavoni. It is currently under review, with the first version of the preprint available at <https://www.researchsquare.com/article/rs-6923904/v1>.

Chapter 3: Human development burdens and incomplete recovery from temperature overshoot and return. The third chapter examines whether welfare losses incurred during temperature overshoot are reversed when temperatures subsequently decline. It develops a trajectory-sensitive climate emulator that preserves the temporal structure of overshoot pathways and combines it with empirically estimated impact functions to simulate human development outcomes under alternative scenarios. The analysis highlights the importance of exposure duration and magnitude to elevated temperatures and suggests that cumulative welfare losses depend not only on peak warming or end-of-century levels, but also on the full trajectory of climate forcing. The manuscript of this work, coauthored by Carlos Rodriguez Pardo and Massimo Tavoni, is being prepared for peer review.

Chapter 4: Multi-year droughts and their compounding economic impacts in Europe. The fourth chapter, finally, focuses on drought as a slow-onset, multi-year hazard and

1| Introduction

examines its medium-term economic impacts in European regions. Using regional panel data at the NUTS3 level and distributed lag models, it estimates the dynamic effects of drought on economic activity and identifies additional losses associated with consecutive-year drought episodes. A complementary climate storyline approach is used to assess how recent drought events would differ under higher levels of global warming. The findings indicate that drought impacts accumulate over time and that multi-year events generate larger total losses than contemporaneous estimates alone suggest, with substantial regional heterogeneity. This work, coauthored by Louis Daumas, Maximilian Kotz, and Massimo Tavoni, was submitted for peer review and a preprint is available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=6786478.

Across chapters, the thesis makes four main contributions. First, it provides a joint empirical assessment of climate impacts on income, health, and education using global sub-national data and then on disaggregated and sectoral European outputs, thereby moving beyond single-outcome analyses. Second, it incorporates a broad set of climate variables, including extremes, variability, and complex hazards such as droughts, rather than relying solely on mean temperature. Third, it allows for dynamic adjustment through distributed lag specifications that recover the temporal structure of impacts. Fourth, it quantifies uncertainty in two complementary ways: climate impact projections by decomposing the contributions of climate models, socio-economic pathways, and impact-function specifications.

More broadly, the results highlight that both the magnitude and persistence of climate damages depend critically on the structure and timing of climate exposure, and that conclusions based on static or single-dimensional representations of climate change may understate the full extent of its effects on human development.

2 | Past and Projected Climate Impacts on Human Development

2.1. Introduction

Global warming interacts with human development, especially in developing regions, through rising temperatures and altered rainfall patterns (Intergovernmental Panel On Climate Change (IPCC), 2023; World Bank Group, 2023; Hill et al., 2024). Climate extremes disproportionately affect populations with weaker institutional governance or those residing in socio-economically precarious regions (Diffenbaugh and Burke, 2019; Commission of the European Union. Joint Research Centre., 2015; Dang et al., 2024). Assessing these impacts and developing counter-measures is crucial for designing effective strategies. However, the impact of climate cannot be studied in isolation, but must be understood depending on socio-economic development conditions, driven by global and local factors. Quantitative research on climate change impacts has expanded significantly in recent decades, exploring effects on health, mortality, education, energy systems, and agricultural productivity (Carleton and Hsiang, 2016). Moreover, the intensification of climate hazards has been linked to rising poverty and forced migration, compounding existing vulnerabilities and threatening sustainable development progress (Hallegatte and Rozenberg, 2017; Cappelli et al., 2021; Pérez-Peña et al., 2021).

A substantial body of empirical literature has focused on economic variables (Chang et al., 2023), establishing a non-linear relationship between temperature and GDP (Burke et al., 2015; Kotz et al., 2022b; Dell et al., 2014). Recent econometric studies using global panels of regional GDP highlight the importance of incorporating extreme weather measures into climate-economy analyses, as these events have statistically significant impacts on economic output (Kotz et al., 2021, 2022b; Callahan and Mankin, 2022a; Waidelich et al., 2024). More broadly, intensifying climate hazards elevate societal risks, necessitating integrated studies at both micro and macro levels (Sillmann and Sippel, 2020). Recent contributions also highlight the complex interaction between precipitation regimes and inequality (Palagi et al., 2022), as well as climate-related productivity shocks (Sheng and Xu, 2019).

Despite the growing body of economic research, studies on composite indices such as the Human Development Index (HDI) remain comparatively scarce. Nevertheless, evaluating climate impacts on non-economic dimensions of human welfare represents an essential area of inquiry

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(United Nations, 1990; Menk et al., 2022; Lutz et al., 2021). While in a minority of studies, scholars have begun exploring how climate impacts subjective well-being and material quality of life, particularly in vulnerable settings (Bedran-Martins et al., 2018; Liu et al., 2024). Such multidimensional assessments are crucial to understanding the broader implications for sustainable development. The Human Development Index, introduced in 1990 by the United Nations Development Programme (United Nations, 1990), provides a simple but established measure of human well-being by incorporating education and health dimensions alongside economic factors. To our knowledge, a global empirical assessment of climate means and extremes' impacts on sub-national human development and their projections is lacking. Addressing these impacts at the sub-national level is crucial for revealing heterogeneity within countries, as local patterns of climatic deviation may be obscured when focusing solely on national aggregates (Kotz et al., 2022b; Damania et al., 2020; World Bank, 2020). This granularity matters because climate hazards and extremes are fundamentally local meteorological phenomena. Malpede and Percoco (Malpede and Percoco, 2023) pioneered work in this area by utilizing the Sub-National Human Development Index (Smits and Permanyer, 2019) to identify long-term negative impacts of temperature variations and potential evapotranspiration on two HDI components.

Other research has documented the impacts of extreme heat and weather variability on human health, including mortality risks (Ariyaningsih et al., 2022) and disease prevalence (Aadil et al., 2020). Extreme heat, cold, and increased temperature variability are consistently associated with elevated mortality risks across regions (Anderson and Bell, 2009; Gasparrini et al., 2015; Shi et al., 2015). Large-scale multi-country studies quantify how both high and low temperatures increase excess deaths and project worsening outcomes under scenarios with higher warming rates (Gasparrini et al., 2017b; Guo et al., 2018; Bressler et al., 2021). Vulnerable populations, including children and older people, are especially susceptible, and geographic disparities suggest that poorer and hotter regions face the highest health burdens (Watts et al., 2019; Sheffield and Landrigan, 2011; Carleton et al., 2022b). Studies project excess deaths due to rising heat under various warming scenarios, with evidence that climate inaction will lower life expectancy in many regions (Carleton et al., 2022b; Hauer and Santos-Lozada, 2021). Beyond mortality, climate change has wide-ranging effects on public health, including exacerbation of respiratory and cardiovascular diseases, mental health disorders, and productivity losses due to heat stress (Orlov et al., 2020; Deepak et al., 2024; Gulzar et al., 2021). Moreover, systematic reviews highlight the interconnectedness of climate-driven health risks, emphasizing the need for adaptive capacity and health-centered mitigation strategies (Rocque et al., 2021a; Costello et al., 2009; Romanello et al., 2023).

The education dimension has also been investigated in relation to climatic shocks and extreme events. Extreme weather events such as floods, droughts, and storms can disrupt school attendance, damage infrastructure and lower educational attendance and scores, and exacerbate educational inequality, especially among marginalized communities both in developed and developing countries (Huang and Dong, 2025; Munsaka et al., 2020; Venegas Marin et al., 2024;

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Boutin, 2014; Groppo and Kraehnert, 2017; Goodman et al., 2018; Sheffield et al., 2017). Moreover, extreme heat can affect educational attainment through multiple channels including school closures and reduced cognitive performance (Graff Zivin et al., 2018; Park et al., 2021; Venegas Marin et al., 2024). Broader reviews and case studies further emphasize the compounding effect of climate stressors on long-term educational attainment and inter-generational development (Prentice et al., 2024; Leal Filho et al., 2023; Jacob, 2018). Educational disruption can have enduring impacts on well-being and socio-economic mobility, reinforcing the importance of integrating climate resilience into school planning and policy (Sheffield et al., 2017; Ogendi and Ogendi, 2023). As the risks build, education also plays a critical role in climate adaptation and awareness, making climate change education itself a strategic imperative for sustainable development (Yusuf et al., 2024). Nevertheless, although literature highlights that education attainment is likely affected by climate change (mainly through climate extremes) work is still needed to characterize the magnitude of such effects (Prentice et al., 2024; Sprague et al., 2025).

In addition to these studies, recent work has sought to quantify multi-dimensional climate impacts on well-being indicators beyond GDP (Alamgir and Shan, 2023). This has led international institutions such as the World Bank (World Bank Group, 2023) to outline how climate change may push millions into poverty by reducing health outcomes, educational achievement, and livelihoods in vulnerable regions. As a result, the integration of climate risk adjustments to the HDI have been proposed (Menk et al., 2022).

Projections of baseline HDI trajectories under the SSPs have been developed by several studies (Crespo Cuaresma and Lutz, 2015; O'Neill et al., 2020; Hanna et al., 2024; Hughes et al., 2012), providing important context for our climate impact estimates. Our contribution adds a climate damage layer on top of these baseline projections, enabling a direct comparison between the magnitude of climate impacts and the underlying development trajectory. The empirical relationship between climate and economic outcomes that underpins part of our analysis remains subject to ongoing debate in the literature (Curtin and Burgess, 2026), and we discuss the implications of this uncertainty in following sections, testing a wide set of models and providing a flexible, dynamic impact specification.

This chapter advances the understanding of climate impacts through three main contributions. First, we globally assess both contemporaneous and lagged effects of mean climate and climate extremes separately on each HDI component, employing a structured variable selection framework with extensive robustness checks. Second, we use the estimated damage functions to project the impacts of climate change on HDI across many climate and socio-economic pathways and their uncertainties (see Fig. 2.1 for a graphical overview of our approach). Finally, we use global sensitivity methods to quantify the sources of uncertainties for HDI projections, helping improve robustness.

We employ sub-national data on the Human Development Index and its components spanning 1,773 regions worldwide from 1990 to 2020, built from household surveys, statistical offices and censuses (Smits and Permanyer, 2019). To identify causal effects of weather and climate varia-

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tions on individual index components, we deploy various climate variables computed from ERA5 and aggregate them at the same geographical level as the HDI data. We test for effects of regional mean temperature, total rainfall, daily temperature variability, heat extremes, and rainfall extremes.

We model potential climate impacts on inter-annual log differences of HDI components, testing multiple model specifications consistent with the econometric climate impact literature. We implement panel two-way fixed effects regression to account for unobserved region-specific and year-specific factors. We also allow time-varying country trends to capture common non-climate-related changes in indices over time, thereby better addressing potential omitted variables. We select preferred specifications with different lagged weather shocks potentially interacted with mean climatic conditions, testing up to 9 lags for each output-climate variable combination.

We then project climate change impacts on future trajectories of income, life expectancy, and education across four Shared Socioeconomic Pathways (SSPs) (O'Neill et al., 2014; Riahi et al., 2017), coupled with climate model projections from ISIMIP (ISIMIP Repository, 2021, 2023). We assess projected climate damages on the individual components and the aggregate HDI index by deriving regional socio-economic projections from IIASA and the Wittgenstein Centre for Demography and Global Human Capital. We utilize 5-10 ISIMIP climate models (depending on the SSP) and derive future subnational climate variables from gridded data. Finally, we apply our impact functions to each component to estimate future subnational HDI losses due to climate change for each year-SSP-model combination.

We find statistically significant, predominantly adverse effects of weather variations on each HDI component. Gross National Income per Capita growth is affected by mean temperature, heat extremes, and rainfall extremes (consistent with the most recent literature); Life Expectancy at Birth is influenced by temperature variability, heatwaves, and rainfall extremes; and rainfall extremes and temperature variability impact Expected Years of Schooling growth. Our projections reveal a global loss of HDI up to around 2% by the end of the century in the warmest scenarios (SSP5-8.5 and SSP5-3.70); when including non-economic dimensions of wellbeing, almost all regions of the world are worse off because of climate change.

2.2. Empirical Impact Functions

The first part of our analysis builds on HDI components, spatially and temporally matched with historical climate variables, to isolate significant climate impacts on Gross National Income per Capita (GNIPC), Expected Years of Schooling (EYS), and Life Expectancy at Birth (LEB). We do this by first testing each climate variable on each component with contemporaneous effects and then including time lags in a distributed lag model (DLM) fashion. Secondly, we construct comprehensive DLM models for each component, including all the significant climate variables together.

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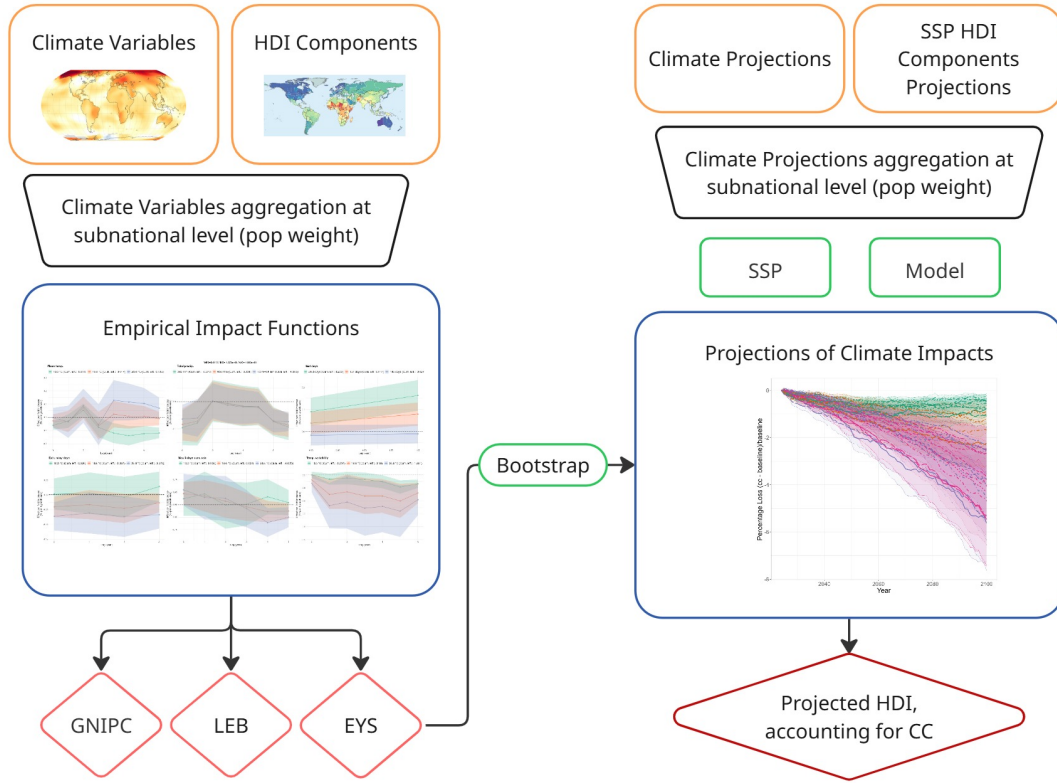


Figure 2.1: Flowchart of the main methodological steps adopted in the study. Yellow boxes contain the data we employ; back boxes represent the aggregation steps of original data into compatible climate and socio-economic data at the same temporal and spatial resolution; blue boxes contain the main methodological steps of the analysis; green boxes represent uncertainty sources; finally, red rhombuses indicate the results of the study. GNIPC stands for Gross National Income per Capita, LEB stands for Life Expectancy at Birth, and EYS stands for Expected Years of Schooling. These are the three HDI (Human Development Index) variables we study. See Methods for additional information on data sources and statistical methods.

2.2.1. One-at-the-time Extremes Inclusion

To accurately represent the non-linear impacts of climate extremes on human well-being, damage functions must reflect not only macroeconomic losses but also the precise causality channels through which climate stress diminishes quality of life, which differ across economic sectors and call on physical and physiological factors. Empirical work by Burke et al. (Burke et al., 2015) and Kotz et al. (Kotz et al., 2021) demonstrates that elevated temperatures significantly suppress labor productivity, particularly in low-income settings where outdoor and informal labor predominate. Similarly, exposure to sustained heat or precipitation extremes disrupts agricultural cycles, leading to food insecurity and subsequent malnutrition, especially among children, bearing well-documented long-run developmental impacts (Intergovernmental Panel On Climate Change (IPCC), 2023; Aadil et al., 2020). Moreover, repeated exposure to extreme events compromises health systems through infrastructural damage and direct burden on people, exacerbating mortality and morbidity (Ariyaningsih et al., 2022; Guo et al., 2017). These intertwined routes suggest that damage functions linking climate shocks to well-being must incorporate multi-dimensional human outcomes beyond GDP, encompassing health, education, nutrition, and mental resilience, to avoid systematically underestimating the real cost of climate extremes.

We begin by testing individual extreme variables in impact models for each outcome variable, examining both first differences and level effects: this is important given the open debate on level versus growth impact functions, which has emerged in the climate econometrics literature of the recent past (Kalkuhl and Wenz, 2020). Details of tested specifications are reported in Table A.1. Table 2.1 summarizes statistically significant climate variables for each outcome. Across all outcomes, selected variables show significance with robust standard errors clustered at the country level to conservatively address spatio-temporal error dependence.

Our findings suggest that all three HDI components respond significantly to climate trends and extremes. Gross National Income per Capita growth is strongly affected by temperature variables, both mean and extreme, consistent with previous studies (Carleton et al., 2022b; Orlov et al., 2020). Wet days also negatively affect income as in (Kotz et al., 2022a), while we don't find evidence for extreme precipitation. Life expectancy responds to wet days, temperature variability and heatwaves, in line with evidence showing increased mortality from high temperatures and precipitation extremes (Gasparrini et al., 2015; Guo et al., 2018; Ebi et al., 2021). We find expected years of schooling are susceptible to wet days, echoing the work of Munsaka and Mutasa (Munsaka et al., 2020), who show lasting effects on education outcomes after flooding events. Temperature variability also affects education, consistent with recent findings from Park et al. (Park et al., 2021) and Prentice et al. (Prentice et al., 2024), which link both heat and extreme precipitation events to reduced academic performance and long-term attainment. For detailed model specifications and comprehensive regression results, see Appendix A.1, in particular Tables A.2, A.3, and A.4.

This initial iteration of impact models indicates the relevance of extreme events when studying

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Variable effect in level	RX	PEXT	WD	TVAR	HW
Gross National Income per Capita			x		
Expected Years of Schooling	x	x	x	x	
Life Expectancy at Birth	x			x	
Variable effect in first diff	RX	PEXT	WD	TVAR	HW
Gross National Income per Capita			x		x
Expected Years of Schooling					
Life Expectancy at Birth	x	x	x	x	x

Table 2.1: Summary of climate variables tested, when inserted one at a time in the impact function, for each HDI component. Variables are marked as statistically significant with an "x" when demonstrating a p-value for the T-test of less than 0.1, with errors clustered by country. We test these variables in the model independently or interacted with mean temperature or total rainfall, with and without mean climate controls. Abbreviations: *TM* = mean annual temperature ($^{\circ}\text{C}$); *RR* = total annual precipitation (mm); *TVAR* = day-to-day temperature variability, computed as the annual mean of within-month standard deviations of daily mean temperature ($^{\circ}\text{C}$); *HW* = heatwave severity, annual sum of degree-days above the 90th percentile threshold during heatwave events ($^{\circ}\text{C}\cdot\text{days}$); *WD* = wet days, annual count of days with rainfall $>1\text{mm}$ (days); *PEXT* = extreme precipitation, annual sum of rainfall on days exceeding the 99.5th percentile of the 1981–2010 baseline (mm); *RX* = maximum 5-day cumulative precipitation (mm). Checkmarks indicate significance for Gross National Income per Capita, Life Expectancy at Birth, and Expected Years of Schooling (EYS). Tables A.2, A.4, A.3 report coefficients and T-tests for each variable and combination of variables we find significant.

income, education, and health at the sub-regional level. We also test the persistence of the effect of climate on our variables of interest, differentiated by regional historical climate conditions. We construct a set of distributed lag models with climate first differences, both independently and interacted with different mean regional climatic conditions informed by the previous model iteration, and implement a structured lag selection methodology based on different statistical metrics, including information criteria and cross validation, testing up to 9 lags. Section 2.5.5 provides a detailed explanation of this procedure, while Appendix A.1 contains the results of the lag selection (Figs. A.2, A.1, and A.3) and extremes (Figs. A.6, A.5, and A.4).

2.2.2. Comprehensive Impact Models

We estimate comprehensive models with all relevant climate variables informed by the previous section and keep lag blocks retaining joint significance. This allows us to control for their correlation and isolate the most robust predictors of each HDI component. Fig. 2.2 presents cumulative impacts over time for a standard deviation shock to each selected variable, with effects differentiated by regional climatic conditions, in our preferred specification (see Section 2.5.5). Fig. A.7 in Appendix A.1 contains extensive summaries of the effects of each variable on the outcomes in each time stamp. Consistent with prior work (Kalkuhl and Wenz, 2020; Burke et al., 2015), we find that income is most adversely affected by persistent increases in mean temperature, especially in already hot regions (Fig. 2.2, GNIPC panel). We find a cumulative effect of one standard deviation temperature increase (across years in every region) over eight years of up to -3.74 percentage points in the hot regions, at the 75% percentile of the historical mean temperature distribution. These findings align with (Burke et al., 2015) and support

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(Kalkuhl and Wenz, 2020; Bastien-Olvera et al., 2022)’s claim that even transient climate shocks can create long-lasting macroeconomic effects. The economic literature has also shown that extreme heat particularly impairs growth in warm, poor countries where adaptive capacity is lower (Carleton et al., 2022b; Deschênes and Greenstone, 2011; Gilli et al., 2023). We find heatwaves, net of mean temperature, further depress income growth, especially in colder regions. This is echoed in studies showing productivity losses and economic damages from thermal stress (Orlov et al., 2020; Armstrong et al., 2017). Temperature variability negatively affects the economy at high temperatures (Kotz et al., 2021), and wet days show higher negative impacts in dry regions (-2.90% for one standard deviation increase, cumulatively over 9 years), in accordance with the idea that concurrent wet and dry conditions can harm the economy, especially through the agricultural sector (Watanabe et al., 2018).

For education (Fig. 2.2, EYS panel), rainfall-related variables exert significant negative impacts, particularly under higher rainfall regimes, in line with the literature (Huang and Dong, 2025; Jacob, 2018; Munsaka et al., 2020). A standard deviation increase in wet days entails a cumulative loss of approximately one month and a half. Our finding that temperature variability has stronger adverse effects in hottest regions supports a heterogeneous climate vulnerability hypothesis, also observed in Graff Zivin et al. (Graff Zivin et al., 2018), who found reduced test scores due to high temperatures. A one standard deviation increase in temperature variability is associated with a cumulative loss of about 10 months of expected schooling in an average region, rising to over a year and a half (19 months) in the hottest regions.

Life expectancy (Fig. 2.2, LEB panel) is adversely affected by heatwaves and temperature variability, as extensively documented in health literature (Guo et al., 2017; Ebi et al., 2021; Gasparini et al., 2017b; Anderson and Bell, 2009; Bressler et al., 2021; Deschênes and Greenstone, 2011; Shi et al., 2015). Wet days reduce life expectancy growth by about 2.6 months in an average region, especially in dry regions, confirming the nuanced role of hydrological balance on public health (He et al., 2024; Ban et al., 2024). Interestingly, we find weaker regional heterogeneity in the impacts of heatwaves on life expectancy (-0.3 months on average), which could reflect a universal biological vulnerability.

A caveat applies to the heterogeneity analysis: baseline climate conditions and socio-economic development are correlated (a Pearson correlation of approximately 0.50 between regional mean temperature and log income per capita), so differences in estimated impacts across cool/hot, dry/wet regions could partly reflect development gradients rather than purely climatic factors. To assess this, we re-estimate our preferred specifications replacing, and then supplementing, each baseline-climate moderator with regional development level (Appendix Table A.7). Temperature-variability heterogeneity for income and schooling, and income’s response to precipitation extremes, remain significant controlling for development. Overall, the heterogeneity we report appears predominantly climate-driven, with a modest, variable-specific role for development.

Overall, this empirical evidence complements the recent literature by showing how climate damages extend beyond economic indicators, as key human development metrics — health and edu-

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Cumulative Distributed-Lag Effects of one SD Shock of Climate Variables under Different Conditions

Dry/Cold, Average, and Wet/Hot correspond to 25th, 50th, and 75th percentile climatic regimes

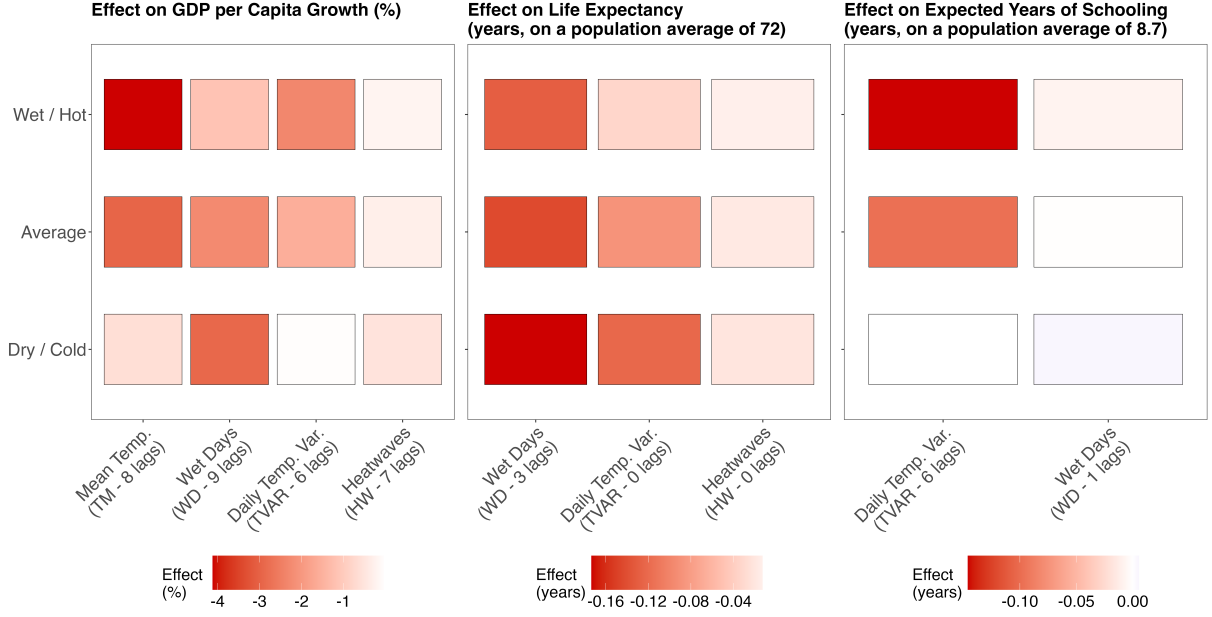


Figure 2.2: Cumulative impacts of climate trends and extremes on the HDI components, calculated by summing all lagged terms of the damage functions, of one standard deviation change in each climate variable (x-axis) on response variables (y-axis), for three different quartiles of the moderating climate variable (25%, median, and 75% from the bottom to the upper position in each subplot). These moderating variable values are, respectively: 12.3°C, 21.3°C, and 25.7°C for mean temperature; 687mm, 1060mm, and 1710.6mm for total rainfall; 1.69°C, 4.5°C, and 8.58°C for heatwaves; 0.86, 1.58, and 2.74 for temperature variability; and 103mm, 150mm, and 204mm for wet days. Rainfall based shocks are interacted with rainfall mean controls or temperature mean controls, while temperature based shocks are interacted with temperature mean controls. Shocks should be interpreted while holding all other model variables constant. See the Methods Section 2.5.5 for details of how climate variables in the x-axis impact the growth of response variables.

cation — exhibit significant and long-lasting sensitivity to climate (Bressler et al., 2021; Prentice et al., 2024; Romanello et al., 2023). Our findings, however, add refinement to the global impacts literature by quantifying these effects through a unified HDI lens and highlighting the conditionality of impacts on baseline climate, which can guide region-specific adaptation strategies.

2.3. Projected HDI impacts due to Climate Change

We use the empirical relations identified on historical data to project the future impacts of climate change on HDI. We apply the empirical functions to future scenarios of climate change and socio-economic development (SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5), accounting for the different sources of uncertainty in shaping these projections - including the uncertainties in the impact function themselves as well as in the climate models. SSP5-8.5 is included as a sensitivity bound and for comparability with prior literature; this scenario has been assessed as increasingly implausible given current policy trajectories (Hausfather and Peters, 2020; Hausfather, 2025), and summary statistics in the text focus on SSP3-7.0 as the high-end scenario. Using population-

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weighted global and regional averages, we report impacts primarily as percentage changes from projected baseline values without climate change. See Methods (2.5) for additional details.

2.3.1. Global results

Fig. 2.3a illustrates the projected percentage loss in global HDI from climate change across different Shared Socioeconomic Pathways (SSPs) and climate models. The human development index is projected to be lower than its no-climate-change baseline across all rates of warming, but in different ways. Under the high-emission scenario SSP5-8.5, global HDI (population-weighted mean across regions) decreases by 1.89% [1.46%, 2.27%] (90% confidence interval) by 2100. A comparable loss of 2.27% [1.74%, 2.80%] is projected under the regional rivalry scenario SSP3-7.0. Under more optimistic scenarios, impacts persist but stabilize at lower values (0.85% [0.65%, 1.05%] for SSP2-4.5 and 0.34% [0.26%, 0.42%] for the Paris-compliant SSP1-2.6). For comparison, during the COVID-19 pandemic, global HDI experienced a sharp yet temporary decline of 0.36% (using the same bounds for indices calculations and weighting scheme). We find that socio-economic development matters more than background warming. The SSP5-8.5 pathway is characterized by very high warming but also by unprecedented socio-economic development, leading to an 11-fold increase in world GDP throughout this century and rapid economic convergence between developing and industrialized economies. Under such a positive economic development outlook, despite rising temperatures, the share of foregone development remains below 6% (inset in panel 2.3a). On the other hand, under the 'regional rivalry' SSP3 with stagnant and unequal economies, more than a fifth of the development gains could be compromised by rising temperatures and climate extremes. In the other two scenarios of lower warming and relatively high socio-economic development (especially SSP1), the missed development would be below 3% of the gains over the century.

All HDI components are projected below their no-climate-change baselines, but in differentiated ways (panel 2.3b). Income constitutes the largest contributor to overall HDI loss; although less pronounced, significant and persistent declines in life expectancy and expected years of schooling, also projected relative to baseline. We summarize global mean percentage and absolute losses from baseline of underlying indices components and original variables across models, for each SSP, in 2050 and 2100 in Tables A.8 and A.9 in Appendix A.3. Under the high emission scenarios we project an absolute median decline in Life Expectancy of almost two months and a half (SSP3-7.0) and half year of life (SSP5-8.5) by the end of the century, and around 0.89 months (SSP3-7.0) and 1.38 months (SSP5-8.5) of absolute median loss for expected schooling. Income per capita losses range between 3.3 and 5.5% in 2050 across all scenarios ([2.4%-7.1%] 90% confidence intervals), significantly rising and diverging thereafter, with significant economic output losses in the worst-case scenarios. To be able to compare directly the percentage losses in the three dimensions, we also report the percentage and absolute changes from baseline of each index, calculated with a min-max normalization from the original variables. Time-series plots of individual index percentage losses (Figs. A.14, A.12, A.13), alongside a breakdown of

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each index's contribution over the whole projection horizon 2024–2100 (Fig. A.11), offer a more granular view of the composition of the development index loss under climate change.

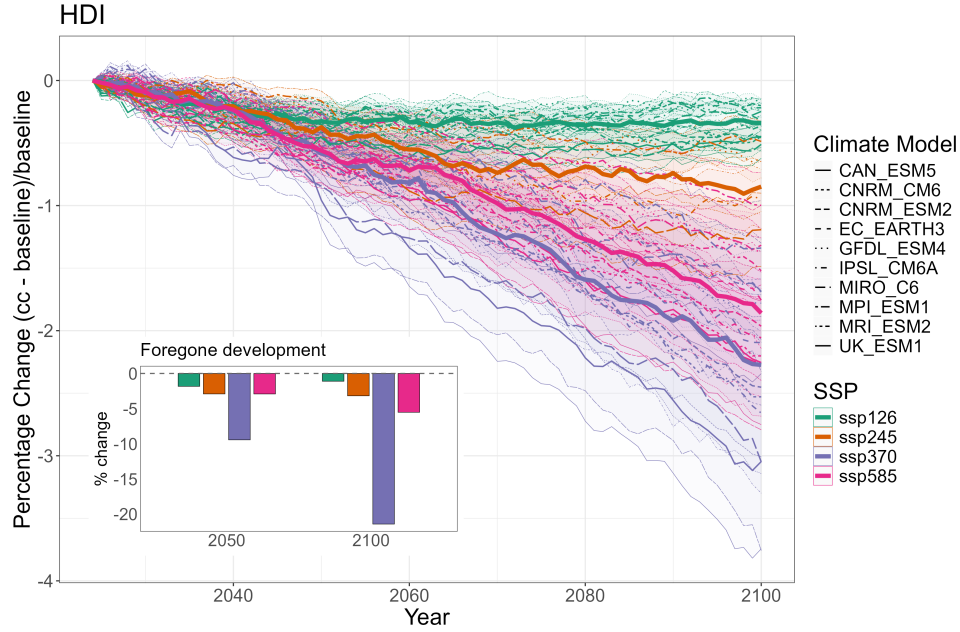
2.3.2. Regional Patterns

At the regional level, climate change impacts on HDI are quite generalized, though with substantial heterogeneity. Under the SSP3-7.0 scenario, significant losses occur across most central and low-latitude regions, as well as high-latitude areas (Fig. 2.4a). Hatched regions indicate insufficient model agreement to consider losses statistically significant at the 90% confidence level (following IPCC 2/3 model agreement threshold (Intergovernmental Panel On Climate Change (IPCC), 2023)). The spatial distribution of component-level impacts reveals important regional contrasts. As shown in Appendix A.3, Income Index losses are particularly severe in equatorial regions (Fig. A.19), with economic gains present in the northern latitudes, in line with the literature (Burke et al., 2015). On the other hand, Education Index losses (Fig. A.27) are more pronounced at higher latitudes, while Lifex Index losses (Fig. A.23) are quite spread across the whole world. These patterns reflect the geographically differentiated effects of climate change on economic productivity, healthcare systems, and educational infrastructures. The findings indicate that, when accounting for both economic and non-economic metrics of development, most regions in the world face adverse impacts.

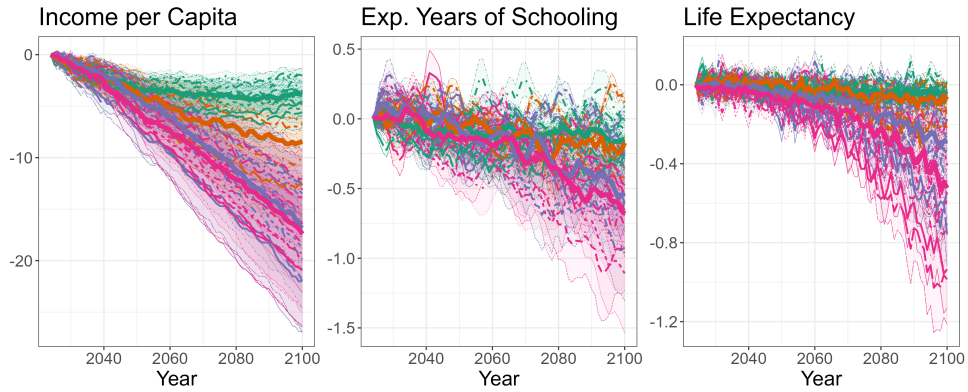
Panel 2.4b further demonstrates how HDI component contributions vary by region. While specific magnitudes differ, the spatial patterns remain broadly consistent across SSPs. This scenario consistency stems from the fact that the primary geographic "hotspots" of climate impact - regions where temperature and extremes increase at a faster rate - are largely invariant to emission pathways, with higher emission trajectories accelerating, rather than relocating, damage accumulation. We observe particularly high impacts in northernmost countries such as Russia regarding the Education Index (driven mostly by a decrease in temperature variability, as the coldest countries benefit from higher temperature fluctuations, see A.33), while a temperature increase itself benefits the economy at very high latitudes and, on the contrary, hotter countries like Ethiopia suffer more extensive economic losses. Life expectancy losses are expected quite uniformly across the globe with a prevalence in central latitudes, especially under high emission pathways. We further confirm these impact distributions by inspecting regional percentage losses maps by index component and SSP in 2100, in Appendix A.3, accounting for error clustering at both regional and country level when bootstrapping to provide a lower and upper bound on uncertainty (SSP1-2.6 in Fig. A.25, A.17 and A.21, SSP2-4.5 in Fig. A.26, A.18 and A.22, SSP3-7.0 in Fig. A.27, A.19 and A.23, SSP5-8.5 in Fig. A.28, A.20 and A.24). We also report HDI regional impacts by SSP in 2100 in Fig. A.29, A.30, A.31, A.32.

Additionally, Fig. A.16 in Appendix A.3 compares the temporal evolution of index losses in selected countries. Life expectancy losses generally track income losses over time, particularly in southern developing regions like Ethiopia and India where income and life expectancy decline steeply, while diverge in some northern regions like Russia, where income registers gains from

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(a) Median global HDI percentage impact (population-weighted) with respect to a baseline without climate change, by climate model and SSP. The inset displays total development losses since 2024 for each SSP, computed as the percentage difference between climate-change and baseline trajectories evaluated at 2050 and 2100 (median across models, bootstrap replicates). Detailed values are reported in Supplementary Tables A.10 and A.11.



(b) Median global percentage impact (population-weighted) of the three components of HDI, with respect to the baseline without climate change, before the transformation into indices, by climate model and SSP.

Figure 2.3: Global (population-weighted) climate impacts on HDI (panel 2.3a) and its components (panel 2.3b). To compute HDI impacts, bootstrapped impacts from 1000 Monte Carlo samples of multivariate impact function coefficient distributions are applied to SSP projections for income, life expectancy, and expected years of schooling. The three indices (Income Index, Lifex Index, and Edu Index) are derived from the underlying components for each region, year, SSP (including baseline), model, and bootstrap run, then combined into the HDI using a geometric mean. For all variables, the set of bootstrapped percentage changes relative to a baseline without climate change is calculated, followed by population-weighted averaging of regional values to retrieve global bootstrapped impacts, from which we compute 90% confidence intervals. For each SSP, a thicker line represents the median impact across models. Errors are clustered by region when bootstrapping. Fig. A.15 in Appendix A.3 reports the same results when clustering impact function errors by country.

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warming conditions. The education index exhibits more idiosyncratic behavior, with countries like India and Russia showing divergent trends compared to the other components. Ethiopia and Venezuela show a higher level of consistency across dimensions.

2.3.3. Uncertainty Decomposition

To quantify our HDI projections' robustness and uncertainty drivers, we perform a variance decomposition using Sobol indices, as described by (Saltelli et al., 2010b). This method attributes the variance in projected index values to three key sources: (1) scenario uncertainty (differences across SSPs), (2) climate model uncertainty, and (3) statistical uncertainty from impact function estimation (regression coefficient variability). See Methods Section 2.5.7 for details.

We find differentiated results for the drivers of the variance of HDI's components (Fig. 2.5).

The variance of gross national income per capita projections (Panel 2.5a) shifts over time: early-century projections are primarily influenced by differences across climate models and impacts uncertainty, while scenario uncertainty becomes the dominant factor in the latter half of the century. This transition reflects the cumulative effects of divergent emissions trajectories, which increasingly outweigh model-specific differences as the century progresses.

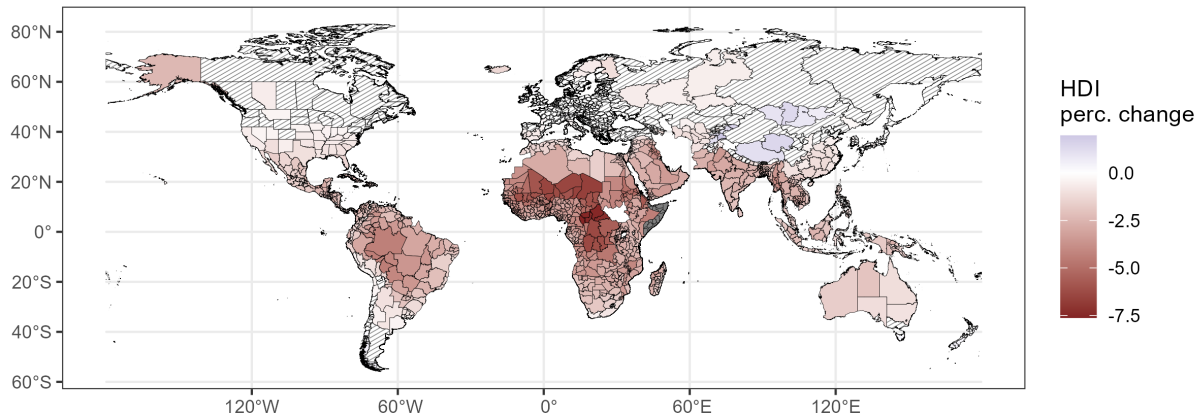
For expected years of schooling projections (Panel 2.5b), variance is dominated by interaction terms uncertainty. This indicates that the effect of one input parameter on the output is dependent on the value of the other interacting parameters, especially earlier in time: in this case, the effect of the SSP scenario on the outcome depends strongly on which climate model is used, or equivalently, the climate model response differs across SSPs.

For life expectancy at birth (Panel 2.5c), variance is also dominated by interaction terms uncertainty in the beginning, while by the end of the century by the single terms of scenario and model uncertainty. Overall, the results confirm the growing role over time of socio-economic drivers, the major uncertainties on the economic impact functions, and the crucial interaction between evolving climate variables and socio-economic development for the non-economic dimensions. Because scenario uncertainty is partly rooted in policy-amenable development trajectories rather than purely irreducible physical or statistical uncertainty, reducing it and the vulnerability it reflects is itself a viable channel for climate policy, distinct from mitigation of warming per se.

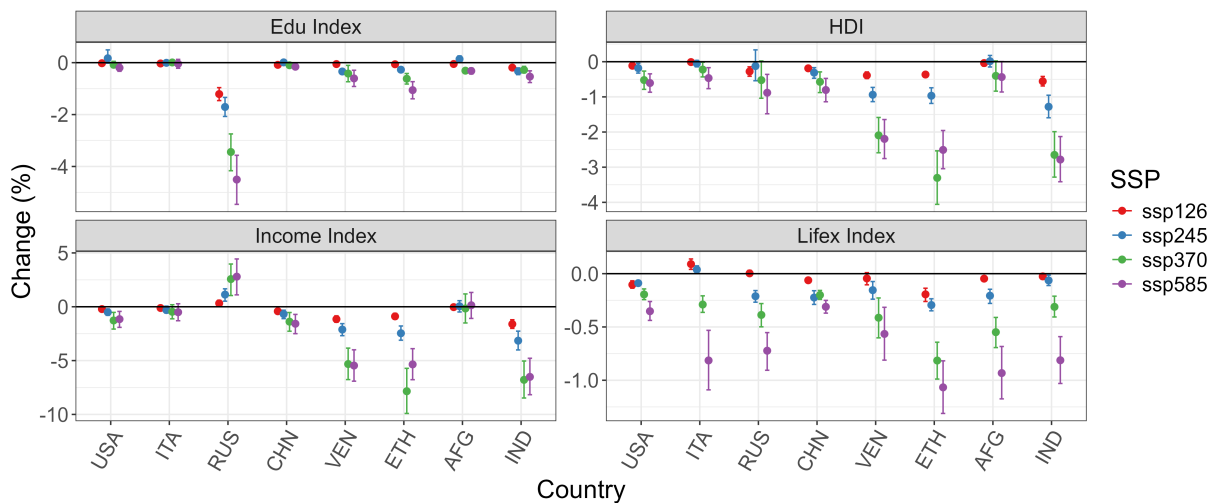
2.4. Discussion

This chapter uses a global panel of regions to investigate the impacts of mean and extreme climate on human development. Building on empirical methodologies and previous work at regional and global scales, we assess the relationships between various measures of climate extremes and the Sub-National Human Development Index through its components. Our study offers new empirical evidence of how climate change can affect human development and its relation to diverse socio-economic conditions. By applying a high-resolution impact function capturing temporal climate

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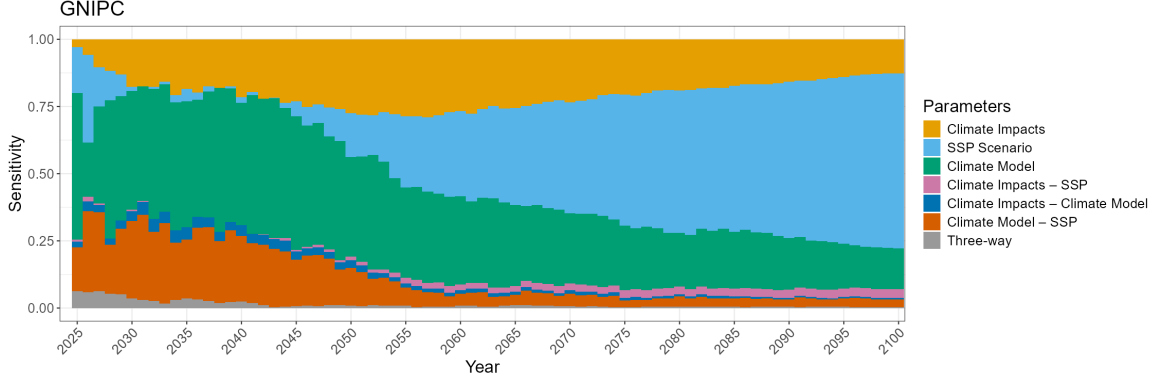
(a) Regional HDI percentage loss in 2100, SSP3-7.0. Hatched regions represent non-significant values, where we define significance as percentage loss at the 90% level with at least 2/3 of models in agreement. Here, errors clustered by region are used to define significance. Fig. A.31 in Appendix A.3 reports the same result when clustering errors by country.



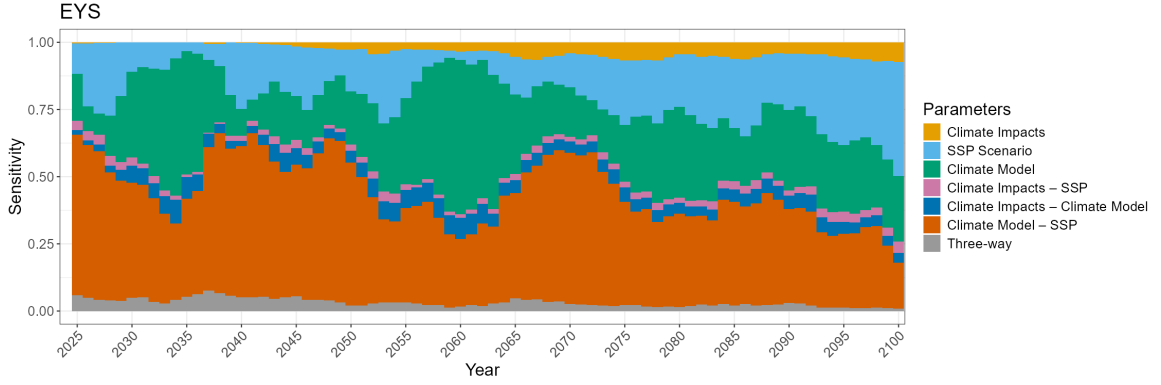
(b) HDI and component percentage losses across SSPs, for selected countries in 2100. Countries shown were selected as representative of major world regions and among the most populous within each: United States (North America), Italy (Europe), Russia (northern latitudes), China and India (Asia), Ethiopia (Sub-Saharan Africa), Afghanistan (Central Asia), and Venezuela (Latin America). Impacts are aggregated from the regional level using population weighting and errors are clustered by region.

Figure 2.4: HDI regional percentage impacts (median across models) and channels through Income Index, Edu Index, and Lifex Index for a sample of countries.

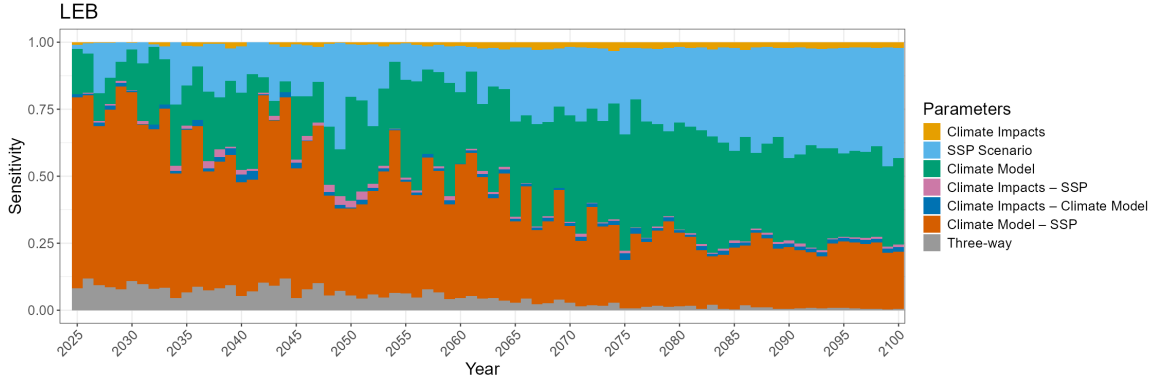
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(a) Variance decomposition of global impacts for Gross National Income per Capita



(b) Variance decomposition of global impacts for Expected Years of Schooling



(c) Variance decomposition of global impacts for Life Expectancy at Birth

Figure 2.5: Variance decomposition of global (population-weighted) projected impacts on the three HDI components through Sobol indices (see Section 2.5.7), across three independent sources of uncertainty over time: SSP scenario (s), climate model (m), and climate impact function (b , from bootstrapped coefficient distributions). The stacked areas show the contribution of each source to total projection variance. First-order Sobol indices (S_s , S_m , S_b) capture the variance explained by each source independently. Second-order interaction indices (S_{sm} , S_{sb} , S_{mb}) capture additional variance arising from the joint effect of two sources beyond their individual contributions; *Climate impacts - SSP* corresponds to S_{sb} , *Climate model - SSP* to S_{sm} , and *Climate impacts - Climate model* to S_{mb} . The residual area (labeled *Residual*) captures the third-order interaction S_{smb} and any remaining numerical approximation error.

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nonlinearities, our results underscore the susceptibility of human development to increasingly frequent and intense climate shocks and reinforce the importance of socio-economic resilience in shaping the future response to intensified climate change.

Some caveats regarding our damage functions warrant acknowledgment. First, our distributed lag approach assumes stable climate-outcome relationships over time, yet these relationships may evolve as societies adapt to changing climate conditions through infrastructure improvements, behavioral changes, and institutional responses. For education specifically, while our results are grounded in established mechanisms linking extreme weather to school attendance, infrastructure damage, and cognitive performance, the empirical literature on climate-education linkages remains more limited compared to climate-economy or climate-health research. On the other hand, our impact functions are estimated from historical climate variability and may not fully capture responses to unprecedented climate states outside the range of historical experience, particularly under high-emission scenarios where warming exceeds anything observed in our estimation period. Despite these limitations, our multi-dimensional approach, uncertainty quantification through ensemble projections and bootstrapping, and robustness checks show that climate trends and extremes affect human welfare, but depending on the rate of socio-economic development.

A further consideration concerns the level of aggregation inherent in the HDI components. Our approach captures net effects of climate shocks on annual growth rates of income, life expectancy, and expected years of schooling at the regional level. This top-down perspective complements the extensive micro-level literature that identifies specific climate-outcome channels, such as the effects of extreme heat on mortality, morbidity, and infectious disease, or the effects of temperature and flooding on test scores and school attendance (Carleton et al., 2022b; Graff Zivin et al., 2018; Park et al., 2021; Huang and Dong, 2025). The advantage of our approach is the ability to capture aggregate net effects across all channels simultaneously, at global scale and across multiple dimensions of wellbeing. The limitations are that underlying mechanisms are masked in the aggregate signal, and that HDI components may be less responsive than more direct measures (such as mortality rates or test scores) to short-run climate shocks, potentially leading to an underestimate of impacts on specific channels. Our results should therefore be interpreted as net composite effects, best understood alongside mechanism-specific studies that illuminate the pathways through which climate extremes affect human development.

Our findings also have important implications for the geographical distribution of climate impacts and reaffirm the spatial and socio-economic asymmetries in their distribution. Even when controlling for baseline HDI levels, we observe generalized reductions in well-being metrics relative to their no-climate-change baseline trajectories following exposure to temperature shocks, heatwaves, and rainfall anomalies. When accounting for broader dimensions of well-being, the impacts also occur at northern latitudes, highlighting spatially differentiated underlying mechanisms. Though low-latitude, development-poor regions remain most at risk, these results point to geographically generalized impacts from climate change. Our analysis highlights some priorities

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for future climate-development research. The decomposition results emphasize the importance of improving statistical inference for damages, refining long-term socio-economic scenario design (particularly regarding economic metrics), and enhancing convergence across climate model outputs. These represent major sources of structural uncertainty which, if unaddressed, may limit the precision of existing assessments. Addressing these uncertainties is essential for enhancing the reliability of projections that guide both climate policy and development planning. Our results account for these uncertainties through robust estimation methods and uncertainty-aware modeling strategies. By incorporating ensemble climate simulations and robust statistical model designs, the analysis ensures that the observed effects are not artifacts of specific model configurations or scenario assumptions. This methodological approach supports our central claim: climate trends and extremes are interconnected with human development, and the assessment of climate change cannot be done in isolation but depends on the socio-economic context.

Our findings have several policy implications. First, climate adaptation financing must extend beyond infrastructure resilience to include soft adaptive systems that directly mediate well-being outcomes, such as health, education, and social protection mechanisms. These systems constitute the first line of defense when climate disasters strike, particularly for vulnerable populations lacking insurance or access to relocation options. Second, our results emphasize the need for well-being-centered metrics in climate impact modeling and in the design of adaptation policies. Conventional economic assessments often obscure the lived experiences of harm (Menk et al., 2022). By integrating HDI-related outcomes into climate damage assessments and showing the relevance of socio-economic development, we can better understand the relationship between climate and development and inform debates, including on Loss&Damage (Tavoni et al., 2024). Third, our findings reinforce the relevance of long-lasting, multi-generational perspectives on climate policy. As related literature demonstrates (Groppo and Kraehnert, 2017; Goodman et al., 2018), educational disruption and childhood health effects can have long-lasting, compounding effects across life cycles and generations. Therefore, adaptation must account for both immediate impacts and the persistent legacies of climate exposure, focusing on strategies that help promote resilient socio-economic development and thus minimize the impact of climate on human wellbeing.

2.5. Methods

2.5.1. Historical Climate Data

Our primary source for historical climate data is the European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ERA-5) of historical observations. We access the post-processed daily statistics on single levels from 1940 to present through the Climate Data Store API (Copernicus Climate Change Service, 2024). In particular, we use sub-daily frequency sampling of 1 hour and download mean, maximum, and minimum 2m temperature and total precipitation, at the daily timescale and on a regular $0.25^\circ \times 0.25^\circ$ grid. We then compute annual values from these daily

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statistics, aggregating temperature and rainfall values in each grid cell depending on the need. We construct the following indicators: mean annual temperature (TM) and total precipitation (RR); heatwaves (HW), measured as the total severity (Tx - Tx90th) in a year of days within the event, defined when at least five consecutive days have maximum temperature above the 90th percentile with respect to the 1981-2010 period, and maximum temperature above 30°C (computed only over the warmest six months in the year, i.e. Apr-Sep for the Northern Hemisphere, Oct-Mar for the Southern Hemisphere, including the following year in this case); extremely rainy days total precipitation (PEXT), meaning sum of rainfall quantities in days where total rainfall is above 99.5th percentile with respect to the 1981-2010 period; the maximum 5-day precipitation cumulative over the year (RX), which is the maximum precipitation amount that occurred over 5 consecutive days during the year; the number of wet days (WD), when rainfall exceeds 1mm; daily temperature variability (TVAR), computed as the annual mean of within-month standard deviations of daily mean temperature, where deviations are taken from the year-specific monthly mean. This construction removes the seasonal cycle and isolates variability from current seasonal expectations, ensuring that TVAR captures day-to-day unpredictability independent of changes in mean temperature.

Spatial Aggregation

To match climate data with socio-economic data, we aggregate the indicators at the regional level employing the following algorithm and weighting by population:

$$x_{i,t,w,T} = \frac{\sum_{j \in J_i} a_j * f_{i,j} * w_{j,T} * z_{i,t}}{\sum_{j \in J_i} a_j * f_{i,j} * w_{j,T}}. \quad (2.1)$$

where $x_{i,t,w,T}$ is the value of the climate variable x in the geographical unit i (sub-national regions in our case) at time t weighted by proxy w measured in base year T . In this application, $w_{j,T}$ represents the population density in the grid point j for base year $T=2015$. Population density grid data were obtained from the NASA Socioeconomic Data and Applications Center (SEDAC) (Center for International Earth Science Information Network - CIESIN - Columbia University, 2018) and resampled on the climatic grid. J_i is the set of grids intersecting the geographic unit i ; $f_{i,j}$ is the fraction of grid j which intersects the geographic unit i ; a_j is the area of the grid j ; $z_{i,t}$ is the raw grid climate indicator.

2.5.2. Climate Projection Data

We use bias-adjusted daily climate projections from ISIMIP3b (ISIMIP Repository, 2023, 2021), at 0.5° gridded resolution, providing 2015-2100 values for ssp126, ssp245, ssp370, ssp585. Bias-adjustment follows the ISIMIP3BASD trend-preserving quantile-mapping protocol, in which raw GCM output is statistically corrected against the W5E5 observational reference dataset — itself

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derived from ERA5 — ensuring consistency between our historical (ERA5-based) and projected climate variables. This bias-adjustment and downscaling to a common 0.5° grid is what allows GCM output, otherwise available at coarser and heterogeneous native resolutions, to be used consistently across models and scenarios. While finer-resolution regional climate products exist for specific areas, ISIMIP remains the standard, most widely validated source for global, multi-model climate projections and is the basis for most existing sub-national and regional climate-damage assessments (Callahan and Mankin, 2022a; Waidehlich et al., 2024), in the absence of a globally consistent higher-resolution alternative. The simulation ensemble ranges from 5 to 10 models, depending on the scenario. We compute the same indicators as the historical, maintaining the same thresholds for quintile-based variables. We then aggregate by population at the subnational level using the latest available yearly ISIMIP projections in 2015-2100 (ISIMIP Repository, 2017)

2.5.3. Human Development Data

The Sub-National Human Development Index (HDI) used in this study is derived from the UNDP’s official HDI (hdr.undp.org), tailored for sub-national analysis. Data are publicly available through the Global Data Lab Project (Smits and Permanyer, 2019).

The HDI combines sub-national values across three key areas: education, health, and standard of living. Education is assessed through "Mean years of schooling of adults aged 25 and above" and "Expected years of schooling of children aged 6"; health is evaluated by "Life expectancy at birth"; standard of living is determined by "Gross National Income per capita (PPP, 2011 US\$)". Each component is then min-max normalized, resulting in three indices: Health Index, Education Index, and Income Index. HDI is then obtained as a geometric mean of the three. Further insights on the choice of the variables can be found in the Human Development Report (United Nations, 1990).

Smits and Permanyer (Smits and Permanyer, 2019) originally built on this data and produced a set of indices for the period 1990–2018. To do this, they collected the sub-national disparities in health, education, and income indicators from various sources, including household surveys, censuses, and statistical offices. They aligned them with national data sourced from the UNDP website. When combinations of regions and years were unavailable, interpolations and extrapolations were performed, while always ensuring that the population-averaged indicators of the areas matched the national ones. Data were then maintained on the Global Data Lab Project and updated until 2021. We use Sub-National HDI components data for 1773 regions over 30 years from 1990 to 2020.

2.5.4. SSP Socio-Economic Projections Data

We compute the total projected population by country using ISIMIP projections (ISIMIP Repository, 2017). We also check that aggregated values are the same as from Wittgenstein Centre Data Explorer Version 3.0 at <https://dataexplorerer.wittgensteincentre.org/wcde-v3/>.

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We download Life Expectancy at Birth projections by country from the Wittgenstein Centre Data Explorer Version 3.0. From the same source we retrieve Mean Years of Schooling by Broad Age, which we use for estimating Expected Years of Schooling based on a historical linear regression fit between the two measures using country level data in 1990-2020 (Rsquared 0.67). We retrieve national projections of GDP (PPP, US\$ 2005) from the SSP database hosted by IIASA at https://iiasa.ac.at/models-tools-data/search?search_api_fulltext=income. Again, we model the historical relationship between Gross National Income per Capita and Gross Domestic Product per Capita (on a logarithmic scale, obtaining an R-squared of 0.9916) and use it to project income. To ensure consistency with historical values, we shift all national projected values of each variable such that the 2024 values correspond. This is needed as we calculate baseline indices (Income Index, Education Index, and Life Expectancy Index, which we refer to as LIFEX Index) and HDI over all periods under consideration (1990-2100).

2.5.5. Empirical Model

To assess climate impacts on HDI growth, we deploy a fixed effects panel model with regional, year fixed effects and quadratic time varying country trends, following previous similar impact work (Burke et al., 2015; Kotz et al., 2022b; Callahan and Mankin, 2022a; Malpede and Percoco, 2023). We fit the same kind of model for each of the variables composing the HDI:

$$y_{i,t} = f_e(E_{i,t}) + f_t(T_{i,t}, T_{i,t-1}) + f_r(R_{i,t}, R_{i,t-1}) + \sigma_i + \omega_t + \delta(t)_c. \quad (2.2)$$

Where $y_{i,t}$ represents the log difference (between year t and year $t-1$) of one of the socio-economic variables: expected years of schooling (eys), life expectancy at birth (leb), gross national income per capita (gnipc). Given the long-term definition of this variable, we discard mean years of schooling from this exercise, accounting for the completed years of schooling of people aged 25+: if we were to capture climate impacts on this dimension, we would need a dataset on education spanning well beyond our time horizon and going back to the actual time people were enrolled in primary or higher education.

$f_t(T_{i,t}, T_{i,t-1})$ and $f_r(R_{i,t}, R_{i,t-1})$ represent the functions of temperature and precipitation which work as controls in this framework: across specifications we use squared temperature and precipitation in region i , year t , the difference between temperature at year t and year $t-1$ (and same for precipitation) and interactions of the terms. $f_e(E_{i,t})$ is the function accounting for extreme variables, possibly different for each of the HDI component. We first test each climate extreme or hazard entering the impact function alone, in one of three fashions: as a shock in each year with respect to the previous one, as levels, or as distributed lag shocks. For example, $diff_PEXT_{i,t}$ represents the inter-annual difference ($PEXT_{i,t} - PEXT_{i,t-1}$) of extreme rainfall, and a negative coefficient would entail an adverse effect on growth when an annual increase in this variable is

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registered. On the other hand, $PEXT_{i,t}$ entering the function with a negative coefficient would mean that a high level of extreme rain decreases growth. As in Burke et al. (2015), we also test level variables in quadratic form, allowing for a convex or concave relationship of extremes and growth. Finally, we employ a damage function like the one Kotz et al. (2025) uses, in a distributed lag fashion.

The second part of our analysis attempts to identify impact models for each response variable, with all essential climate variables together. This allows for a comprehensive additive interpretation of the coefficients, as the variables are naturally correlated. We do this conservatively by selecting extremes in the one-at-the-time models which show a non negligible effect and significance at 0.1 level when clustering errors by country (Kotz et al., 2022b), to account for the bias induced in the variance-covariance matrix when dealing with possibly correlated observations in space and time, such as our case.

For every model reported we use year (ω_t), region (σ_i) fixed effects and country quadratic time trends ($\delta(t)_c$), to allow the specification to be flexible into accounting for unobserved differences among regions and years and to account for specific time trends, characteristic of each variable, which are not climate dependent but possibly correlated with it. We use this fixed effects scheme as it is consistent with previous studies (Malpede and Percoco, 2023) and because it represents a good trade-off in terms of complexity.

Table 2.1 summarizes variables observed to be significant with robust standard errors across various specifications. This conservative choice allows us to better control for type I error of falsely rejecting the null hypothesis in the presence of heteroskedasticity (in time or between regions).

We test, for each response variable, the different specifications reported in table A.1. In particular, we follow three possible approaches: one takes inspiration from the damage function in (Burke et al., 2015), and assumes a quadratic effect of the level of mean temperature, controlling by the quadratic total precipitation and adding the same quadratic structure for extremes; the other builds on (Kalkuhl and Wenz, 2020) and considers variables in their first difference, possibly interacted with the level of a control variable to introduce spatial heterogeneity; finally, following (Kotz et al., 2021, 2022b) we control for differences in mean climate and we include extremes in level.

Given recent literature advancements on climate impact function test and find finite persistency of weather shocks on GDP growth (Kotz et al., 2025; Nath et al., 2024a), we also test a distributed lag model framework. For each outcome variable, we first include climate variables one at a time and select lag length through information criteria (Akaike, Bayesian and Hannan–Quinn, which balances model fit and complexity and is well fit for time series (Hannan and Quinn, 1979)), one-year-out cross-validation (following the pre-estimation demeaning approach described in (Newell et al., 2021)). Then, we analyze the joint significance of the lagged terms block selected. We do these steps while controlling for other climate variables, in particular

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rainfall when testing temperature, temperature when testing rainfall, and both temperature and rainfall when testing extremes (for the metrics values, see Figures A.4, A.5, A.6 and table A.5 in appendix A.1). Finally, we include all variables retaining block joint significance when together in the model (see Table A.5 in appendix A.1). We obtain the following functional forms for our preferred specifications, based on information criteria lag selection and dropping variables no longer significant when in the complete model:

$$\begin{aligned}
 gr_eys_{i,t} \sim & \sum_{k=0}^7 (\text{lag}(diff_TM_{i,t}, k) + \text{lag}(TM_mean_i * diff_TM_{i,t}, k)) \\
 & + \sum_{k=0}^2 (\text{lag}(diff_RR_{i,t}, k) + \text{lag}(RR_mean_i * diff_RR_{i,t}, k)) \\
 & + \sum_{k=0}^1 (\text{lag}(diff_WD_{i,t}, k) + \text{lag}(WD_mean_i * diff_WD_{i,t}, k)) \\
 & + \sum_{k=0}^6 (\text{lag}(diff_TVAR_{i,t}, k) + \text{lag}(TM_mean_i * diff_TVAR_{i,t}, k)) \\
 & + \sigma_i + \omega_t + \delta(t)_c
 \end{aligned} \tag{2.3}$$

$$\begin{aligned}
 gr_leb_{i,t} \sim & \sum_{k=0}^1 (\text{lag}(diff_TM_{i,t}, k) + \text{lag}(TM_mean_i * diff_TM_{i,t}, k)) \\
 & + \sum_{k=0}^5 (\text{lag}(diff_RR_{i,t}, k) + \text{lag}(RR_mean_i * diff_RR_{i,t}, k)) \\
 & + \sum_{k=0}^0 (\text{lag}(diff_HW_{i,t}, k) + \text{lag}(HW_mean_i * diff_HW_{i,t}, k)) \\
 & + \sum_{k=0}^0 (\text{lag}(diff_TVAR_{i,t}, k) + \text{lag}(TVAR_mean_i * diff_TVAR_{i,t}, k)) \\
 & + \sum_{k=0}^3 (\text{lag}(diff_WD_{i,t}, k) + \text{lag}(TM_mean_i * diff_WD_{i,t}, k)) \\
 & + \sigma_i + \omega_t + \delta(t)_c
 \end{aligned} \tag{2.4}$$

2| Past and Projected Climate Impacts on Human Development

$$\begin{aligned}
gr_gnipc \sim & \sum_{k=0}^8 (\text{lag}(diff_TM_{i,t}, k) + \text{lag}(TM_mean_i * diff_TM_{i,t}, k)) \\
& + \sum_{k=0}^0 (\text{lag}(diff_RR_{i,t}, k) + \text{lag}(RR_mean_i * diff_RR_{i,t}, k)) \\
& + \sum_{k=0}^7 (\text{lag}(diff_HW_{i,t}, k) + \text{lag}(TM_mean_i * diff_HW_{i,t}, k)) \\
& + \sum_{k=0}^9 (\text{lag}(diff_WD_{i,t}, k) + \text{lag}(RR_mean_i * diff_WD_{i,t}, k)) \\
& + \sum_{k=0}^6 (\text{lag}(diff_TVAR_{i,t}, k) + \text{lag}(TM_mean_i * diff_TVAR_{i,t}, k)) \\
& + \sigma_i + \omega_t + \delta(t)_c
\end{aligned} \tag{2.5}$$

A visual representation of our preferred model specification is reported in supplementary Fig. A.7. We do several robustness checks on these models: we substitute the historical mean interacting variables with 10-years moving windows, to possibly capture an increasing adapting capacity, and obtain virtually equal results (supplementary Fig. A.8); we weight climate by area instead of by population (supplementary Fig. A.9); we add as controls the growth rates of the other two output variables (for instance, when testing models for growth in income, we include growth of life expectancy and expected years of schooling) and controls at the country level coming from the World Bank, specifically public expenditure in education and health, percentage of GDP deriving from trade, weather a country was in conflict or not throughout the years (supplementary Fig. A.10).

As an additional check, we test the complete models with LASSO at different penalty values and grouped LASSO (grouping together lags of the same variable). We use a varying penalty term that denotes the amount of shrinkage, either 0, 1, 0.5, and in all cases the methods select all variables with a number of lags which is higher than in our final specification (see Table A.6 in appendix A.1). Moreover, the pairwise correlation between coefficients fitted by the three methods is always higher than 98%. Finally, grouped Lasso selects all groups for each outcome, so all temperature terms are selected, all temperature terms interactions are selected and so on.

All analyses are done within R through the package "fixest" (Bergé, 2018).

2.5.6. Future Climate Impacts Calculation

We project climate impacts on top of current SSP trajectories (Riahi et al., 2017) for a socioeconomic variable y (income, education, and health) under climate change. The baseline trajec-

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tory of y , assuming no climate change, follows the growth process as:

$$y_{r,t}^{s,base} = y_{r,t-1}^{s,base} (1 + g_{r,t}^s),$$

where $y_{r,t}^{s,base}$ represents the projected value of y for region r , year t , and scenario s and $g_{r,t}^s$ is the annual growth rate under SSP s for region r and year t .

The coefficient vector β is estimated from historical data and held fixed throughout the projection period. This implies that the sensitivity of each HDI component to climate shocks does not change endogenously as countries develop over time. This is a distinct assumption from "no adaptation" in the climate-specific policy sense: rather than assuming no climate-specific adaptive measures are taken, we assume a fixed vulnerability relationship derived from the historical period.

Under climate change, the growth rate of y is impacted by climate-induced damages. The climate-induced deviation $\delta_{log,r,t}^{m,s}$ (calculated as impact on the log differences of the output) for region r , year t , model m and scenario s is expressed as:

$$\delta_{log,r,t}^{m,s} = \mathbf{X}_{r,t}^{m,s} \cdot \beta,$$

where $\mathbf{X}_{r,t}$ is the vector of climate variables we use in each impact function and β is the correspondent vector of coefficients estimated from historical panel models.

In this approach, the climate-induced delta $\delta_{log,r,t}^{m,s}$ is not directly applied as an additive term but is rather back-transformed to the original scale of y using an exponential transformation. In fact, let δ denote a logarithmic growth rate. The evolution of y would then satisfy

$$\frac{y_{r,t}}{y_{r,t-1}} - 1 = \exp(\delta) - 1. \quad (2.6)$$

which transforms the delta into a percentage change.

Thus, the climate-adjusted projection of levels of y , assuming persistence of effects and combining baseline growth rates and climate deltas, is:

$$y_{r,t}^{m,s} = y_{r,t-1}^{m,s} \cdot \left((\exp(g_{log,r,t}^s) - 1 + \exp(\delta_{log,r,t}^{m,s}) - 1 + 1) \right).$$

To account for the uncertainty in the climate damage function, we perform a bootstrapping procedure. First, we draw $N = 1000$ bootstrap samples of the coefficient vector $\beta^{(n)}$ from a multivariate normal distribution:

$$\beta^{(n)} \sim \mathcal{N}(\beta, \Sigma),$$

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where Σ is the estimated variance-covariance matrix of the coefficients. For each bootstrap sample, we recalculate the climate-induced deviation $\delta_{r,t}^{(n),m,s}$ using the new coefficients, and compute the corresponding climate-adjusted projection:

$$y_{r,t}^{(n),m,s} = y_{r,t-1}^{m,s} \cdot \left(\exp(g_{log,r,t}^s) + \exp(\delta_{log,r,t}^{(n),m,s}) - 1 \right).$$

This procedure results in a distribution of climate-adjusted projections for each region, climate model, and SSP scenario.

2.5.7. Sobol Indeces Calculation

Let $f(s, m, b)$ be a square-integrable function of the three independent uncertain inputs s, m, b . The total variance of the output is:

$$\text{Var}[f(s, m, b)] = V = V_s + V_m + V_b + V_{sm} + V_{sb} + V_{mb} + V_{smb}$$

where:

$$\begin{aligned} V_s &= \text{Var}(\mathbb{E}[f|s]) \\ V_m &= \text{Var}(\mathbb{E}[f|m]) \\ V_b &= \text{Var}(\mathbb{E}[f|b]) \\ V_{sm} &= \text{Var}(\mathbb{E}[f|s, m]) - V_s - V_m \\ V_{sb} &= \text{Var}(\mathbb{E}[f|s, b]) - V_s - V_b \\ V_{mb} &= \text{Var}(\mathbb{E}[f|m, b]) - V_m - V_b \\ V_{smb} &= \text{Var}[f] - V_s - V_m - V_b - V_{sm} - V_{sb} - V_{mb} \end{aligned}$$

Each V_* term represents a contribution to the total variance from: First-order effects: V_s, V_m, V_b Second-order interactions: V_{sm}, V_{sb}, V_{mb} Third-order interaction: V_{smb} The corresponding (normalized) Sobol' indices are given by dividing each term by the total variance V , for example:

$$S_s = \frac{V_s}{V}$$

In Fig. 2.5 we report S_s (scenario), S_b (bootstrapped coefficients), S_m (climate model) indices, and the residual sum of the remaining variance contributions, identifying interaction terms.

Sobol indeces are computed through R package `sensobol` (Puy et al., 2022b).

3 | Human Development Burdens and Recovery of Climate Overshoot and Return

3.1. Introduction

The increasing likelihood of temporarily exceeding warming thresholds, commonly termed climate overshoot and return, raises questions about the recovery capacity of human societies and ecosystems. It is now virtually certain that global temperature will exceed 1.5°C above pre-industrial levels, and might also exceed 2°C (Reisinger et al., 2025; Intergovernmental Panel On Climate Change (IPCC), 2023; Tavoni et al., 2026). Physical and ecological risks of sustained warming and overshoot, including sea-level rise, biodiversity loss, and intensifying extreme weather, are extensively documented (Meyer et al., 2022; Anderson et al., 2020; Schleussner et al., 2024; Nusbaumer and Matsumoto, 2008). Whether warming will ever be reversed is unknown, as this would require carbon emission to be net-negative. Nevertheless, overshoot and return remains a crucial topic, and its human dimension is largely unexplored.

Empirical climate-economics research has established historical relationships linking temperature changes to income, mortality, labor productivity, and educational outcomes (Burke et al., 2015; Kahn et al., 2021b; Waidehlich et al., 2024). These studies demonstrate sensitivity in the past data not only to mean warming but also to climate variability and extremes. Moreover, efforts to integrate multiple dimensions of climate change, including spatial variation, temporal variability, and extreme events, reveal greater economic damage than previously estimated (Li et al., 2025). Incorporating spatial and temporal variability increases estimated aggregate damages by 17-45% compared to assessments based solely on mean temperature (Estrada et al., 2025), with projections indicating global GDP losses approaching 10% at +3°C and disproportionately severe impacts in low-latitude, lower-income regions (Waidehlich et al., 2024; Callahan and Mankin, 2022a). A critical and still unresolved empirical question is whether these temperature impacts affect economic and human development outcomes at the level only, in which case damages would reverse once temperatures decline, or whether they affect growth rates, causing damages to compound and persist over longer times (Bastien-Olvera et al., 2022; Callahan and Mankin, 2023a; Kahn et al., 2021b). The answer to this question has direct consequences for evaluating the human cost of overshoot: even assuming reversible impacts and climate dy-

3| Human Development Burdens and Recovery of Climate Overshoot and Return

namics, the temporal compounding of annual damages over the overshoot period can generate hysteresis in the drawdown phase. Humanitarian assessments similarly emphasize that overshoot pathways amplify risks to livelihoods, migration, governance stability, and conflict in vulnerable populations (Kruczkiewicz et al., 2025; Theokritoff et al., 2025). Accounting for the economic benefits of limiting warming alongside mitigation costs indicates that ambitious climate action is economically justified even under conservative damage assumptions (Drouet et al., 2022, 2021).

Despite these advances, quantitative integration of overshoot (and overshoot and return) climate trajectories with empirically grounded impact functions for socio-economic and human development outcomes is only beginning to emerge (Schoengart et al., 2025). Most overshoot analyses focus exclusively on physical and ecological responses (Anderson et al., 2020; Meyer et al., 2022; Bauer et al., 2023; Douglas et al., 2025), while social assessments remain predominantly qualitative (Kruczkiewicz et al., 2025). Moreover, quantitative development-impact models typically assume monotonic warming trajectories, neglecting the peak-and-decline dynamics that characterize overshoot and return, and existing work on economic damages under overshoot has focused primarily on GDP rather than on broader measures of human welfare (Schoengart et al., 2025; Drouet et al., 2021).

Recent simulations reveal that regional climates may not fully revert to their pre-overshoot states, with persistent asymmetries in temperature and precipitation extremes arising from hysteresis in ocean circulation and sea ice (Douglas et al., 2025; Marshall et al., 2025; Roldán-Gómez et al., 2025). These findings underscore that for overshoot pathways, the trajectory of warming matters as much as the ultimate stabilization level (Meyer and Trisos, 2023; Tavoni et al., 2026). Nevertheless, the dominant spatial patterns of anthropogenic warming can be characterized as functions of global-mean temperature, motivating the widespread application of temperature-driven pattern scaling and simple climate models (SCMs) for impact assessment (Tebaldi and Arblaster, 2014; Goodwin et al., 2018). These computationally efficient frameworks underpin widely adopted emulators, including MAGICC, FaIR, and STITCHES (Meinshausen et al., 2011; Leach et al., 2021; Tebaldi et al., 2022; Bauer et al., 2023), and remain indispensable for exploring large scenario ensembles under overshoot conditions, where different temporal dynamics preclude exhaustive sampling by full Earth-system models.

To our knowledge, no previous study has assessed the impacts of overshoot and return on human development. The aim of this chapter is to fill this gap by evaluating overshoot and return pathways varying the magnitude of overshoot and stabilization temperature, and assessing their implications for Human Development Index (HDI) components across a multi-model climate ensemble. To quantify the climate consequences of overshoot pathways, we implement a trajectory-sensitive climate emulator employing spline representations and gradient-weighted matching to identify optimal multi-year temperature windows from ISIMIP-CMIP6 simulations across different climate models. Unlike existing emulators that rely solely on temperature levels, our approach explicitly accounts for warming and cooling rates, enabling physically consistent emulation of the post-peak decline phase. This enables rapid evaluation of diverse overshoot

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magnitudes, durations, and cooling rates while preserving the temporal features that are essential for socio-economic impact modeling under novel pathways with no direct ESM analog. The climate scenarios considered exhibit modest returns from overshoot, and we implicitly assume reversible climate dynamics. Climate reversibility from overshoot might not be possible if temperature exceedance is too large, or even at all in specific regions (Roldán-Gómez et al., 2025). Thus, our estimates are intended as lower-bounds. We couple the climate emulator with empirically estimated impact functions developed in the previous chapter. These provide granular and dynamic information on the impacts of a variety of climate metrics -means and extremes of temperature and precipitation- for gross regional income, life expectancy, and expected years of schooling, at subnational levels. This chapter makes three specific contributions.

First, we provide the first systematic quantification of overshoot impacts on all three HDI components simultaneously, across seven scenarios designed to isolate the effects of peak warming magnitude, overshoot duration, and end-of-century stabilization level. Second, we develop a trajectory-sensitive climate emulator, enabling physically consistent emulation of novel overshoot-and-return pathways with no direct ESM analog and applicability beyond this study to any impact assessment requiring post-peak climate trajectories. Third, we provide sub-national maps of recovery, residual damage, and cumulative loss across the main overshoot scenarios, quantifying the geography of committed harm at the regional level with explicit model-agreement significance criteria. A visual representation of our methodological pipeline is reported in Figure 3.1.

Even under climate dynamics and damage reversibility as estimated empirically, our results reveal potential hysteresis: human development losses incurred during overshoot persist long after global temperatures return to lower levels. At peak warming, global HDI losses from baseline range from -0.19 to -0.69 index points ($\times 100$) across scenarios, corresponding to 2.5 and 12 years of development lost on the baseline path, respectively. Recovery by 2100 is incomplete in all cases: between 19% and 70% of peak damages are reversed depending on scenario, leaving residual HDI losses of up to -0.36 index points even after temperatures decline. The total cumulative burden, integrated over 2020–2100, ranges from -12.7 to -31.7 index points $\times$ years, remaining negative across the full model ensemble and uncertainty sources. Critically, a 3°C peak scenario stabilizing at 2°C by the end of the century generates $\sim 25\%$ more cumulative damage than a scenario peaking at the same level but returning to 1.5°C , illustrating that the cooling trajectory is as consequential as the peak itself.

3.2. Results

We assess how temporary and persistent temperature overshoot affects the components of the Human Development Index (HDI) using three impact functions developed in the previous chapter. In particular, we deploy a flexible Distributed Lag Model to examine the effects of climate shocks on the growth of the three components of the index — Income per Capita, Expected Years of Schooling, and Life Expectancy at Birth. The climate variables included in the impact functions are Mean Temperature, Total Precipitation, Number of Wet Days, Daily Temperature

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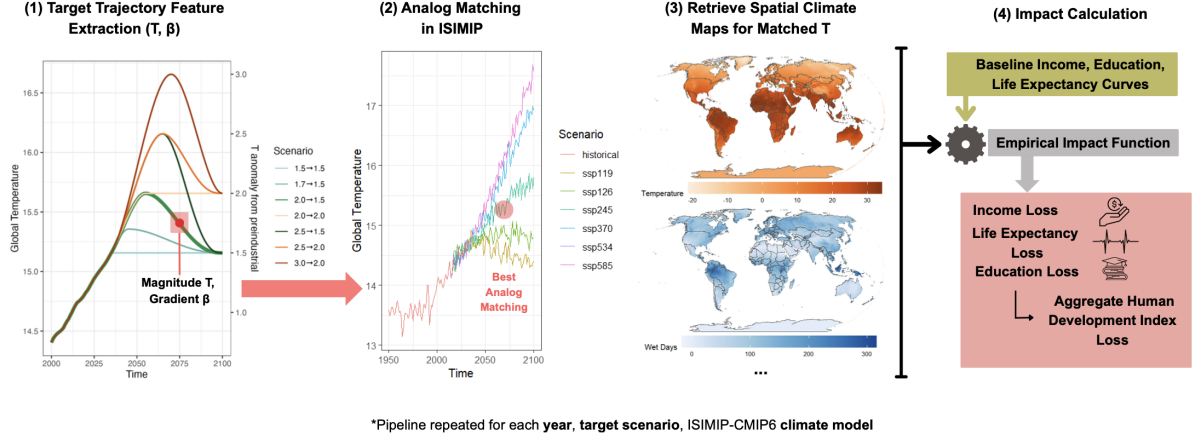


Figure 3.1: Methodology pipeline, repeated for each ISIMIP-CMIP6 model, described in detail in Appendix B.4. Panel (1) shows global mean surface temperature (left y-axis) and anomaly w.r.t. 1850-1900 (right y-axis) trajectories for the seven scenarios we investigate. For each candidate scenario and year, the global temperature T and curve gradient β are extracted and matched to the best candidate across ISIMIP scenarios (Panel (2)). The regional climate indicators for the selected year, global temperature, scenario are retrieved (Panel (3)). The climate variables we use are: Mean Temperature, Total Precipitation, Number of Wet Days, Daily Temperature Variability, and Heatwave Index. Finally, the three impact functions for Income, Education and Life Expectancy are applied to the full regional temporal trajectory, allowing for the construction of a baseline HDI and a HDI under future climate change (Panel 4).

Variability, and a Heatwave Index. A detailed summary of these functions and the projection strategy is also provided in Methods, Section 3.5.1. We combine these impact functions with seven synthetic GMT (Global Mean Temperature) scenarios: five overshoot-and-return pathways and two stabilization scenarios at 1.5°C and 2°C above preindustrial levels (Figure 3.1, panel (1)). From now on, we refer to each scenario as peak°C→end-of-century°C. These scenarios allow us to analyze different overshoots in terms of peak level (1.7, 2, 2.5, and 3°C), reversal (0, 0.2, 0.5, and 1°C), and overshoot integral (0, 5, 7.5, 10, and 15 degree-years). The amount of cooling we consider reflects the high levels of mitigation and carbon dioxide removal that are increasingly recognized as necessary to meet climate targets (Keller et al., 2018). Although illustrative, these scenarios are comparable to the newest community scenarios (Van Vuuren et al., 2026). The scenarios returning from 1.5°C include a Paris-compatible case (1.7→1.5), and one that slightly exceeds the agreement (2→1.5). Higher overshoots are within the range explored in the new Scenario MIP, with the highest one (3→2) similar to the High-Low case, though with a faster cooling. We remain agnostic on how these scenarios are achieved, e.g. through which CO₂ removal method or other climate intervention. Frameworks to start capturing the activities needed to recover from overshoot into climate models are beginning to emerge but not yet available in regional simulations (Roldán-Gómez et al., 2025). In all cases, we assume socio-economic conditions to follow a world with economic growth rates and convergence in line with historical trends (SSP3). For a full characterization of the scenarios, see Methods, Section 3.5.2. To map these GMT trajectories into the regional climate indicators required by the impact functions, we developed a trajectory-sensitive lookup-table emulator that queries a

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precomputed archive of CMIP6 simulations across eight Earth System Models (ESM) and seven SSP scenarios. Our emulator matches sliding 3-year windows of the target emulation trajectory on both temperature level and gradient, retrieving regional indicators from the matched ESM analog (Figure 3.1, panels (2) and (3)). The emulator’s full specification and indicator-level comparison against ISIMIP outputs are reported in Section 3.5.3 and Appendix B.4. Finally, we feed the impact functions with the emulated regional climate variables and calculate the difference in each Human Development component relative to a baseline without climate change (Figure 3.1, panel (4)).

An important point to highlight is that our emulator tracks scenario trajectories primarily through global mean temperature matching. This means we do not make explicit assumptions about climate hysteresis: once temperatures return to a given level after the overshoot peak, the emulator may retrieve the same regional climate patterns as on the way up, implicitly assuming optimistic pre-overshoot local climate conditions after cooling. Therefore, our damage estimates should be interpreted as a lower bound on the true impact of a possible climate hysteresis (Nusbaumer and Matsumoto, 2008; Liu et al.). Moreover, the two SSP scenarios included in the emulator that involve overshoot and return (SSP1-1.9 and SSP5-3.4) both exhibit relatively modest cooling, and their regional climate behavior depends strongly on the structural assumptions of the underlying Earth System Models. As a result, the emulator’s ability to represent the post-peak cooling phase and climate hysteresis is constrained by the limited diversity of cooling dynamics available in the CMIP6 archive.

3.2.1. Human Development Impacts Dynamics Under Overshoot-and-Return Scenarios

All scenarios lower global HDI relative to a no-climate-change baseline throughout the century, with damages increasing with peak warming (Figures 3.2). At peak warming, explored in details in Figure 3.3, the ensemble median HDI impact ranges from -0.19 index points ($\times 100$; 90% CI: $-0.41, -0.03$) in the lowest overshoot scenario ($1.7 \rightarrow 1.5$, peak 2045) to -0.69 (90% CI: $-1.49, -0.07$) in the most extreme case (3°C , peak at 2070). These numbers correspond approximately to 2.5 years (in the low-overshoot case) and 12 years (in the high-overshoot case) of lost development, defined as the number of years of baseline development progress that are offset by climate-induced reductions. Losses are driven primarily by the income index, which reaches -1.51 index points (90% CI: $-3.53, +0.06$) at 3°C , corresponding to 20 years lost on this index. Education and life expectancy show smaller but consistently negative effects across scenarios (full evolution of the three indices reported in Appendix B.5, Figures B.42, B.44 and B.43).

Uncertainty is large across all scenarios, often exceeding the median by an order of magnitude. At 2.5°C peak warming, for example, HDI losses range from 1.47 to 0.02 index points (Figure 3.3). While the central estimate is negative, some model-bootstrap combinations still imply near-zero or even positive effects. This spread we observe is driven by differences across the models and

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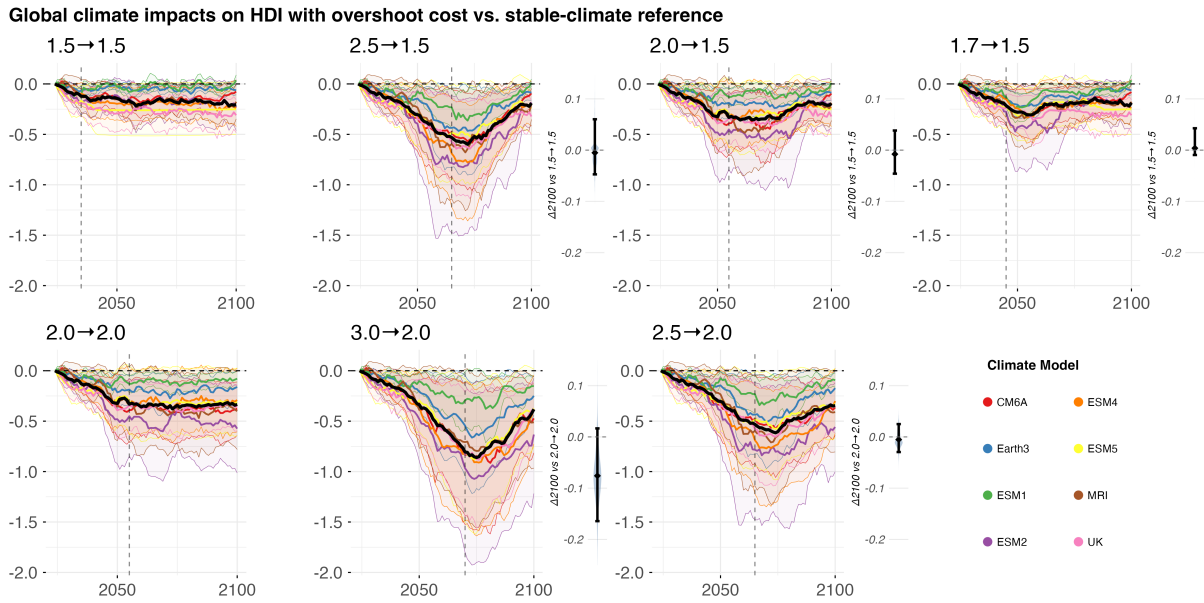


Figure 3.2: Projected climate change impacts on global HDI relative to a counterfactual baseline without climate change, 2020–2100, under seven temperature overshoot scenarios. Coloured lines show individual climate model estimates; the black line shows the cross-model ensemble median; shaded ribbons indicate the 90% bootstrap interval. The vertical dashed line marks the year of peak warming for each scenario. Panel titles indicate peak and end-of-century warming levels, respectively. The small panels on the right of each trajectory show the difference in end-of-century impact ($\Delta 2100$) between the overshoot scenario and its stable-climate reference (1.5→1.5 or 2.0→2.0): the shaded area shows the pooled bootstrap distribution, the bold black line and diamond show the pooled 90% interval and mean, and the coloured lines show the 90% interval for each individual climate model. Appendix B.5 contains component-specific global evolutions. Appendix B.6, Figure B.49, reports detailed model-by-model differences at the end of the century between each overshoot scenario and its reference one.

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Figure 3.3: Distribution of projected impacts on HDI and its components at the year of peak warming across overshoot scenarios, climate models, and bootstrap draws. Each color corresponds to a scenario ordered by peak warming level. The central dot and thick line show the median and 90% bootstrap interval for each individual climate model; separate violin shapes (dodged within scenario) illustrate the contribution of model uncertainty to the overall spread. The triangle and error bar at the top of each scenario group show the pooled median and 90% interval aggregated across all climate models.

sampling variability. We sample from the impact function with country-clustered standard errors when estimating at the sub-national level, thereby imposing conservative bounds on empirical uncertainty. Model-specific medians at peak span most of the pooled distribution (Figure 3.3). Some models systematically project smaller damages, while others produce larger losses. At 3°C, model medians range from about -0.13 to -0.45 , compared to a pooled median of -0.69 . The 90% confidence interval crosses zero in all but the highest warming scenario, meaning that statistically significant aggregate damage is not robust at moderate overshoot levels.

Despite this uncertainty in magnitude, two patterns are consistent. First, peak damages always occur at the time of maximum warming, or a few years later, given the distributed lag structure of the impact function. Second, the ranking of scenarios is preserved across models: higher peak temperatures always produce larger HDI losses and no model reverses this ordering. This reflects the emulator’s general consistency with ESM models in projecting increasing regional mean temperature and extremes with global mean temperature.

Temperature reversal helps reduce the impacts of climate change on human development. By the end of the century, when we compare overshoot scenarios with their reference stabilization scenario, most models do not show a significantly different end-of-century impact, except for 3.0→2.0, where 6 out of 8 models show higher residual damages compared to 2.0→2.0. Nevertheless, most models show heavier tails on the negative side of the distribution of differences. Moreover, scenarios that stabilize at 2°C by 2100 (2.5→2 and 3→2) show substantially higher cumulative exposure than those returning to 1.5°C, reflecting both higher long-term temperatures and longer periods of elevated warming that do not revert rapidly or long enough before

3| Human Development Burdens and Recovery of Climate Overshoot and Return

the end of the century.

3.2.2. Reversion of Peak Impacts at the End of Century

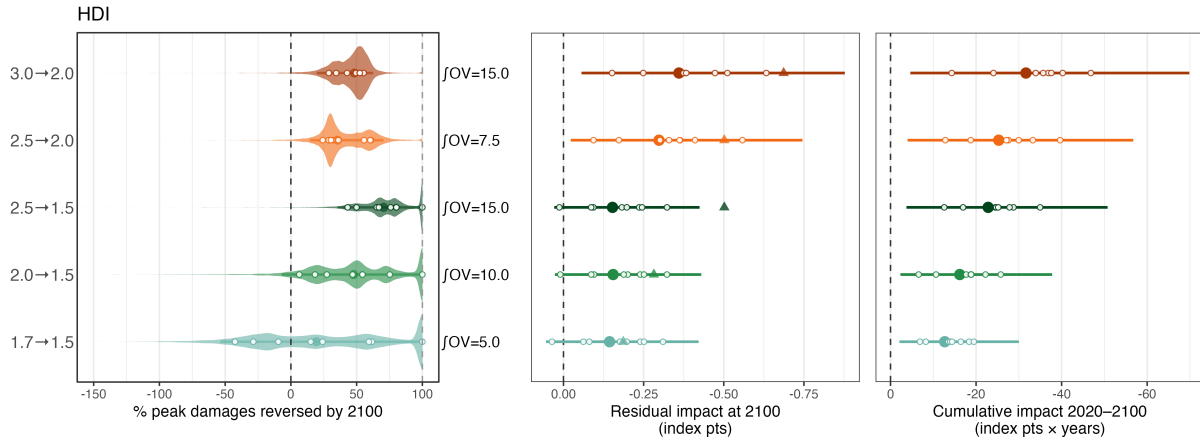


Figure 3.4: Climate change impacts on global HDI across temperature overshoot scenarios. *Left*: distribution of the percentage of peak damages reversed by 2100, pooled across climate models and bootstrap draws; the thick line and dot show the 90% confidence interval and median; open dots show individual climate model medians; the isolated mass at 100% represents draws where impacts are fully reversed by 2100 ($\delta_{2100} \geq 0$); the $\int OV$ annotation indicates the temperature overshoot integral ($^{\circ}\text{C}\cdot\text{years}$); *Centre*: residual HDI impact at 2100 (index points $\times 100$); filled dot = pooled median with 90% CI; open dots = per-model medians; triangle = impact at peak warming for reference. *Right*: cumulative HDI impact integrated over 2020–2100 (index points $\times$ years); filled dot = pooled median with 90% CI; open dots = per-model medians. A detailed explanation of how impact reversion is calculated is reported in the Methods section 3.5.1. Analogous figures for HDI components are reported in Appendix B.7.

Although temperature reversal reduces the HDI damages, a large share of the peak HDI damage persists after global temperatures return to lower levels by 2100 (Figure 3.4, central panel). The median percentage of peak damages reversed by 2100 ranges from 19% (90% CI: -54% , $+100\%$) for the 1.7 $\rightarrow$ 1.5 scenario to 70% (90% CI: 36%, 100%) for the 2.5 $\rightarrow$ 1.5 scenario - the scenario with the largest absolute overshoot but also full return to 1.5 $^{\circ}\text{C}$. For scenarios that stabilize at 2 $^{\circ}\text{C}$ by end of century, recovery is more limited: the 2.5 $\rightarrow$ 2 and 3 $\rightarrow$ 2 scenarios show median recovery of 35% (90% CI: 14%, 71%) and 48% (90% CI: 20%, 63%) respectively, with residual damages at 2100 of 0.30 and 0.36 index points compared to peak losses of 0.50 and 0.69 index points.

Uncertainty in recovery is very large: in most scenarios, the 90% confidence interval spans outcomes from continued deterioration to full recovery. The lower bound is negative for the 1.7 $\rightarrow$ 1.5 and 2 $\rightarrow$ 1.5 scenarios, indicating that some model–bootstrap draws show further HDI losses even during cooling. At the same time, scenarios reaching 1.5 $^{\circ}\text{C}$ at the end of the century also allow for full recovery. A formal variance decomposition using Sobol sensitivity indices (Appendix B.8, Figure B.54) shows that climate model uncertainty represents the majority of the variance in recovery across scenarios, increasing in the income dimension for higher overshoot scenarios. For the cumulative damages, uncertainty is roughly equally attributable to climate and

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damage function uncertainty, as the integral over the full projection period amplifies sensitivity to the estimated impact coefficients and their temporal lags.

The relationship between recovery and overshoot characteristics is informative. Comparing the two scenarios that peak at 2.5°C, the 2.5→1.5 scenario recovers 70% of peak damage against 35% for 2.5→2. The difference is attributable to the lower end-of-century temperature and the higher overshoot integral ($\int OV$). Similarly, the 2→1.5 and 2.5→1.5 scenarios, which both return to 1.5°C, show increasing median recovery (48% vs. 70%) with higher peak warming, confirming that larger overshoot magnitudes create stronger recovery dynamics at lower temperatures, though at the cost of substantially larger peak damages and cumulative losses. For scenarios stabilizing at 2°C, peak recovery is more limited given the higher residual warming. The 2.5→2 and 3→2 scenarios show median recovery of 35% (90% CI: 14%, 71%) and 48% (90% CI: 20%, 63%), with residual HDI impacts at 2100 of -0.30 and -0.36 index points compared to peak impacts of -0.50 and -0.69 .

An explicit panoramic of the relationship between overshoot integral, peak temperature, and absolute recovery is reported in Appendix B.7, Figure B.50. Both the pooled and model-by-model results confirm that a higher overshoot integral produces higher peak recovery. Nevertheless, for the same overshoot integral, in median across models, the lower the peak temperature, the higher the recovery.

Figure B.45 in Appendix B.6 further provides a model-by-model, scenario-pair comparison of peak impacts and percentage recovery. For peak damage levels, differences in peak HDI losses between scenarios with distinct peak warming levels are statistically significant in the majority of models, with a consistent direction across all models (lower damage for the lower-peak scenario). The difference in recovery between scenarios that share the same peak but differ in end-of-century temperature (2.5→1.5 vs 2.5→2) or share the same end-of-century temperature and differ in peak temperature is also significant in more than half of the models, with higher overshoot robustly producing higher recovery. Comparing the remaining scenario pairs reveals higher model uncertainty. The only exception is the couple (2.5→1.5 vs 3→2), where, despite the same overshoot amount and rate, the lower peak and lower end-of-century temperatures yield a higher percentage recovery, significant in most models.

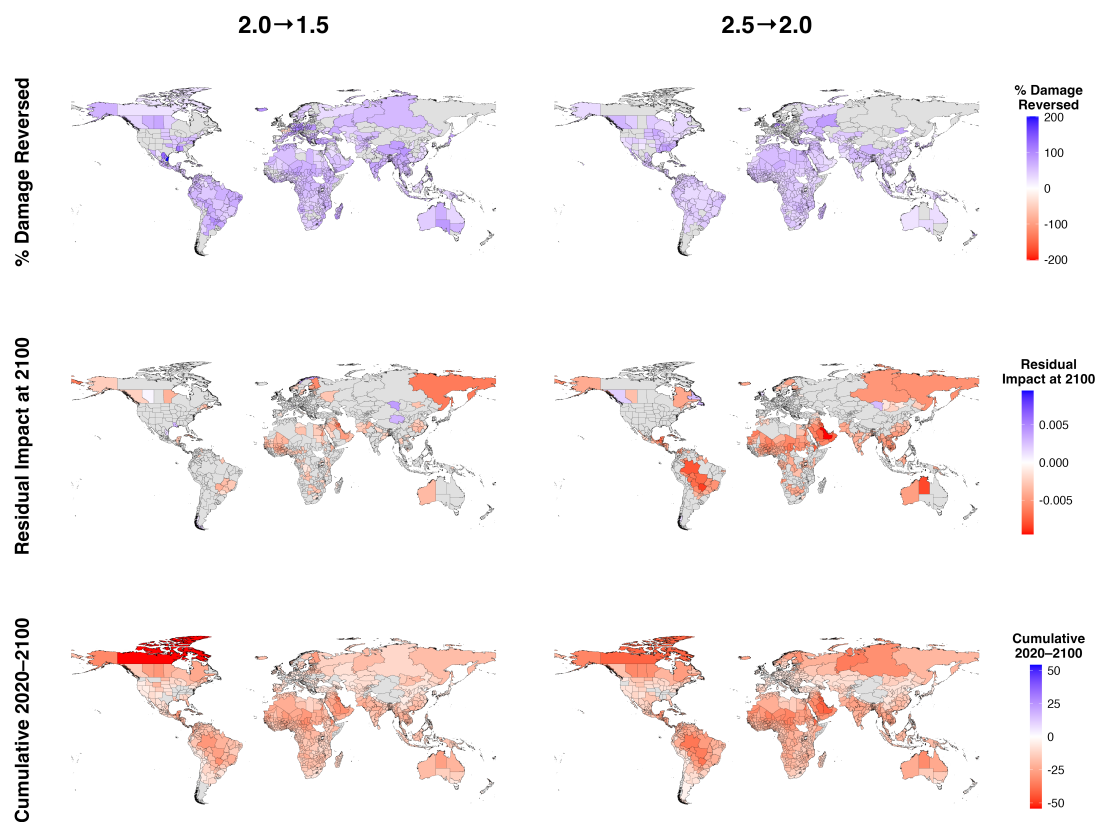
The cumulative impact panel of Figure 3.4 further reveals that the total burden of overshoot, integrated over the entire century (2020–2100), increases in both peak temperature and end-of-century stabilization temperatures. Median cumulative HDI losses range from 12.7 index point-years (90% CI: 30.0, 2.1) for the 1.7→1.5 scenario to 31.7 (90% CI: 69.9, 4.6) for the 3→2 scenario. The 2.5→2 scenario, which peaks with 2.5→1.5 but stabilizes higher, generates -25.3 index points-years against -22.8 . Critically, even the lower bound of the 90% CI is negative for all scenarios across the cumulative metric, indicating that the sign of the cumulative damage is the most robust finding of the analysis, even in the face of large uncertainty in both peak and end-of-century levels.

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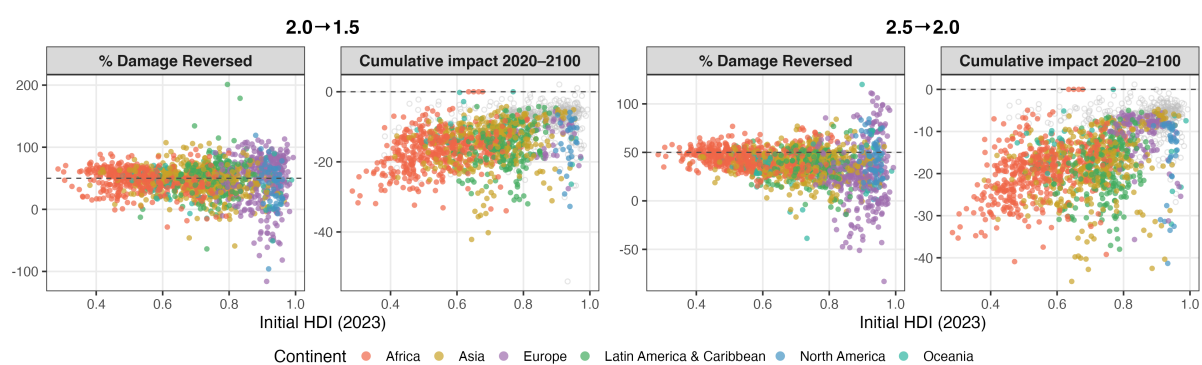
Patterns are broadly consistent across HDI components, though with differences in magnitude and recovery rates (Appendix B.7). The income index shows the largest losses and peak recovery rates, similar to the aggregate HDI (6%–71% across scenarios). Education exhibits a higher average recovery (51–66% in lower-overshoot cases) but very wide uncertainty, often including zero or negative values. Life expectancy losses are smaller but more robust, with fully negative confidence intervals for cumulative impacts in higher overshoot scenarios and recovery rates of 47–65%. Model-by-model comparisons across components (in Appendix B.6, Figures B.46, B.47, B.48) generally follow the HDI behavior, even though with lower model agreement, especially in the Education and Lifex dimensions of percentage recovery.

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3.2.3. Regional Differences



(a) Subnational HDI impacts across two overshoot scenarios (rows) and three metrics (columns): percentage of peak damages reversed by 2100 (left); residual impact at 2100 in index points × 100 (centre); cumulative impact 2020–2100 in index points × years (right). Grey regions lack sufficient model agreement. Blue = recovery; Red = persistent damage. Scenarios labeled peak°C→end-of-century°C.



(b) Initial HDI (2023) versus projected impact metrics across overshoot scenarios, for percentage of peak damages reversed by 2100 and cumulative impact 2020–2100. Each dot is a region. Coloured points have a statistically significant signal (90% CI excludes zero); grey open circles do not. Points coloured by continent.

Figure 3.5: Spatial patterns and equity dimensions of HDI impacts under temperature overshoot. Panel (a) maps regional recovery and cumulative damages; Panel (b) relates projected impacts to initial development levels.

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Regional heterogeneity in both the magnitude of overshoot damages and the extent of their subsequent recovery is substantial (Figure 3.5, panel 3.5a). The model agreement is highest for cumulative damages, with 87–90% of subnational regions showing a statistically significant signal in the same direction across at least half of the climate models. Agreement is lower for the percentage of peak damage reversed by 2100 (71–86% depending on scenario) and weakest for the residual impact at 2100 (19–34%), reflecting greater uncertainty in end-of-century projections.

Where recovery occurs, it partially overlaps with the damage pattern: regions with the largest peak damages, predominantly in the tropics, also tend to show the largest recovery by 2100 under both scenarios. However, many regions that were significantly affected retain negative HDI impacts at 2100 relative to the baseline (panel 3.5a, center column), confirming that percentage recovery from the peak does not translate into a return to pre-overshoot levels.

The spatial pattern of residual damage is concentrated in tropical and subtropical regions across both scenarios, consistent with the established amplification of climate impacts at lower latitudes, and becomes more geographically widespread as we move from 2→1.5 to 2.5→2. In East and South Asia, including India and Bangladesh, the Middle East, Central Africa, and South and Central America, both residual and cumulative losses are among the largest globally under both scenarios, but the transition from 2→1.5 to 2.5→2 deepens damage across large parts of the subcontinents.

These spatial patterns carry a clear equity dimension (Figure 3.5, panel 3.5b). Regions with lower initial HDI, concentrated in Sub-Saharan Africa, South Asia, and parts of South America, consistently display larger cumulative losses in overshoot and return scenarios while exhibiting less volatile, stronger recovery from peak impacts. Higher-HDI regions, predominantly in Europe and East Asia, show lower cumulative losses -given their lower exposure and vulnerability- but greater variation in the extent of recovery.

3.3. Discussion

Our results show that temperature overshoot produces long lasting and only partially reversible losses in human development, even under the conservative assumption of reversible climate dynamics and limited persistency of climate impacts. Across scenarios, damages increase monotonically with peak warming, most peak losses are not recovered by 2100, and uncertainty is large enough to prevent precise statements about the magnitude of any individual outcome. Persistent damage, limited recovery, and deep uncertainty define the central findings of this study.

Partial recovery is an optimistic lower bound. The finding that, across scenarios, on average 19%–70% of peak HDI losses are reversed by 2100 is notable because it emerges from a framework that does not impose structural irreversibility in the damage process. The model allows for both contemporaneous and lagged effects of climate on growth rates, but does not include any permanent damage stock or state variable that mechanically enforces persistence

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independent of future climate conditions. Persistence arises solely from distributed lag effects and the dynamic accumulation of growth rates into levels. Full reversibility is not guaranteed because HDI evolves as the time integral of growth responses, so recovery requires future positive deviations large enough to offset earlier negative shocks. Although this is theoretically possible under cooling, it does not generally occur in the simulated trajectories, given the estimated dynamic response to contemporaneous and lagged climate changes. Recovery, therefore, reflects the interaction of the overshoot pathway with these dynamic growth responses, rather than any explicit irreversible damage mechanism.

This dynamic is consistent with empirical evidence showing that climate shocks affect growth trajectories rather than only output levels, with effects persisting for at least a decade in many contexts (Bastien-Olvera et al., 2022; Kahn et al., 2021b), and that climate variability shocks can generate persistent deviations in economic performance even after conditions normalize (Callahan and Mankin, 2023a). Our results extend this logic to human development outcomes.

This interpretation aligns with a growing literature suggesting that overshoot impacts may be more persistent than implied by simple level-based damage functions. Schoengart et al. (2025) show that empirically estimated persistence in economic responses can translate transient warming into long-run losses. Schleussner et al. (2024) argue that scenario analyses may understate risks from temporary exceedance. Physical climate systems also exhibit partial irreversibility due to ocean and cryosphere inertia (Douglas et al., 2025; Roldán-Gómez et al., 2025; Marshall et al., 2025). Our contribution is to show that even without incorporating such mechanisms, aggregated development outcomes display incomplete recovery driven purely by time aggregation of growth effects.

If additional persistence mechanisms operate in reality, as suggested by physical evidence, then actual recovery would likely be weaker than estimated here.

Uncertainty is structural, asymmetric, and policy-relevant. Recovery outcomes are highly uncertain, with 90% confidence intervals spanning from negative values to full reversal in some scenarios. The distribution is asymmetric, with heavier lower tails in higher overshoot scenarios, suggesting that outcomes involving continued deterioration during the cooling phase cannot be ruled out.

Climate model uncertainty accounts for the majority of the variance in absolute recovery across scenarios and components, while impact function uncertainty contributes a smaller share, consistent with prior multi-model assessments of overshoot risks (Bauer et al., 2023; Drouet et al., 2021) and reflecting the limited basis for representing overshoot-and-reversal dynamics.

Importantly, this uncertainty is not merely a limitation but a result that is outcome-relevant. The lower tail of the pooled recovery distribution includes scenarios in which HDI continues to decline even as temperatures fall. This implies that conclusions based on median outcomes understate downside risk in overshoot pathways.

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For decision-making under uncertainty, particularly in highly exposed regions, the relevant distributional feature is therefore not the central estimate but the lower tail of outcomes.

Peak warming, cooling trajectory, and the overshoot integral. Both peak warming and post-peak cooling jointly determine outcomes. Comparing scenarios with identical peak warming (2.5°C) shows that recovery increases from 35% under $2.5 \rightarrow 2$ to 70% under $2.5 \rightarrow 1.5$, indicating that end-of-century temperatures, and thus the global cooling, strongly condition the extent of recovery.

Conversely, comparing scenarios with identical end-of-century temperature (1.5°C) shows that higher peak warming increases both recovered shares (48% vs. 70%) and absolute damages. Larger overshoot therefore increases both the scale of damage accumulation and the potential for partial recovery.

These patterns imply that neither peak temperature nor end-of-century temperature alone characterizes the welfare implications of overshoot pathways. Instead, outcomes depend on the full temperature trajectory.

The overshoot integral provides a compact summary of this trajectory, capturing both the magnitude and the duration of the exceedance. This aligns with its use in physical climate and mitigation assessments (Bauer et al., 2023; Tavoni et al., 2026). In our results, cumulative HDI losses (2020–2100) show the strongest consistency across models (87–90% agreement), precisely because they reflect integrated exposure rather than single-year outcomes. End-of-century metrics alone, therefore, can understate the total burden of overshoot, consistent with findings in physical risk assessment frameworks (Drouet et al., 2022).

Heterogeneity across dimensions of human development. HDI components respond differently to overshoot. Life expectancy losses are relatively small but statistically robust, with consistently negative cumulative impacts in high-overshoot scenarios. Income drives the largest absolute losses but also the widest uncertainty range. This reflects sensitivity to multiple climate variables and the broader effect of climate on economic growth dynamics (Burke et al., 2015; Kahn et al., 2021b; Estrada et al., 2025). It also reflects strong geographic heterogeneity in exposure, particularly in low-latitude regions (Callahan and Mankin, 2022a). Education outcomes are the least constrained, with the widest model disagreement, indicating that climate–education linkages remain the most empirically uncertain. This heterogeneity implies that aggregate HDI masks important differences in persistence and uncertainty across development dimensions. Policies designed to protect human development under overshoot conditions will benefit from being dimension-specific rather than relying on a single composite indicator.

Regional concentration and the geography of committed loss. Damages are strongly concentrated in tropical and subtropical regions, consistent with established spatial gradients in climate impacts (Waidelich et al., 2024; Estrada et al., 2025; Callahan and Mankin, 2022a).

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Model agreement on cumulative damages is high, indicating a robust spatial signal. Most impacts occur during the overshoot period rather than in the final year. Regions with the largest cumulative losses are also those with lower baseline HDI, reinforcing the distributional concentration of overshoot damages among more vulnerable populations. Even where percentage recovery is substantial, absolute HDI levels remain below baseline at 2100. This implies that overshoot produces persistent committed losses rather than temporary deviations around a recoverable baseline. Under higher overshoot, residual impacts are more widespread and severe, with limited recovery in many tropical regions. These findings are directly relevant for Loss and Damage frameworks (Kruczkiewicz et al., 2025; Theokritoff et al., 2025), which require quantifiable estimates of persistent development losses.

3.4. Conclusion

This study shows that temperature overshoot leads to substantial and only partially reversible losses in human development. Across all scenarios, HDI damages increase monotonically with peak warming, and only a fraction of peak losses is recovered by 2100. While recovery occurs when temperatures decline, it is incomplete and highly uncertain, reflecting the accumulation of growth-rate impacts over time rather than any structural reversibility in the model.

Uncertainty is large across all outcomes and is driven by differences across climate models and parametric uncertainty in the impact functions. In several scenarios, the lower tail of the distribution includes continued HDI deterioration even during the post-peak cooling phase, highlighting substantial downside risk in overshoot pathways.

Regional results show that both recovery and damage are especially concentrated in tropical and subtropical regions, with high model agreement on cumulative losses at the end of the century. Most of the burden of overshoot is incurred during periods of elevated warming, but residual losses at the end of the century are especially pronounced in scenarios that stabilize at 2°C.

All our analysis is conducted within this century: existing overshoot scenarios designed for systematic multi-model assessment, such as SSP5-3.4, complete their cooling phase within this same window (Tebaldi et al., 2021). The incomplete recovery we find, therefore, reflects the limited time available for socio-economic systems to recover within the window in which cooling occurs.

Several limitations qualify these results. First, the model does not include explicit structural irreversibility or state dependence in the damage process. While this allows for a clean identification of trajectory effects, it also implies that all persistence arises from the temporal accumulation of growth-rate shocks. If real-world systems exhibit additional irreversible mechanisms, such as capital destruction or institutional weakening, actual recovery would likely be lower than estimated here (Schoengart et al., 2025; Bastien-Olvera et al., 2022; Callahan and Mankin, 2023a). Second, the analysis is based on a single impact function for each component, limiting variation in development trajectories and adaptive capacity. Third, the emulator builds upon ISIMIP

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scenarios that provide limited analogs for post-peak cooling, and it does not explicitly model climate hysteresis.

Despite these limitations, the core findings are robust across models and specifications. Temperature overshoot increases both the magnitude and persistence of human development losses, and these losses are not fully undone within the century even under optimistic assumptions about reversibility. The benefits of limiting overshoot, therefore, extend beyond reducing peak impacts to reducing persistent and inequitable losses in global human development.

3.5. Methods

3.5.1. Impact Functions

The empirical damage functions used in this study are fully described and estimated in the previous chapter. We provide here a brief recap of the functional form and projection methodology.

Functional form. Impact functions are estimated separately for each of the three HDI components - gross national income per capita (GNI), life expectancy at birth (LEB), and expected years of schooling (EYS) - using a two-way fixed effects panel distributed lag model (DLM) estimated on 1,773 subnational regions over the period 1990-2020. The dependent variable in each model is the log first difference of the HDI component, i.e. its annual growth rate. Climate variables enter the model as first differences. The full model for component $h_{r,t}$ in region r at time t takes the form:

$$\Delta \ln h_{r,t} = \sum_{k=0}^K \beta_k \Delta c_{r,t-k} + \sum_{k=0}^K \gamma_k (\Delta c_{r,t-k} \times \bar{c}_r) + \alpha_r + \lambda_t + \delta_r \cdot t + \varepsilon_{r,t} \quad (3.1)$$

where $c_{r,t}$ denotes the relevant climate variable(s), $\bar{c}_r$ is the long-run regional mean climate (the moderating variable), α_r are region fixed effects, λ_t are year fixed effects, and $\delta_r \cdot t$ are country-specific quadratic time trends. Up to $K = 9$ lags are tested for each climate-outcome pair, with lag selection based on information criteria. Standard errors are clustered at the country level.

The climate variables entering each component's preferred specification are:

- **GNI per capita:** mean temperature, heatwaves, and number of wet days (rain over 1mm).
- **Life expectancy:** temperature variability, heatwaves and number of wet days.
- **Expected years of schooling:** temperature variability and number of wet days.

The precise construction of each climate indicator is reported in Chapter 2, Section 2.5.1.

Uncertainty quantification. Coefficient uncertainty is propagated through 1,000 Monte Carlo bootstrap draws from the joint multivariate distribution of the estimated coefficients, preserving

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the covariance structure across all lag terms and interaction effects within each component’s model. Errors are clustered at the country level, consistent with the most conservative specification in Chapter 2. For each bootstrap draw, the full set of HDI component projections is computed for each region, year, and scenario, and combined into the HDI aggregate via the standard UNDP geometric mean formula. This produces a distribution of 1,000 HDI trajectories per region, scenario, and climate model. The reported pooled 90% confidence intervals reflect the joint uncertainty across both bootstrap draws and the eight CMIP6 climate models: for each scenario, the distribution of $1,000 \times 10 = 10,000$ trajectories is used to compute quantiles, so that the reported uncertainty envelope captures both statistical uncertainty in the damage functions and structural uncertainty across climate models simultaneously. As documented in the Results, the dominant source of uncertainty is the spread across climate models rather than within-model sampling variability.

Impact projection. To project future climate-driven HDI losses, we apply the estimated impact functions to annual subnational climate indicator trajectories produced by the emulator for each scenario and CMIP6 model. For each region r , year t , scenario s , climate model m , and bootstrap draw b , we compute the climate-driven deviation from the baseline HDI component trajectory as:

$$\Delta \ln \hat{h}_{r,t,s,m,b} = \sum_{k=0}^K \hat{\beta}_{k,b} \Delta \hat{c}_{r,t-k,s,m} + \sum_{k=0}^K \hat{\gamma}_{k,b} (\hat{c}_{r,t-k,s,m} \times \bar{c}_r) \quad (3.2)$$

where $\hat{c}_{r,t,s,m}$ denotes the emulated climate indicator for region r at time t under scenario s and model m , and $\hat{\beta}_{k,b}$, $\hat{\gamma}_{k,b}$ are the bootstrapped coefficient draws. The baseline trajectory $h_{r,t,s}^0$ is the projected HDI component under the same socio-economic pathway but without climate change, taken from the SSP database. The climate-change trajectory is then obtained by accumulating the annual growth deviations on top of the baseline:

$$\ln h_{r,t,s,m,b}^{cc} = \ln h_{r,t_0,s}^0 + \sum_{\tau=t_0}^t \left(\Delta \ln h_{r,\tau,s}^0 + \Delta \ln \hat{h}_{r,\tau,s,m,b} \right) \quad (3.3)$$

where t_0 is the start of the projection period (2020). The climate damage in absolute terms is $\delta_{r,t,s,m,b} = h_{r,t,s,m,b}^{cc} - h_{r,t,s}^0$, and the percentage damage is $\delta_{r,t,s,m,b}^{\%} = \delta / h_{r,t,s}^0$. HDI indices for income, life expectancy, and schooling are then derived from the underlying component values for each combination using the standard UNDP min-max normalization, and combined into the aggregate HDI via geometric mean. Population-weighted averages across regions are used to obtain global and macro-regional aggregates.

Impact reversion metrics. To quantify the extent to which peak climate damages are reversed by end of century, we define three complementary metrics computed for each region r ,

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climate model m , bootstrap draw b , and scenario s .

Percentage of peak damages reversed. Let $\delta_{r,t}^{(m,b,s)}$ denote the climate damage in absolute terms at time t . The peak damage is $\delta_r^* = \delta_{r,t^*}$, where t^* is the year of peak warming. The damage at end of century is $\delta_{r,2100}$. The absolute recovery between peak and 2100 is:

$$\rho_r^{(m,b,s)} = \delta_{r,2100} - \delta_r^* \quad (3.4)$$

This quantity is positive when HDI impacts partially revert toward baseline. The percentage of peak damages reversed is then:

$$\rho_r^{\%} = \begin{cases} 100 & \text{if } \delta_r^* < 0 \text{ and } \delta_{r,2100} \geq 0 \\ \frac{\rho_r}{|\delta_r^*|} \times 100 & \text{if } \delta_r^* < 0 \text{ and } \delta_{r,2100} < 0 \text{ and } |\delta_r^*| > \epsilon \\ \text{undefined} & \text{otherwise} \end{cases} \quad (3.5)$$

where ϵ is a small threshold (10^{-3} index points) to exclude draws where peak damage is negligible. This metric is only defined for draws where the peak damage is negative (i.e. where a genuine damage occurred), and is set to missing otherwise. Values at 100% indicate that the HDI impact returns to or above its baseline by 2100; values below 100% indicate partial recovery; negative values indicate continued deterioration during the cooling phase.

Residual impact at 2100. The absolute damage remaining at end of century, $\delta_{r,2100}^{(m,b,s)}$, is reported directly in index points ($\times 100$). Negative values indicate that HDI remains below its counterfactual no-climate-change baseline at 2100. This metric captures the committed development loss that persists even after temperatures have stabilized.

Cumulative impact. The cumulative HDI loss over the projection period is:

$$\Delta_{r,s,m,b}^{\text{cum}} = \sum_{t=t_0}^{2100} \delta_{r,t}^{(m,b,s)} \quad (3.6)$$

reported in index point-years. This integral captures the total burden of climate change over time, weighting periods of larger damage more heavily, and is insensitive to the specific end-of-century value. It therefore provides the most robust aggregate summary of the overshoot burden.

All three metrics are computed at the subnational level and then aggregated to global and regional levels using population weights. For global figures, the pooled distribution across climate models and bootstrap draws is used to compute the reported medians and 90% confidence intervals. Model agreement for the regional maps is assessed by requiring that at least half of the climate models show a statistically significant signal in the same direction, based on the 90% bootstrap confidence interval not crossing zero.

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Interpretation and implications for reversibility. Because the dependent variable is the growth rate of each HDI component, a climate shock in year t affects the *level* of the component permanently: the lost growth is never mechanically recovered, simply because the climate forcing declines subsequently. However, because the shock enters in first differences rather than levels, the effect on the growth rate itself is transient - the growth rate returns to its baseline path once the lagged effects of the shock have dissipated. The net result is a damage function that represents a persistent but not permanent effect on growth: a climate shock reduces the growth rate for $K + 1$ years and then the growth rate recovers, but the level of the component is permanently lower than it would have been in the absence of the shock (Burke et al., 2015; Kalkuhl and Wenz, 2020).

3.5.2. Scenarios

Socio-economic baseline. For all projections, socio-economic components of HDI (income, life expectancy, and schooling in the absence of climate change) follow the SSP3-7.0 trajectory, sourced from the IIASA SSP database and the Wittgenstein Centre for Demography and Global Human Capital (Riahi et al., 2017).

Temperature scenarios. We design seven global mean surface temperature (GMST) scenarios specifically to isolate the contributions of different overshoot characteristics to human development outcomes. The scenarios are characterised by two quantities: the peak warming level T_{peak} (the maximum GMST anomaly relative to pre-industrial) and the end-of-century stabilization level T_{2100} . Scenarios are labelled $T_{\text{peak}} \rightarrow T_{2100}$ throughout. The seven scenarios are schematically presented in Table 3.1.

Table 3.1: Climate overshoot scenarios

Scenario	Peak T anomaly (°C)	Year of peak	2100 T increase (°C)	OV (°C)	OV integral (°C·yr)
<i>1.5°C target group</i>					
1.5→1.5	1.5	2035	1.5	0.0	0.0
1.7→1.5	1.7	2045	1.5	0.2	5.0
2→1.5	2.0	2055	1.5	0.5	10.0
2.5→1.5	2.5	2065	1.5	1.0	15.0
<i>2°C target group</i>					
2→2	2.0	2055	2.0	0.0	0.0
2.5→2	2.5	2065	2.0	0.5	7.5
3→2	3.0	2070	2.0	1.0	15.0

This design is purposeful. The two reference scenarios (1.5→1.5 and 2→2) provide non-overshoot baselines against which the overshoot scenarios are compared. The pairs (2→1.5, 2→2) and (2.5→1.5, 2.5→2) share identical peak warming but differ in their end-of-century stabilization level, isolating the effect of the cooling trajectory from peak magnitude. The pairs (2→1.5, 2.5→1.5) share the same end-of-century target but differ in peak warming, isolating the effect

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of peak magnitude. The 3→2 scenario provides a high-end overshoot case with elevated residual warming. Together, these scenarios allow for the systematic attribution of human development impacts to the three key characteristics of any overshoot pathway: peak temperature, end-of-century temperature, and the overshoot integral (the area under the temperature-exceedance curve).

The GMST trajectories are constructed as smooth, analytical paths consistent with the target peak and end-of-century values, and are designed to be physically plausible given the range of past scenario emulations (Intergovernmental Panel On Climate Change (IPCC), 2023). They are then passed to the trajectory-sensitive emulator described in Section 3.5.3 to generate regional climate indicator trajectories for each of the 10 CMIP6 models.

3.5.3. Emulator

To project spatially-resolved climate impacts under novel temperature overshoot pathways not available from simulations from Earth System Models, we develop a trajectory-sensitive emulation algorithm.

System Overview Our climate emulator uses a non-parametric, gradient-sensitive matching approach. To avoid potential inaccuracies present that may arise from machine learning-based emulators, ours works as a query engine over a pre-computed lookup table (LUT) of CMIP6 simulations. For each N-year segment of a target temperature trajectory, it computes the closest multi-year analog in the LUT based on both temperature levels and warming/cooling trends. This enables our emulator not only to find matching global temperatures but also to account for their first-order gradients, resulting in less noisy outputs while preserving high accuracy at low computational cost. Conceptually related to STITCHES (Tebaldi et al., 2022), which constructs novel scenarios by concatenating long segments from existing simulations, our approach instead performs year-by-year analog selection over short windows. This trades segment-level coherence for finer trajectory resolution, which is essential when impact functions depend on year-on-year first differences of climate variables, as ours do.

Reference LUT and Climate Indicators Our LUT is built from 10 CMIP6-ESMs spanning historical data (1850-2014) and SSP futures (SSP1-1.9 to SSP5-8.5), including SSP5-3.4 to capture cooling dynamics. Each entry is indexed by model m , scenario s and year y .

Daily climate outputs were processed into annual grids of nine impact indicators $\mathbf{C} \in \mathbb{R}^9$ relevant to human development:

- **Average metrics:** Mean temperature (TM), temperature variability (TVAR), Rainfall (RR), Wet-day frequency (WD)
- **Climate Extreme indicators:** Heatwave (HW), Precipitation Extreme (PEXT), Maximum Precipitation (RX)

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Indicators are aggregated to national (ISO3) and sub-national regions using population-weighted, resulting in the queryable LUT.

Trajectory representation with Splines To capture temporal dynamics, our emulator matches multi-year temperature windows rather than single years. For a target GMST trajectory $\mathbf{T} = (T_1, \dots, T_N)$, sliding windows of size W are extracted centered on each time step i to be emulated (default $W = 3$ years).

Then, each window is fitted with a univariate B-spline (degree $k = 1$ in our default configuration). The derivative of this spline yields a gradient term β that encodes warming or cooling rates, allowing the our LUT to distinguish rising from falling trajectories at identical global temperature levels.

Sequence Matching Algorithm For each target window, the emulator finds the closes analog triple m^*, s^*, y^* in the LUT by minimizing a composite loss function:

$$\mathcal{L}_{\text{seq}} = \omega_{\alpha} d_g(\mathbf{T}^{(W)}, \boldsymbol{\tau}^{(W)}) + \omega_{\beta} \|\boldsymbol{\beta}_{\text{target}} - \boldsymbol{\beta}_{\text{ref}}\|_2 \quad (3.7)$$

We use weights $\omega_{\alpha} = 0.9$ and $\omega_{\beta} = 0.1$ to balance magnitude fidelity with trend consistency. The weighted temperature term is defined as:

$$d_g = \sum_{j=0}^{W-1} w_j |T_{i+j-\lfloor W/2 \rfloor} - \tau_{y_{\text{ref}}+j}| \quad (3.8)$$

where τ represents the reference window starting at year y_{ref} . The temporal weights w_j follow a Gaussian profile $w_j \propto \exp(-\gamma(j - j_{\text{center}})^2/W)$ with $\gamma = 2.0$, prioritizing accuracy at the window's center while using the boundaries to establish the trend.

Appendix B.4 contains extensive details on the emulator construction and validation of emulation results against CMIP6 simulations.

4 | Multi-Year Droughts and Their Compounding Economic Impacts in Europe

4.1. Introduction

Droughts are among the most economically costly natural hazards, and their frequency, intensity and spatial extent are increasing under climate change (OECD, 2025). In Europe, weather-related economic losses totaled €738 billion between 1980 and 2023, with €208 billion recorded in the four years 2021–2024 alone (European Environment Agency, 2024). Freund et al. (2023) show that the most recent sequence of summer drought (2015–2018) is unprecedented over the past four centuries in large parts of Europe. The 2022 summer drought - the most widespread soil moisture deficit recorded in at least six decades - caused agricultural losses estimated to €25–30 billion across the EU-27 (Pinke et al., 2024), while human-induced warming contributed more than 30% to its intensity through enhanced evaporation (Bevacqua et al., 2024). Climate projections indicate that such severe conditions could occur once every decade as early as in the 2030s, and that multi-year megadroughts across Europe will become plausible by mid-century (Suarez-Gutierrez et al., 2023). Against this backdrop, quantifying the full economic cost of drought - across sectors, time horizons, and regions - is a prerequisite for designing effective adaptation policy and assessing climate risk.

The economic literature documents the costs of drought across multiple channels but leaves important gaps. Reviews of drought impact assessment identified persistent limitations in methodological consistency and the capacity to capture economy-wide transmission (Ding et al., 2011; Fleming-Muñoz et al., 2023). General equilibrium analyses show that an initial agricultural productivity shock can propagate through input-output linkages into services and industry, so that direct crop losses understate total welfare costs (Kilimani et al., 2018). This transmission is documented empirically across diverse settings: in the Western United States, drought reduces agricultural output, depresses local economic activity, and raises public health costs (Manning et al., 2021); in Brazil, municipality-level evidence shows that services and industry contract more severely than agriculture following drought, with persistent effects on formal employment and population density (Marca et al., 2026). Conceptually, Freire-González et al. (2017) argue that standard natural hazard frameworks are inadequate for drought because they do not account

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for the timing of the event, the distinct economic pathways of soil moisture versus surface and groundwater deficits, or the mediating role of infrastructure capacity and policy. These features imply that both the magnitude and the timing of economic impacts depend on conditions that single-period analyses cannot capture.

Beyond sectoral transmission, a growing body of macro panel evidence confirms that water scarcity depresses aggregate output at national and sub-national scales. Below-average water runoff reduces local economic activity, with effects concentrated in middle-income regions and economies dependent on hydropower (Russ, 2020). Moreover, the income response to precipitation depends on the partition between blue water (surface runoff affecting industry, energy, and municipal supply) and green water (soil moisture affecting agriculture) as well as on the availability of surface and groundwater stocks that can buffer or amplify shocks (Bareille et al., 2024). Bellon et al. (2022b) confirms that severe droughts reduce GDP and that fiscal policy partially offsets these effects. At the European regional level, using a local projection framework, (Usman et al., 2024) find that summer droughts result in lower medium-term output and trigger population decline, with impacts accumulating over several years beyond the event. Naumann et al. (2021) project that annual drought-related losses in Europe could reach €65 billion under 3°C of warming, while Motta et al. (2025) find sharp spatial asymmetry in future exposure, with losses in southern and south-eastern Europe reaching 1-2% of regional GDP under high warming levels. The OECD (2025) identifies drought as one of the most economically disruptive natural hazards globally, and yet notes that evidence on its direct impact on GDP levels and growth rates remains limited.

This task is complicated by the specific features of droughts. Droughts have no universally accepted definition. They develop slowly, may persist for multiple years, cover large areas, and propagate through multiple phases, thereby affecting different sectors, from meteorological precipitation deficits to hydrological and, ultimately, socio-economic impacts. Moreover, drought pathways depend on local climate, geology, land use, and water management (Van Loon, 2015). Widely used tools for drought monitoring - such as the Standardized Precipitation Index (SPI) and the Standardized Precipitation-Evapotranspiration Index (SPEI) - have a multiscale structure and probabilistic comparability across climates (Vicente-Serrano et al., 2010), but econometric assessments rarely consider and compare these different definitions. Their flexible accumulation periods ranging from 1 to 24 months and ability to distinguish meteorological from agricultural and hydrological drought signals present opportunities to explore the nuance of impact across different economic sectors and timescales, yet such assessments are lacking.

At the same time, the existing literature is barely starting to address the persistence and potential compounding of drought impacts over time. (Berlemann and Wenzel, 2015) provide cross-country evidence that a moderate precipitation deficit depresses GDP growth for up to 14 years, suggesting that single-year estimates substantially understate the total cost. (Tintchev and Jaramillo, 2024) use a panel autoregressive distributed lag model and find that worsening drought conditions produce long-term scarring of real GDP per capita growth, operating through reduced

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crop productivity and slower investment accumulation. Using local projections at the country level, Ehlers et al. (2025) find that average-duration droughts reduce GDP by approximately 2% over four years, with agriculture, energy, mining, and construction all negatively affected. At the sub-national level, Lee et al. (2023) shows that consecutive dry years substantially amplify the growth damage of a subsequent dry shock, providing evidence that multi-year drought spells generate compounding effects.

This review highlights several research gaps. First, while there is evidence that drought effects persist and accumulate, no study models the full distributed lag response at fine spatial resolution and tests explicitly whether multi-year drought spells compound their economic consequences. Second, most analyses operate at the national or NUTS-2 level, focusing solely on GDP, aggregating away the within-country heterogeneity in drought exposure and economic structure that is both theoretically and policy-relevant: sectoral composition, irrigation infrastructure, groundwater dependence, and adaptive capacity vary across sub-national territories, and national estimates mask the concentration of losses in specific regions. Third, the hydroclimatic and economic literatures have developed largely in parallel. Economic studies rarely exploit the multiscale structure of SPI and SPEI indicators or systematically compare accumulation periods, while hydrological studies document drought impacts without quantifying macroeconomic magnitudes. Integrating these two bodies of evidence is necessary to produce economically interpretable estimates.

To address these limitations, we use NUTS-3 regional data on output, sectoral gross value added, investment, employment, and migration across Europe for the period 1995–2023, combined with high-resolution climate observations from E-OBS at 0.1° resolution, which we aggregate to NUTS-3 regions. With a panel approach, we study the full temporal profiles of how drought severity and duration affect regional economic outcomes. We characterize drought using SPI and SPEI at 3-, 6-, and 12-month accumulation periods, distinguishing the economic signatures of meteorological drought, ranging from short-term agricultural and long-term hydrological stress (Stagge et al., 2015). We then test whether multi-year drought spells compound their consequences beyond what single-year models predict, using both an interaction specification and a spell-based indicator (Wang et al., 2016). Finally, we complement the regression analysis with a storyline exercise that traces the regional economic footprint of the 2015–2018 and 2022 European drought events and projects their consequences as if they occurred under a 2°C warming scenario.

Given the need to track both the immediate and persistent effects of drought on regional economies, our identification strategy relies on an Autoregressive Distributed Lag (ARDL) framework. This allows us to estimate the full distributed lag profile of a drought shock — distinguishing contemporaneous responses from effects that materialize one, two, or more years after the event — and to recover cumulative impulse responses that reflect the total economic cost of a persistent drought. We further explore compounding dynamics through two complementary specifications: an interaction model that tests whether a drought shock hitting on top of a prior-year drought has a larger marginal effect, and a spell model that disentangles whether regions deeper into a multi-year continuous drought suffer a larger per-year cost as the spell extends.

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Our results reveal several patterns that single-year estimates would miss. A one-standard-deviation drought shock reduces GDP per capita growth by approximately 0.16–0.27 percentage points on impact, with effects accumulating to roughly 0.5–1 percentage point over a six-year horizon, depending on the accumulation period considered. Investment responds more slowly but more persistently, consistent with capital adjustment frictions and the gradual depletion of water storage capacity. Employment and migration effects are small on average but emerge at longer lags, suggesting that demographic adjustment to drought operates over multi-year horizons. Sectoral analysis shows that agriculture is most sensitive to short-accumulation indices (SPEI3), reflecting its dependence on soil-moisture availability, while manufacturing and services respond primarily to longer-accumulation indices (SPEI12), consistent with their greater dependence on surface water and hydrological stocks. The spell model reveals a non-linear amplification of the per-year cost of drought for spells of five years or longer, while the interaction model finds no evidence that the one-year-lag interaction drives this compounding. Applied to the 2015–2018 European drought event, one of the most severe and sustained events, our ARDL estimates imply a cumulative loss of approximately -2.75% in GDP per capita growth, concentrated in Southern and Central Europe; under a scenario of +2°C of global warming, expected within the next 20 years, this would intensify to approximately -5.23%.

This chapter advances the literature on climate-economy interactions on three grounds. First, we provide estimates of the full multi-year distributed lag response of drought at NUTS-3 resolution in Europe, encompassing GDP, investment, employment, and migration. Earlier sub-national European studies, most notably Usman et al. (2024), establish that drought effects persist beyond the event year, but do so in a Diff-in-Diff setting with 1-year-lasting droughts only, and neither account for severity nor test for multi-year compounding. Our NUTS-3 panel allows us to exploit within-country variation in both drought exposure and economic structure that is invisible at coarser scales and that matters for the spatial targeting of adaptation investments. By modeling investment, employment, and migration alongside output, we also track the transmission channels through which drought generates medium-term economic scarring. Moreover, we provide direct empirical tests of whether multi-year drought spells compound their economic consequences. Lee et al. (2023) show that consecutive dry years amplify the growth damage of a subsequent dry shock, while Berlemann and Wenzel (2015) document that precipitation deficits depress GDP growth for up to 14 years. Yet, neither study isolates whether the within-spell dynamics are driven by non-linear interactions between consecutive drought years or by the simple accumulation of lagged linear effects. Our interaction and spell models disentangle these mechanisms: the interaction model tests whether the contemporaneous cost of drought rises non-linearly with the prior year’s drought intensity, while the spell model asks whether regions two or more years into a continuous drought pay a higher per-year cost than regions earlier in a spell. This design provides a more granular picture of compounding than is available in the existing literature and has direct implications for how drought risk accumulates over time.

Second, we bridge the hydroclimate and economics literatures by systematically exploiting the

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multiscalar structure of SPI and SPEI. Economic studies on drought typically use a single index and accumulation period, without comparing how the choice of accumulation period shapes the estimated economic response. We estimate all six combinations of SPI/SPEI at 3-, 6-, and 12-month accumulation periods and show that different sectors respond to different accumulation scales in economically interpretable ways: agriculture responds to short-accumulation indices that capture soil moisture availability, while manufacturing and services respond to longer-accumulation indices that track hydrological stocks. This result provides a data-driven validation of the hydrological pathways through which drought propagates into different parts of the economy and suggests that single-index analyses conflate economically distinct shocks.

Third, we connect the regression evidence to observed events through a storyline analysis of the 2015–2018 (and 2022) European droughts. The storyline approach is a relatively recent methodological development that complements traditional projection-based approaches. Rather than asking how the frequency or severity of a class of events will change on average, it asks how a specific event would have differed in a warmer world. This framing enhances the salience of climate risk communication (Doblas-Reyes et al., 2026). Implemented alongside other commonplace tools in climate science, such as spectral nudging (von Storch et al., 2000) and machine learning, it is gaining traction in the physical climate sciences as a tool for event attribution and adaptation stress-testing (Grayson et al., 2026; Callahan et al., 2026a). Our approach applies an analogous framework to drought and economic output. We translate our reduced-form ARDL estimates into event-specific regional damage maps for the 2015-2018 and 2022 European droughts. We then project how those damages would scale under $+2^{\circ}\text{C}$ of global warming, directly connecting the regression evidence to the policy-relevant question of how climate change alters the economic cost of observed extreme events.

The remainder of this chapter is organized as follows. Section 4.2 provides a detailed description of our data. Section 4.3 expounds our multi-tier empirical strategy. Section 4.4 presents our estimation results. Section 4.5 provides some robustness checks. Section 4.6 presents our storyline results before we conclude in Section 4.7.

4.2. Data

4.2.1. Drought Index Construction

Our drought measures are computed from raw data provided by E-OBS, version 31.0e (Cornes et al., 2018), a gridded observational dataset covering the European domain at 0.1° resolution, providing daily fields of minimum temperature (TN), maximum temperature (TX), and precipitation (RR) over the period 1920-2024.

We derive two complementary families of drought indices – the Standardized Precipitation Index (SPI; McKee et al., 1993) and the Standardized Precipitation-Evapotranspiration Index (SPEI; Vicente-Serrano et al., 2010) – at three accumulation scales (3, 6, and 12 months), yielding six indices in total. The decision to retain both SPI and SPEI is deliberate: SPI captures meteorological drought driven solely by precipitation deficits, while SPEI also accounts for atmospheric evaporative demand, making it sensitive to temperature-driven drought intensification — a distinction that becomes particularly relevant under climate change scenarios. All indices are computed at the native 0.1° grid resolution before spatial aggregation, ensuring that the standardization and accumulation are performed at the finest available scale rather than on pre-aggregated regional data, which would introduce aggregation bias in the tails of the distribution.

Potential Evapotranspiration For the SPEI family, we first compute monthly potential evapotranspiration (PET) using the Hargreaves-Samani formula (Hargreaves and Samani, 1985), which requires only temperature inputs and is therefore well-suited to the available E-OBS fields:

$$\text{PET}_{\text{daily}} = 0.0023 \cdot R_a \cdot (T_{\text{mean}} + 17.8) \cdot \sqrt{\max(T_{\text{max}} - T_{\text{min}}, 0)} \quad (4.1)$$

where T_{mean} , T_{max} , and T_{min} are mean, maximum, and minimum monthly temperature ($^\circ\text{C}$), and R_a is extraterrestrial radiation (mm day^{-1} equivalent), computed following Allan et al. (1998) as a function of latitude and the mid-month day of year. Specifically, for each calendar month m we use a fixed representative Julian day ($J_m \in \{15, 46, 74, 105, 135, 166, 196, 227, 258, 288, 319, 349\}$) to compute the inverse relative Earth-Sun distance d_r , solar declination δ , and sunset hour angle ω_s :

$$R_a = \frac{24 \times 60}{\pi} \cdot G_{sc} \cdot d_r \cdot (\omega_s \sin \phi \sin \delta + \cos \phi \cos \delta \sin \omega_s) \cdot \frac{1}{2.45} \quad (4.2)$$

where $G_{sc} = 0.0820 \text{ MJ m}^{-2} \text{ min}^{-1}$ is the solar constant and ϕ is latitude in radians. The resulting daily PET estimate is multiplied by the number of days in each month to obtain the monthly PET in millimeters. The water balance series used as input to SPEI is then defined as $WB_t = RR_t - \text{PET}_t$, where RR_t is monthly precipitation.

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Standardization SPI and SPEI are computed by fitting a Gamma distribution and a Log-Logistic, respectively, to the accumulated series. Prior to distribution fitting, precipitation (for SPI) and water-balance (for SPEI) series are accumulated over the target window of $k \in \{3, 6, 12\}$ months by computing rolling sums, where each month t receives the value $\sum_{i=0}^{k-1} X_{t-i}$. Distribution parameters are estimated using the unbiased probability-weighted moments (ub-pwm) estimator, and the series is standardized with respect to a fixed reference period of 1951–2010. The choice of a fixed reference period rather than a rolling or full-period climatology is essential for consistency across observed and counterfactual scenarios: by anchoring standardization to the same 1951–2010 climatology in all cases, any shift in index values between the observed and perturbed series reflects only the perturbation applied to the climate inputs, and not a change in the reference distribution. Standardization is applied pixel-wise over the full 1920–2024 series using the SPEI R package (Beguería and Vicente-Serrano, 2011).

Monthly Drought Episodes Definition From the standardized index series, we identify drought episodes using a threshold-based approach. A grid cell is considered to be in drought in month t if the index value falls below a threshold τ , sustained for at least three consecutive months. We apply three severity thresholds: moderate drought ($\tau = -1.0$), severe drought ($\tau = -1.5$), and extreme drought ($\tau = -2.0$), following the classification of McKee et al. (1993).

Annual Drought Metrics From the monthly drought series, we derive two annual metrics for each grid cell, index, accumulation scale, and severity threshold: drought *severity* (the annual sum of absolute index values during drought months) and drought *duration* (the annual count of months in drought). These yield annual rasters for each metric covering 1920–2024.

Spatial Aggregation Annual drought rasters are aggregated to NUTS3 regions using population density-weighted means via the `exactextractr` R package (Baston, 2019). Population weights are drawn from the HYDE 3.3 dataset (Klein Goldewijk et al., 2017), which provides annual gridded population estimates at 0.25° resolution for 1920–2024. For each event year, the population layer for that year is used as the weighting surface, ensuring that the aggregated drought exposure reflects the contemporaneous population distribution. This final annual regional drought metric is the one that enters the regression models. The number of drought events identified by the SPEI index at different accumulation periods in Europe in 1995–2023 and their relative persistence is reported in Figure 4.1. A corresponding panoramic using the SPI index instead is reported in Appendix C.9, Figure C.55. Here, we define a multi-annual drought as one that occurs when our annual drought severity metric is above zero for more than one year. From this figure, we notice how the second period we investigate (2010–2023) is generally more prone to multi-annual drought than the earlier one (1995–2009).

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Counterfactual Drought Scenarios Under +2°C Global Warming

To assess how the economic impacts of the observed drought events would differ in a world 2°C warmer than pre-industrial levels, we construct counterfactual drought indices using a physically grounded climate storyline approach (Shepherd et al., 2018; van den Hurk et al., 2023; Grayson et al., 2026; Callahan et al., 2026a). The core idea is to ask: given the same atmospheric circulation patterns and large-scale dynamics that produced the observed drought, how would drought severity and duration change if the background climate were 2°C warmer? We apply this approach to one of the most severe and sustained recent drought events in Europe: the multi-year drought of 2015-2018, which affected large portions of central and western Europe and ranks among the most intense in the instrumental record (Ionita et al., 2025; Freund et al., 2023). Results for another extreme European event (the 2022 drought) are reported in Appendix C.11. This framing holds the dynamical component of drought fixed and attributes differences in outcomes solely to the thermodynamic response to global warming, making it a well-defined and interpretable counterfactual. The construction proceeds in four steps: (i) identification of the year at which each climate model’s projection crosses the +2°C global warming level (GWL); (ii) computation of monthly climate deltas between the +2°C world and the reference period (2015–2018 or 2022) for each model; (iii) perturbation of the observed E-OBS temperature and precipitation fields with these deltas for each model; (iv) recomputation of SPEI and SPI on the perturbed fields using the same methodology as for the observed indices.

Step 1: Global Warming Level Crossing Years We use output from four bias-adjusted CMIP6 models available through the ISIMIP3b protocol (Lange, 2019) under the SSP5-8.5 scenario: CanESM5, EC-Earth3, MRI-ESM2-0, MPI-ESM1-2-HR. For each model, we compute the global mean surface temperature anomalies relative to the 1850-1900 pre-industrial baseline using the model’s historical run (1850-2014) spliced with the SSP5-8.5 projection (2015-2100). We then apply a 20-year centered rolling mean to the annual anomaly series - consistent with the IPCC AR6 definition of global warming levels (Masson-Delmotte et al., 2021) - and identify the first year in which the smoothed anomaly reaches or exceeds 2°C. The resulting crossing years span from 2024 (CanESM5) to 2059 (MPI-ESM1-2-HR), reflecting the spread of climate sensitivity across the ensemble, and are reported in Table 4.1. The same table reports the warming in Europe only, spanning from +2.3°C to almost +3°C.

Step 2: Monthly Climate Deltas For each model and each set of event years, we compute monthly climate deltas as the difference in climatological mean conditions between the +2°C world and the reference period. This symmetric 20-year window design ensures that the delta captures the climatological shift associated with the +2°C GWL rather than inter-annual variability.

For each model, variable (mean temperature TM and precipitation RR), and calendar month $m \in \{1, \dots, 12\}$, the delta is defined as:

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Table 4.1: CMIP6 model crossing years for the $+2^\circ\text{C}$ global warming level under SSP5-8.5, identified as the first year in which the 20-year centered rolling mean of the global mean surface temperature anomaly (relative to 1850-1900) reaches or exceeds 2°C . The third column reports the European warming (cell area weighted) for the corresponding year, averaging on a 20-year window, in each model.

Model	Crossing Year	Europe-Only Warming
CanESM5	2024	$+2.5^\circ\text{C}$
EC-Earth3	2035	$+2.9^\circ\text{C}$
MRI-ESM2-0	2038	$+2.9^\circ\text{C}$
MPI-ESM1-2-HR	2059	$+2.3^\circ\text{C}$

$$\Delta V_m = \bar{V}_m^{+2^\circ\text{C}} - \bar{V}_m^{\text{ref}} \quad (4.3)$$

where $\bar{V}_m^{+2^\circ\text{C}}$ and $\bar{V}_m^{\text{ref}}$ are the climatological monthly means averaged over the $+2^\circ\text{C}$ and reference windows, respectively, computed on the native ISIMIP 0.5° grid.

Step 3: Perturbation of E-OBS Fields The monthly delta rasters are then bilinearly interpolated from the native ISIMIP 0.5° grid to the 0.1° E-OBS grid.

The perturbation is applied to a window covering the year preceding the event through the final event year: January 2021 through December 2022 for the 2022 event, and January 2014 through December 2018 for the 2015-2018 event. The inclusion of the pre-event year in the window is essential for multi-month accumulation indices: SPEI-12 for January of the event year requires the full 11 months preceding it to compute the 12-month accumulation, so those months also reflect the $+2^\circ\text{C}$ climate. Months outside the splice window retain the original observed E-OBS values, ensuring that the standardization reference period (1951-2010) is unaffected by the perturbation and remains identical between the observed and counterfactual series.

Step 4: Recomputation of Drought Indices PET is recomputed on the perturbed TN and TX fields (using the same TM delta for both) with the Hargreaves-Samani formula described above, yielding a perturbed water balance series $WB_t^{+2^\circ\text{C}} = RR_t^{+2^\circ\text{C}} - \text{PET}_t^{+2^\circ\text{C}}$. SPEI and SPI are then recomputed on the full 1920-2024 perturbed series. Critically, the Gamma distribution is fitted and standardization applied against the same fixed 1951-2010 reference period used for the observed indices.

The perturbed indices are computed separately for each of the four models included in the counterfactual analysis (CanESM5, EC-Earth3, MRI-ESM2-0, MPI-ESM1-2-HR), and for each combination of index type (SPI, SPEI), accumulation scale (3, 6, 12 months), severity threshold (moderate, severe, extreme), and event year set (2022; 2015-2018). Annual drought metrics and their NUTS3 population-weighted aggregates are then derived from the perturbed indices using the same procedure as for the observed series, enabling direct comparison of observed and counterfactual drought exposure at the regional level.

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4.2.2. Economic data

We rely on data provided by the European Commission’s ARDECO initiative (<https://territorial.ec.europa.eu/ardeco/explorer>), 2026 vintage. Variables are downloaded at the NUTS3 level. Zero points are conservatively considered as non-available values and variables are rescaled to match the same magnitude orders. For dataset extensions used in robustness checks on Turkey and the UK, relevant variables were respectively drawn from ARDECO and the ONS’s ITL3 data <https://www.ons.gov.uk/search?q=ITL3> and Local indicator portal <https://www.ons.gov.uk/explore-local-statistics/indicators>. For the UK, we use the PPP-2020 conversion rates from the European Commission to match ARDECO’s conventions. To address ITL version conflicts across UK data vintages, ONS equivalence tables were used. When UK regions had to be split for some variables (about 10 ITL units in total), a disaggregation key based on GVA, which was available for the most recent ITL version, was used.

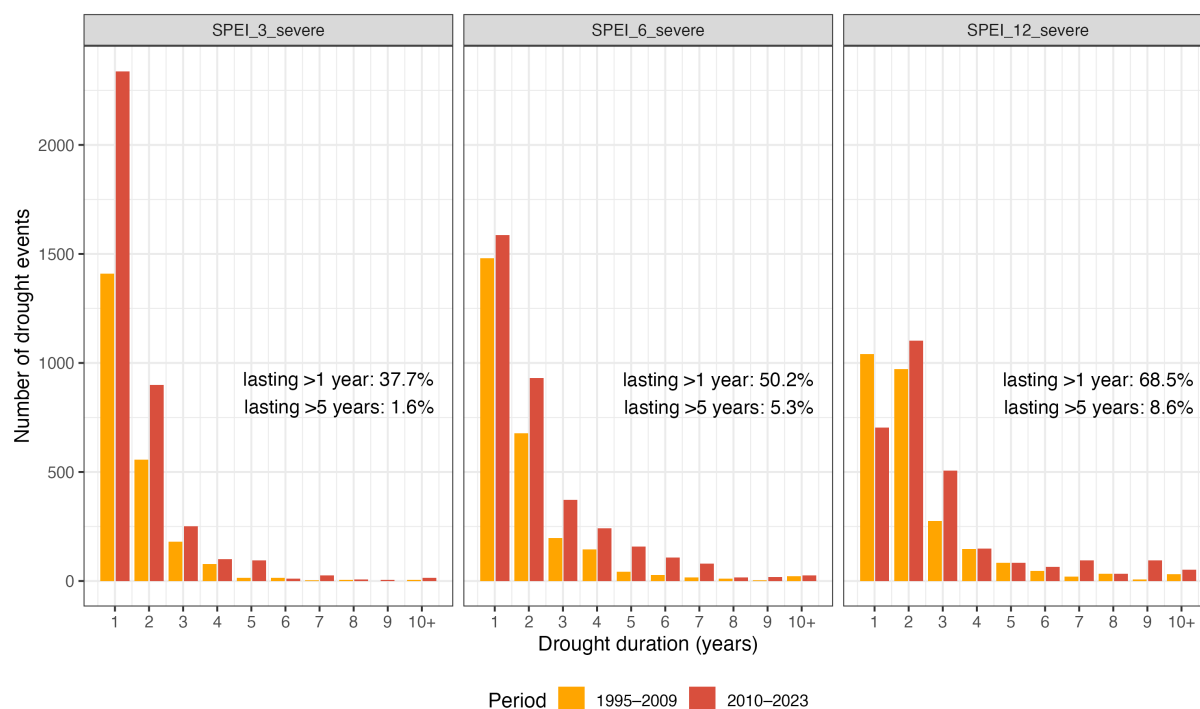


Figure 4.1: Drought persistence in European Nuts3 regions for the SPEI drought index, in 1995-2023.

4.3. Empirical Strategy

4.3.1. Data and Setting

Our analysis combines regional economic data for European NUTS3 regions with high-resolution climate indicators over the period 1995-2023. The outcome variables are expressed in log levels multiplied by 100, so that first differences are interpretable as approximate percentage-point growth rates, as in Usman et al. (2024). The only exceptions is migration per capita, which we

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test in levels and report as a number of people per 100 inhabitants.

Drought exposure is measured using two standardized indices – the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI) – computed at accumulation periods of 3, 6, and 12 months. For each index and accumulation period, we construct two complementary drought metrics: a *severity* measure that captures the total annual intensity of drought conditions during drought episodes (values below a given threshold) and a *duration* measure that captures the cumulative annual length, in months, of drought exposure. Duration is used as a robustness result. All drought metrics are computed as population-weighted spatial means over each NUTS3 territory. We consider three drought thresholds corresponding to normal, severe, and extreme drought conditions, and treat results across thresholds as a robustness check, with severe conditions in the main specification.

4.3.2. Distributed Lag Model

Our main model is an autoregressive distributed lag (ARDL) model in first differences. Let y_{it} denote the log-level outcome for region i in year t , and let d_{it} denote the drought metric of interest. We estimate:

$$\Delta y_{it} = \alpha_i + \lambda_t + \gamma_i t + \sum_{j=0}^J \beta_j \tilde{d}_{i,t-j} + \mathbf{X}'_{it} \boldsymbol{\delta} + \varepsilon_{it}, \quad (4.4)$$

where $\Delta y_{it} = y_{it} - y_{i,t-1}$ is the annual growth rate of the outcome, α_i is a region fixed effect, λ_t is a year fixed effect, and $\gamma_i t$ is a region-specific linear time trend included to absorb differential long-run trajectories across territories. $\Delta y_{it} = y_{it} - y_{i,t-1}$ is substituted with y_{it} when the outcome is migration rate. The variable $\tilde{d}_{i,t-j}$ is the standardised drought measure at lag j , obtained by subtracting the sample mean and dividing by the sample standard deviation of the raw drought variable across all observations; the resulting coefficients β_j are therefore interpretable as the effect on annual growth (in percentage points) or on migration rate (in persons per 100 inhabitants) of a one standard-deviation increase in drought exposure j years prior.

The vector $\mathbf{X}_{it}$ contains a set of control variables. To account for short-run persistence in growth, we include the lagged first differences $\Delta y_{i,t-1}$, $\Delta y_{i,t-2}$, and $\Delta y_{i,t-3}$ ($y_{i,t-1}$, $y_{i,t-2}$, and $y_{i,t-3}$ for migration rate). Temperature and precipitation controls (TM_{it} , RR_{it}) are included to partial out the contemporaneous climatic environment beyond the drought index itself. In specifications for aggregate economic outcomes, we additionally control for initial sectoral composition using the value-added shares of agriculture, manufacturing, construction, and market services, thereby accounting for cross-regional differences in structural exposure to climate shocks.

Lag Length Selection

The maximum lag length J in equation (4.4) is selected separately for each outcome-drought-variable pair using the Bayesian Information Criterion (BIC). Specifically, for each combination

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we estimate models with $J \in \{1, \dots, J_{\max}\}$ (with $J_{\max} = 12$) and retain the lag length that minimizes BIC. This data-driven procedure guards against both under-fitting, which would omit economically relevant delayed responses, and over-fitting, which would inflate standard errors and reduce power.

Cumulative Effects

To summarize the total impact of drought exposure over a horizon of h years, we compute the cumulative impulse response:

$$B_h = \sum_{j=0}^h \hat{\beta}_j, \quad h = 0, 1, \dots, J. \quad (4.5)$$

Standard errors for B_h are obtained via the delta method, using the full $(h+1) \times (h+1)$ sub-block of the estimated variance-covariance matrix: $\text{Var}(\hat{B}_h) = \mathbf{1}'_{h+1} \hat{V}_{h+1} \mathbf{1}_{h+1}$, where $\hat{V}_{h+1}$ is the upper-left block of the coefficient covariance matrix corresponding to lags 0 through h .

4.3.3. Spell-Specific Model

A possible limitation of the standard distributed lag model in equation (4.4) is that the β_j coefficients are identified from all observations regardless of whether drought persisted continuously across lags. A region experiencing drought only in year t and a region experiencing uninterrupted drought since year $t-j$ both contribute to the estimation of β_j , yet their economic trajectories may differ if prolonged drought has non-linear or compounding effects.

To isolate the effect of continuously sustained drought, we complement the ARDL with a spell-specific model (Wang et al., 2016). We begin by assigning each observation to a drought spell of length k , defined as the number of consecutive years (up to and including year t) in which the drought index exceeds zero. Formally:

$$k_{it} = \max\{k \in \{1, \dots, K\} : d_{i,t} > 0, d_{i,t-1} > 0, \dots, d_{i,t-k+1} > 0\}, \quad k_{it} = 0 \text{ otherwise}, \quad (4.6)$$

with observations in spells exceeding K years discarded to avoid contamination from very long episodes; we set $K = 12$ throughout.

For each spell length $k = 1, \dots, K$, we construct the cumulative drought total:

$$D_{it}^{(k)} = \mathbf{1}\{k_{it} = k\} \cdot \sum_{j=0}^{k-1} d_{i,t-j}, \quad (4.7)$$

which equals the sum of drought values over the k -year spell for observations currently in a spell

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of exactly length k , and zero otherwise. Each $D_{it}^{(k)}$ is standardized prior to estimation. The spell-specific estimating equation is then:

$$\Delta y_{it} = \alpha_i + \lambda_t + \gamma_i t + \sum_{k=1}^K \theta_k \tilde{D}_{it}^{(k)} + \mathbf{X}'_{it} \boldsymbol{\delta} + \varepsilon_{it}, \quad (4.8)$$

where $\tilde{D}_{it}^{(k)}$ is the standardized version of $D_{it}^{(k)}$. Because $\tilde{D}_{it}^{(k)}$ is non-zero only for observations in a spell of exactly k years, the coefficients θ_k are identified exclusively from within-region variation in growth rates during spells of that particular length. By design, a single observation contributes to at most one spell regressor. The coefficient θ_k thus captures the contemporaneous growth effect of a one-standard-deviation increase in cumulative drought exposure during a k -year continuous episode, providing a clean test of whether prolonged drought carries disproportionate or compounding costs compared to what the additive ARDL predicts.

Notice that each region-year observation is assigned to exactly one spell bin k , where k is the number of consecutive drought years currently experienced: $d_t > 0, d_{t-1} > 0, \dots, d_{t-k+1} > 0$ but $d_{t-k} = 0$. The regressor for bin k is the cumulative drought total $D^{(k)} = \sum_{j=0}^{k-1} d_{t-j}$, standardized. To make coefficients comparable across spell lengths, we apply the rescaling $\theta_k^{**} = \theta_k \times \text{SD}_k / (k \cdot \text{SD}_{L0})$, which converts each θ_k to the effect of a one- SD_{L0} increase in the *average annual* drought intensity within the spell. Comparing θ_k^{**} across k then directly tests whether spell depth amplifies the per-year cost of drought: a "1 unit" move in the rescaled regressor corresponds to a spell where intensity is uniformly 1 SD per year throughout, so if θ_k^{**} becomes more negative as k grows, regions deeper into a continuous spell suffer a larger growth penalty per unit of average annual intensity than regions earlier in a spell.

4.3.4. Interaction Model

As a further diagnostic, we estimate an interaction specification that tests whether the contemporaneous effect of drought is amplified by prior-year drought exposure:

$$\Delta y_{it} = \alpha_i + \lambda_t + \gamma_i t + \beta_0 \tilde{d}_{it} + \beta_1 \tilde{d}_{i,t-1} + \beta_{01} \tilde{d}_{it} \cdot \tilde{d}_{i,t-1} + \mathbf{X}'_{it} \boldsymbol{\delta} + \varepsilon_{it}. \quad (4.9)$$

The marginal effect of a contemporaneous drought shock conditional on the prior-year drought level v (expressed in standard deviations) is:

$$\left. \frac{\partial \mathbb{E}[\Delta y_{it}]}{\partial \tilde{d}_{it}} \right|_{\tilde{d}_{i,t-1}=v} = \hat{\beta}_0 + \hat{\beta}_{01} v. \quad (4.10)$$

We evaluate this marginal effect at the empirical distribution of $\tilde{d}_{i,t-1}$: at zero (no prior drought), and at the 25th, 75th, and 90th percentiles of the standardized lagged drought variable.

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4.3.5. Fixed Effects and Inference

All specifications include region and year fixed effects. Our preferred specification additionally includes region-specific linear time trends to absorb differential pre-existing growth trajectories that may be correlated with long-run climate conditions (see, e.g., Burke et al., 2015; Dell et al., 2012b). We report results without trends as a robustness check.

Inference is conducted under alternative assumptions about the error structure. Our preferred specification uses Conley (1999) spatial standard errors with a 500 km cutoff (see Appendix Figure C.56), which account for heteroskedasticity, temporal autocorrelation, and cross-sectional dependence arising from spatially correlated climate shocks - a natural concern in this setting, where weather can affect contiguous regions simultaneously. As a robustness check, we also report standard errors clustered at the NUTS3 region level, which allow for arbitrary serial correlation within regions but do not account for spatial dependence across regions, and computed following Driscoll and Kraay (1998), which provides another explicit accounting of spatial and temporal error correlation of arbitrary structure and extent.

4.3.6. Historical and Counterfactual Drought Events Impacts Cumulation

Impacts of specific drought events are estimated by applying the ARDL coefficients to observed and counterfactual drought severity. For each region, the cumulative impact of an event spanning years $\mathcal{T}$ is obtained by summing, across all outcome years in the post-event window, the product of the estimated lag- h coefficient $\hat{\beta}_h$ and the drought severity accumulated at that lag:

$$\text{impact}_r = \sum_{h=0}^H \hat{\beta}_h \sum_{t \in \mathcal{T}} X_{r,t} \quad (4.11)$$

where $X_{r,t}$ is the population-weighted drought severity in region r during event year t , and H is the optimal lag length selected by the BIC. This formulation assumes that the lagged responses triggered by each event year accumulate additively over the post-event window.

For the observed event, uncertainty can be characterized analytically. Since the cumulative impact is a linear function of $\hat{\beta}$, its variance is given exactly by:

$$\text{Var}(\text{impact}_r) = \mathbf{c}_r^\top V \mathbf{c}_r \quad (4.12)$$

where $\mathbf{c}_r$ is the vector of accumulated drought exposures across lags and V is the estimated coefficient covariance matrix. A region is considered to have a statistically significant impact if the resulting 90% confidence interval excludes zero.

For the +2°C storyline, two sources of uncertainty are present: uncertainty in the estimated coefficients and uncertainty across climate models. We therefore adopt a Monte Carlo approach with $n = 500$ draws. In each draw s , a coefficient vector $\boldsymbol{\beta}^{(s)}$ is sampled jointly from the

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multivariate normal distribution:

$$\beta^{(s)} \sim \mathcal{N}(\hat{\beta}, V) \quad (4.13)$$

and a climate model $m^{(s)}$ is drawn uniformly from the four available $+2^\circ\text{C}$ perturbation experiments. The cumulative impact for draw s is then:

$$\text{impact}_r^{(s)} = \mathbf{C}_r^{(m^{(s)})} \beta^{(s)} \quad (4.14)$$

where $\mathbf{C}_r^{(m^{(s)})}$ is the vector of accumulated drought exposures under the sampled $+2^\circ\text{C}$ scenario. Point estimates are taken as the mean across draws, and a region is considered to have a statistically significant impact if the 90% interval across draws excludes zero. When aggregating at the country or European level, the observed event intervals are also calculated via Monte Carlo sampling. In both cases, all draws are aggregated at the desired level and intervals are then computed for assessing uncertainty.

4.4. Estimation results

4.4.1. Dynamic and cumulative impacts of droughts

Macroeconomic outcomes

Figures 4.2 and 4.3 present the estimated responses and cumulative effects from the ARDL models described in Section 4.3, for macroeconomic and sectoral outcomes, respectively. All results are reported for SPEI3 as the primary drought measure unless otherwise noted; SPEI6 and SPEI12 are used mainly for comparison.

The drought variable entering the model is the population-weighted annual total severity in severe drought conditions, standardized. Across the estimation sample, a one-standard-deviation shock corresponds to approximately 2.4 months of severe drought per year under SPEI3, 3.5 months under SPEI6, and 4.3 months under SPEI12 - reflecting the longer accumulation windows that tend to generate more persistent drought spells. Mean exposure across our sample is below one standard deviation for all indices (0.85, 1.49, and 1.91 months respectively), indicating that severe drought conditions are concentrated in a subset of region-year observations; at the upper end, the most severely affected regions experience up to 27.5 (SPEI3), 31.3 (SPEI6), and 36.3 (SPEI12) months of severe drought in a single year. All point estimates below should therefore be interpreted as the expected change in logarithmic growth rates, or approximate percentage points, associated with a one-standard-deviation increase in drought severity, with 90% confidence intervals calculated following Conley (1999).

Drought shocks generate heterogeneous dynamic effects across macroeconomic outcomes, with impacts that are not confined to the contemporaneous year but compound over a multi-year

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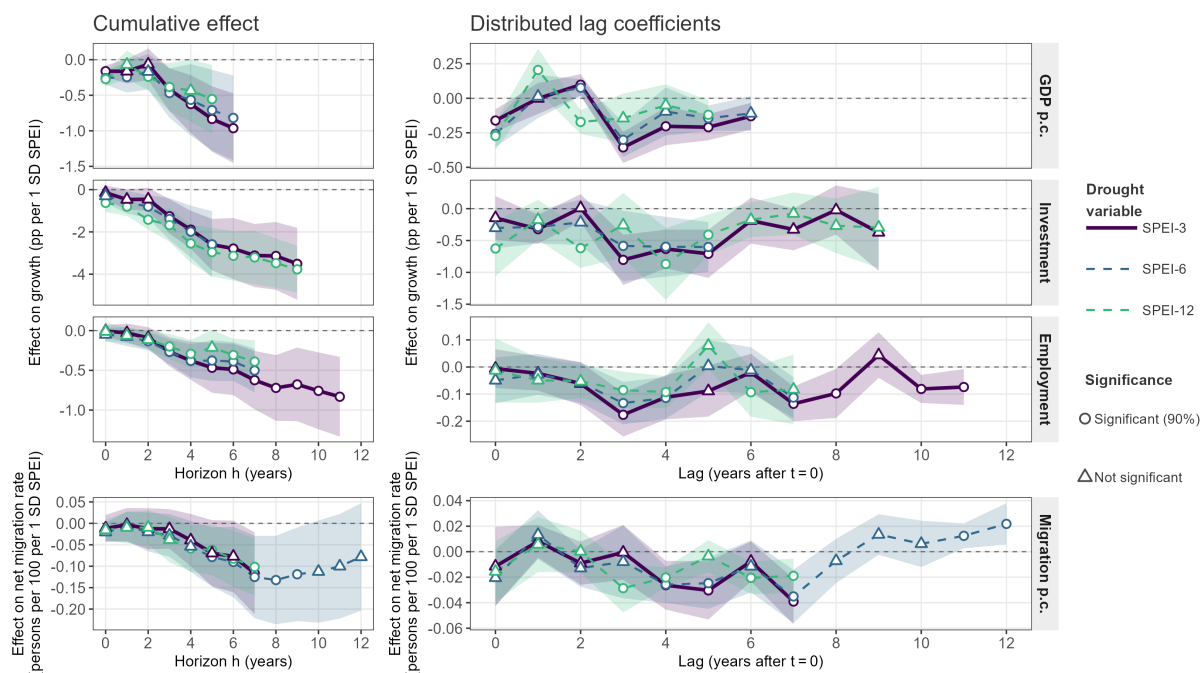


Figure 4.2: ARDL model results for the response of macroeconomic outcomes to drought exposure. Right-hand panels show the effect of a one-unit severe drought shock at each lag; left-hand panels show the cumulative effect under a persistent shock lasting 1-12 years. Standard errors are calculated following Conley (1999) to account for heteroskedasticity, temporal autocorrelation, and spatial autocorrelation between regions up to a distance of 500 km.

horizon.

Context Theoretically, droughts are an unambiguous adverse productivity shock. They affect labor productivity through a variety of channels (working conditions, health (Fleming-Muñoz et al., 2023)), but also capital returns, through higher operating expenses, for instance for machine cooling (Kilimani et al., 2018) in many critical sectors like energy (Byers et al., 2020). Droughts can also increase loan risk premia and induce credit rationing, thereby increasing the cost of capital (Kempa, 2026), especially if the fundamentals of companies are durably affected by the initial shock - e.g., due to costly adaptation investments (European Investment Bank, 2022). Droughts, finally, affect land, through lower crop yields (Chambers et al., 2020; Musungu et al., 2024). Motta et al. (2025) also reports that they can negatively affect infrastructure and buildings through land subsidence, thereby exacerbating the negative productivity shock by increasing transaction and/or coordination costs and diminishing the overall region's attractiveness due to reduced construction opportunities. Droughts can also have adverse demand effects through, e.g., lower tourism demand (McCarroll et al., 2024); reduced investment spending; consumption reallocation towards energy, typically not locally produced, for cooling if droughts are also hot (Zhang et al., 2022); or reduced income, notably in agriculture-intensive regions (San-

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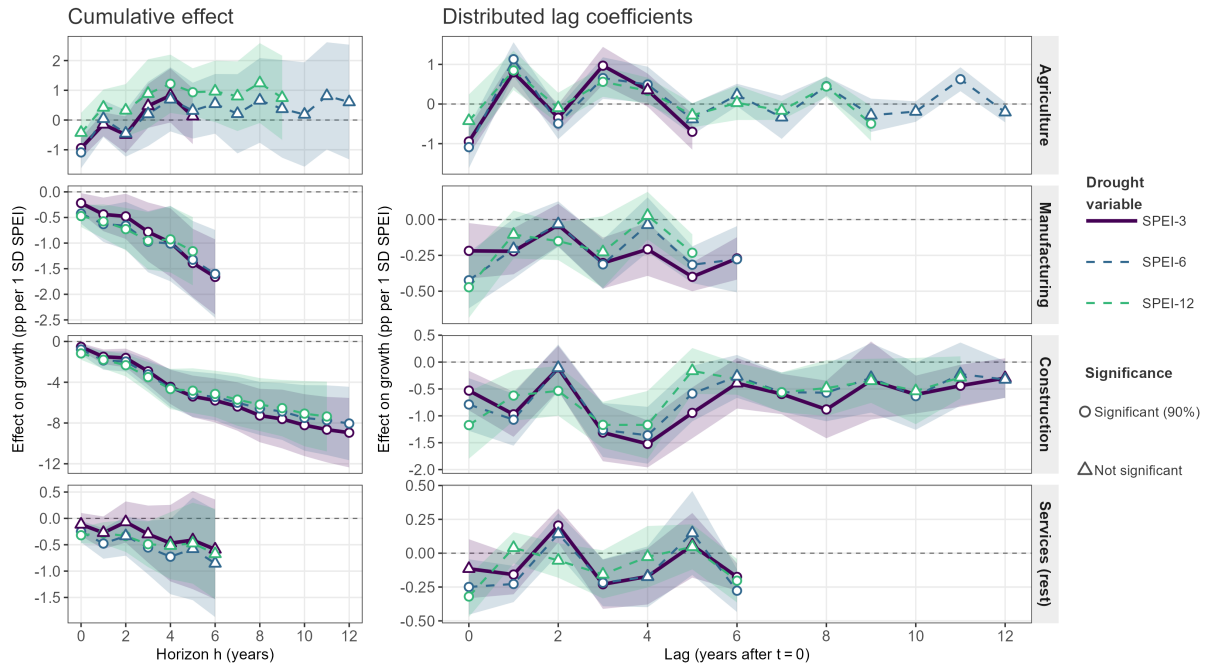


Figure 4.3: ARDL model results for the response of sectoral outputs (components of Gross Value Added) to drought exposure. Right-hand panels show the effect of a one-unit severe drought shock at each lag; left-hand panels show the cumulative effect under a persistent shock lasting 1-12 years. Standard errors are calculated following Conley (1999) to account for heteroskedasticity, temporal autocorrelation, and spatial autocorrelation between regions up to a distance of 500 km.

tini et al., 2022).¹ These effects can compound at the regional level, either through direct losses in production, like crop losses or more difficult working conditions, or through demand effects. Productivity effects can persist in the long run if drought spells extend beyond one or two years – through a sequence of productivity shocks. These can further compound by durably affecting local productivity-enhancing infrastructures (Motta et al., 2025), or reduce the productivity of capital because of (i) loss on capital-accumulation externalities in an endogenous-growth fashion (Romer, 1986) and (ii) investment reorientation towards less productive adaptation investment (Millner and Dietz, 2015). Recent evidence has also highlighted the persistence effects even of only one-year spells on productivity and other outcomes (Usman et al., 2024). Although exploring all these possible channels is beyond the scope of this chapter due to data limitations and the need for proper investigation, we diagnose, in the following, the effects of multi-year droughts on several key macroeconomic indicators other than regional value-added to form an interpretative picture. Note that our main specification controls at least partly for cross-regional spillovers by applying spatial correction errors *à la* Conley (1999).

GDP per capita GDP per capita exhibits a non-linear pattern in our model estimation. The instantaneous impact is negative, amounting to about -0.16 p.p. loss for SPEI3. After a faint

¹For this latter item, Fleming-Muñoz et al. (2023) argue that income effects need not necessarily be incurred in the short run, thanks to insurance mechanisms or transitory high prices, but in the longer run, when additional recovery expenses have to be met, *e.g.* in case of cattle.

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recovery over two years, possibly due to government intervention (Edwards et al., 2024), the long-run GDP impact over the three years post-impact is clearly negative, amounting to around 0.25 p.p. loss each year. Cumulative impact amounts to roughly 1 p.p growth loss after 6 years. These are significant economic magnitudes compared to the average historical economic growth rate of 8.9 p.p. over 6 years. Our results thus highlight that, despite a measurable recovery in the years following the shock, severe drought spells have long-lasting effects on GDP growth. This pattern is qualitatively² consistent with existing evidence, both for short-run impacts (Andersson et al., 2026; Costa and Hooley, 2025) and long-run scarring effects of droughts (Naumann et al., 2021; Usman et al., 2024).

Investment By studying investment effects, we further examine how droughts affect a particularly sensitive component of current GDP and long-run growth, both through capital expansion and productivity increases from R&D. Investment effects are delayed and markedly more severe than those on GDP per capita, consistent with the higher volatility of investment. Contemporaneous effects are small and insignificant (except for severe SPEI12 droughts), while investment growth reaches a trough at $t + 3$ and has very long-lasting effects. Hence, droughts do not affect investment plans immediately, but they substantially reduce the economic attractiveness of regions over time. Firm-level evidence also shows that small firms sensitive to weather events and more credit-constrained may cut investment plans after a shock (Benincasa et al., 2024). Droughts can also lead to the shutdown or default of some firms (Campiglio et al., 2022), especially in agriculture (Pastor-Sanz et al., 2025). All these factors increase the cost of capital by raising risk premia when lenders learn about the riskiness of territories (Kempa, 2026). These developments drive downward GDP growth in this territory through a direct demand channel and, potentially, through less productivity-enhancing investment. Furthermore, it is possible that investments in the medium run are reallocated towards adaptation expenses, which may be less productive than traditional investments, thereby further decreasing factor productivity in these regions while deteriorating firm balance sheets (Millner and Dietz, 2015; European Investment Bank, 2022).

Employment Employment exhibits no contemporaneous response to drought, reflecting the well-documented rigidity of labour markets in the short run. Furthermore, Franklin and Labonne (2019) show that the primary employment adjustment following climate events is through working hours instead of outright layoffs (see also Ireland et al. (2024)). However, our results highlight sizeable labour market losses (0.2 p.p) after three years. This suggests a scarring effect of droughts on employment opportunities, likely from the long-run effects on firm profitability.

Net migration The picture on employment and investment is well complemented by a view on migration patterns, which provide a sense of spatial adaptation behaviors. While droughts do not trigger significant population movements in the short run, longer lags show modest but

²As sketched in the introduction, droughts can be measured in many ways, and the literature does not provide a metric-consistent picture that would allow for faithful quantitative comparisons.

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significant migration effects (around 0.02% of the population), declining to 0.1% after 7 years of persistent shock. The contemporaneous drop in employment and increase in migration outflows are consistent with the well-documented idea that regional relative (un)employment rates are "push" factors for migration (Afonso et al., 2025; Piras, 2017). However, we document here that labor reallocation across regions is very sticky, even after long and severe drought spells.³

Sectoral outcomes

We further examine the underlying effects of droughts by differentiating across sectors of gross value-added. Sectoral responses to drought differ substantially in timing, magnitude, and persistence, reflecting differences in direct climate exposure and adaptive capacity across industries (Figure 4.3).

Agriculture Agriculture bears the largest immediate losses of any sector, with a contemporaneous decline of -0.945 p.p. under SPEI3, consistently with well-documented losses in crop yields due to water scarcity (Edwards et al., 2024). However, dynamic effects show a quick recovery, with non-significant impacts from year 3 onward. This pattern is consistent with the adaptation capacity of the agricultural sector, *e.g.* by the use of drought-resistant crops, input substitution or the adoption of insurance mechanisms (Miao, 2020). An upward adjustment in crop prices due to expected scarcity could also raise income, thereby watering down the initial downward impact on value added in the medium run (Letta et al., 2022). Finally, we may capture some short-run governmental (either central or regional) rescue plans and/or prepared reactions (Biella et al., 2026).

Manufacturing Manufacturing exhibits a more persistent response, albeit only on more intensive drought types (SPEI6 and SPEI12). While the sector suffers from a contemporaneous shock roughly half the size of agriculture's, it exhibits a slower recovery and a much more significant cumulative effect. Since our metric also accounts for heat, short-run effects capture both potential shocks to labour productivity beyond agriculture (Costa et al., 2024) on top of potential disturbances due to water scarcity (Rao et al., 2019).⁴ More long-lasting effects can be attributed to lingering productivity effects, like persistent impacts on productivity-enhancing infrastructure or costly adaptation expenses.

Construction Construction is the most severely and persistently affected sector. Drought reduces construction output growth by -0.530 p.p. contemporaneously under SPEI3, with losses intensifying over subsequent years and peaking at lag 4 (-1.522 p.p.). The cumulative five-year effect reaches -5.396 p.p. under SPEI3, consistently with other SPEI metrics. The magnitude and persistence of construction losses can be attributed to various factors. Given high exposure to heat in this sector, construction workers are particularly sensitive to hot and dry weather, with

³Determining whether these patterns are also partly driven by harder living and working conditions (amenity shocks in economic geography parlance) is beyond the scope of this study.

⁴Manufacturing accounts for around 15% of Europe's water demand (European Environment Agency, 2025).

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few adaptation options beyond putting work on hold (Lee et al., 2026). Lower overall investment also directly affects demand for buildings. Longer run effects can be associated with the long-run decrease in investment demand, typically long-lasting land subsidence (Kilimani et al., 2018), and, more modestly, given our estimates, adverse migration patterns that reduce demand for housing (Mangum and Molloy, 2021).

Services Services display the most attenuated and least persistent response. The contemporaneous effect under SPEI3 is insignificant, while SPEI6 and SPEI12 suggest a significant moderate immediate impact (-0.249 p.p. and -0.320 p.p. respectively). Cumulative effects are small and insignificant after two years. Given the sector’s significant heterogeneity, this lack of significance may mask disparities we are unfortunately unable to explore due to data limitations. The short-term downward effect observed for more severe droughts, which reflects the manufacturing sector, could be attributed to transient demand effects, either through fewer tourism arrivals in affected regions (Mathivha et al., 2017) or income losses from more directly affected sectors, such as agriculture and construction.

4.4.2. Spell-Specific and Interaction Models

The ARDL model estimates how a drought shock propagates forward over time — it is a dynamic model identified from all region-years with nonzero drought, regardless of spell history. The spell and interaction models, described in Section 4.3, ask complementary but distinct questions:

- The *spell model*, adapted from Wang et al. (2016), elucidates whether, among regions currently at spell depth k , a higher average annual drought intensity over the spell translates into a larger contemporaneous growth cost. It also explores whether this relationship strengthens as k increases.
- The *interaction model* measures the extent to which the current-year effect of a drought shock depends on whether the prior year was also a drought year.

Neither model serves as a robustness check for the DLM. Instead, they identify different objects and should be read on their own terms. Results are shown in Figure 4.4.

Spell model: macroeconomic outcomes For GDP per capita, under SPEI12, the rescaled coefficients reveal a clear pattern: the first-year effect is $\theta_1^{**} = -0.073$ p.p. and statistically significant, drops to near zero and insignificant for $k = 2-4$, then re-emerges as significant and negative from $k = 5$ (-0.021 p.p.) through $k = 8$ (-0.014 p.p.). The middle-spell plateau suggests that being two to four years into a continuous drought does not amplify the per-year cost beyond what a single-year exposure of the same intensity would produce. It is specifically at $k \geq 5$ that spell depth begins to matter: regions five or more years into a continuous drought suffer a statistically detectable additional growth penalty per unit of average annual intensity relative to regions earlier in a spell. Under SPEI3 the rescaled coefficients follow the same directional pattern at $k = 5, 6$, and 8 , though smaller in magnitude.

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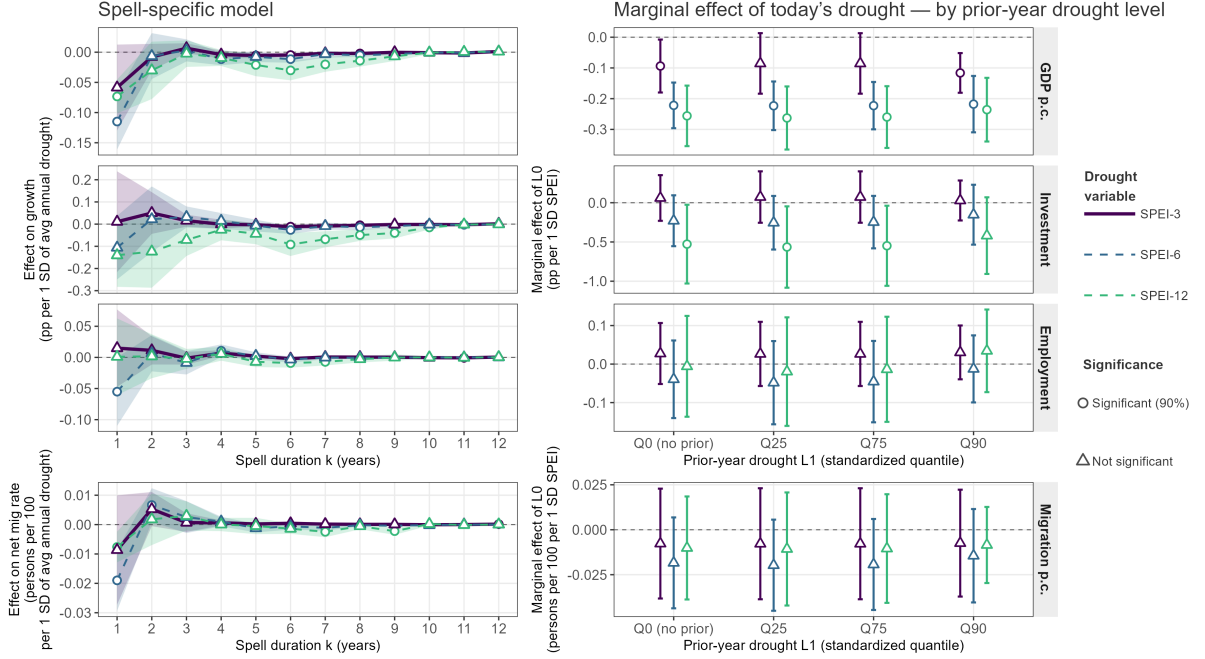


Figure 4.4: Spell-specific model results (left panels) and interaction model results (right panels) for each macroeconomic output. **Spell panels:** the x-axis is the consecutive drought spell length k ; each coefficient θ_k is rescaled as $\theta_k^{**} = \theta_k \times \frac{SD_k}{k} \times \frac{1}{SD_{L0}}$, where SD_k is the standard deviation of the k -year cumulative drought total and SD_{L0} is the standard deviation of the single-year (L0) drought variable. The rescaled coefficient θ_k^{**} is the effect on contemporaneous growth of a one-SD increase in average annual drought intensity within the current spell. A detailed explanation of the coefficients' interpretation is presented in the Methods section 4.3. Because the reference unit (SD per year) is the same at every k , coefficients at different spell depths are directly comparable: a more negative θ_k^{**} at larger k indicates that spell depth amplifies the per-year cost of drought. **Interaction panels:** each point shows the marginal effect of a contemporaneous drought shock evaluated at a given quantile of the prior-year drought distribution. Standard errors are calculated following Conley (1999) to account for heteroskedasticity, temporal autocorrelation, and spatial autocorrelation between regions up to a distance of 500 km; shaded bands and error bars are 90% confidence intervals.

For investment, the rescaled coefficients under SPEI12 are consistently negative and grow in absolute value from $k = 6$ (-0.092 p.p.) through $k = 9$ (-0.040 p.p.), with significant effects from $k = 6$ onward. Under SPEI3 the effects are very small after rescaling, suggesting that investment costs in short-accumulation drought spells are driven more by total cumulative exposure than by prolonged exposure, consistent with the ARDL finding that SPEI3 investment effects can accumulate across many individually triggered lagged responses.

Employment and migration spell effects are largely insignificant and negligible in magnitude after rescaling, consistent with the interpretation that these outcomes respond to drought through slow-moving adjustments that the spell model's contemporaneous design does not capture.

Interaction model: no evidence of non-linear amplification The interaction model tests whether the contemporaneous effect of a drought shock is amplified when the prior year also experienced drought — i.e., whether the marginal impact of $\tilde{d}_{it}$ increases in $\tilde{d}_{i,t-1}$. Across all

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macroeconomic outcomes and drought indices, the interaction coefficient $\hat{\beta}_{01}$ is consistently small and statistically indistinguishable from zero. The marginal effect of a contemporaneous drought shock on GDP per capita growth evaluated at no prior drought ($\tilde{d}_{i,t-1} = 0$) under SPEI3 is -0.094 p.p. $[-0.180, -0.008]$, and remains essentially unchanged across the empirical distribution of lagged drought: at the 25th, 75th, and 90th percentiles of $\tilde{d}_{i,t-1}$ the marginal effect is -0.085 , -0.085 , and -0.116 p.p. respectively, with overlapping confidence intervals. The same pattern holds for investment, employment and migration: the interaction term $\hat{\beta}_{01}$ is near zero and consistently insignificant.

Results for the interaction model indicate that the contemporaneous cost of a drought shock does not depend materially on whether the prior year was also a drought year, at least within the single-lag horizon this model captures. There is no evidence of non-linear amplification of the kind where a drought landing on top of a previous drought year hits harder than an isolated shock of the same size. Whatever compounding emerges in the ARDL's distributed lag profile is therefore not driven by a non-linear interaction between consecutive drought years at the one-lag horizon, though the interaction model cannot rule out non-linearities operating at longer lags.

4.5. Robustness

To validate our results, we perform a series of robustness checks, reported in Appendix C.9. In our main specification, we defined drought spells using a severe threshold (-1.5) for the standardized SPI and SPEI distributions. As a first check, we change the thresholds for drought definition, testing moderate droughts (restricting the threshold to -1) and extreme droughts (extending it to -2). In both cases, the threshold is used to monthly drought conditions with accumulation periods of 3, 6 and 12 months; we then compute the annual total severity used in the regressions. We report results in Figures C.58, C.57, C.60, C.59. While we observe differences in magnitudes and confidence intervals for some variable-lag pairs, qualitative conclusions remain unchanged. Additionally, we run the same models with SPI in place of SPEI to define drought conditions. Results are very similar (Figures C.63, C.64, C.65, and C.66). We also use drought duration (in months) in place of severity to define our regressors, obtaining identical conclusions, as shown in Figures C.61 and C.62. We test the addition of the United Kingdom and Turkey data for GDP p.c. and find results, reported in Figure C.67, virtually identical to those of the main specification. We test the main model without regional time trends and find similar overall behavior, with generally lower effects, especially for migration (Figure C.68). This behavior is expected if the average long-run regional trend, possibly spurious, is positive and partly captured by regression coefficients. A similar behavior was observed by Callahan and Mankin (2022a), who found that adding trends amplified the negative effects of heatwaves. We keep trends in the main analysis to account for these long-run changes in climate and economic conditions (Burke et al., 2015). This said, the qualitative results of the ARDL model are preserved in the absence of such trends. To test for the influence of outliers on the results, we trim the distribution of each outcome variable at the 25% and 75% quintiles, retaining the bulk of the data points (the central 50%). Results

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are reported in Figure C.74 and are virtually identical to the main model. Moreover, given the relatively short time dimension of our panel, we apply the Split Panel Jackknife debiasing of coefficients (Dhaene and Jochmans, 2015) to tackle an eventual Nickell bias. Figure C.73 reports results directly compared with estimates from the whole panel, showing that for most of the outcomes-lags the Nickell bias is most likely upwards, while the general ARDL curve is very similar to the original model. Finally, we report in Figures C.69, C.70, C.71, C.72 our main model results when clustering standard errors by NUTS3 (less conservative than Conley) or following Driscoll-Kraay (Driscoll and Kraay, 1998), which account for temporal and spatial auto-correlation of errors at arbitrarily large spatial scales (more conservative than Conley).

4.6. Storyline Analysis: The 2015-2018 Drought

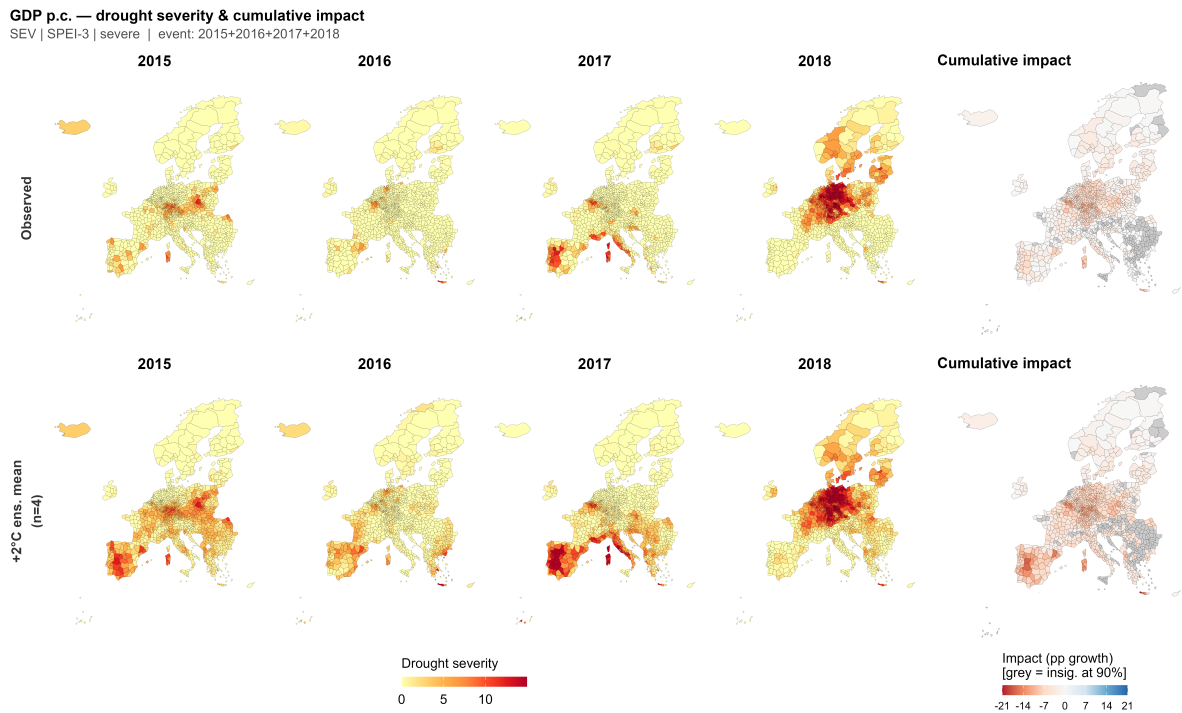


Figure 4.5: The cumulative GDP per capita impacts of the 2015-2018 drought event at NUTS-3 level, under the observed climate (upper) and under a +2°C global warming storyline (lower). Impacts are computed by convolving the observed (or counterfactual) SPEI-3 drought severity series over the event years with the ARDL distributed lag coefficients, integrated over the full response horizon selected by BIC (6 years for SPEI-3). The unit is percentage-point cumulative growth. The +2°C storyline perturbs the observed temperature and precipitation fields with CMIP6-derived monthly climate deltas (ensemble mean of four models: CanESM5, EC-Earth3, MRI-ESM2-0, MPI-ESM1-2-HR) and recomputes the drought index on the perturbed fields. Details can be found in Section 4.2.1. Grey regions indicate NUTS-3 areas where the cumulative impact is not statistically significant at the 90% level; uncertainty is characterized via Monte Carlo draws ($n = 500$) jointly over coefficient uncertainty and climate model uncertainty for the +2°C scenario. Results for the 2022 event are reported in Appendix C.11.

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Table 4.2: Macro-region cumulative drought impacts (SPEI3) — event years 2015–2018 (UN M49 macro-region classification). Cumulative drought impacts (SPEI3), 90% MC confidence intervals in brackets. Observed uncertainty: ARDL coefficient estimation. +2°C: additionally captures uncertainty across four climate models. See notes below table for row definitions.

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Europe	GDP p.c. (pp growth)	-2.72 [-4.01, -1.43]	-5.21 [-10.15, -1.47]
	<i>GDP loss (bn €)</i>	-438.9 [-647.8, -230.9]	-760.0 [-1423.6, -230.7]
	<i>% of 2015 base</i>	-3.11 [-4.60, -1.64]	-5.39 [-10.10, -1.64]
	Investment (pp growth)	-10.65 [-16.42, -5.28]	-20.38 [-40.48, -6.38]
	<i>Investment loss (bn €)</i>	-350.4 [-540.2, -173.7]	-594.1 [-1118.3, -192.7]
	<i>% of 2015 base</i>	-12.23 [-18.85, -6.06]	-20.74 [-39.03, -6.73]
	Employment (pp growth)	-2.60 [-4.09, -1.04]	-5.07 [-10.49, -1.58]
	<i>Employment loss (m persons)</i>	-5.75 [-9.06, -2.30]	-10.80 [-22.02, -3.40]
	<i>% of 2015 base</i>	-2.73 [-4.30, -1.09]	-5.13 [-10.46, -1.61]
	Migration p.c. [†] (pers./100)	-0.35 [-0.60, -0.07]	-0.72 [-1.59, -0.06]
Northern	GDP p.c. (pp growth)	-1.88 [-2.77, -0.99]	-2.18 [-3.58, -0.85]
	<i>GDP loss (bn €)</i>	-28.7 [-42.3, -15.1]	-34.0 [-55.3, -13.3]
	<i>% of 2015 base</i>	-1.80 [-2.66, -0.95]	-2.14 [-3.47, -0.84]
	Investment (pp growth)	-7.36 [-11.34, -3.65]	-8.47 [-14.35, -3.63]
	<i>Investment loss (bn €)</i>	-25.0 [-38.5, -12.4]	-29.2 [-48.9, -12.7]
	<i>% of 2015 base</i>	-6.97 [-10.75, -3.46]	-8.15 [-13.65, -3.56]
	Employment (pp growth)	-1.80 [-2.83, -0.72]	-2.08 [-3.63, -0.79]
	<i>Employment loss (m persons)</i>	-0.32 [-0.51, -0.13]	-0.37 [-0.65, -0.14]
	<i>% of 2015 base</i>	-1.80 [-2.84, -0.72]	-2.09 [-3.62, -0.80]
	Migration p.c. [†] (pers./100)	-0.24 [-0.41, -0.05]	-0.29 [-0.57, -0.03]
Western	GDP p.c. (pp growth)	-4.09 [-6.03, -2.15]	-6.03 [-10.48, -2.05]
	<i>GDP loss (bn €)</i>	-326.0 [-481.1, -171.5]	-482.9 [-845.2, -163.1]
	<i>% of 2015 base</i>	-4.09 [-6.03, -2.15]	-6.05 [-10.59, -2.04]
	Investment (pp growth)	-16.01 [-24.68, -7.94]	-23.44 [-41.05, -7.96]
	<i>Investment loss (bn €)</i>	-264.3 [-407.4, -131.0]	-392.2 [-694.1, -129.7]
	<i>% of 2015 base</i>	-15.66 [-24.13, -7.76]	-23.23 [-41.11, -7.68]
	Employment (pp growth)	-3.91 [-6.15, -1.56]	-5.81 [-10.78, -1.88]
	<i>Employment loss (m persons)</i>	-3.74 [-5.89, -1.50]	-5.46 [-10.06, -1.79]
	<i>% of 2015 base</i>	-4.00 [-6.29, -1.60]	-5.84 [-10.74, -1.91]

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Table 4.2: Macro-region cumulative drought impacts (SPEI3) — event years 2015–2018. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Eastern	Migration p.c. [†] (pers./100)	-0.52 [-0.90, -0.10]	-0.81 [-1.62, -0.07]
	GDP p.c. (pp growth)	-2.00 [-2.95, -1.05]	-4.46 [-9.86, -1.00]
	<i>GDP loss (bn €)</i>	-27.0 [-39.8, -14.2]	-53.2 [-109.9, -13.4]
	<i>% of 2015 base</i>	-2.44 [-3.60, -1.28]	-4.81 [-9.93, -1.22]
	Investment (pp growth)	-7.83 [-12.08, -3.88]	-17.49 [-39.32, -3.64]
	<i>Investment loss (bn €)</i>	-23.0 [-35.5, -11.4]	-45.0 [-93.2, -10.3]
	<i>% of 2015 base</i>	-9.51 [-14.65, -4.71]	-18.55 [-38.47, -4.25]
	Employment (pp growth)	-1.91 [-3.01, -0.77]	-4.34 [-10.19, -0.91]
	<i>Employment loss (m persons)</i>	-0.78 [-1.22, -0.31]	-1.74 [-4.06, -0.37]
	<i>% of 2015 base</i>	-1.95 [-3.08, -0.78]	-4.38 [-10.23, -0.93]
	Migration p.c. [†] (pers./100)	-0.25 [-0.44, -0.05]	-0.63 [-1.54, -0.04]
	GDP p.c. (pp growth)	-1.62 [-2.38, -0.85]	-5.36 [-11.71, -1.51]
	<i>GDP loss (bn €)</i>	-54.7 [-80.7, -28.8]	-179.6 [-388.4, -49.7]
	<i>% of 2015 base</i>	-1.66 [-2.45, -0.87]	-5.46 [-11.81, -1.51]
Southern	Investment (pp growth)	-6.33 [-9.75, -3.14]	-21.08 [-46.62, -6.40]
	<i>Investment loss (bn €)</i>	-37.0 [-57.0, -18.3]	-123.7 [-272.2, -36.8]
	<i>% of 2015 base</i>	-6.52 [-10.05, -3.23]	-21.81 [-48.01, -6.50]
	Employment (pp growth)	-1.54 [-2.43, -0.62]	-5.28 [-12.17, -1.46]
	<i>Employment loss (m persons)</i>	-0.86 [-1.35, -0.34]	-2.97 [-6.89, -0.81]
	<i>% of 2015 base</i>	-1.53 [-2.41, -0.61]	-5.31 [-12.32, -1.45]
	Migration p.c. [†] (pers./100)	-0.21 [-0.36, -0.04]	-0.76 [-1.84, -0.07]

[†] Migration p.c. in persons per 100 inhabitants; all other pp rows are percentage-point growth. Loss rows in bn€ (GDP, investment) or millions of persons (employment). % rows express loss as % of group 2015 base.

To translate the estimated ARDL models into economically interpretable magnitudes, we apply a climate storyline approach (as described in Section 4.2.1) to one of the most severe and sustained recent drought events in Europe: the multi-year drought of 2015–2018, which strongly affected central and western Europe, mainly (Ionita et al., 2025; Freund et al., 2023).

Spatial pattern of impacts Figure 4.5 maps the cumulative GDP per capita impacts of the 2015–2018 drought at the NUTS-3 level under the observed climate and under the +2°C storyline, described in detail in Section 4.2.1. The observed impacts display a clear spatial gradient, with

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Table 4.3: Macro-region lookup (UN M49 geoscheme)

Macro region	Countries
Northern	Denmark, Estonia, Finland, Ireland, Iceland, Lithuania, Latvia, Norway, Sweden
Western	Austria, Belgium, Switzerland, Germany, France, Liechtenstein, Luxembourg, Netherlands
Eastern	Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia
Southern	Albania, Bosnia and Herzegovina, Cyprus, Spain, Greece, Croatia, Italy, Montenegro, North Macedonia, Malta, Portugal, Serbia, Slovenia, Kosovo

the most severe losses concentrated in central Europe — particularly Germany, Czechia, Belgium, and Luxembourg —and in parts of the Iberian Peninsula. Northern and north-eastern Europe are comparatively less affected, consistent with the spatial footprint of the 2015–2018 drought as captured by SPEI3. Under a scenario of +2°C global warming, impacts intensify broadly across the continent, with the largest absolute amplification concentrated in south-western Europe and the Balkans, where additional warming translates into substantially hotter and drier conditions through increased evaporative demand, compounding the already severe precipitation deficits of the observed event.

Aggregate and macro-regional impacts Table 4.2 reports cumulative impacts by macro-region.⁵

At the European aggregate, the 2015–2018 drought is estimated to have reduced GDP per capita growth by –2.72 p.p. cumulatively, corresponding to a total GDP loss of €439 bn, or –3.11% of the 2015 base. Investment bears the largest proportional losses, at –12.23% of base, while employment fell by approximately 5.8 million jobs (–2.73% of the 2015 workforce). Net migration is increased by –0.35 persons per 100 inhabitants.

Under the +2C storyline, all impacts roughly double at the European aggregate level. GDP per capita losses reach –5.21 p.p. (–5.39% of base; €760 bn), investment –20.74% of base, and employment approximately 10.8 million jobs. Migration increases to –0.72 persons per 100 inhabitants.

Macro-regional heterogeneity is substantial. Western Europe - the most exposed sub-region - accounts for the bulk of aggregate losses under the observed climate, with a GDP per capita decline of –4.09 p.p. and an investment loss of –16.01 p.p. alongside 3.7 million jobs lost. Under +2°C, Western Europe’s GDP loss escalates to –6.03 p.p. and its investment loss to –23.23%. Southern Europe, by contrast, experiences only moderate losses under the observed climate (–1.62 p.p. GDP per capita growth) but faces the sharpest proportional amplification under warming: GDP losses more than triple to –5.36 p.p. and investment growth falls from

⁵We follow the UN macro-region definition <https://unstats.un.org/unsd/methodology/m49/> also reported in Table 4.3.

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−6.33 to −21.08 p.p. with more than tripled jobs lost from 2015. Eastern Europe similarly sees a more than doubling of impacts at +2°C, from −2.00 to −4.46 p.p. in GDP per capita growth and from −7.83 to −17.49 p.p. in investment growth. Northern Europe is least affected in both scenarios, with GDP growth losses remaining below 2.2 p.p. and employment impacts below −2.1 p.p. even under warming. This pattern has strong policy implications for adaptation. To the extent that we capture current adaptation practices through our fixed-effect structure, these impacts account for the fact that Southern countries are usually better prepared than Northern countries due to longer exposure to droughts (Biella et al., 2026). Our results suggest that current adaptation levels in these countries are relatively adequate for current drought intensities, as indicated by their relatively modest relative growth losses during the observed 2015-2018 drought spell, the smallest in Western Europe. However, the same spell under 2°C of warming is four times the estimated one, indicating that current adaptation measures would hardly be able to absorb a shock of this magnitude.

Country-level impacts Country-level results are reported in Table C.14 in Appendix C.10, alongside a corresponding plot (Figure 4.6). Among the most severely affected countries under the observed climate, Luxembourg (−9.20 p.p. GDP per capita growth), Belgium (−6.64 p.p.), Germany (−6.34 p.p.), and Czechia (−5.32 p.p.) stand out, reflecting both their high exposure to the 2015–2018 drought footprint and their tight integration into drought-sensitive supply chains. Latvia (−3.84 p.p.) and Switzerland (−3.74 p.p.) are also among the hardest hit. Investment losses follow similar patterns and are particularly severe in Luxembourg, Belgium, and Germany, with growth losses between −24.82 p.p. and −36.04 p.p..

The +2°C scenario reshapes the geographic distribution of impacts considerably, as we already noticed with macro regions. The largest absolute amplifications are concentrated in south-western Europe and the western Balkans: Spain sees its GDP per capita growth loss more than triple, from −2.17 p.p. to −7.69 p.p., while Greece goes from −1.43 to −5.52 p.p., Portugal from −2.35 to −5.99 p.p., and Albania from −1.14 to −5.88 p.p.. Countries in south-eastern Europe that experienced relatively modest observed impacts — Bulgaria (−0.06 p.p.), Serbia (−0.03 p.p.), Montenegro (−0.07 p.p.), and North Macedonia (−0.03 p.p.) — face a dramatic reversal under +2°C, with losses rising to −2.73, −3.86, −3.87, and −4.31 p.p. respectively. Investment losses follow an analogous but amplified pattern: Spain’s investment impact rises from −8.50 to −30.33 p.p., Greece’s from −5.61 to −22.16 p.p., and Albania’s from −4.47 to −23.43 p.p.. Again, this points to a limited ability of current adaptation measures to absorb shocks consistent with a 2°C warming. By contrast, northern countries show limited or slightly attenuated impacts under +2°C. Central European countries already heavily exposed — Germany, Belgium, Czechia — continue to face large losses under +2°C, though the proportional amplification is more moderate ($\times 1.2$ – 1.4) than in the south and Balkans, as these regions were already highly exposed under the observed climate. These results highlight the limits to adaptation of the most exposed European regions.

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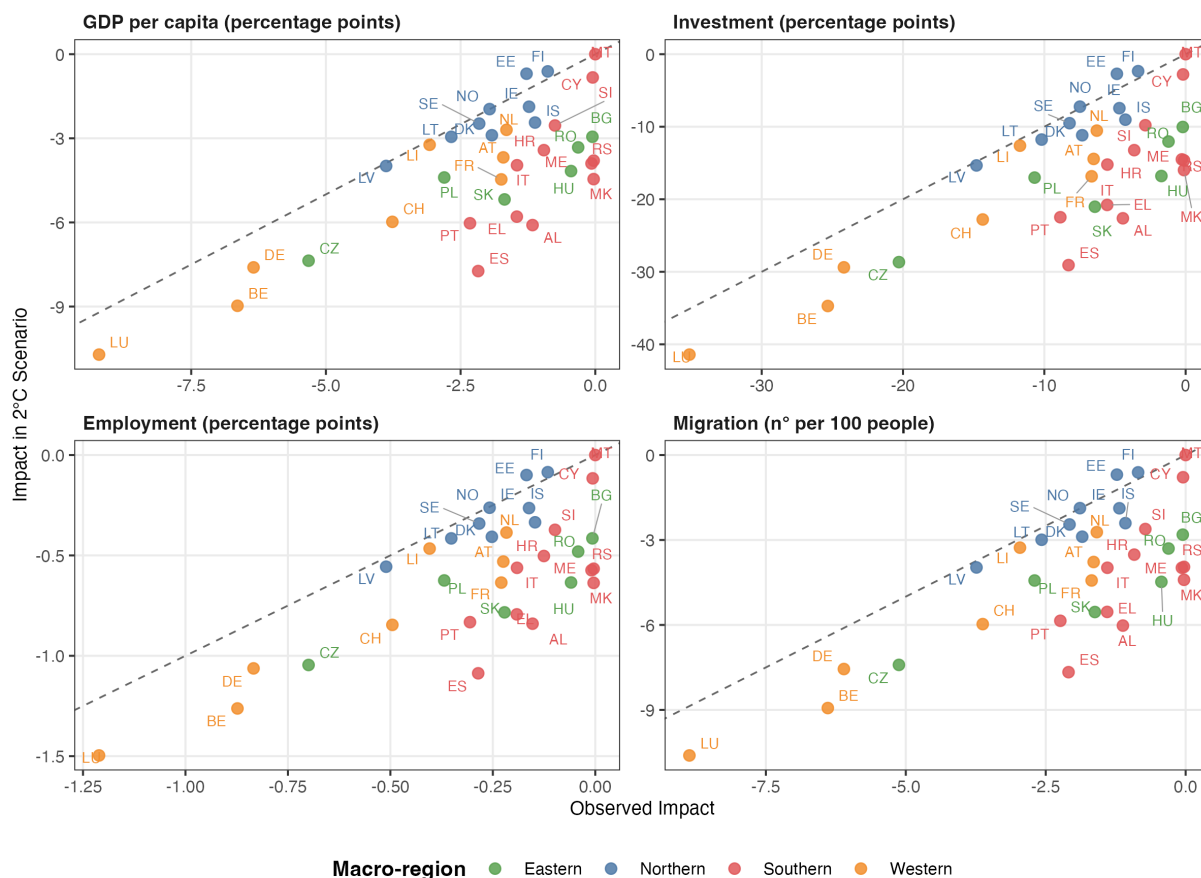


Figure 4.6: Distribution of country impacts for the 2015–2018 drought (SPEI3) event and corresponding +2°C storyline. The x-axis reports observed effects estimated under our main model specification, while the y-axis shows results from our 2°C storyline. The dashed line is the 45°line.

The fairly similar behavior of impact multipliers across the variables we estimate impacts for, evident in Figure 4.6, reflects the similar linear cumulative response shown in Figure C.61. Inter-annual dynamics arising from the ARDL model are not shown in these figures due to space constraints.

Comparison with The 2022 Drought The 2022 drought provides a useful point of comparison for the 2015–2018 event. Appendix C.10 contains detailed tables and figures applying the same kind of exercise as per the 2015–2018 event. As a single-year event, it generated substantially smaller cumulative losses than the multi-year 2015–2018 drought, consistent with the distributed lag structure’s role in capturing the persistent and compounding nature of prolonged drought exposure. At the European aggregate, the 2022 event reduced GDP per capita growth by -1.35 p.p. corresponding to a GDP loss of €203 bn (-1.44% of 2015 base). Investment declined by -5.38% of base and employment by -1.26% of base. Net migration increased by -0.18 persons per 100 inhabitants. Under +2°C, the 2022 losses also roughly double: GDP per capita falls to -2.33 p.p., investment to -8.63 p.p., and employment to -2.21 p.p.. The macro-regional

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pattern mirrors that of 2015–2018. Western Europe again accounts for the bulk of observed losses (−1.77 p.p. GDP per capita; −6.88 p.p. investment), while Southern Europe displays the sharpest climate-change amplification, with GDP per capita losses rising from −1.63 to −2.94 p.p. and investment from −6.31 to −10.94 p.p. Northern Europe remains the least affected in both scenarios. See Table C.15 in Appendix C.11) for details. Country-level results are reported in Table C.16.

4.7. Conclusion

This chapter developed a multi-tier methodology to assess the impact of droughts throughout their entire duration. Using different panel models, we provide measurements of the impacts of droughts on the economies of affected territories. We measure sizable effects on synthetic indicators such as GDP and document a variety of impact magnitudes on other, more precise metrics. In particular, investment seems particularly sensitive. More importantly, we clearly establish that failing to account for the multi-annual nature of drought spells, as well as their lagged and compounding impacts, omits a significant part of the picture, notably the long-lasting, accumulating impacts on exposed regions.

While some economic variables seem little affected in the very year of the drought, we document long-lasting, scarring effects on many key macroeconomic variables. We document that capital variables (notably investment) are more affected than labor variables (employment/migration). These results therefore suggest that long-lasting effects may stem from a higher cost of capital, attributable to lower productivity or higher risk premia in these territories. Sectoral impacts are also highly differentiated, with the more persistent impacts observed in manufacturing and construction. On the other hand, more directly affected sectors, such as agriculture, recover pretty quickly after an initially large shock. Our results further suggest that drought effects compound almost linearly after the first year (ARDL), and that adaptation margins are exhausted after a certain number of years of uninterrupted drought (5-6 years in spell models). Finally, using an innovative storyline approach, we further quantify that the EU-27 would have faced close to double the observed impact of the 2015-2018 drought spell in a 2°C world (−5.21 p.p. of growth each year instead of −2.72). Regionally, this ratio can reach fourfold in Southern European countries, highlighting possible limits to adaptation in countries which are currently better prepared for droughts (Biella et al., 2026) but which are already drier and more exposed.

This chapter therefore provides solid grounds for exploring adaptation measures to address the observed long-lasting effects of droughts. In particular, our framework highlights that persistent effects can often be larger in non-agricultural sectors except services, underscoring the need for nuanced adaptation responses that account for the economic fallout in economically relevant sectors. Our characterization of the compounding and dynamic nature of drought shocks is crucial in furthering our understanding of the impacts of extreme events under a changing climate. Finally, current policies project global warming to reach between +2.1 and +3.3 °C. Our storyline results underscore the urgency of keeping it well below +2 °C to avoid a non-linear increase in

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negative growth impacts relative to the observed impacts under the current climate.

However, this study is not without limitations, which call for further work. In particular, given the reduced number of variables at the desired geographical disaggregation for Europe as a whole, our interpretation of the relative impacts across different sectors is largely qualitative. While the literature has explored the potential channels of these different impacts to some extent (Freire-González et al., 2017), further investigation would be fruitful. For example, the large, long-run effects on capital dynamics suggest that exploring the link between droughts and the cost of capital would be a valuable avenue — for instance, by using existing data on regional financial flows and interest rates for countries like Spain or Italy that are heavily exposed. Additional work on the dynamics of productivity and the quality of geographical amenities would also be worthwhile. Another important aspect is to explore the potential for adaptation in response to drought exposure. While our panel approach in time and space arguably captures part of the adaptation dynamics at the regional level, a direct future line of work would be to quantify the adaptation response after a drought spell across various sectors.

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5.1. Summary of Main Findings

This thesis has examined how climate change affects human development and regional economic systems under conditions of deep uncertainty. It argues that standard climate impact assessments systematically understate climate impacts by under-weighting four interconnected dimensions: welfare losses beyond income, climate hazards beyond mean temperature, the persistent effects of climate impacts, and the consequences of complex, long-duration hazards such as drought. Across the three chapters, the thesis developed empirical and methodological approaches that incorporate multidimensional welfare outcomes, dynamic impact processes, and uncertainty across climate models, socio-economic pathways, and event realizations. The findings support a broader, more temporally explicit and uncertainty aware accounting of climate costs.

The first chapter established that climate change impacts are substantially more pervasive than income-only assessments suggest. All three components of the Human Development Index (HDI) - gross national income per capita, life expectancy at birth, and expected years of schooling - respond significantly and adversely to both mean climate changes and climate extremes, although through distinct climatic channels and at different temporal scales. Approximately one-fifth of projected global human development gains are lost under high-emission, low-development pathways. Once health and education dimensions are incorporated, virtually all regions can experience adverse impacts, representing a qualitative departure from aggregate income projections. At long time horizons, uncertainty in socio-economic pathways and their interaction with climate uncertainty dominate projection variance, highlighting that near-term development policy is itself a first-order determinant of future climate impacts.

The second chapter extended this framework to temperature overshoot-and-return scenarios, examining whether developmental losses accumulated during periods of temperature exceedance are recovered once global temperatures decline. Even under the conservative assumption that underlying damage functions are fully reversible, recovery remains incomplete and highly uncertain. The median share of peak HDI losses recovered by 2100 ranges from 19% to 70%, depending on the magnitude and duration of overshoot. Development losses depend not only on peak warming and end-of-century temperatures, but on the full temporal profile of warming exposure. Cumulative HDI losses integrated over the century increase with both peak temperature and

stabilization level. These findings demonstrate that overshoot pathways impose a developmental burden that is invisible to end-of-century or global-warming-level assessments, and that the costs of temporarily exceeding a temperature target cannot be fully offset by subsequently returning below it, even when physical or societal tipping points are not accounted for.

The third chapter focused on the dynamics of multi-year drought in European regions, where fine-grained spatial analysis reveals how persistence and compounding amplify economic costs beyond what single-year or contemporaneous damage assessments capture. Cumulative GDP per capita losses from the 2015–2018 drought are estimated at approximately 2.75%, nearly doubling to more than 5% under 2°C global warming. This amplification would remain largely underexplored in static damage frameworks. Importantly, the largest persistent effects emerge not in agriculture, which recovers relatively quickly, but in capital-intensive sectors such as manufacturing and construction. This finding suggests that the dominant channel of long-run economic scarring operates through investment dynamics and the cost of capital rather than through direct productive disruption alone. The non-linear increase in annual damages for drought spells lasting more than five consecutive years further indicates that adaptive capacity is not unlimited: once drought persists long enough, historical buffering mechanisms become progressively exhausted.

5.2. Cross-Cutting Themes and Synthesis

Across the three chapters, a common conclusion emerges: climate impacts can be broader, more persistent, more risky and more trajectory-dependent than standard assessment frameworks imply. This pattern appears across welfare dimensions, temporal scales, and different forms of climatic hazard. More broadly, the thesis suggests that climate impacts cannot be understood solely as static responses to contemporaneous temperature levels. Across welfare outcomes and hazard types, impacts emerge as cumulative processes shaped by the kind of socio-economic variable, climate hazard, persistence and exposure duration.

The three chapters are also methodologically and substantively linked. The overshoot analysis in Chapter 3 relies directly on the damage functions estimated in Chapter 2, meaning that the incomplete recovery documented under overshoot-and-return scenarios is not merely a consequence of trajectory dynamics but is amplified by the persistence and lag structure identified in Chapter 2: losses compound over the overshoot period precisely because climate shocks affect welfare with multi-year delays. Similarly, the finding in Chapter 4 that manufacturing and construction, more than agriculture, carry the bulk of long-run drought-induced scarring resonates with the income persistence mechanism documented globally in Chapter I, and suggests that capital adjustment frictions and investment dynamics may be a general channel through which climate shocks generate lasting welfare losses across different hazard types. Taken together, the three chapters provide mutually reinforcing evidence that persistence, compounding, and trajectory dependence are pervasive features of climate impacts on human development.

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5.2.1. Unaccounted Impacts Beyond GDP

The first chapter demonstrates that a substantial share of climate impacts, particularly those operating through health and educational channels, remains invisible to income-focused assessments. Yet the multidimensional welfare agenda remains incomplete, and this thesis's findings point to several important frontiers for future research.

One limitation concerns the Human Development Index's aggregation structure. The index combines income, health, and education through a geometric mean, implicitly allowing substitution across dimensions that may not reflect actual welfare trade-offs or the lived experience of climate-exposed populations. Welfare frameworks that preserve the multidimensional structure of human capabilities may therefore provide a richer characterization of climate vulnerability.

Beyond this conceptual limitation, the thesis also abstracts from adaptation as an explicit forward-looking process. The estimated damage functions are grounded in historical climate variability and therefore implicitly capture the average adaptive responses already in place during the estimation period. They do not, however, model adaptation as a dynamic policy or investment choice. As climatic conditions move beyond the historical range, extrapolating historical dose-response relationships becomes increasingly uncertain. A central unresolved question is therefore how investments in cooling infrastructure, public health systems, educational resilience, and social protection alter climate sensitivity across welfare dimensions. Existing work on adaptation costs and benefits has focused predominantly on income channels (Bento et al., 2023; Bowen et al., 2012). Extending this literature to multidimensional welfare outcomes is both a scientific priority and a policy necessity.

Another limitation concerns the scale of welfare aggregation. Although the subnational disaggregation employed in this thesis represents a substantial advance over country-level analyses, regional HDI data still aggregates across populations with highly heterogeneous exposures, incomes, and adaptive capacities. The groups most vulnerable to climate extremes, including outdoor agricultural workers, urban populations without access to cooling, and children in poorly adapted educational systems, remain largely invisible in regional development statistics. Linking individual-level welfare trajectories to climate exposure would allow future work to estimate the distributional structure of climate impacts that regional aggregates necessarily obscure (Halle-gatte and Rozenberg, 2017; Cappelli et al., 2021).

Finally, a major frontier is integrating ecosystem integrity into multidimensional welfare assessment. The HDI captures dimensions of human welfare that are directly measurable in development statistics, but well-being is also materially and non-materially constituted by ecosystems and biodiversity. Biodiversity loss and ecosystem degradation interact with climate change both as parallel drivers of welfare deterioration and as feedbacks that amplify climate impacts. Pollinator decline affects food security independently of temperature trends, wetland degradation reduces protection against flooding and storm surge, forest loss accelerates local warming, alters precipitation patterns, and weakens hydrological regulation. These pathways remain invisible

in standard socio-economic-based assessments. Emerging natural capital accounting frameworks and biodiversity metrics (see, e.g., Dasgupta, 2024; IPBES, 2019) provide an opportunity to extend multidimensional climate impact assessment beyond anthropocentric welfare indicators alone.

5.2.2. Extremes, Dynamics, Multi-Annual Hazards, and the Need for an Integrated Perspective

A consistent finding across all three chapters, contributing to a fast-emerging body of literature, is that mean temperature alone is an insufficient summary of the climatic drivers of welfare losses. Heatwaves affect income and mortality; temperature variability influences life expectancy and schooling; precipitation extremes impair health and education; drought severity across multiple accumulation periods determines the magnitude and sectoral distribution of economic scarring. The climatic variable that matters depends on the welfare outcome under consideration and the physical mechanism through which damage occurs. At the same time, allowing for flexible dynamic structures in empirical models reveals that many climate impacts can persist beyond the period of direct exposure.

This finding has broader methodological implications. The choice of climate index, including the climatic variable, temporal aggregation, accumulation period, and threshold definition, is not a neutral technical decision. It fundamentally shapes which impacts are identified and which sectors or populations appear vulnerable. The drought analysis illustrates this clearly: SPEI calculated over short accumulation periods captures agricultural stress, whereas longer accumulation periods better capture hydrological and industrial impacts. Analyses relying on a single index risk conflate economically distinct shocks and may misattribute impacts. More generally, climate impact research would benefit from shared frameworks for comparing findings across indices and event definitions (Bellon et al., 2022a), thereby facilitating integrated multi-hazard assessments.

Compound climate events represent an important emerging research area that none of the three chapters directly addresses, but that all three implicitly motivate. A region simultaneously exposed to drought and extreme heat faces a fundamentally different risk profile from one exposed to either hazard independently. Standard empirical damage functions, which typically estimate climatic effects separately and combine them linearly, are therefore likely to underestimate damages in the extreme scenarios most relevant for adaptation policy. Empirical frameworks capable of modeling joint hazard distributions and their interaction with socio-economic vulnerability remain scarce and constitute a major direction for future research (Zscheischler et al., 2020).

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5.2.3. Uncertainty, Trajectories, and the Complementarity of Scenario and Storyline Approaches

The three chapters employ distinct but complementary approaches to uncertainty and future climate risk: scenario projections across SSPs and climate models (Chapter 2), trajectory-sensitive overshoot emulation (Chapter 3), and physically grounded event storylines (Chapter 4). Their juxtaposition highlights a broader tension in climate impact communication between scenarios and event-specific relevance.

Scenario-based projections remain essential for long-run strategic planning, for comparing alternative emissions pathways, and for identifying the socio-economic conditions under which damages become most severe. Variance decomposition approaches additionally clarify where uncertainty originates and, therefore, where scientific and policy investments are most needed.

The overshoot analysis sharpens this scenario perspective by demonstrating that climate impacts depend not only on the amount of warming but also on its temporal trajectory. Identical end-of-century temperatures can generate substantially different cumulative welfare losses depending on whether warming follows a smooth stabilization pathway or an overshoot-and-return profile. The overshoot integral - the cumulative exceedance of temperature above a threshold - therefore provides a compact representation of trajectory dependence. This has direct implications for evaluating delayed mitigation strategies: emissions that contribute to temporary overshoot impose not only long-run damages, but also additional cumulative welfare losses during the overshoot period itself.

Climate storylines, as employed in Chapter 4, are complementary. Rather than estimating expected impacts across distributions of possible futures, they examine how specific experienced events would unfold under alternative warming levels. This framing connects abstract warming targets to recognizable lived experiences following a hazard, such as water stress across Europe. For regional governments, affected communities, and financial institutions, the concreteness of a storyline can be more actionable than probabilistic confidence intervals around aggregate economic indicators (Shepherd et al., 2018). The relatively limited application of storyline methods to economic outcomes, therefore, represents an important opportunity for future climate-economics research.

Integrating these approaches into a coherent framework for uncertainty communication remains an open methodological challenge. Scenario projections define the strategic envelope of possible futures; overshoot analyses reveal the importance of temporal trajectories within that envelope; and storylines ground abstract projections in physically and socially recognizable events. Used together, these approaches provide a more complete characterization of climate risk than any single framework in isolation.

5.3. Policy Implications

The findings of this thesis carry several implications for climate policy and impact assessment.

First, adaptation strategies focused narrowly on income protection are insufficient. Health system resilience, educational infrastructure, and social protection mechanisms are not secondary components of adaptation policy but central to limiting climate impacts that conventional economic metrics fail to capture. Health and education respond to climate through distinct channels, at different temporal scales, and with regional distributions that differ from those of income, implying that populations most exposed to non-income damages are not necessarily those most affected by income losses. As a result, adaptation strategies are calibrated solely to GDP impact risk, misallocating resources toward regions and sectors with the largest income losses rather than those experiencing the greatest welfare deterioration. Incorporating multidimensional welfare indicators into national adaptation planning, climate finance allocation, and vulnerability assessment is therefore essential to capture the full social cost of climate change.

Second, long-term impact assessments that go beyond single-shock frameworks are necessary for both risk modeling and policy design. Climate damages accumulate over time, and their temporal structure is as important as their magnitude in determining welfare outcomes. Single-year assessments and static damage functions fail to capture the persistent and compounding effects documented across income, health, education, and regional economic outcomes. Risk models used by governments, development banks, and insurers should therefore incorporate dynamic damage processes with multi-year exposure, lagged effects, and spell-duration dependence. This is particularly important for sovereign risk and fiscal planning in highly exposed regions, where the long-run consequences of repeated shocks can substantially exceed event-based estimates.

Third, the overshoot results indicate that temporary exceedance of temperature targets results in distinct, only partially reversible developmental losses, with direct relevance for Loss and Damage discussions under the UNFCCC. Because impacts accumulate during overshoot periods, even after temperatures decline, overshoot scenarios cannot be treated as equivalent to pathways that avoid exceedance altogether. This provides a quantitative basis for treating overshoot-specific damages as a distinct category of climate harm. The overshoot integral — cumulative temperature exceedance above a target — offers a tractable metric for linking these losses to emissions pathways and potentially to historical responsibility allocations (Tavoni et al., 2024; Callahan and Mankin, 2022b). The geographic distribution of these damages further underscores their equity implications, as the largest cumulative losses occur in regions with low historical emissions and limited capacity to absorb persistent welfare declines.

Fourth, the drought analysis highlights the importance of multi-year horizons and long-duration hazards in regional climate risk assessment. Insurance and risk frameworks based on annual loss events are likely to underestimate the costs of persistent drought sequences, which generate compounding economic losses that increase non-linearly with duration. The results show that investment is the primary channel of long-run scarring, suggesting that drought exposure reduces

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expected returns to capital and raises risk premia, with effects on productive capacity that persist beyond the hazard itself. Regional governments, development banks, and insurers in drought-exposed areas therefore require models that explicitly incorporate persistence, duration dependence, and the capital-cost channel of climate damage.

Finally, the decomposition of uncertainty carried out in this thesis has implications for both research prioritization and policy communication. For income outcomes, scenario uncertainty dominates by mid-century, indicating that emissions trajectories are the primary driver of long-run uncertainty. For health and education, uncertainty is driven earlier by interactions between climate models and socio-economic assumptions, implying that improvements in any single modeling component are insufficient to substantially reduce uncertainty. This heterogeneity matters for communication: some welfare dimensions are structurally more uncertain than others, and lower-tail outcomes may be more policy-relevant than central projections, even if they receive less attention in aggregate assessments.

5.4. Directions for Future Work

Several directions for future research emerge naturally from the findings and limitations of this thesis.

The most immediate extension of Chapter 2 is the explicit incorporation of adaptation as a determinant of climate sensitivity across HDI dimensions. The current framework treats adaptation as implicitly embedded within historical relationships. A forward-looking extension would instead quantify how investments in adaptive systems alter estimated damage functions, including cooling infrastructure, public health capacity, and resilient educational systems. Linking macro-panel approaches with sector-specific adaptation cost data and institutional capacity measures would provide more actionable guidance for adaptation finance allocation across welfare dimensions.

For Chapter II, the most important extension is the relaxation of the reversibility assumption. The current framework effectively provides a lower bound on the costs of overshoot by assuming that all climate impacts are, in principle, reversible. Introducing mechanisms of structural irreversibility, including capital destruction, institutional weakening, and persistent human capital deficits, would likely substantially increase estimates of residual damages. Addressing this question would require coupling empirical climate impact functions with structural models of capital and human capital accumulation.

Chapter 4 could be extended in two complementary directions. First, the storyline framework could be systematically applied across a broader set of European extreme events and warming levels, generating an event-based database of counterfactual impacts for regional stress testing and adaptation planning. Second, the economic transmission channels identified in the analysis, particularly the interaction between drought persistence, investment dynamics, and capital costs, warrant further investigation at finer sectoral and financial resolution. Data on regional credit conditions, insurance penetration, and firm-level investment responses could help identify the

mechanisms through which prolonged drought generates persistent economic scarring.

It is worth noting explicitly what this thesis does not claim. The reduced-form panel approach identifies average historical climate-welfare relationships and projects them forward under alternative scenarios; it does not constitute a full structural welfare model and is not directly suited to cost-benefit analysis of specific adaptation policies without further assumptions. Migration, conflict, and institutional erosion are not modeled as welfare channels, nor does the framework capture potential tipping points or non-linearities beyond the historical range of climate variability. These are not incidental omissions but reflect the inherent limits of the empirical panel tradition: they define the boundary at which the econometric approach developed here should be complemented by structural and process-based models.

More broadly, integrating the approaches developed across this thesis into a unified climate risk framework remains a central methodological challenge for future climate impact science. Current integrated assessment models project smooth scenario trajectories at coarse temporal resolution and remain poorly suited to capturing the persistence and compounding of extreme events, as well as the multidimensional nature of welfare losses. Bridging the empirical panel tradition of climate econometrics with the forward-looking structural logic of integrated assessment models, while preserving the temporal and welfare complexity emphasized throughout this thesis, represents an important frontier for the next generation of climate impact research.

Accounting for climate change as a multidimensional, dynamic, and trajectory-dependent process is therefore not simply an extension of existing impact assessment frameworks; it is necessary for accurately characterizing the scale, persistence, and distribution of climate risk in the twenty-first century.

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Appendix A

A.1. Models Extended Summaries

In every table and figure, the significance of each term is reported next to the coefficient value: *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$, + for $p < 0.1$, where p is the p-value of the t-test for significance of the variables when errors are clustered by country.

Lag Selection Procedure

For each outcome-climate variable combination, we select the number of distributed lags through a two-step procedure. In the first step, we estimate a distributed lag model (DLM) for each climate variable individually, testing all lag lengths from 0 to 9. The DLM includes, for each lag k , both the first-differenced climate variable $\Delta x_{i,t-k}$ and its interaction with the regional historical mean of the moderating variable, selected from the previous models (see column *mean_var_used* in Table A.5). When testing mean temperature, we control for total rainfall with 8 lags of its first difference and interaction; when testing total rainfall, we control for mean temperature with 8 lags; when testing any extreme variable, we control for both mean temperature and total rainfall with 8 lags each.

For each lag length $k \in \{0, \dots, 9\}$, we compute four model selection metrics: the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), the Hannan–Quinn Information Criterion (HQ), and the leave-one-year-out cross-validation error (LOYOCV). LOYOCV is computed following the pre-estimation demeaning approach of (Newell et al., 2021): fixed effects are removed by demeaning the data prior to estimation, and then each year is left out in turn as the validation set, with the model re-estimated on the remaining years; the reported metric is the mean squared prediction error across all left-out years. AIC, BIC, and HQ are computed from the log-likelihood of the fixed effects model, counting all estimated parameters including fixed effects. HQ applies a penalty of $2 \log(\log(n))$ per parameter, which is stricter than AIC but less strict than BIC, making it well suited to time series contexts (Hannan and Quinn, 1979).

In the second step, we select the lag length minimising HQ, and test whether the selected lag block - comprising all lags from 0 to the selected length, for both the first-differenced term and its interaction - is jointly significant via a Wald test with errors clustered by country. A variable is retained as a candidate if this joint p-value is below 0.1. Variables not meeting this threshold are excluded from the comprehensive model; mean temperature and total rainfall are retained as

Variable
TM
TM_2
RR
RR_2
EXT
EXT_2
TM*EXT
RR*EXT
diff_TM
TM*diff_TM
diff_RR
RR*diff_RR
lag(diff_TM)
lag(TM*diff_TM)
lag(diff_RR)
lag(RR*diff_RR)
diff_EXT
diff_EXT*TM
diff_EXT*EXT
diff_EXT*RR

Table A.1: Model specifications tested. This is intended for a single extreme variable (EXT) and each response variable. An x on the line means the variable is included in the model.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TM	$8.55 \times 10^{-3*}$						
TM_2	$-3.41 \times 10^{-4**}$						
RR	1.46×10^{-6}						
RR_2	-2.21×10^{-10}						
diff_TM		5.51×10^{-3}	2.22×10^{-3}	2.76×10^{-3}			2.88×10^{-3}
TM_i_diff_TM		-3.42×10^{-4}	-8.76×10^{-5}	-1.56×10^{-4}			-1.37×10^{-4}
diff_RR		1.96×10^{-6}	-3.99×10^{-6}	1.23×10^{-6}			-3.91×10^{-6}
RR_i_diff_RR		-9.44×10^{-10}	1.42×10^{-9}	-8.65×10^{-10}			1.39×10^{-9}
l(diff_TM, 1)		$8.66 \times 10^{-3**}$					
l(TM_i_diff_TM, 1)		$-6.06 \times 10^{-4**}$					
diff_WD			$2.26 \times 10^{-4*}$		$1.79 \times 10^{-4+}$		$2.16 \times 10^{-4*}$
RR_i_diff_WD			$-1.43 \times 10^{-7**}$		$-1.25 \times 10^{-7*}$		$-1.37 \times 10^{-7**}$
diff_HW				$-1.70 \times 10^{-4+}$		-1.48×10^{-4}	-1.37×10^{-4}
TM_i_diff_HW				$9.09 \times 10^{-6+}$		$7.90 \times 10^{-6+}$	7.46×10^{-6}

Table A.2: Summary of Gross National Income per Capita (GNIPC) growth models, one climate variable at a time, with errors clustered by country. Each column represents a different model specification (see Table A.1). Only variables that reach statistical significance at $p < 0.1$ are reported among those tested. Abbreviations: TM = mean annual temperature (level); TM_2 = squared mean annual temperature; RR = total annual precipitation (level); RR_2 = squared total annual precipitation; $diff_TM$ = first difference of mean annual temperature; $TM_i_diff_TM$ = interaction of mean temperature with its first difference; $diff_RR$ = first difference of total annual precipitation; $RR_i_diff_RR$ = interaction of mean rainfall with its first difference; $l(diff_TM, 1)$, $l(TM_i_diff_TM, 1)$ = one-year lags of the above; $diff_WD$ = first difference of wet days (annual count of days with rainfall $> 1\text{mm}$); $RR_i_diff_WD$ = interaction of mean rainfall with the first difference of wet days; $diff_HW$ = first difference of heatwave severity (annual sum of degree-days above the 90th percentile threshold during heatwave events); $TM_i_diff_HW$ = interaction of mean temperature with the first difference of heatwave severity. Significance codes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

Appendix A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
diff_TM	$-1.63 \times 10^{-3*}$	$-1.55 \times 10^{-3*}$	$-1.61 \times 10^{-3*}$	$-1.56 \times 10^{-3*}$	-8.47×10^{-4}					-7.93×10^{-4}	-7.85×10^{-4}
TM_i_diff_TM	1.05×10^{-4}	1.05×10^{-4}	1.04×10^{-4}	1.04×10^{-4}	8.23×10^{-5}					8.36×10^{-5}	8.30×10^{-5}
diff_RR	-1.73×10^{-6}	-2.45×10^{-6}	-1.70×10^{-6}	-2.01×10^{-6}	-1.59×10^{-6}					-2.44×10^{-6}	-2.13×10^{-6}
RR_i_diff_RR	$6.42 \times 10^{-10*}$	$9.22 \times 10^{-10*}$	$6.61 \times 10^{-10*}$	$6.88 \times 10^{-10*}$	$6.17 \times 10^{-10*}$					$8.98 \times 10^{-10*}$	$8.77 \times 10^{-10*}$
WD		1.01×10^{-4}				7.20×10^{-5}				9.66×10^{-5}	9.89×10^{-5}
WD_2		$-2.85 \times 10^{-7+}$				$-2.35 \times 10^{-7+}$				$-2.73 \times 10^{-7+}$	$-2.80 \times 10^{-7+}$
PEXT			2.61×10^{-5}				2.46×10^{-5}			1.35×10^{-5}	2.13×10^{-5}
TM_i_PEXT			$-1.32 \times 10^{-6+}$				$-1.29 \times 10^{-6+}$			-1.50×10^{-6}	$-1.51 \times 10^{-6+}$
RX				$3.55 \times 10^{-5+}$				3.09×10^{-5}		1.39×10^{-5}	
TM_i_RX				-1.49×10^{-6}				-1.41×10^{-6}		-1.51×10^{-7}	
TVAR					$4.48 \times 10^{-3+}$				$4.26 \times 10^{-3*}$	$4.42 \times 10^{-3+}$	$4.45 \times 10^{-3+}$
TM_i_TVAR					-2.78×10^{-4}				$-2.56 \times 10^{-4+}$	-2.49×10^{-4}	-2.50×10^{-4}
PEXT_2										$5.21 \times 10^{-8*}$	$4.52 \times 10^{-8+}$

Table A.3: Summary of Expected Years of Schooling (EYS) growth models, one climate variable at a time, with errors clustered by country. Each column represents a different model specification (see Table A.1). Only variables that reach statistical significance at $p < 0.1$ are reported among those tested. Abbreviations: *diff_TM* = first difference of mean annual temperature; *TM_i_diff_TM* = interaction of mean temperature with its first difference; *diff_RR* = first difference of total annual precipitation; *RR_i_diff_RR* = interaction of mean rainfall with its first difference; *WD* = wet days in levels (annual count of days with rainfall >1mm); *WD_2* = squared wet days; *PEXT* = extreme precipitation in levels (annual sum of rainfall on days exceeding the 99.5th percentile of the 1981–2010 baseline); *TM_i_PEXT* = interaction of mean temperature with PEXT; *RX* = maximum 5-day cumulative precipitation in levels; *TM_i_RX* = interaction of mean temperature with RX; *TVAR* = day-to-day temperature variability in levels (annual mean of within-month standard deviations of daily mean temperature, following (Kotz et al., 2021)); *TM_i_TVAR* = interaction of mean temperature with TVAR; *PEXT_2* = squared PEXT. Significance codes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
diff_TM	2.00×10^{-4}	2.05×10^{-4}	4.05×10^{-4}	2.75×10^{-4}	2.44×10^{-4}	1.73×10^{-4}					3.99×10^{-4}	3.92×10^{-4}
TM_i_diff_TM	7.07×10^{-6}	1.20×10^{-5}	-6.51×10^{-6}	6.16×10^{-6}	5.96×10^{-6}	2.52×10^{-6}					-1.15×10^{-5}	-1.03×10^{-5}
diff_RR	-1.71×10^{-6}	-1.90×10^{-6}	$-1.87 \times 10^{-6+}$	-1.30×10^{-6}	-8.02×10^{-7}	-1.81×10^{-6}					5.89×10^{-7}	-1.37×10^{-6}
RR_i_diff_RR	1.38×10^{-10}	1.67×10^{-10}	2.19×10^{-10}	1.35×10^{-10}	9.44×10^{-11}	1.62×10^{-10}					-7.49×10^{-11}	1.39×10^{-10}
diff_HW		$-1.85 \times 10^{-5*}$					-8.97×10^{-6}				-1.10×10^{-5}	$-1.21 \times 10^{-5+}$
HW_i_diff_HW		1.65×10^{-7}					1.24×10^{-7}				1.17×10^{-7}	1.28×10^{-7}
diff_WD			$4.33 \times 10^{-5*}$					2.65×10^{-5}			1.68×10^{-5}	3.16×10^{-5}
TM_i_diff_WD			$-2.33 \times 10^{-6*}$					$-2.36 \times 10^{-6*}$			$-2.13 \times 10^{-6+}$	$-2.26 \times 10^{-6*}$
RX				1.90×10^{-5}								
TM_i_RX				$-1.36 \times 10^{-6+}$								
diff_RX					1.15×10^{-5}				8.15×10^{-6}		4.64×10^{-6}	
TM_i_diff_RX					$-1.00 \times 10^{-6+}$				$-9.57 \times 10^{-7+}$		-7.43×10^{-7}	
diff_TVAR						$-1.08 \times 10^{-2*}$				$-1.09 \times 10^{-2*}$	$-1.07 \times 10^{-2+}$	$-1.08 \times 10^{-2+}$
TVAR_i_diff_TVAR						$3.06 \times 10^{-3*}$				$3.06 \times 10^{-3+}$	$3.06 \times 10^{-3+}$	$3.10 \times 10^{-3+}$

Table A.4: Summary of Life Expectancy at Birth (LEB) growth models, one climate variable at a time, with errors clustered by country. Each column represents a different model specification (see Table A.1). Only variables that reach statistical significance at $p < 0.1$ are reported among those tested. Abbreviations: *diff_TM* = first difference of mean annual temperature; *TM_i_diff_TM* = interaction of mean temperature with its first difference; *diff_RR* = first difference of total annual precipitation; *RR_i_diff_RR* = interaction of mean rainfall with its first difference; *diff_HW* = first difference of heatwave severity (annual sum of degree-days above the 90th percentile threshold during heatwave events); *HW_i_diff_HW* = interaction of mean heatwave severity with its first difference; *diff_WD* = first difference of wet days (annual count of days with rainfall >1mm); *TM_i_diff_WD* = interaction of mean temperature with the first difference of wet days; *RX* = maximum 5-day cumulative precipitation in levels; *TM_i_RX* = interaction of mean temperature with RX; *diff_RX* = first difference of RX; *TM_i_diff_RX* = interaction of mean temperature with the first difference of RX; *diff_TVAR* = first difference of day-to-day temperature variability (annual mean of within-month standard deviations of daily mean temperature, following (Kotz et al., 2021)); *TVAR_i_diff_TVAR* = interaction of mean TVAR with its first difference. Significance codes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

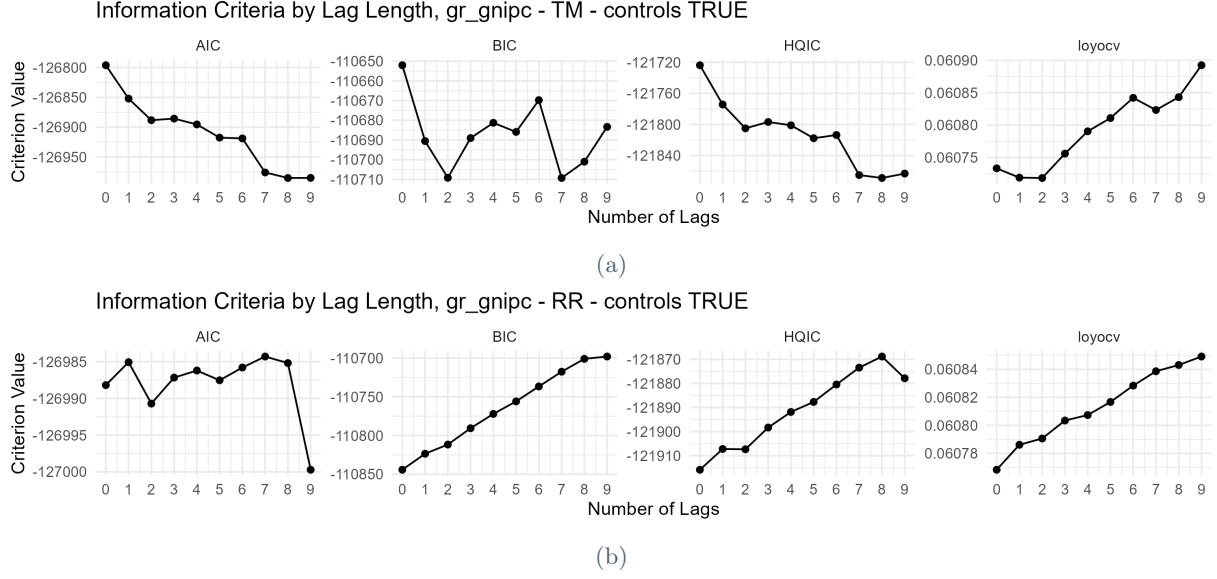


Figure A.1: Lag selection metrics for Gross National Income per Capita (GNIPC), for mean temperature (top panel) and total rainfall (bottom panel). Each subplot shows four metrics as a function of the number of lags tested (0-9): AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), HQ (Hannan-Quinn Information Criterion), and LOYOCV (leave-one-year-out cross-validation error, computed via pre-estimation demeaning following (Newell et al., 2021)). Lower values indicate better model fit. When testing mean temperature, the model controls for total rainfall with 8 lags; when testing total rainfall, the model controls for mean temperature with 8 lags. All specifications include the first-differenced climate variable and its interaction with the regional historical mean of the moderating variable, region and year fixed effects, and country-level quadratic time trends.

controls when not significant. In cases where HQ selects 0 lags but a contemporaneous differenced term is individually significant, the variable is retained with 0 lags (indicated as *Sign diff term* in the reason column of Table A.5). All candidate variables are then included jointly in the comprehensive model and retested; any variable losing joint significance at this stage is dropped and the remaining variables are retested. The p-values reported in column *joint_pval in complete model* of Table A.5 reflect this final iteration. The resulting preferred specifications are reported in Section 2.5.5.

Table A.5 determines which climate variables enter each preferred specification via a joint test of the main and interaction terms together; this test alone cannot indicate whether a variable's significance stems from its average effect on the outcome, from heterogeneity by baseline climate, or from both. Table A.7 decomposes each retained variable into these components, and additionally tests whether the climate-heterogeneity estimate is sensitive to substituting, or supplementing, the baseline-climate moderator with regional development level (log GNIPC). For each variable we report the main effect, the climate-heterogeneity effect estimated alone and adjusting for development, and the development-heterogeneity effect adjusting for climate.

Appendix A

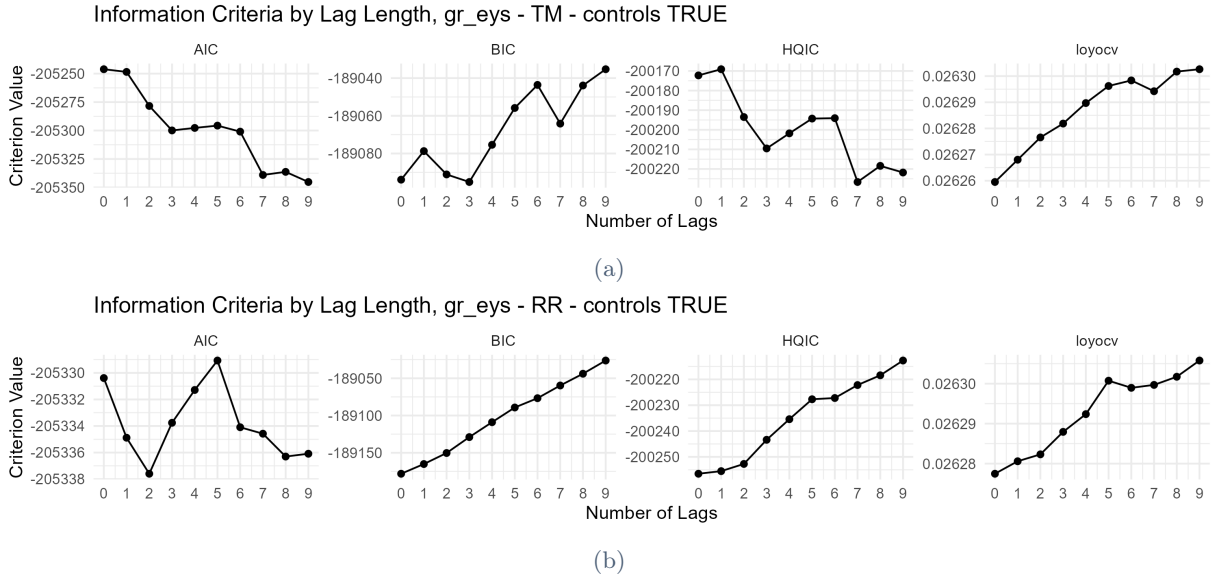


Figure A.2: Lag selection metrics for Expected Years of Schooling (EYS), for mean temperature (top panel) and total rainfall (bottom panel). Each subplot shows AIC, BIC, HQ, and LOYOCV (leave-one-year-out cross-validation error, computed via pre-estimation demeaning following (Newell et al., 2021)) as a function of the number of lags tested (0–9). Lower values indicate better model fit. When testing mean temperature, the model controls for total rainfall with 8 lags; when testing total rainfall, the model controls for mean temperature with 8 lags. All specifications include the first-differenced climate variable and its interaction with the regional historical mean of the moderating variable, region and year fixed effects, and country-level quadratic time trends.

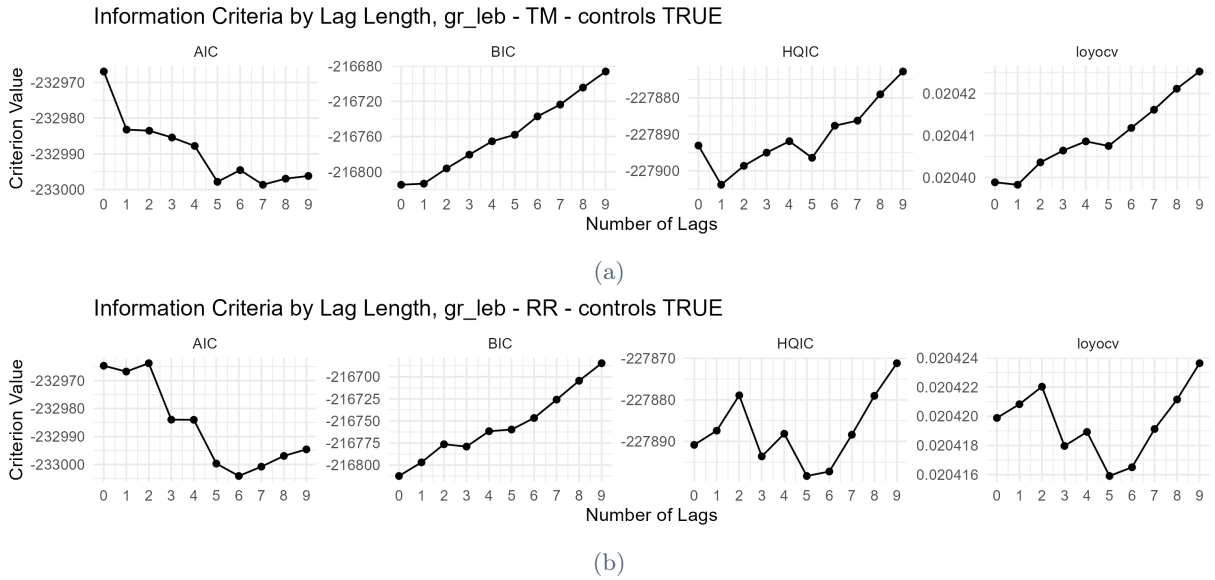


Figure A.3: Lag selection metrics for Life Expectancy at Birth (LEB), for mean temperature (top panel) and total rainfall (bottom panel). Each subplot shows AIC, BIC, HQ, and LOYOCV (leave-one-year-out cross-validation error, computed via pre-estimation demeaning following (Newell et al., 2021)) as a function of the number of lags tested (0–9). Lower values indicate better model fit. When testing mean temperature, the model controls for total rainfall with 8 lags; when testing total rainfall, the model controls for mean temperature with 8 lags. All specifications include the first-differenced climate variable and its interaction with the regional historical mean of the moderating variable, region and year fixed effects, and country-level quadratic time trends.

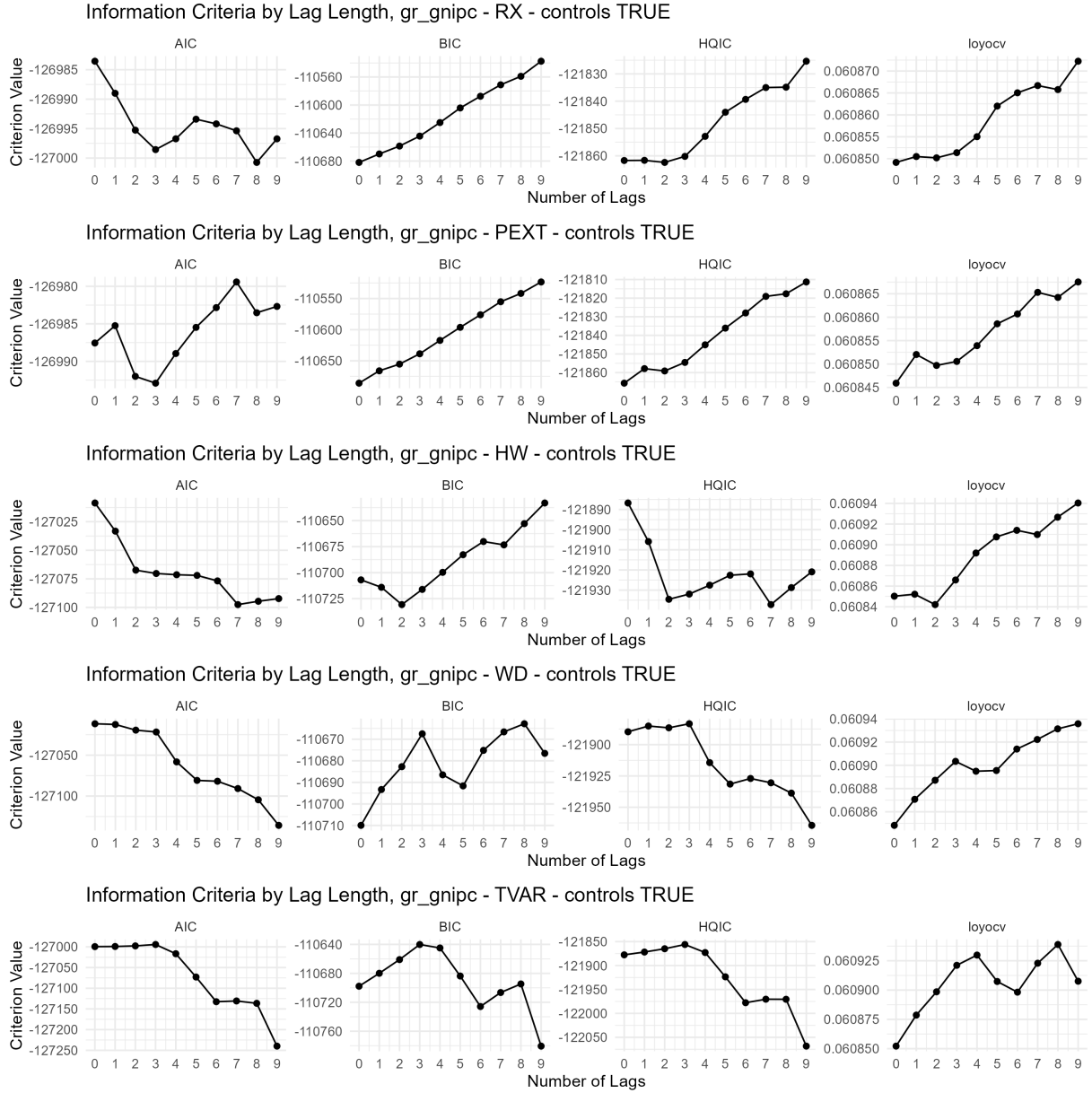


Figure A.4: Lag selection metrics for Gross National Income per Capita (GNIPC), for each extreme climate variable: maximum 5-day cumulative precipitation (RX), extreme precipitation (PEXT), heatwave severity (HW), wet days (WD), and day-to-day temperature variability (TVAR), one per subplot row. Each subplot shows AIC, BIC, HQ, and LOYOCV (leave-one-year-out cross-validation error, computed via pre-estimation demeaning following (Newell et al., 2021)) as a function of the number of lags tested (0–9). Lower values indicate better model fit. All specifications control for mean temperature and total rainfall with 8 lags each, and include the first-differenced extreme variable interacted with its moderating variable (mean temperature for RX, PEXT, HW, and TVAR; mean rainfall for WD), together with region and year fixed effects and country-level quadratic time trends.

Appendix A

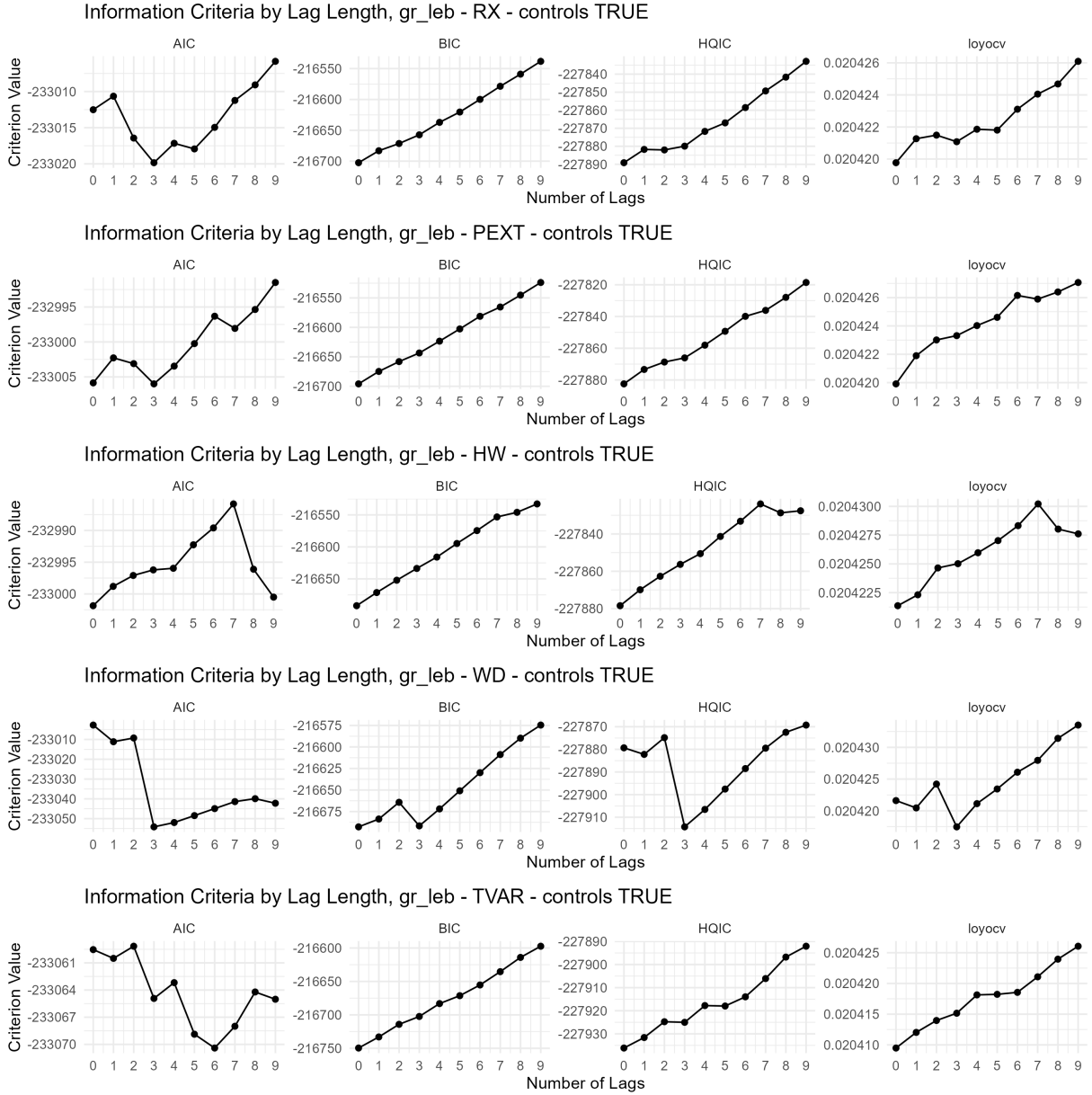


Figure A.5: Lag selection metrics for Life Expectancy at Birth (LEB), for each extreme climate variable: maximum 5-day cumulative precipitation (RX), extreme precipitation (PEXT), heatwave severity (HW), wet days (WD), and day-to-day temperature variability (TVAR), one per subplot row. Each subplot shows AIC, BIC, HQ, and LOYOCV (leave-one-year-out cross-validation error, computed via pre-estimation demeaning following (Newell et al., 2021)) as a function of the number of lags tested (0–9). Lower values indicate better model fit. All specifications control for mean temperature and total rainfall with 8 lags each, and include the first-differenced extreme variable interacted with its moderating variable (mean temperature for RX, PEXT, and WD; TVAR mean for TVAR; HW mean for HW), together with region and year fixed effects and country-level quadratic time trends.

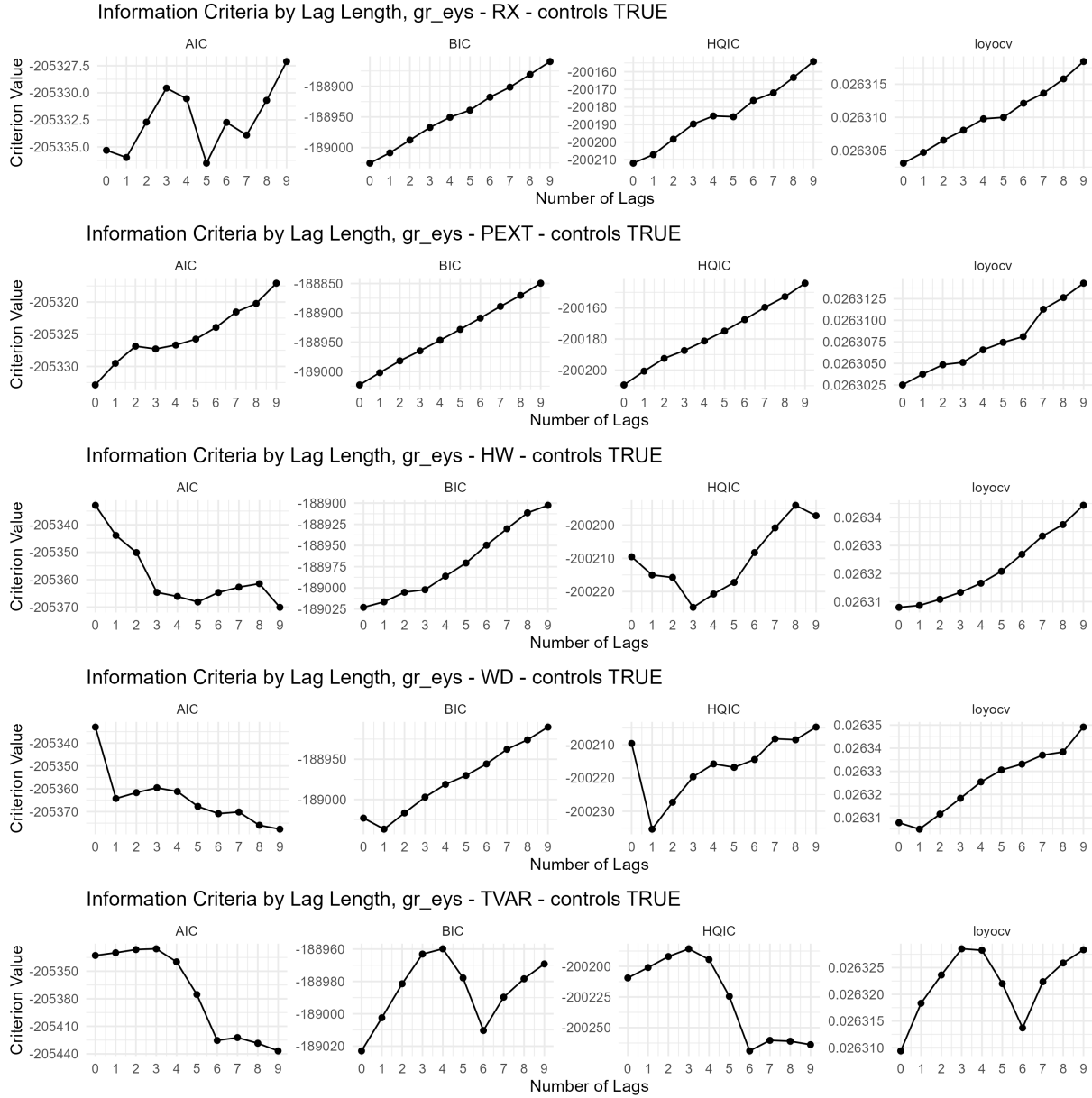
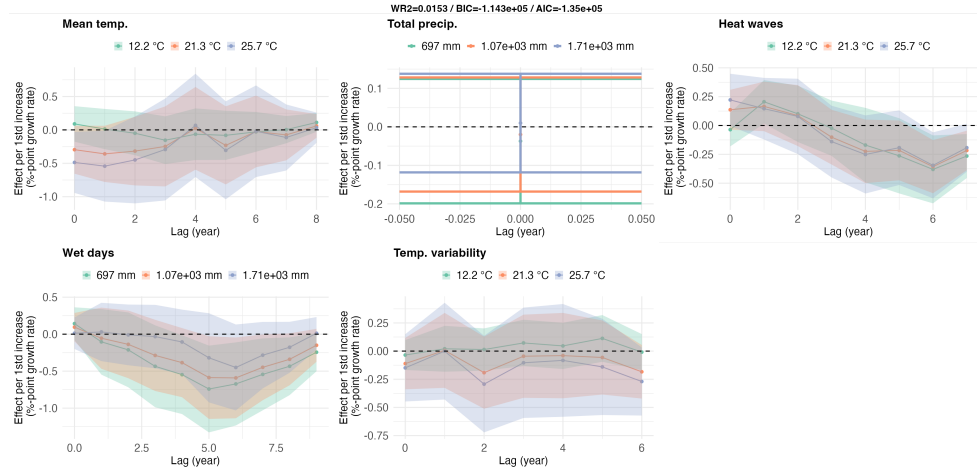
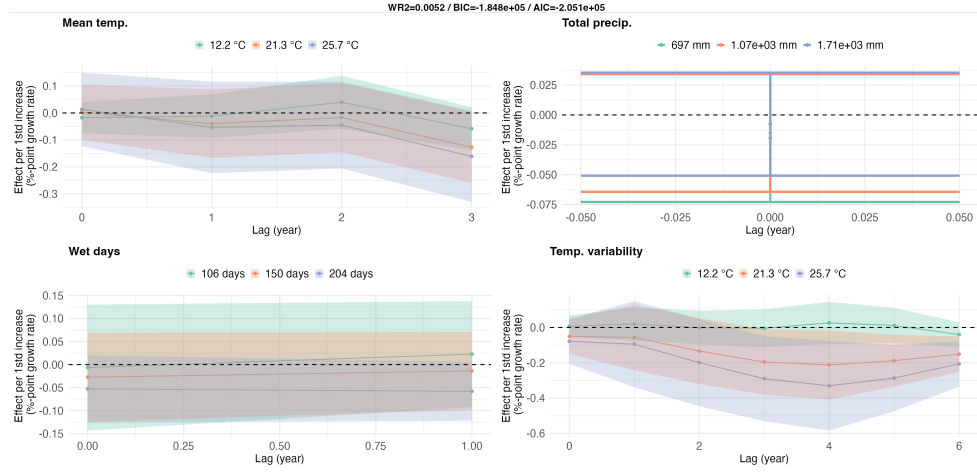


Figure A.6: Lag selection metrics for Expected Years of Schooling (EYS), for each extreme climate variable: maximum 5-day cumulative precipitation (RX), extreme precipitation (PEXT), heatwave severity (HW), wet days (WD), and day-to-day temperature variability (TVAR), one per subplot row. Each subplot shows AIC, BIC, HQ, and LOYOCV (leave-one-year-out cross-validation error, computed via pre-estimation demeaning following (Newell et al., 2021)) as a function of the number of lags tested (0–9). Lower values indicate better model fit. All specifications control for mean temperature and total rainfall with 8 lags each, and include the first-differenced extreme variable interacted with its moderating variable (mean temperature for RX, PEXT, HW, and TVAR; WD mean for WD), together with region and year fixed effects and country-level quadratic time trends.

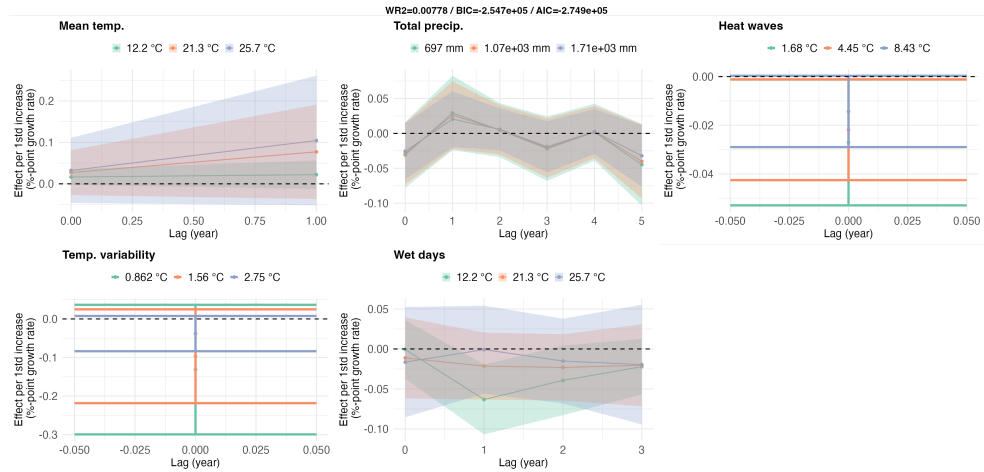
Appendix A



(a) Gross National Income Per Capita



(b) Expected Years of Schooling



(c) Life Expectancy at Birth

Figure A.7: Lagged effects of one sd change of the first differenced variable at different levels of moderating variables (25%, median, 75% quantiles of the regional historical distributions, reported in each subplot in the legends), for each climate, response variable couple. Impacts here are to be interpreted while fixing all other variables in the model.

outcome	climate_var	selected_lags	reason	joint_pval	mean_var_used	joint_pval in complete model
eyes	TM	None (tested 3)	Joint insig	0.211	TM_mean	kept as control
eyes	RR	None (tested 0)	Joint insig	0.105	RR_mean	kept as control
eyes	TVAR	6	Joint sig	0.038	TM_mean	0.029
eyes	RX	None (tested 0)	Joint insig	0.444	TM_mean	
eyes	PEXT	None (tested 0)	Joint insig	0.768	TM_mean	
eyes	WD	1	Joint sig	0.018489738	WD_mean	0.014
eyes	HW	None (tested 3)	Joint insig	0.343779	TM_mean	
leb	TM	None (tested 1)	Joint insig	0.133	TM_mean	kept as control
leb	RR	None (tested 5)	Joint insig	0.154	RR_mean	kept as control
leb	TVAR	0	Sign diff term	0.079	TVAR_mean	0.086
leb	HW	0	Joint sig	0.011	HW_mean	0.098
leb	RX	None (tested 0)	Joint insig	0.204	TM_mean	
leb	WD	3	Joint sig	0.005	TM_mean	0.005
leb	PEXT	None (tested 0)	Joint insig	0.124	TM_mean	
gnipc	TM	8	Joint sig	0.010	TM_mean	0.005
gnipc	RR	None (tested 0)	Joint insig	0.912	RR_mean	kept as control
gnipc	TVAR	6	Joint sig	0.085	TM_mean	0.033
gnipc	HW	7	Joint sig	0.0002	TM_mean	0.001
gnipc	RX	None (tested 2)	Joint insig	0.195	TM_mean	
gnipc	WD	9	Joint sig	0.000007	RR_mean	0.0002
gnipc	PEXT	None	Joint insig	0.286	TM_mean	

Table A.5: Summary of the lag selection procedure for each outcome-climate variable combination. For each pair, we first test the variable alone (controlling for mean temperature and total rainfall in case of climate extremes, for mean temperature in case of total rainfall, for total rainfall in case of mean temperature) and select the lag length using the Hannan-Quinn Information Criterion (HQ), testing up to 9 lags. Column *selected_lags* reports the number of lags retained; *reason* reports whether the selected block was jointly significant (*Joint sig*) or not (*Joint insig*), or whether a specific differenced term was significant (*Sign diff term*). Column *joint_pval* reports the p-value of a Wald test of joint significance for the HQ-selected lag block, with errors clustered by country; a variable becomes a candidate for inclusion when this p-value is below 0.1. Column *mean_var_used* reports the moderating variable used in the interaction term. Column *joint_pval in complete model* reports the p-value of the same Wald test when all candidate variables are included simultaneously; variables losing significance at this stage are dropped and the remaining variables are retested. Even when non-significant, mean temperature and total rainfall lag blocks are retained as controls. The final preferred specifications derived from this procedure are reported in Section 2.5.5.

A.2. Robustness and Tests

We select the fixed effects structure through a set of statistical tests. We apply them to the complete models, accounting for all significant extremes, for each response. We compare a model with only regional fixed effects, a model with year and regional fixed effects, and a random effects model. To decide whether fixed or random effects are preferred, we employ the Hausman Test, which tells us that effects are correlated with climate variables and points towards the use of fixed effects. An F test for two-way effects indicates the fixed effects model is preferred to pooled OLS. Breusch and Pagan’s Lagrangian multiplier test for time fixed effects confirms the need to account for heterogeneous time shocks.

We also fit the same models with climate variables weighted only by the area of the grid points, not by population, as a robustness check, and get consistent results.

To reduce the possibility of omitting important variables influencing our response growth, we test the inclusion in the model of different controls by country: public expenditures in health, public

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outcome	climate_var	selected_lags		
		penalty = 0	penalty = 1	penalty = 0.5
eys	TM	0-9	0-9	0-9
eys	RR	0-9	0-9	0-9
eys	WD	0-9	0-9	0-9
eys	HW	0-9	0,1,2,3,5,6,7,8,9	0,1,2,3,5,6,7,8,9
eys	PEXT	0-9	0,1,2,3,4,6,7,8,9	0,1,2,3,4,6,7,8,9
eys	RX	0-9	0-9	0-9
eys	TVAR	0-9	0-9	0-9
eys	TM interact. diff_TM	0-9	0-9	0-9
eys	RR interact. diff_RR	0-9	0,1,2,4,5,6,7,8,9	0-9
eys	TM interact. diff_HW	0-9	0-9	0-9
eys	WD interact. diff_WD	0-9	0-9	0-9
eys	TM interact. diff_PEXT	0-9	0-9	0-9
eys	TM interact. diff_RX	0-9	0-9	0-9
eys	TM interact. diff_TVAR	0-9	0-9	0-9
leb	TM	0-9	0,1,2,4,5,6,7,8,9	0,1,2,4,5,6,7,8,9
leb	RR	0-9	0,1,2,4,5,6,7,8,9	0,1,2,4,5,6,7,8,9
leb	WD	0-9	0,1,2,3,5,7,8,9	0,1,2,3,5,7,8,9
leb	HW	0-9	0,2,3,4,6,7,8,9	0,1,2,3,4,6,7,8,9
leb	PEXT	0-9	0,2,4,5,6,7,8	0,2,4,5,6,7,8
leb	RX	0-9	0,1,2,5,6,7,8	0,1,2,5,6,7,8
leb	TVAR	0-9	0,1,2,5,6,8,9	0,1,2,5,6,8,9
leb	TM interact. diff_TM	0-9	1,2,3,4,5,7,8,9	1,2,3,4,5,7,8,9
leb	RR interact. diff_RR	0-9	1,3,5,6,7,9	1,3,4,5,6,7,9
leb	HW interact. diff_HW	0-9	0,1,2,3,5,6,7,8,9	0,1,2,3,5,6,7,8,9
leb	TM interact. diff_WD	0-9	0-9	0-9
leb	TM interact. diff_PEXT	0-9	0,1,3,4,5,6,8,9	0,1,3,4,5,6,8,9
leb	TM interact. diff_RX	0-9	0,2,4,5,6,9	0,2,4,5,6,9
leb	TVAR interact. diff_TVAR	0-9	0,1,2,3,4,5,6,7,9	0,1,2,3,4,5,6,7,9
gnipc	TM	0-9	0-9	0-9
gnipc	RR	0-9	0-9	0-9
gnipc	WD	0-9	0-9	0-9
gnipc	HW	0-9	0-9	0-9
gnipc	PEXT	0-9	0,1,2,3,4,6,7,8,9	0,1,2,3,4,6,7,8,9
gnipc	RX	0-9	0,1,2,3,5,6,7,9	0,1,2,3,5,6,7,8,9
gnipc	TVAR	0-9	0-9	0-9
gnipc	TM interact. diff_TM	0-9	0-9	0-9
gnipc	RR interact. diff_RR	0-9	0-9	0-9
gnipc	TM interact. diff_HW	0-9	0-9	0-9
gnipc	RR interact. diff_WD	0-9	0-9	0-9
gnipc	TM interact. diff_PEXT	0-9	0-9	0-9
gnipc	TM interact. diff_RX	0-9	0-9	0-9
gnipc	TM interact. diff_TVAR	0-9	0,2,4,5,6,7,8,9	0,2,4,5,6,7,8,9

Table A.6: Lag selection through different regularization methods. A penalty of 0 represents RIDGE selection (where expectedly all variables are selected), a penalty of 0.5 an elastic net selection, a penalty of 1 LASSO selection.

Outcome	Var	Main effect [†]	Climate het. [†] : alone → adj.	Dev. het. [†] , adj.	Verdict
EYS	TM	−0.07 (0.09)	0.03 (0.05) → −0.02 (0.04)**	−0.10 (0.06)**	Both (suppression)
EYS	RR	0.00 (0.02)	0.00 (0.00) → 0.00 (0.00)	−0.02 (0.02)	Not robust
EYS	WD	0.03 (0.03)	−0.02 (0.01)** → −0.02 (0.01)*	0.02 (0.02)	Climate (marginal)
EYS	TVAR	0.21 (0.07)*	−0.14 (0.04)** → −0.19 (0.04)***	−0.10 (0.05)	Climate
LEB	TM	−0.03 (0.06)	0.04 (0.05) → 0.03 (0.04)	−0.01 (0.02)***	Development
LEB	RR	−0.06 (0.10)	0.01 (0.02) → 0.02 (0.02)	−0.04 (0.10)	Not robust
LEB	HW	−0.03 (0.01)**††	0.01 (0.00) → 0.00 (0.01)	0.00 (0.01)	Not robust (fragile main effect)
LEB	TVAR	−0.18 (0.10)*	0.05 (0.03)* → 0.05 (0.02)**	0.02 (0.02)	Climate [‡]
LEB	WD	−0.19 (0.14)***††	0.01 (0.06) → 0.14 (0.08)	0.26 (0.15)	Not robust (fragile main effect)
GNIPC	TM	2.43 (2.00)**††	−2.04 (1.46)*** → −2.90 (1.63)***	−1.77 (1.20)	Climate
GNIPC	RR	−0.04 (0.11)	0.04 (0.03) → 0.05 (0.03)	−0.04 (0.06)	Not robust
GNIPC	HW	−1.15 (1.85)	0.26 (0.69) → 0.74 (0.93)	0.81 (0.89)	Joint only [§]
GNIPC	WD	−4.18 (2.78)***	1.78 (1.40)*** → 2.16 (1.43)***	1.86 (1.09)**	Both (all-robust)
GNIPC	TVAR	2.29 (1.45)	−1.50 (1.02)** → −1.92 (1.09)**	−0.71 (0.94)	Climate (het. only)

Table A.7: Decomposition of the preferred specifications into main and interaction (heterogeneity) components, comparing baseline climate and development as moderators. *Main effect* reports the cumulative effect of a one-standard-deviation climate shock at the average region, from the main (non-interacted) lag terms. *Climate heterogeneity* reports how much that effect changes for a region one standard deviation above average in baseline climate, estimated first without any development term (*alone*), then with the development interaction included simultaneously (*adj.*). *Development heterogeneity* reports the analogous development effect, adjusted for baseline climate. Standard errors, clustered by country, in parentheses; effects in percentage points (GNIPC) or years (LEB, EYS). *Verdict*: *Climate/Development* indicate heterogeneity attributable to one moderator surviving adjustment for the other; *Both (all-robust)* indicates the main effect and both heterogeneity channels are independently significant; *Both (suppression)* indicates neither heterogeneity channel is significant alone but both become so once entered jointly; *Joint only* indicates the variable’s inclusion (Table A.5) is significant only as a combined main+interaction block, with neither component individually robust; *Not robust* indicates no component reaches significance under any specification. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. [†]Estimated jointly with the development interaction, except the first-listed climate heterogeneity value, which is estimated alone. [‡]TVAR was retained in the LEB specification (Table A.5) on the strength of its main term rather than its interaction; the interaction strengthens, rather than weakens, once development is controlled for. ^{††}Main effect is significant estimated alone but loses significance once the development interaction is added ($p > 0.9$ HW; $p = 0.15$ WD; $p = 0.10$ GNIPC TM, borderline) – flagged as sensitive to specification. [§]Neither the main term nor the interaction term is individually significant (Table A.5: $p = 0.001$), indicating the variable’s overall significance reflects several correlated lags jointly.

expenditures in education, armed conflicts, and the percentage of GDP in trade. We include up to 9 lags of each of these variables in each lag model and conclude that our damage model coefficients do not suffer from omitted variable bias when testing these controls.

A.3. Projections Additional Decompositions

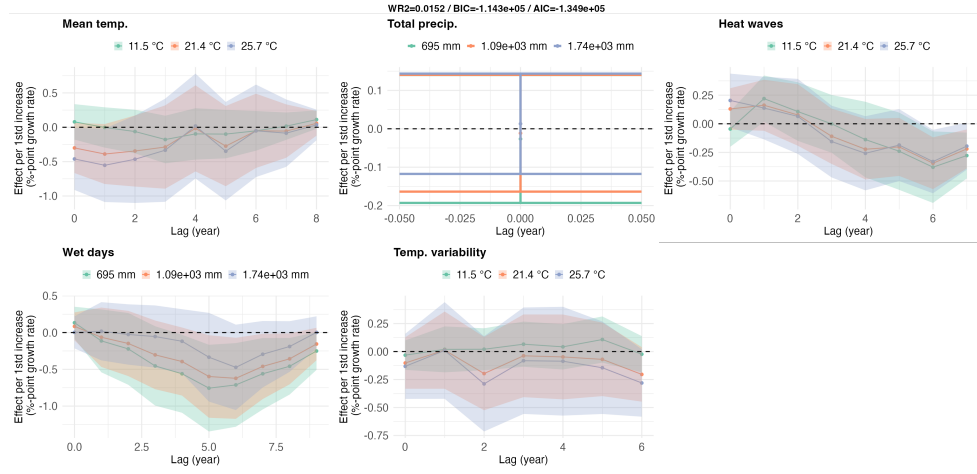
A.3.1. Global HDI percentage loss decomposition into components

We apply some approximations to identify how much the three indices (Income Index, Edu Index, and Lifex Index) contribute to the global percentage change of HDI. The percentage change in HDI from a baseline scenario to a current scenario can be calculated as:

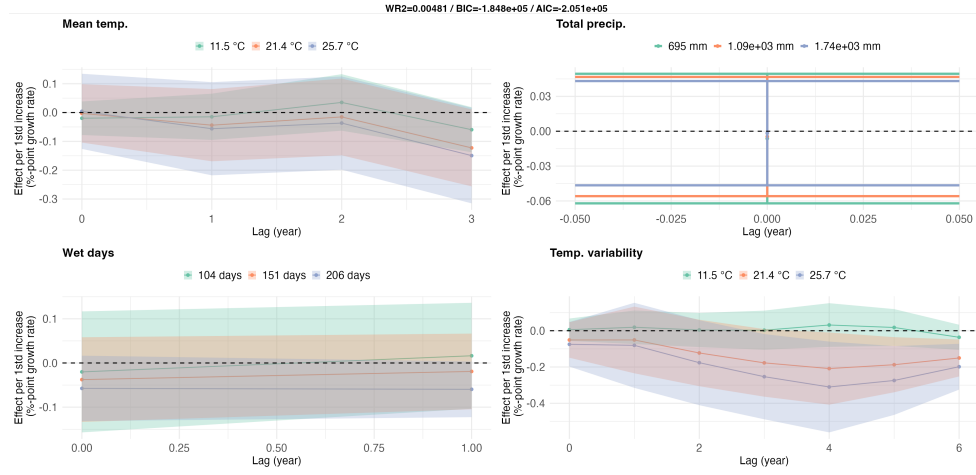
$$\text{Percentage Change in HDI} = \frac{\text{HDI}_{\text{cc}} - \text{HDI}_{\text{baseline}}}{\text{HDI}_{\text{baseline}}}$$

Where HDI_{cc} is the HDI for the current scenario, $\text{HDI}_{\text{baseline}}$ is the HDI for the baseline scenario. To decompose the change in HDI into the contributions of its components (Income Index, Education Index, and Life Expectancy Index), we use the fact that HDI is the geometric mean of

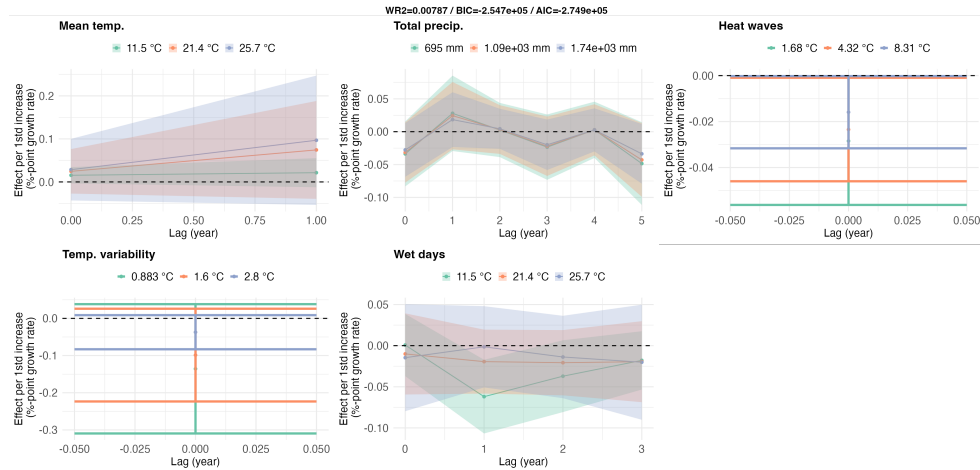
Appendix A



(a) Gross National Income Per Capita

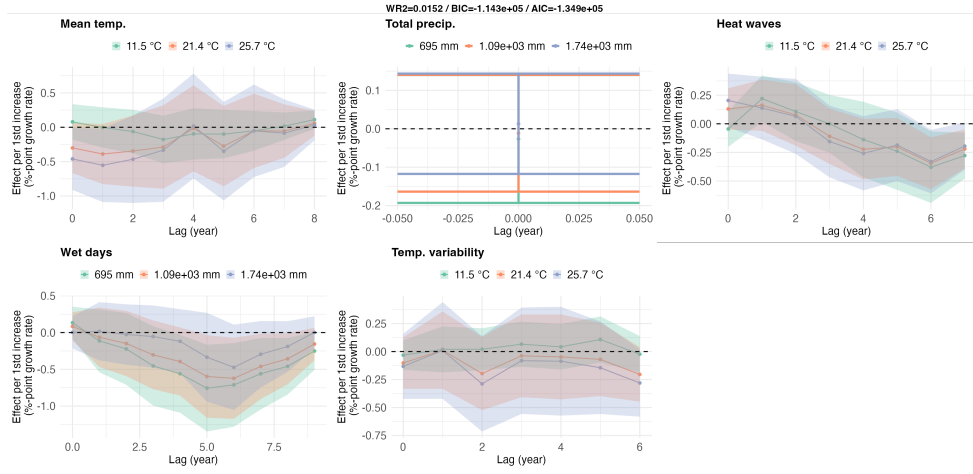


(b) Expected Years of Schooling

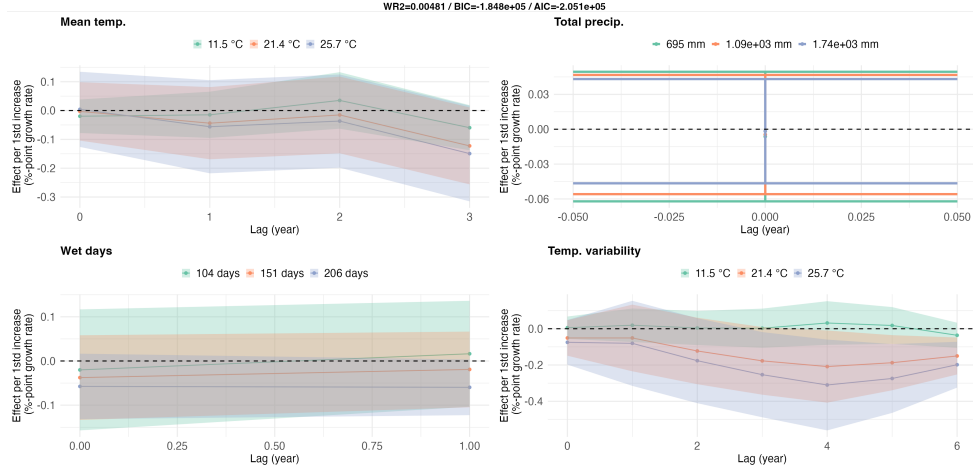


(c) Life Expectancy at Birth

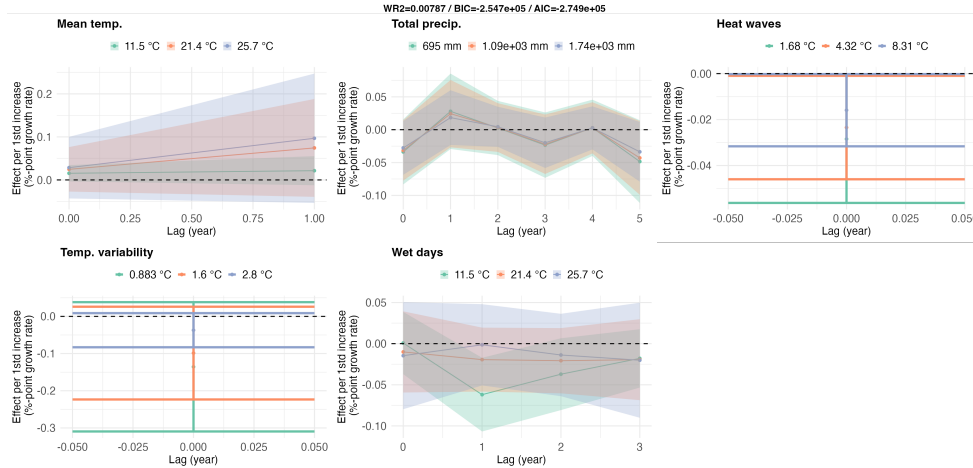
Figure A.8: Lagged effects of one sd change of the first differenced variable at different levels of moderating variables (25%, median, 75% quantiles of the regional historical distributions, reported in each subplot in the legends), for each climate, response variable couple. Impacts here are to be interpreted while fixing all other variables in the model. Models here are estimated with interacting variables calculated on a 10 years moving window, instead of the whole historical mean.



(a) Gross National Income Per Capita



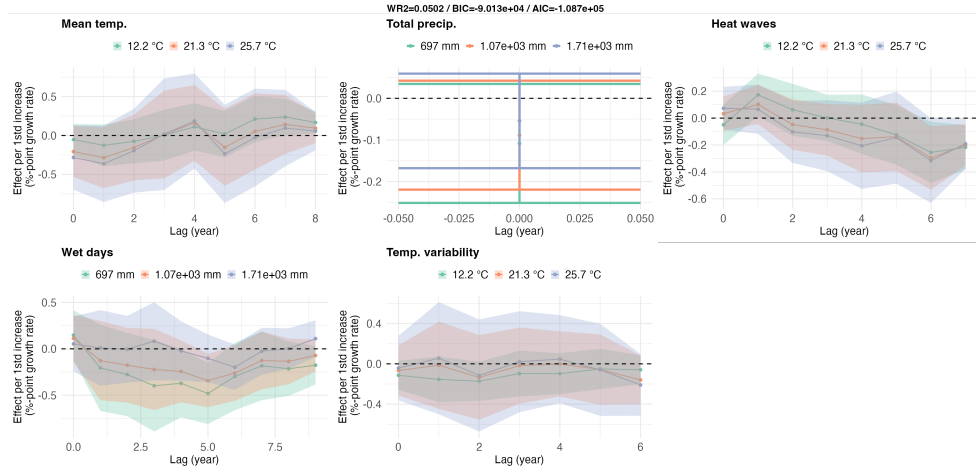
(b) Expected Years of Schooling



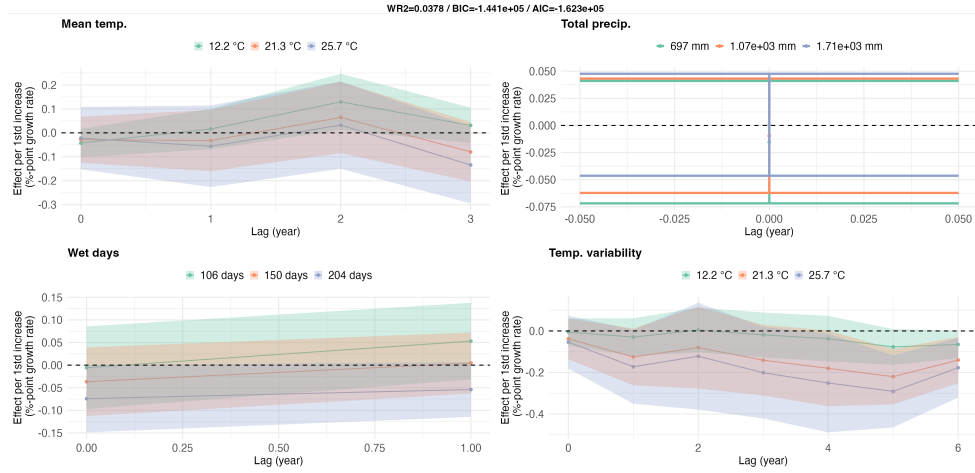
(c) Life Expectancy at Birth

Figure A.9: Lagged effects of one sd change of the first differenced variable at different levels of moderating variables (25%, median, 75% quantiles of the regional historical distributions, reported in each subplot in the legends), for each climate, response variable couple. Impacts here are to be interpreted while fixing all other variables in the model. Models here are estimated with an area-weighting scheme for the climate variables aggregation to the regional level.

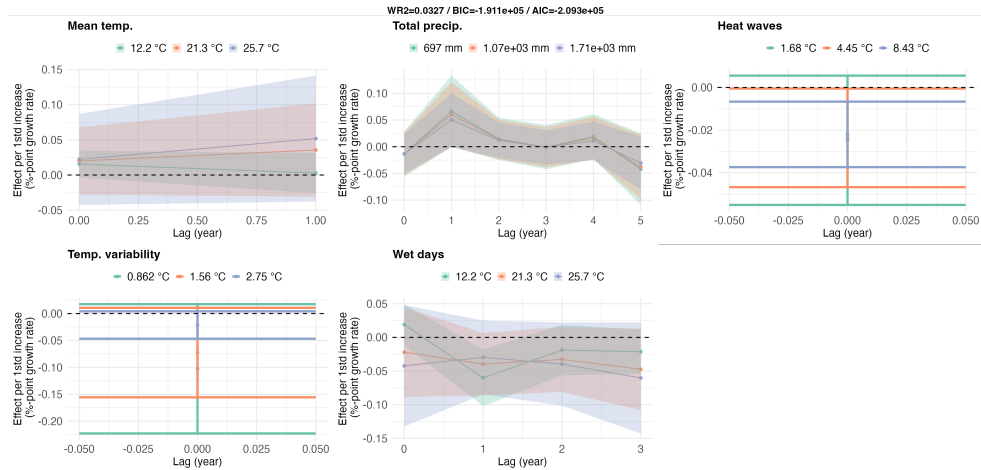
Appendix A



(a) Gross National Income Per Capita



(b) Expected Years of Schooling



(c) Life Expectancy at Birth

Figure A.10: Lagged effects of one sd change of the first differenced variable at different levels of moderating variables (25%, median, 75% quantiles of the regional historical distributions, reported in each subplot in the legends), for each climate, response variable couple. Impacts here are to be interpreted while fixing all other variables in the model. Models here include 6 lags of the control variables and the other components in growth.

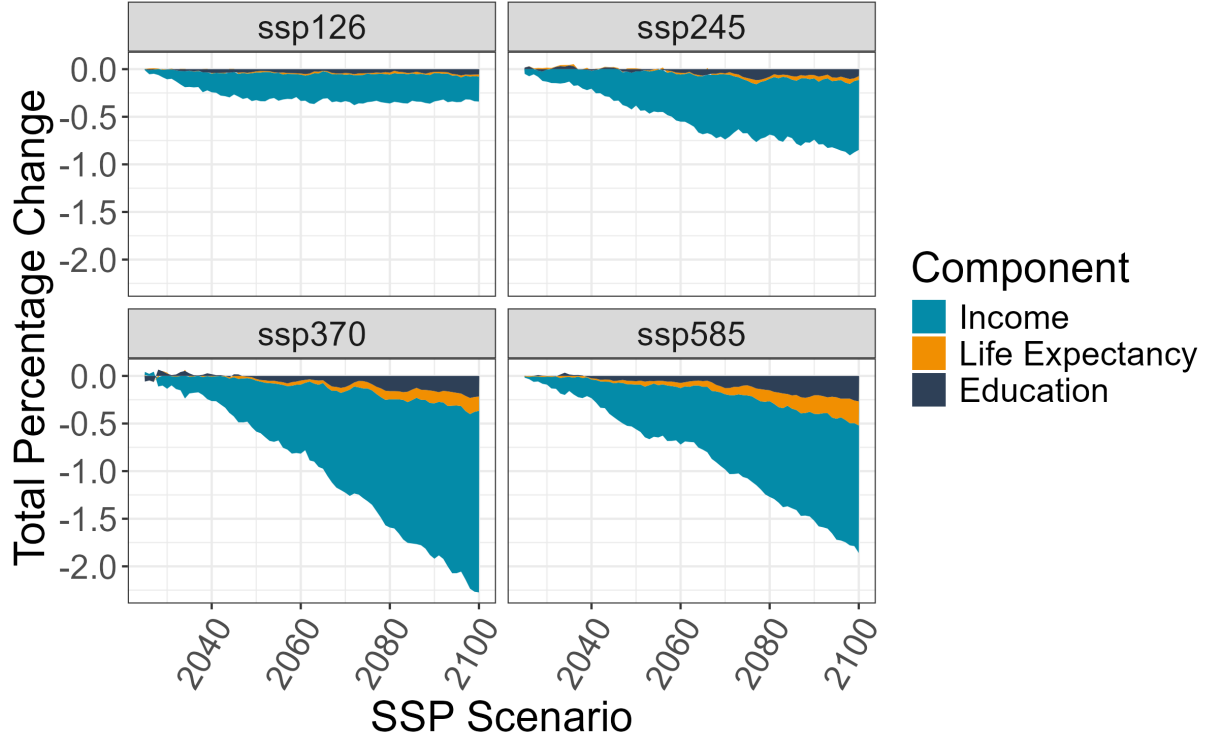


Figure A.11: Global contribution evolution (population weighted, median across models) of the three components on HDI climate change effect.

the components. First, we take the natural logarithm of both sides of the HDI formula:

$$\ln(\text{HDI}) = \frac{1}{3} (\ln(\text{Income Index}) + \ln(\text{Edu Index}) + \ln(\text{Lifex Index}))$$

Next, we approximate the percentage change in HDI as the difference in logarithms:

$$\Delta \ln(\text{HDI}) = \ln(\text{HDI}_{\text{cc}}) - \ln(\text{HDI}_{\text{baseline}})$$

For a small percentage change such as the ones we observe, we can then approximate:

$$\text{Percentage Change in HDI} \approx \frac{1}{3} (\Delta \ln(\text{Income Index}) + \Delta \ln(\text{Edu Index}) + \Delta \ln(\text{Lifex Index}))$$

The sum of these individual contributions is less than the total HDI change because the contributions are proportional to the changes in the logarithms, and the geometric mean formula for HDI results in a compounded effect. Still, the component contributions reflect their relative influence on the HDI change, and we easily rescale them using the original HDI percentage change.

A.3.2. Damages Climate Channels

We report here sub-national index changes for each HDI component, in the four different scenarios, when clustering damage functions errors either by region or country.

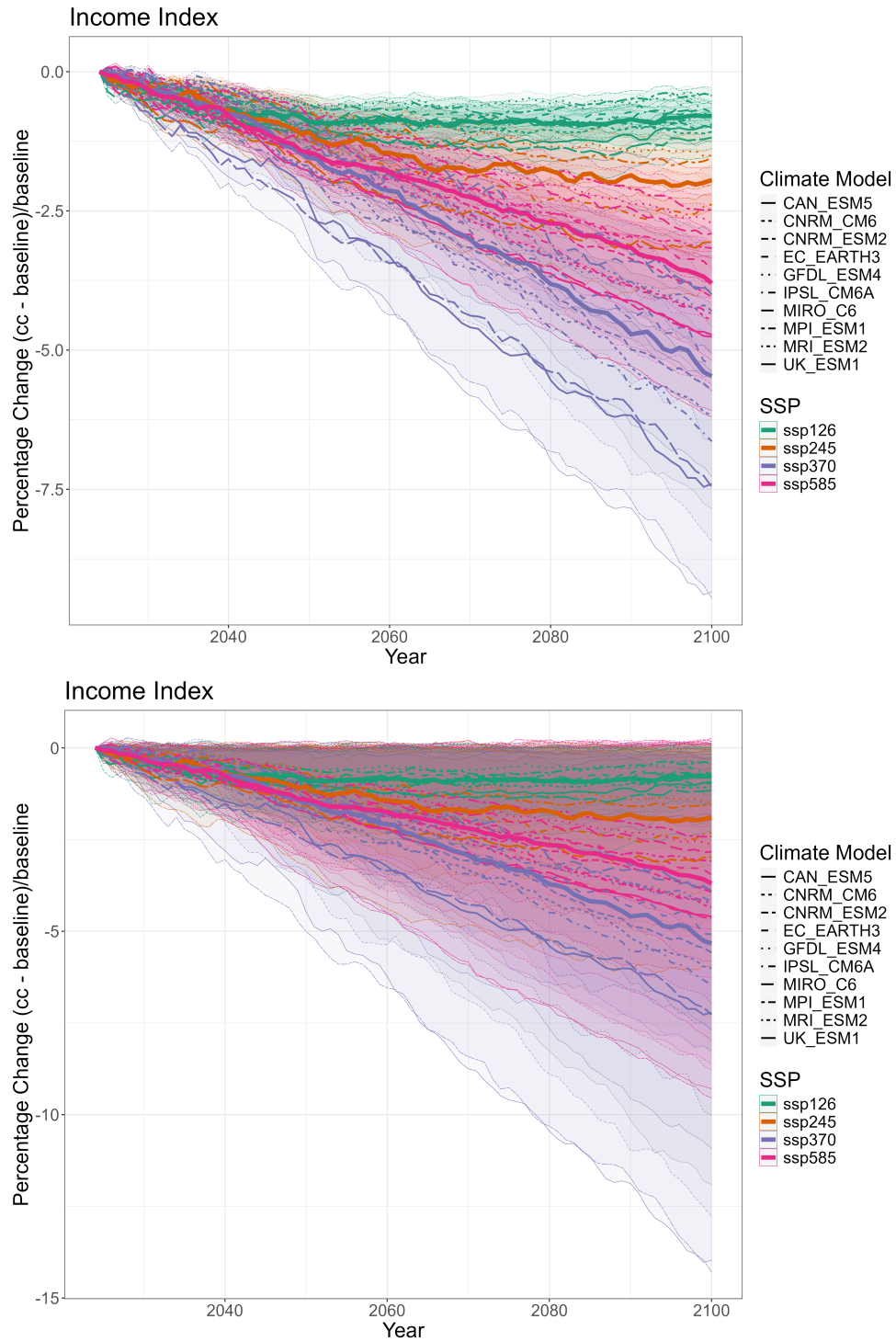


Figure A.12: Mean Income Index percentage impact by model, ssp. Confidence bands represent the 90% bootstrap intervals computed by sampling from the uncertainties of damage functions, either clustering damage functions errors by region (top panel) or by country (bottom panel).

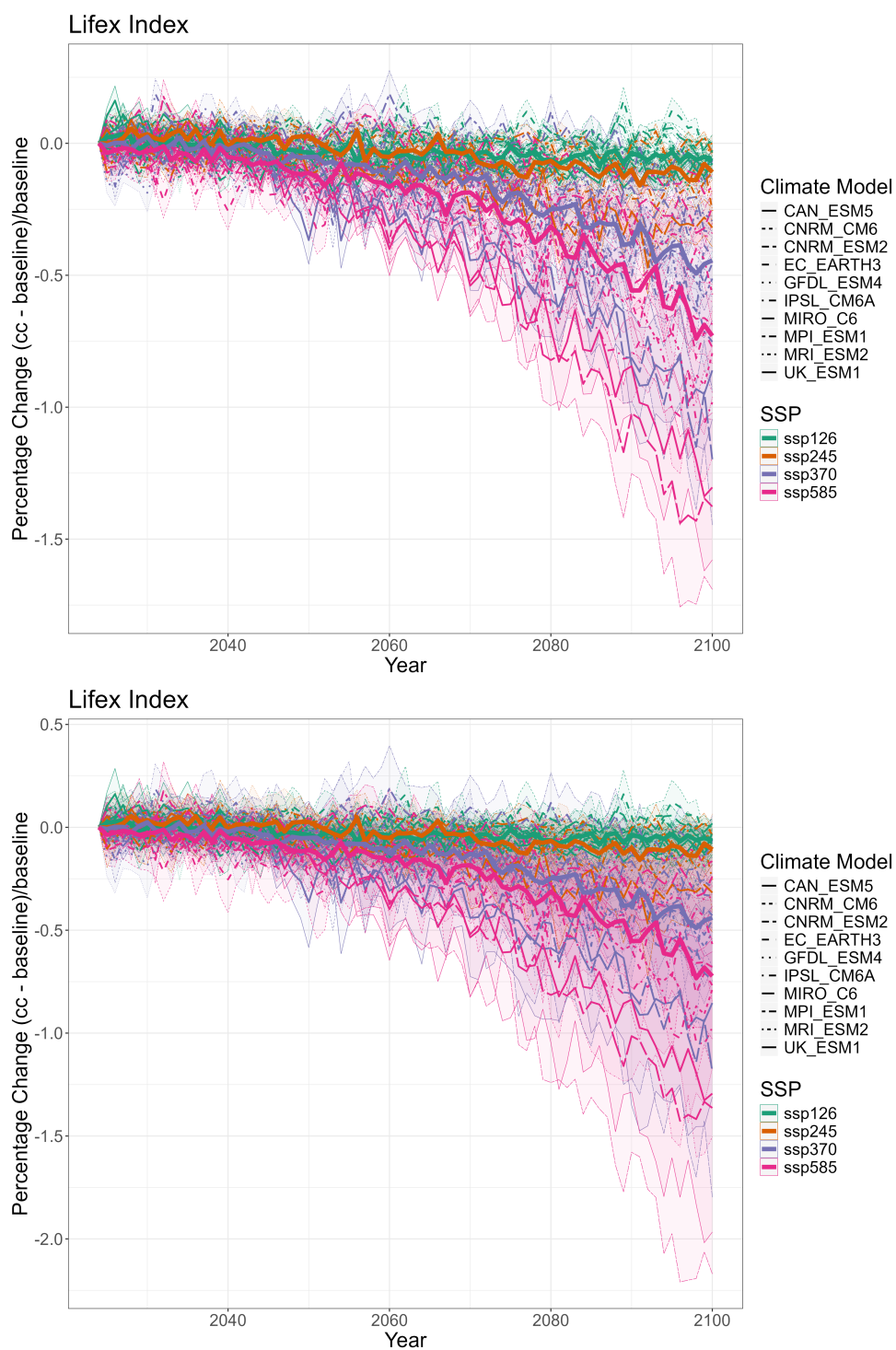


Figure A.13: Mean Lifex Index percentage impact by model, ssp. Confidence bands represent the 90% bootstrap intervals computed by sampling from the uncertainties of damage functions, either clustering damage functions errors by region (top panel) or by country (bottom panel).

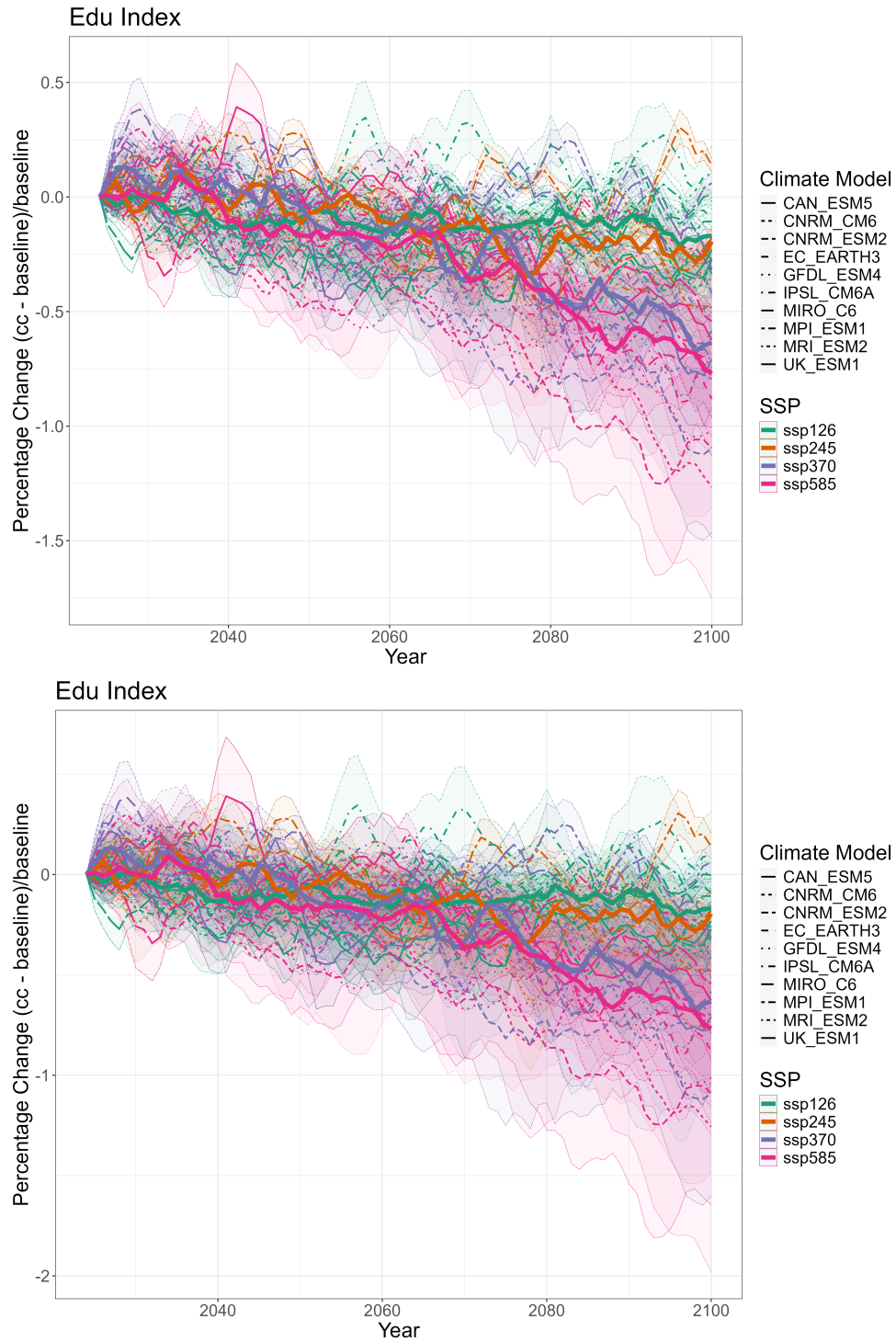
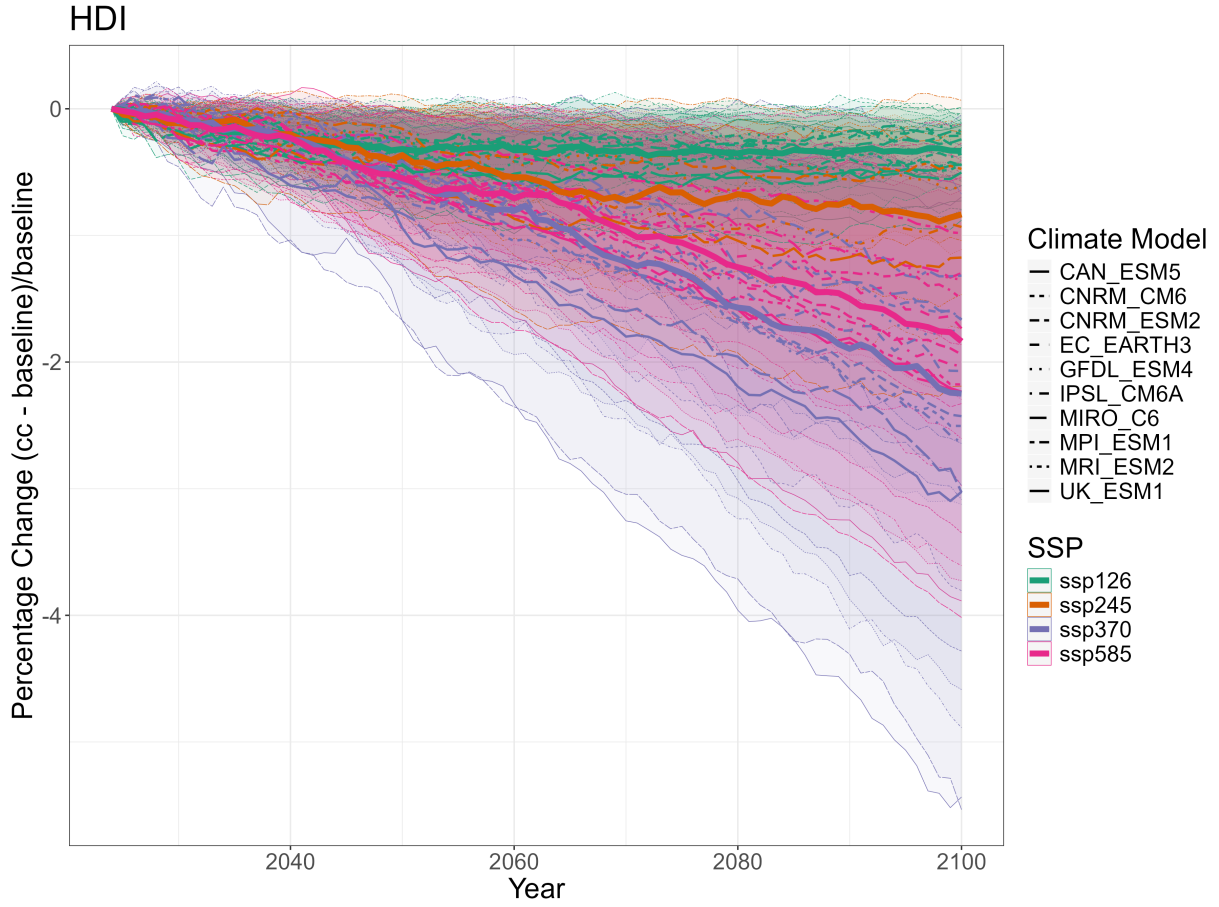
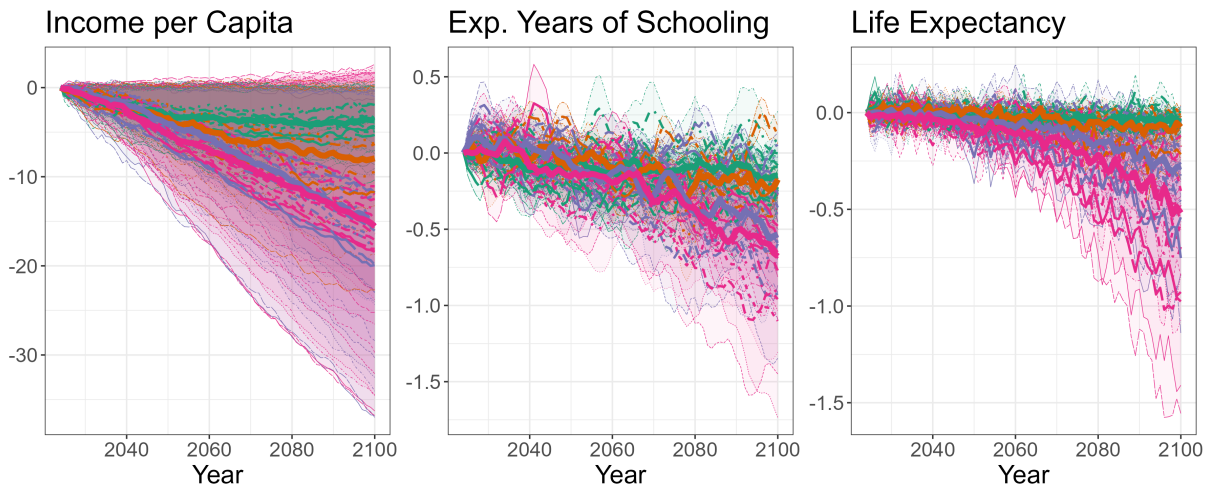


Figure A.14: Mean Education Index percentage impact by model, ssp. Confidence bands represent the 90% bootstrap intervals computed by sampling from the uncertainties of damage functions, either clustering damage functions errors by region (top panel) or by country (bottom panel).



(a) Mean HDI percentage impact by model, ssp. Confidence bands represent the 90% bootstrap intervals computed by sampling from the uncertainties of damage functions, clustering errors by country.



(b) Global percentage change (population-weighted) of the three components of HDI, with respect to the baseline, prior to the transformation into indices. Confidence bands represent the 90% bootstrap intervals computed by sampling from the uncertainties of damage functions, clustering errors by country. We report in Appendix A.3, Fig. A.11, the decomposition of HDI impacts into the impacts of the three indices.

Figure A.15

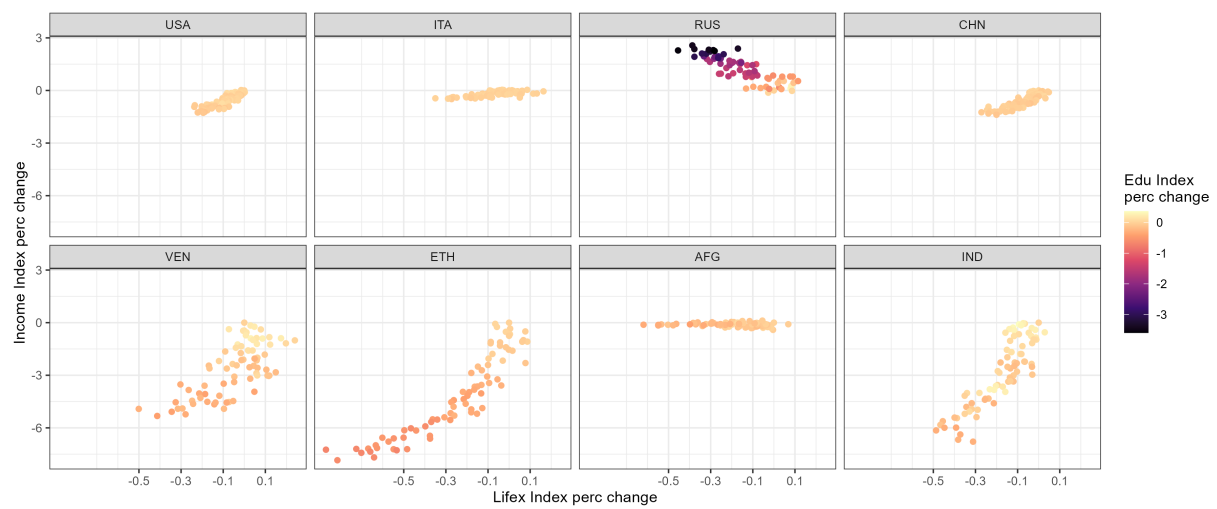


Figure A.16: Comparison of indices percentage changes in selected countries over 2024-2100 under SSP3-7.0.

HDI	perc_change (pp)	change (index pts)
SSP1-2.6	-0.325 (-0.413, -0.238)	-0.200 (-0.255, -0.145)
SSP2-4.5	-0.374 (-0.483, -0.257)	-0.211 (-0.273, -0.146)
SSP3-7.0	-0.584 (-0.736, -0.428)	-0.288 (-0.364, -0.209)
SSP5-8.5	-0.560 (-0.714, -0.409)	-0.354 (-0.453, -0.257)
Income Index	perc_change (pp)	change (index pts)
SSP1-2.6	-0.909 (-1.18, -0.658)	-0.504 (-0.661, -0.362)
SSP2-4.5	-1.08 (-1.41, -0.741)	-0.541 (-0.707, -0.368)
SSP3-7.0	-1.55 (-2.00, -1.09)	-0.654 (-0.847, -0.450)
SSP5-8.5	-1.45 (-1.89, -0.986)	-0.846 (-0.112, -0.569)
Edu Index	perc_change (pp)	change (index pts)
SSP1-2.6	-0.0730 (-0.119, -0.0231)	-0.0437 (-0.0740, -0.0160)
SSP2-4.5	-0.0695 (-0.103, -0.0343)	-0.0396 (-0.0584, -0.0198)
SSP3-7.0	-0.0925 (-0.155, -0.0214)	-0.0509 (-0.0919, -0.00833)
SSP5-8.5	-0.172 (-0.229, -0.115)	-0.113 (-0.149, -0.0760)
Lifex Index	perc_change (pp)	change (index pts)
SSP1-2.6	-0.0353 (-0.0485, -0.0185)	-0.0234 (-0.0304, -0.0122)
SSP2-4.5	0.0262 (0.00361, 0.0437)	0.0177 (0.000362, 0.0300)
SSP3-7.0	-0.0524 (-0.0755, -0.0297)	-0.0265 (-0.0407, -0.0126)
SSP5-8.5	-0.112 (-0.140, -0.0841)	-0.0810 (-0.103, -0.0607)
Income Per Capita	perc_change (pp)	change (\$)
SSP1-2.6	-3.34 (-4.34, -2.40)	-825 (-1109, -517)
SSP2-4.5	-3.57 (-4.62, -2.45)	-684 (-913, -452)
SSP3-7.0	-4.28 (-5.53, -2.97)	-542 (-742, -339)
SSP5-8.5	-5.45 (-7.21, -3.70)	-1580 (-2185, -1002)
Exp. Years Schooling	perc_change (pp)	change (years)
SSP1-2.6	-0.0613 (-0.101, -0.0207)	-0.00891 (-0.0153, -0.00342)
SSP2-4.5	-0.0579 (-0.0867, -0.0280)	-0.00808 (-0.0122, -0.00393)
SSP3-7.0	-0.0801 (-0.134, -0.0177)	-0.0108 (-0.0196, -0.00179)
SSP5-8.5	-0.148 (-0.199, -0.0987)	-0.0235 (-0.0315, -0.0159)
Life Expectancy	perc_change (pp)	change (years)
SSP1-2.6	-0.0232 (-0.0312, -0.0115)	-0.0177 (-0.0232, -0.00897)
SSP2-4.5	0.0176 (0.00150, 0.0289)	0.0140 (0.000322, 0.0228)
SSP3-7.0	-0.0305 (-0.0451, -0.0160)	-0.0201 (-0.0309, -0.00950)
SSP5-8.5	-0.0759 (-0.0951, -0.0566)	-0.0623 (-0.0790, -0.0465)

Table A.8: Summary of global mean changes (absolute or percentages with respect to baseline without climate change) of indices composing HDI and corresponding underlying variables (index points here are ranging in 0-100) with 90% confidence intervals in 2050. Uncertainty here comes from bootstrapping impact function coefficients with robust standard errors, taking the median of each bootstrap across models and finally population weighting regional values to get global means. Then deltas and percentage deltas with respective intervals are calculated.

HDI	perc_change (pp)	change (index pts)
SSP1-2.6	-0.340 (-0.421, -0.260)	-0.266 (-0.328, -0.203)
SSP2-4.5	-0.849 (-1.05, -0.646)	-0.597 (-0.739, -0.454)
SSP3-7.0	-2.27 (-2.80, -1.74)	-1.26 (-1.56, -0.961)
SSP5-8.5	-1.86 (-2.27, -1.46)	-1.49 (-1.82, -1.17)
Income Index	perc_change (pp)	change (index pts)
SSP1-2.6	-0.794 (-1.01, -0.573)	-0.584 (-0.742, -0.421)
SSP2-4.5	-1.95 (-2.48, -1.39)	-1.33 (-1.69, -0.948)
SSP3-7.0	-5.47 (-6.95, -3.96)	-2.83 (-3.60, -2.04)
SSP5-8.5	-3.80 (-4.88, -2.66)	-3.06 (-3.95, -2.14)
Edu Index	perc_change (pp)	change (index pts)
SSP1-2.6	-0.169 (-0.212, -0.111)	-0.124 (-0.156, -0.0838)
SSP2-4.5	-0.194 (-0.241, -0.147)	-0.141 (-0.175, -0.108)
SSP3-7.0	-0.635 (-0.834, -0.421)	-0.355 (-0.468, -0.232)
SSP5-8.5	-0.771 (-1.03, -0.519)	-0.551 (-0.737, -0.371)
Lifex Index	perc_change (pp)	change (index pts)
SSP1-2.6	-0.0664 (-0.0818, -0.0495)	-0.0574 (-0.0711, -0.0432)
SSP2-4.5	-0.110 (-0.138, -0.0829)	-0.0853 (-0.106, -0.0649)
SSP3-7.0	-0.444 (-0.540, -0.347)	-0.263 (-0.322, -0.204)
SSP5-8.5	-0.730 (-0.890, -0.569)	-0.644 (-0.783, -0.503)
Income Per Capita	perc_change (pp)	change (\$)
SSP1-2.6	-3.86 (-4.85, -2.79)	-2611 (-3283, -1903)
SSP2-4.5	-8.50 (-10.6, -6.13)	-4259 (-5340, -3059)
SSP3-7.0	-16.9 (-20.9, -12.5)	-3327 (-4221, -2378)
SSP5-8.5	-17.5 (-22.0, -12.6)	-19424 (-25525, -13254)
Exp. Years Schooling	perc_change (pp)	change (years)
SSP1-2.6	-0.145 (-0.183, -0.0967)	-0.0253 (-0.0320, -0.0173)
SSP2-4.5	-0.172 (-0.214, -0.131)	-0.0298 (-0.0368, -0.0226)
SSP3-7.0	-0.536 (-0.705, -0.355)	-0.0744 (-0.0981, -0.0487)
SSP5-8.5	-0.675 (-0.907, -0.456)	-0.115 (-0.156, -0.0779)
Life Expectancy	perc_change (pp)	change (years)
SSP1-2.6	-0.0472 (-0.0581, -0.0355)	-0.0438 (-0.0542, -0.0329)
SSP2-4.5	-0.0753 (-0.0949, -0.0573)	-0.0651 (-0.0815, -0.0498)
SSP3-7.0	-0.278 (-0.339, -0.216)	-0.201 (-0.246, -0.156)
SSP5-8.5	-0.524 (-0.638, -0.408)	-0.494 (-0.600, -0.385)

Table A.9: Summary of global mean changes (absolute or percentages with respect to baseline without climate change) of indices composing HDI and corresponding underlying variables (index points here are ranging in 0-100) with 90% confidence intervals in 2100. Uncertainty here comes from bootstrapping impact function coefficients with robust standard errors, taking the median of each bootstrap across models and finally population weighting regional values to get global means. Then deltas and percentage deltas with respective intervals are calculated.

Index	SSP	2050				2100			
		Baseline evolution	Baseline % evolution	Absolute loss	Loss (p.p.)	Baseline evolution	Baseline % evolution	Absolute loss	Loss (p.p.)
Human Development Index	SSP126	10.9	19.8	0.2	0.3	24.0	43.4	0.3	0.5
	SSP245	7.2	13.3	0.2	0.4	18.8	34.6	0.6	1.1
	SSP370	3.1	5.68	0.3	0.54	5.9	11.0	1.3	2.37
	SSP585	12.1	21.9	0.3	0.6	27.0	48.7	1.5	2.7
Income Index	SSP126	12.1	24.4	0.6	1.0	25.9	52.4	0.6	1.2
	SSP245	7.9	16.0	0.6	1.1	22.0	45.0	1.3	2.7
	SSP370	2.9	6.06	0.6	1.35	7.9	16.4	2.8	5.9
	SSP585	15.2	30.6	0.9	1.7	34.1	68.6	3.1	6.2
Education Index	SSP126	9.7	17.6	0.1	0.1	18.9	34.3	0.1	0.2
	SSP245	7.2	13.3	0.0	0.1	16.4	30.2	0.1	0.2
	SSP370	4.6	8.55	0.0	0.10	5.2	9.51	0.4	0.65
	SSP585	9.8	17.7	0.2	0.2	19.0	34.5	0.6	1.0
Lifex Index	SSP126	10.5	16.7	0.0	0.0	26.9	42.8	0.1	0.1
	SSP245	6.1	9.88	0.0	0.03	17.2	28.0	0.1	0.2
	SSP370	1.3	2.13	0.0	0.04	4.0	6.58	0.3	0.44
	SSP585	10.7	17.0	0.1	0.1	27.5	43.8	0.6	1.0

Table A.10: Baseline development gains from 2024 and development losses due to climate change for the Human Development Index and its components. For each SSP, results are shown separately for 2050 and 2100. Baseline evolution is reported in absolute index points and percentage changes from 2024. Losses indicate the reduction in absolute gains and in percentage changes (percentage points) under climate change relative to baseline trajectories (median across models and bootstrap replications). Indices range from 0 to 100.

| **Appendix A**

Index	Scenario	SSP	Absolute Change from 2024		Percentage Change from 2024 (%)	
			2050	2100	2050	2100
Human Development Index	Baseline	SSP126	10.9	24.0	19.8	43.4
		SSP245	7.2	18.8	13.3	34.6
		SSP370	3.1	5.9	5.68	11.0
		SSP585	12.1	27.0	21.9	48.7
	Climate Change	SSP126	10.7	23.7	19.5	42.9
		SSP245	7.0	18.2	12.9	33.5
		SSP370	2.8	4.6	5.14	8.63
		SSP585	11.8	25.5	21.3	46.0
Income Index	Baseline	SSP126	12.1	25.9	24.4	52.4
		SSP245	7.9	22.0	16.0	45.0
		SSP370	2.9	7.9	6.06	16.4
		SSP585	15.2	34.1	30.6	68.6
	Climate Change	SSP126	11.5	25.3	23.4	51.2
		SSP245	7.3	20.7	14.9	42.3
		SSP370	2.3	5.1	4.71	10.5
		SSP585	14.3	31.0	28.9	62.4
Education Index	Baseline	SSP126	9.7	18.9	17.6	34.3
		SSP245	7.2	16.4	13.3	30.2
		SSP370	4.6	5.2	8.55	9.51
		SSP585	9.8	19.0	17.7	34.5
	Climate Change	SSP126	9.6	18.8	17.5	34.1
		SSP245	7.2	16.3	13.2	30.0
		SSP370	4.6	4.8	8.45	8.86
		SSP585	9.6	18.4	17.5	33.5
Lifex Index	Baseline	SSP126	10.5	26.9	16.7	42.8
		SSP245	6.1	17.2	9.88	28.0
		SSP370	1.3	4.0	2.13	6.58
		SSP585	10.7	27.5	17.0	43.8
	Climate Change	SSP126	10.5	26.8	16.7	42.7
		SSP245	6.1	17.1	9.91	27.8
		SSP370	1.3	3.7	2.09	6.14
		SSP585	10.6	26.9	16.9	42.8

Table A.11: Absolute and percentage changes from 2024 for Human Development Index and its components (Income, Education, and Life Expectancy indices) in the four SSPs assuming baseline development or accounting for climate change effects (median across models, bootstrap replications). Indices' absolute values here range from 0 to 100.

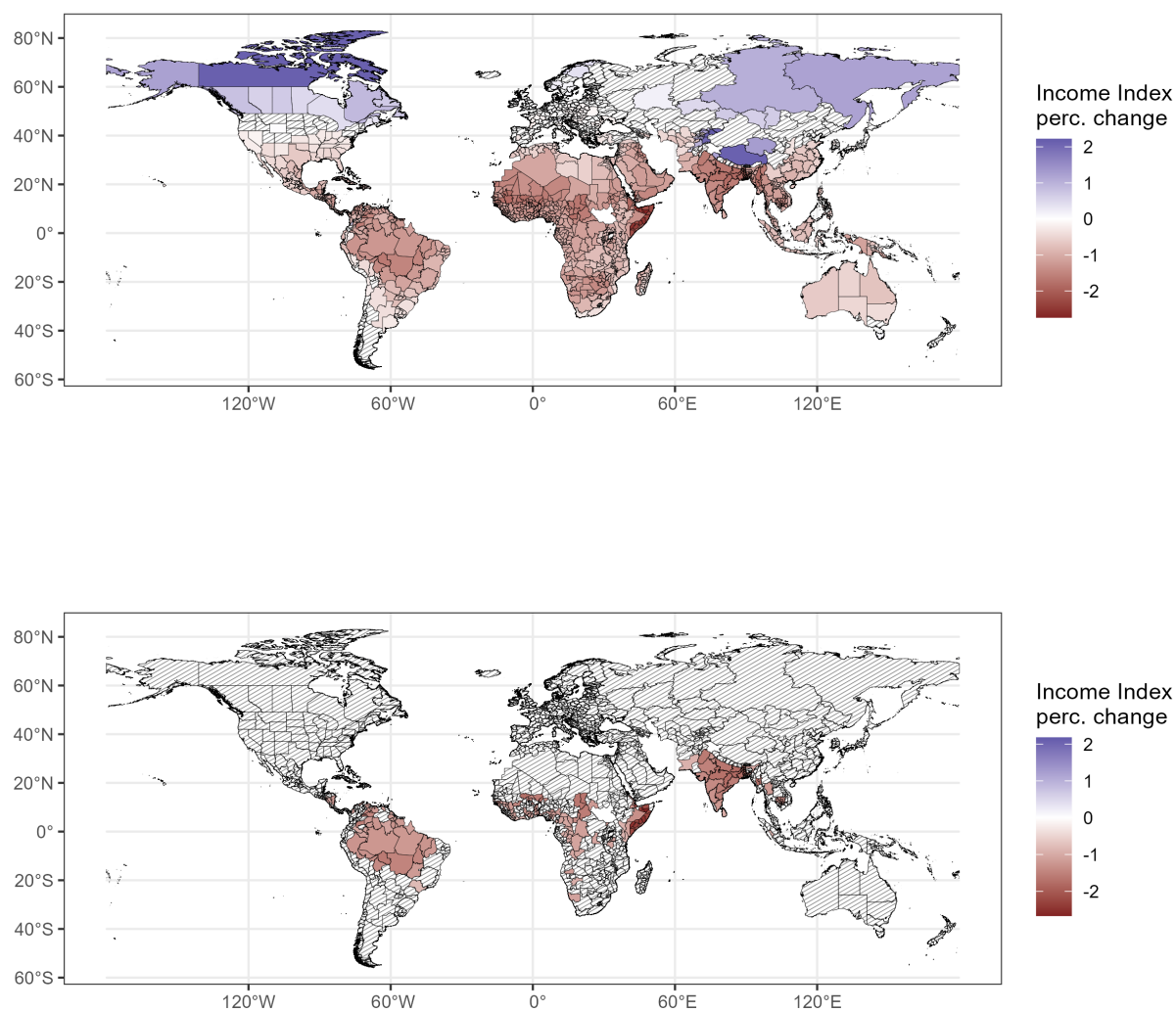


Figure A.17: Income Index percentage change (median across models), in 2100, SSP126, either clustering damage functions errors by region (top panel) or by country (bottom panel).

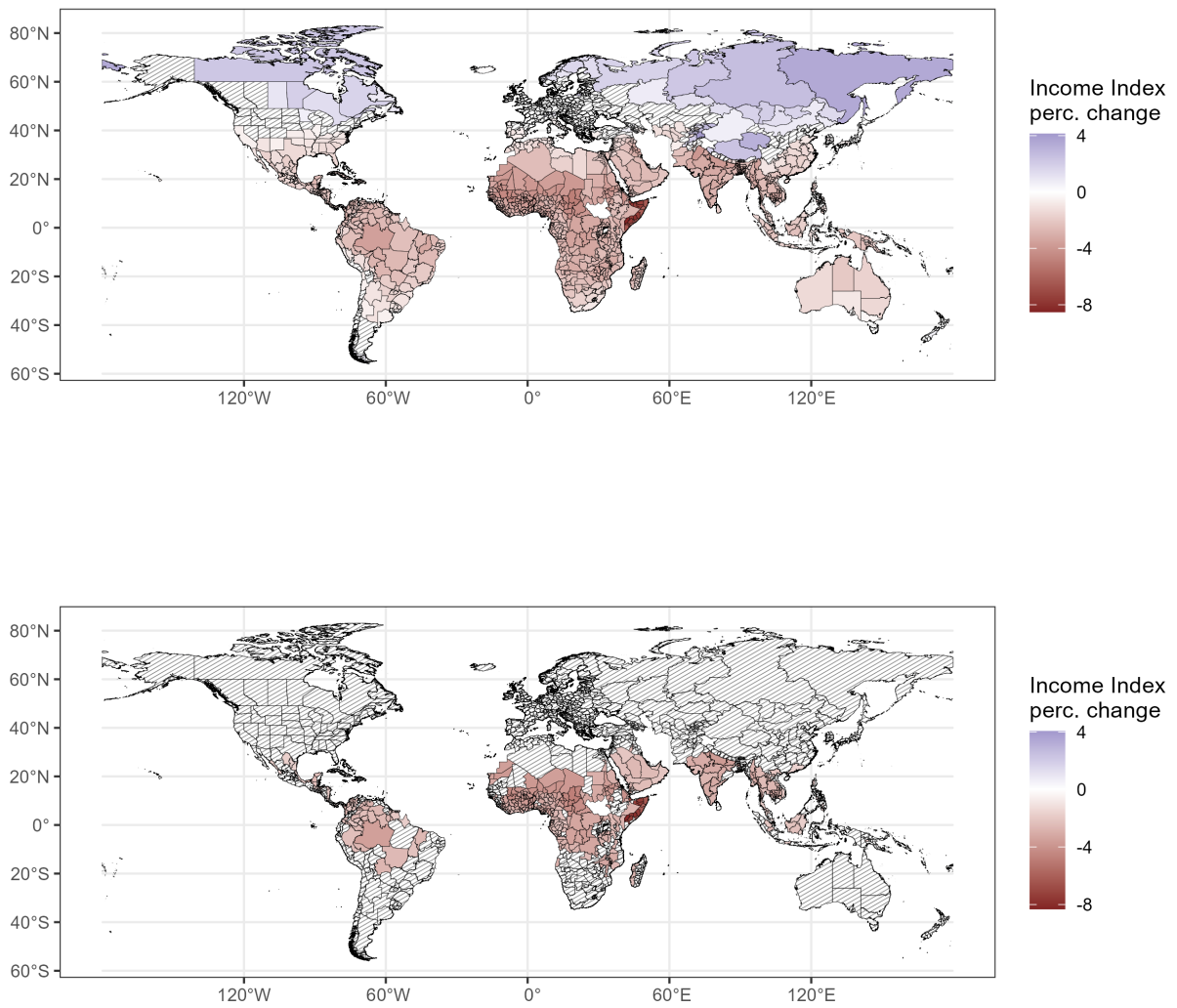


Figure A.18: Income Index percentage change (median across models), in 2100, SSP245, either clustering damage functions errors by region (top panel) or by country (bottom panel).

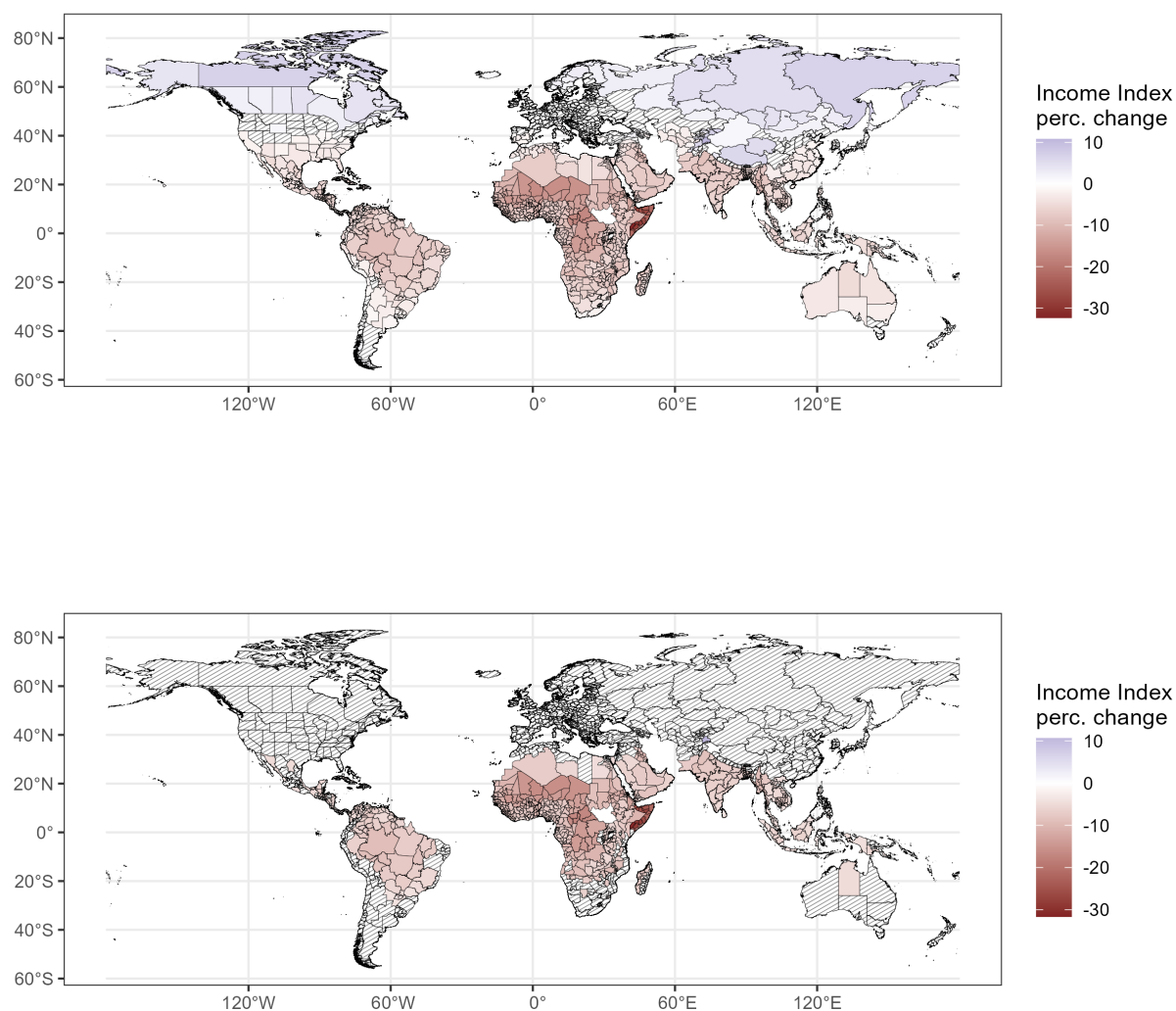


Figure A.19: Income Index percentage change (median across models), in 2100, SSP370, either clustering damage functions errors by region (top panel) or by country (bottom panel).

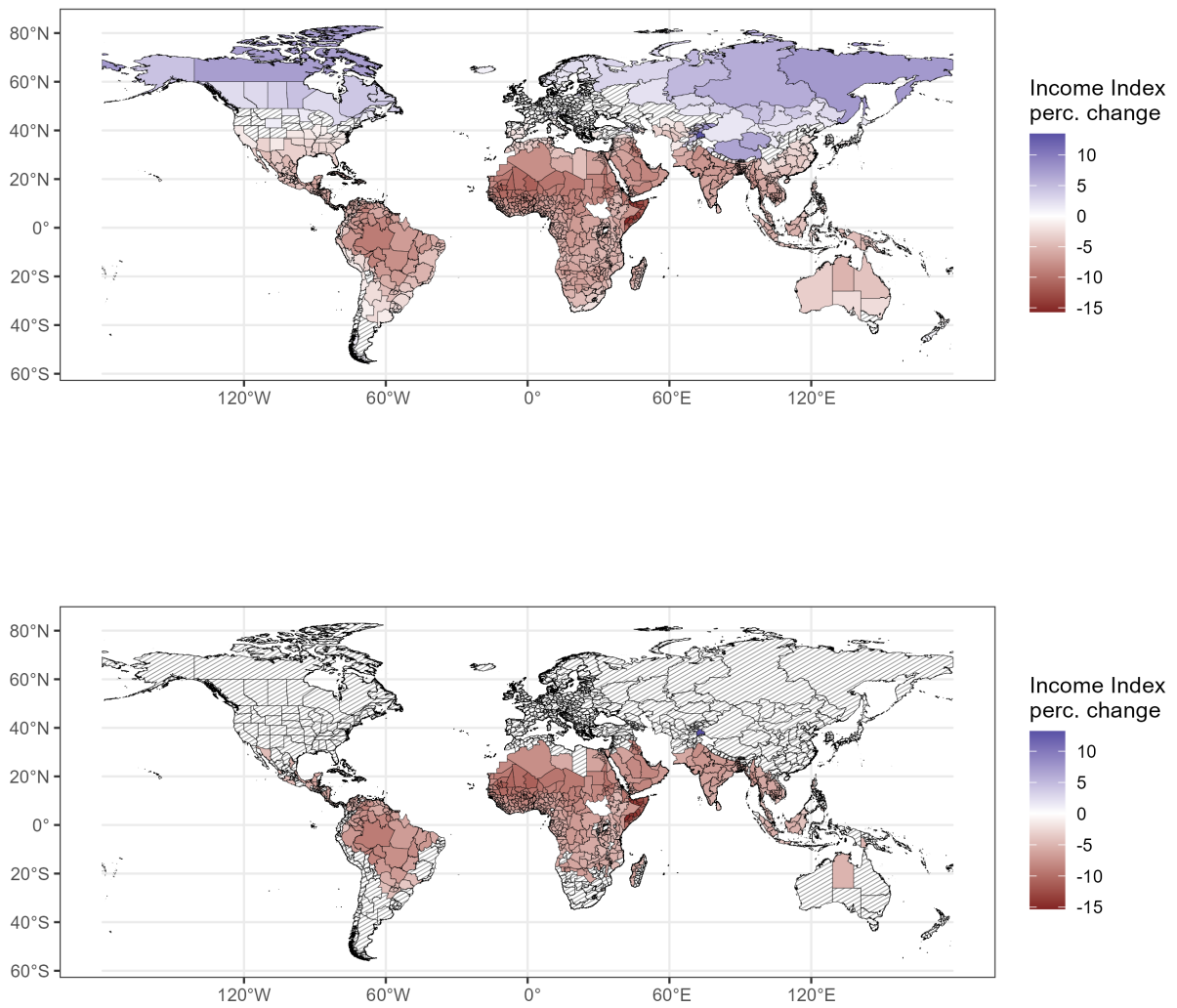


Figure A.20: Income Index percentage change (median across models), in 2100, SSP585, either clustering damage functions errors by region (top panel) or by country (bottom panel).

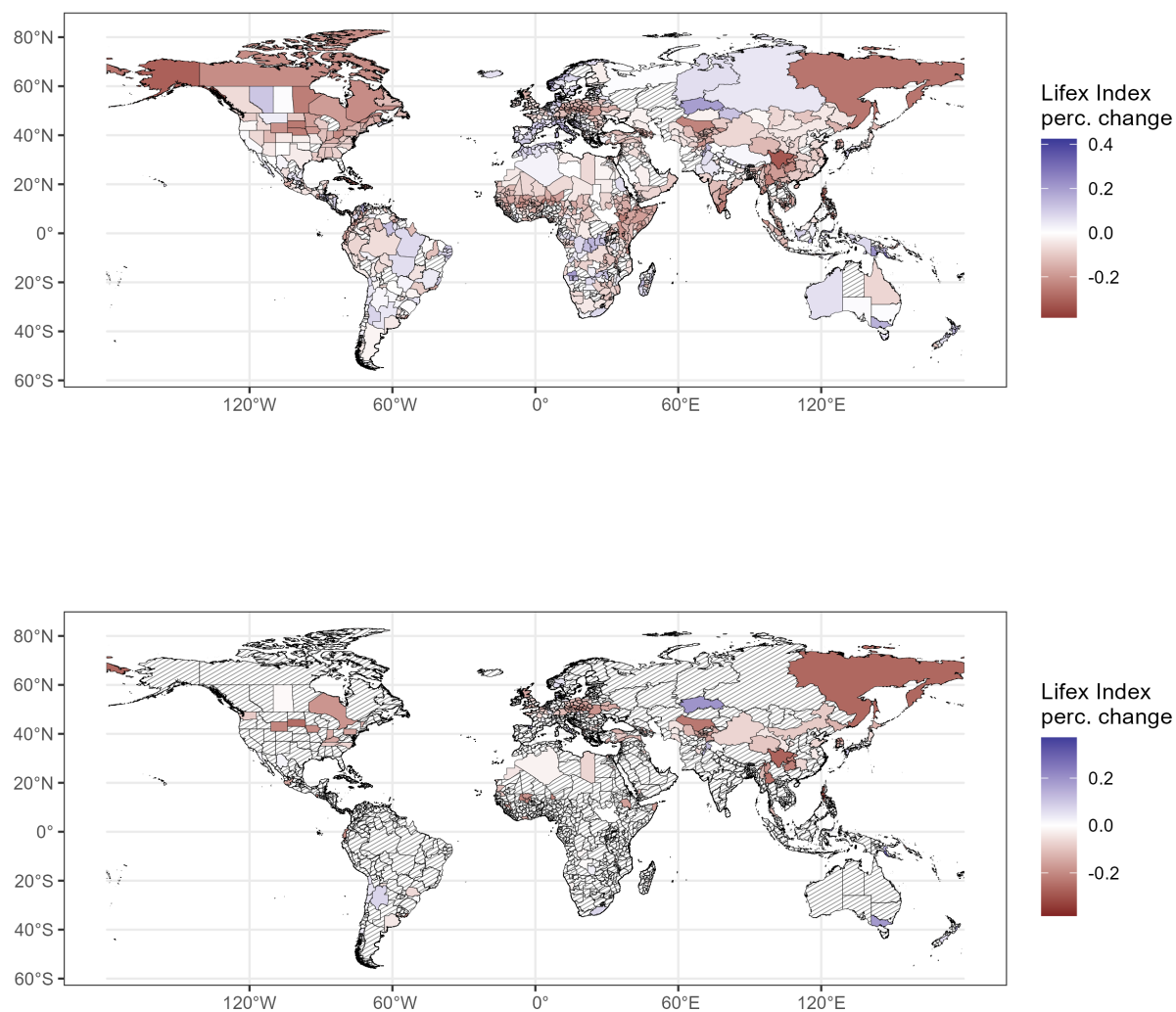
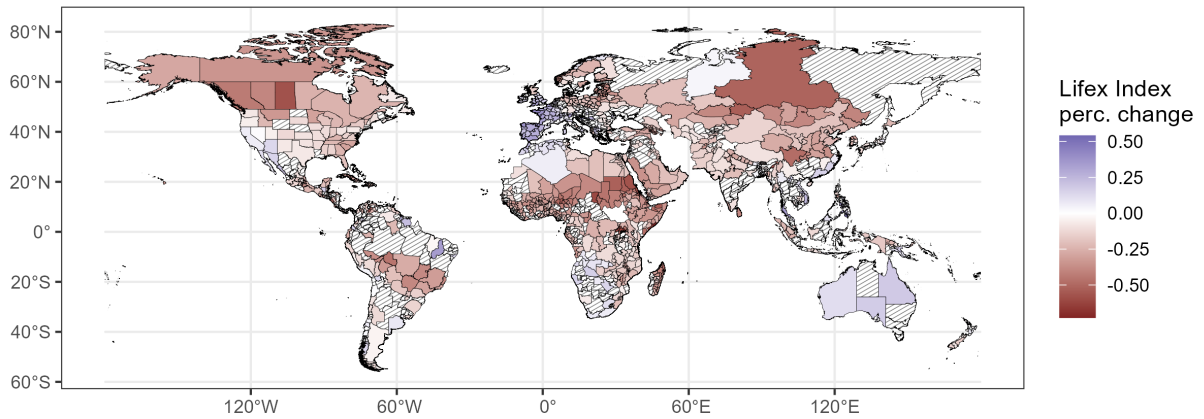


Figure A.21: Lifex Index percentage change (median across models), in 2100, SSP126, either clustering damage functions errors by region (top panel) or by country (bottom panel).



(a)

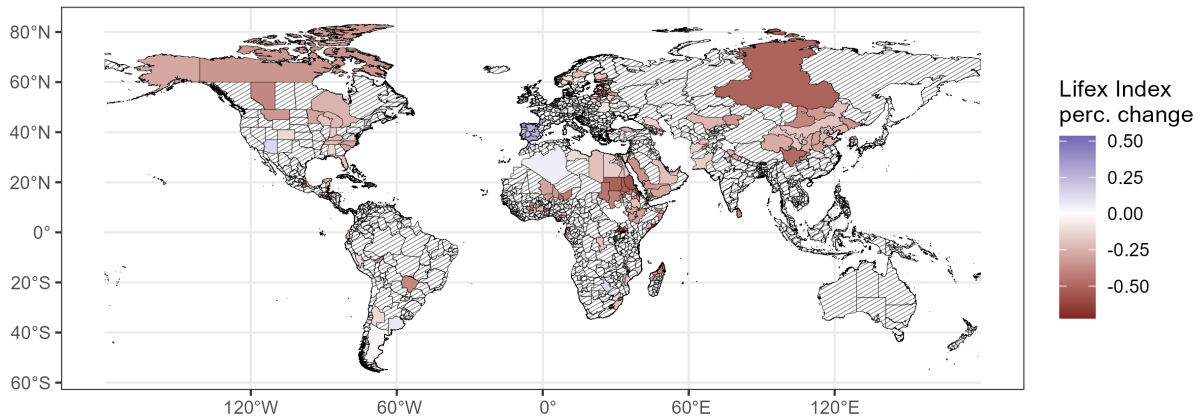


Figure A.22: Lifex Index percentage change (median across models), in 2100, SSP245, either clustering damage functions errors by region (top panel) or by country (bottom panel).

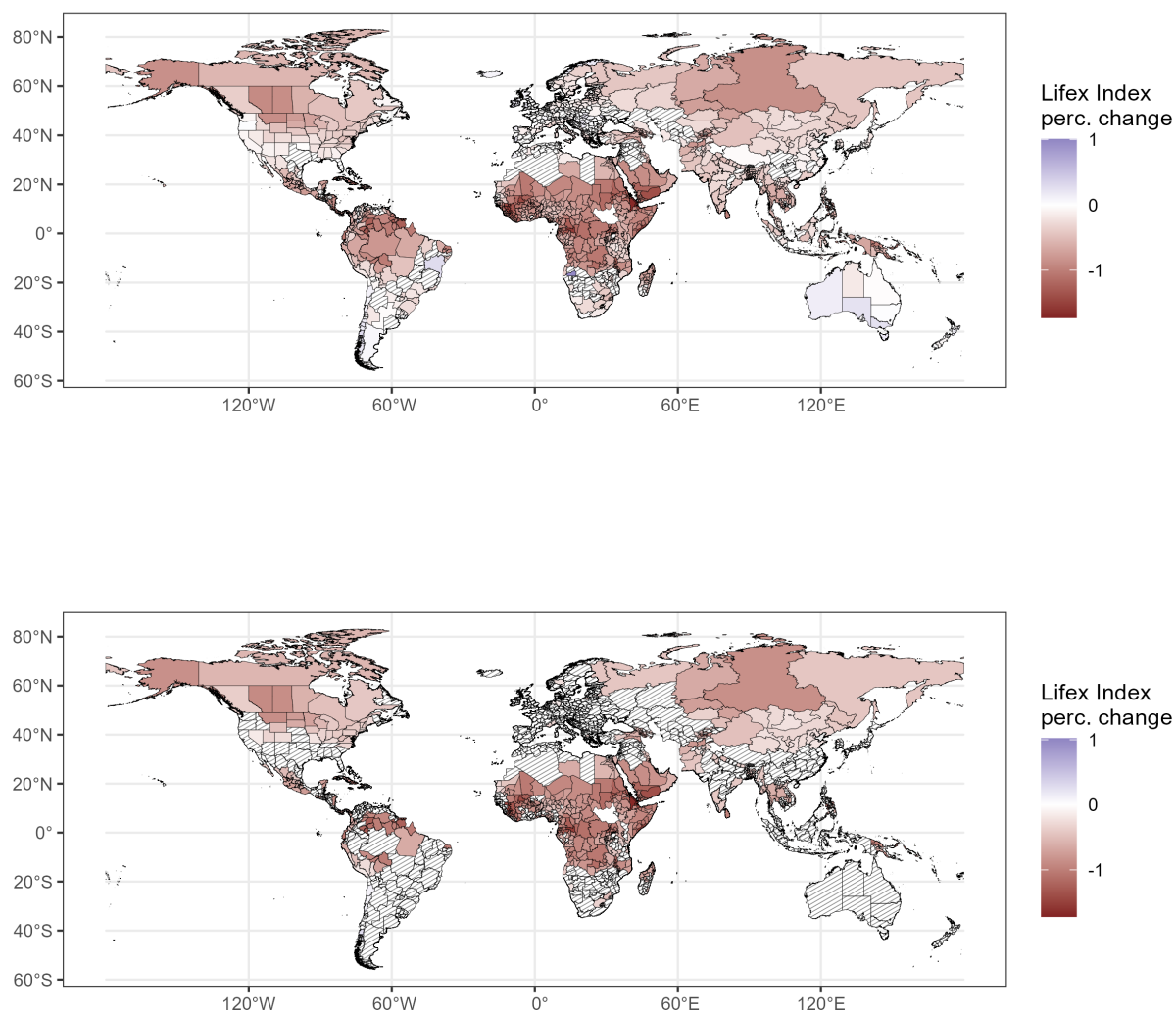


Figure A.23: Lifex Index percentage change (median across models), in 2100, SSP370, either clustering damage functions errors by region (top panel) or by country (bottom panel).

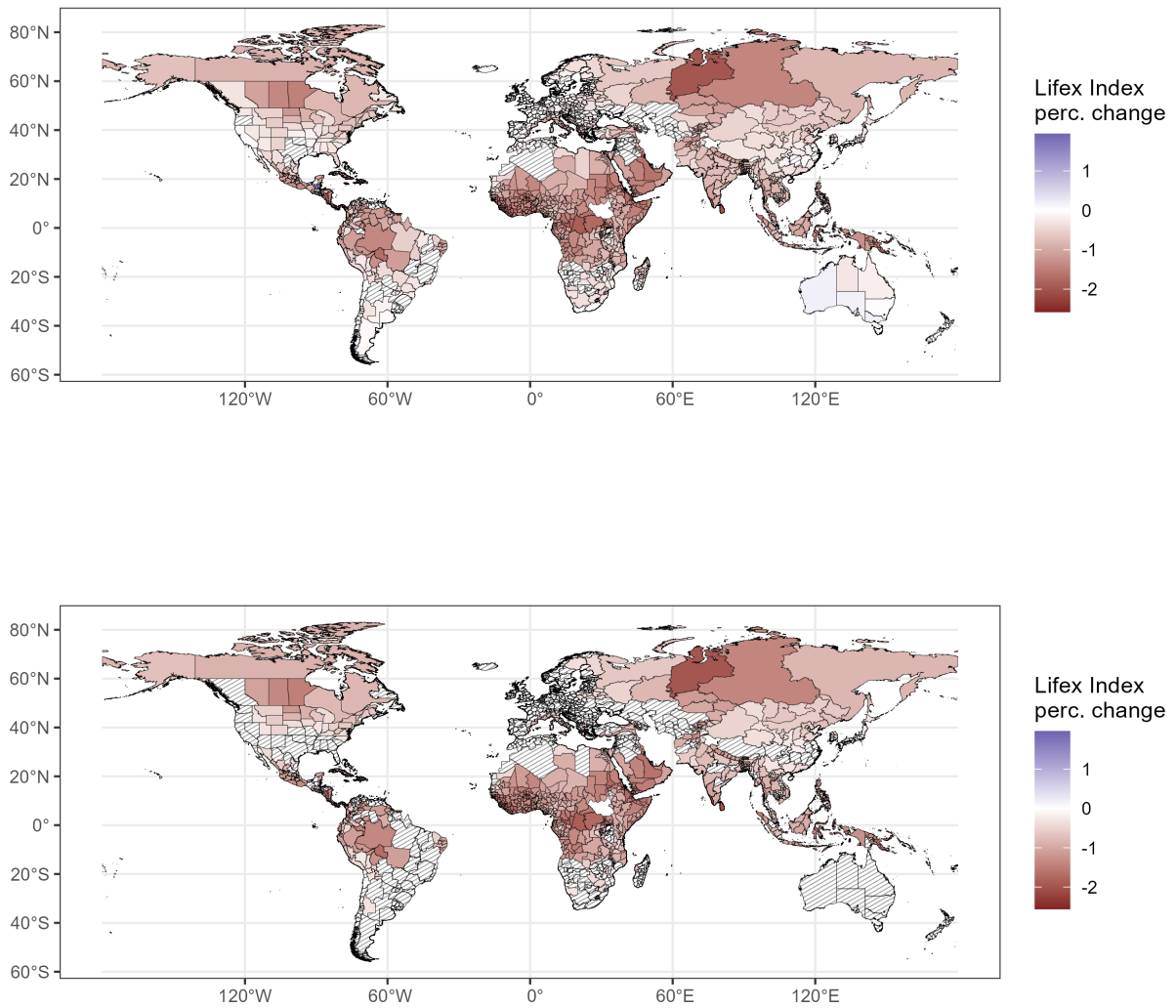


Figure A.24: Lifex Index percentage change (median across models), in 2100, SSP585, either clustering damage functions errors by region (top panel) or by country (bottom panel).

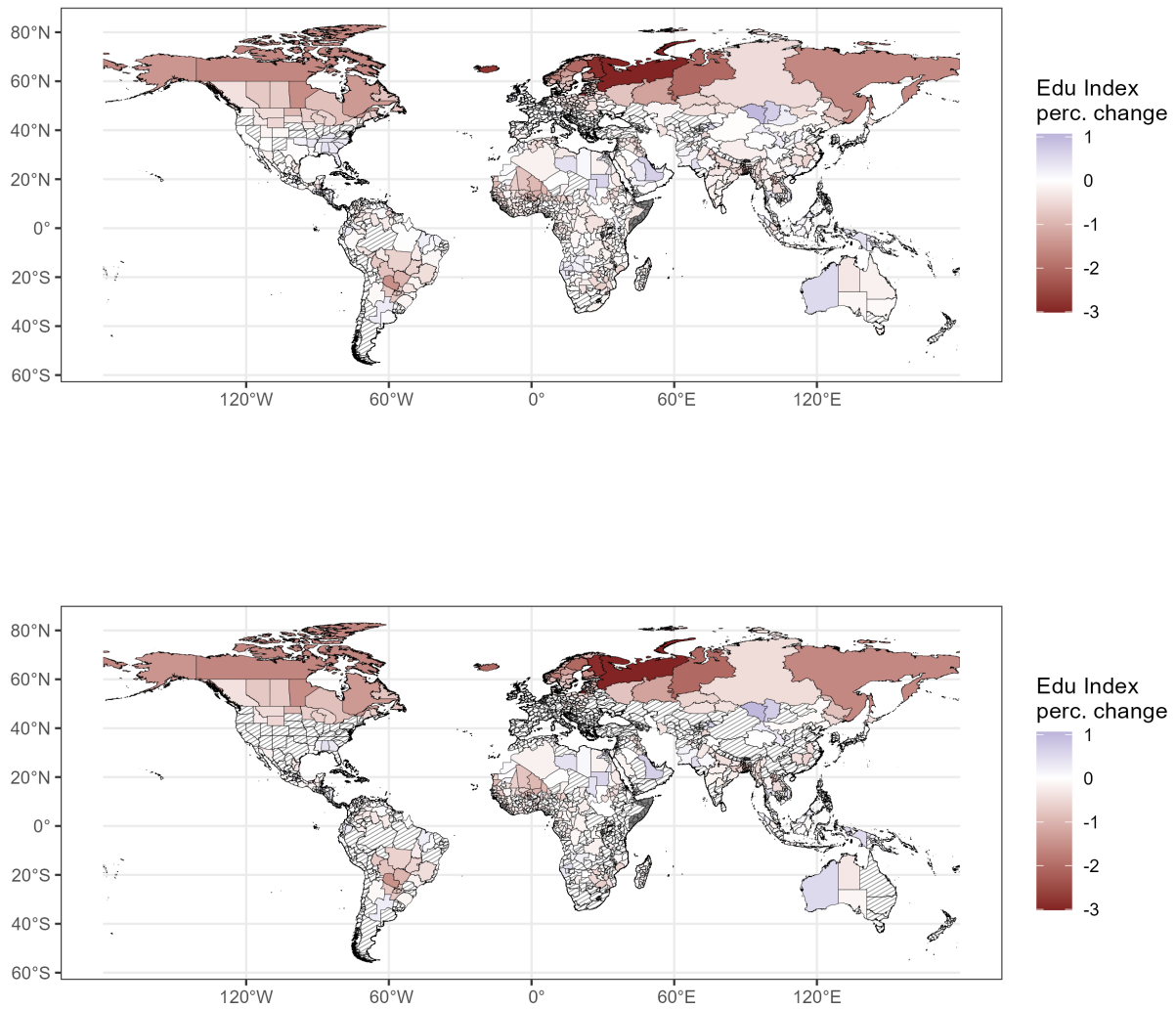
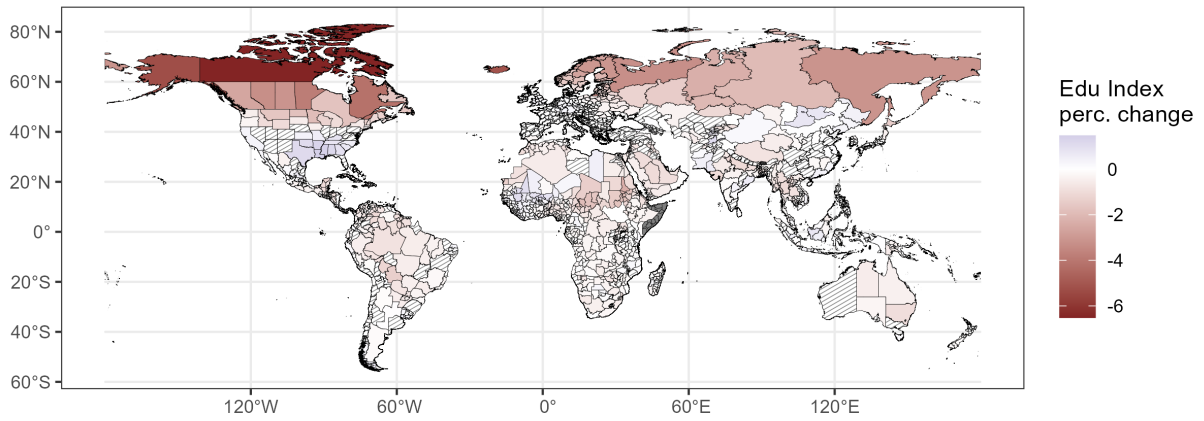


Figure A.25: Education Index percentage change (median across models), in 2100, SSP126, either clustering damage functions errors by region (top panel) or by country (bottom panel).



(a)

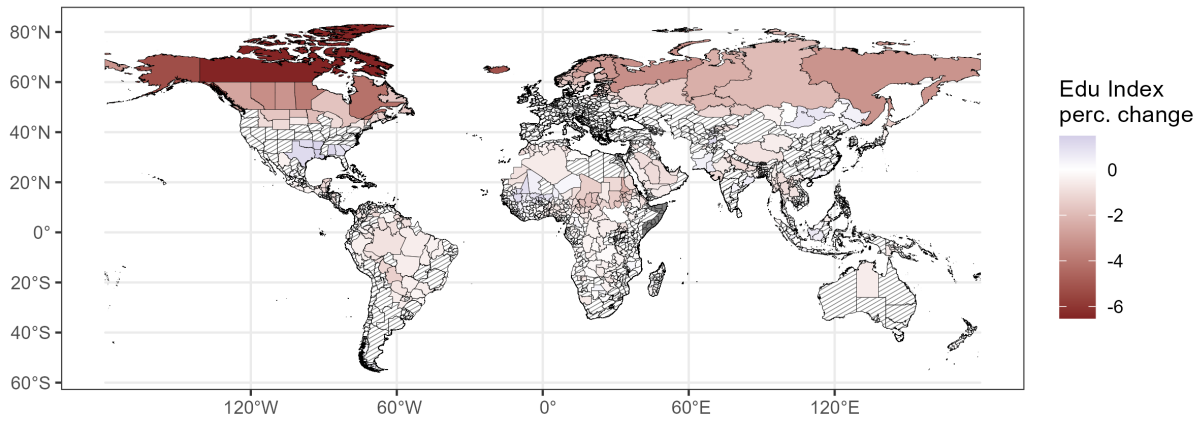


Figure A.26: Education Index percentage change (median across models), in 2100, SSP245, either clustering damage functions errors by region (top panel) or by country (bottom panel).

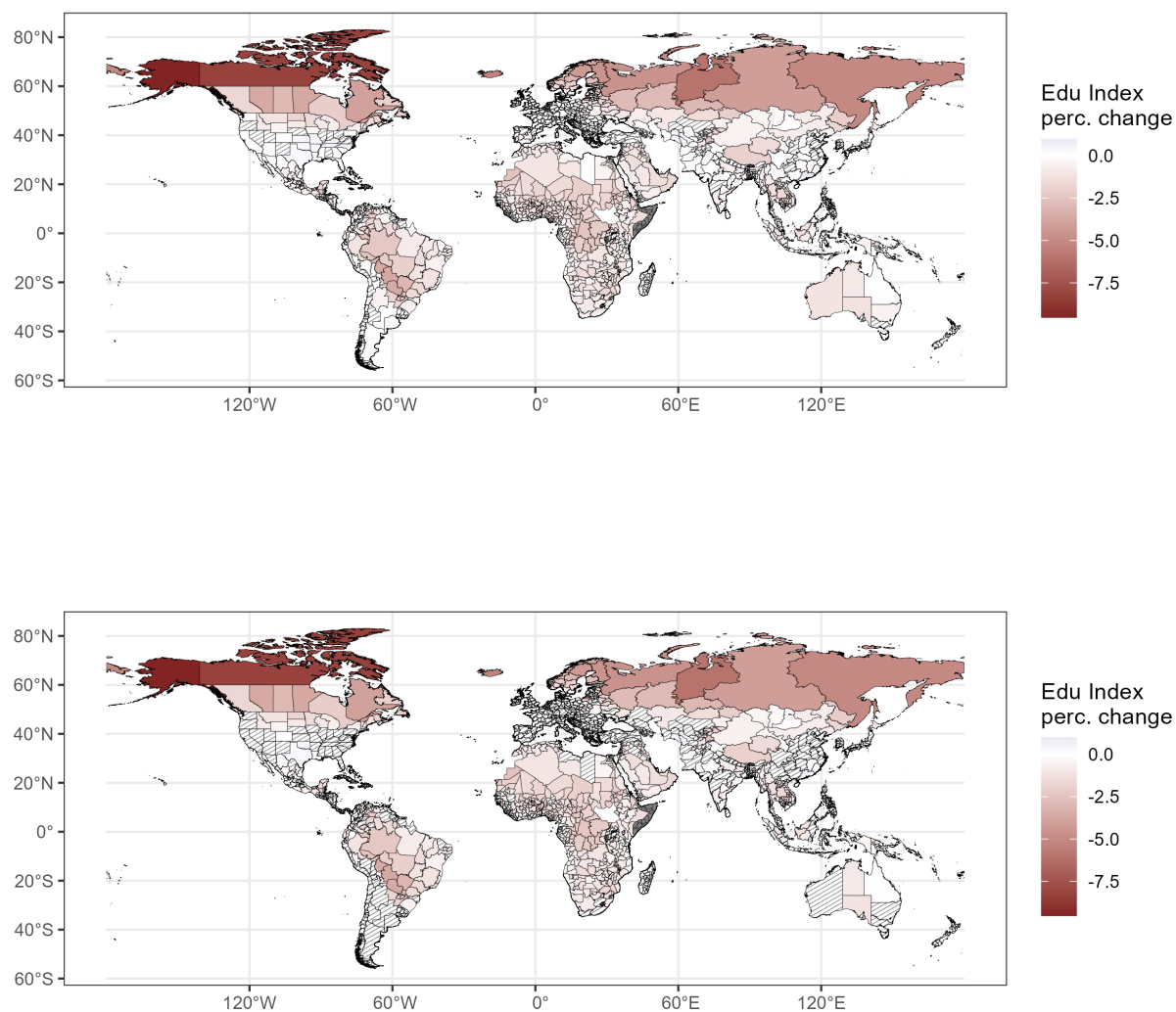


Figure A.27: Education Index percentage change (median across models), in 2100, SSP370, either clustering damage functions errors by region (top panel) or by country (bottom panel).

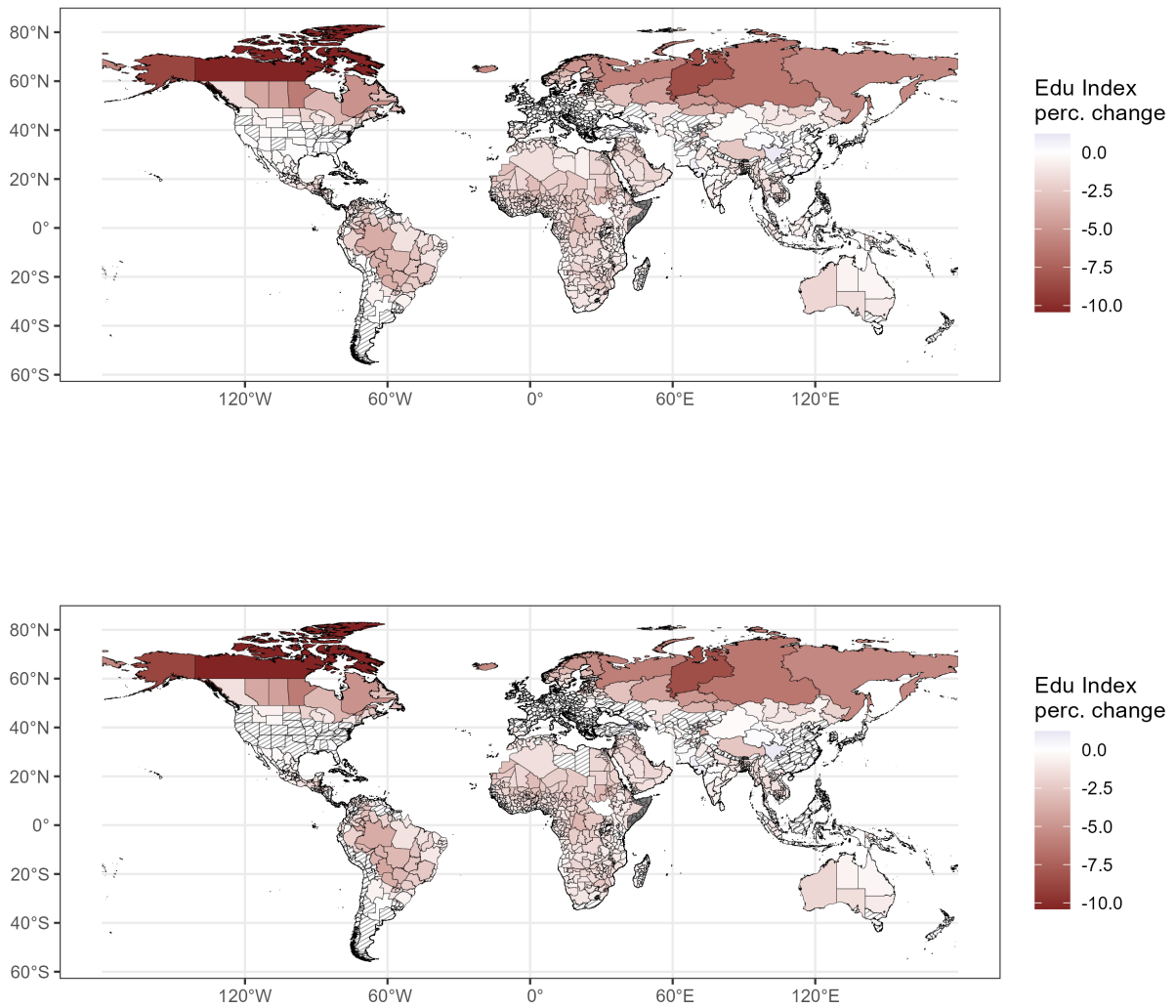


Figure A.28: Education Index percentage change (median across models), in 2100, SSP585, either clustering damage functions errors by region (top panel) or by country (bottom panel).

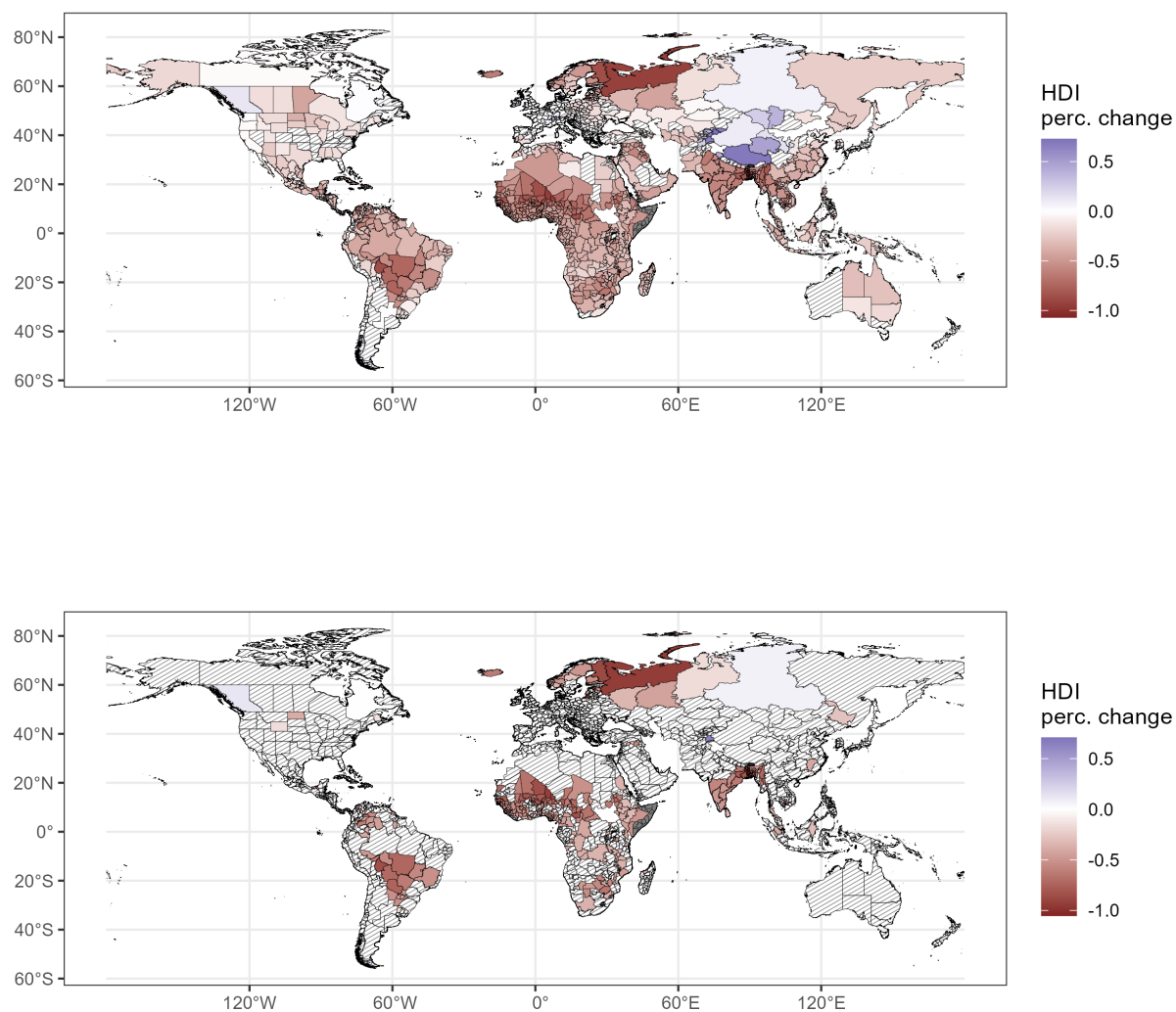


Figure A.29: HDI percentage change (median across models), in 2100, SSP126, either clustering damage functions errors by region (top panel) or by country (bottom panel).

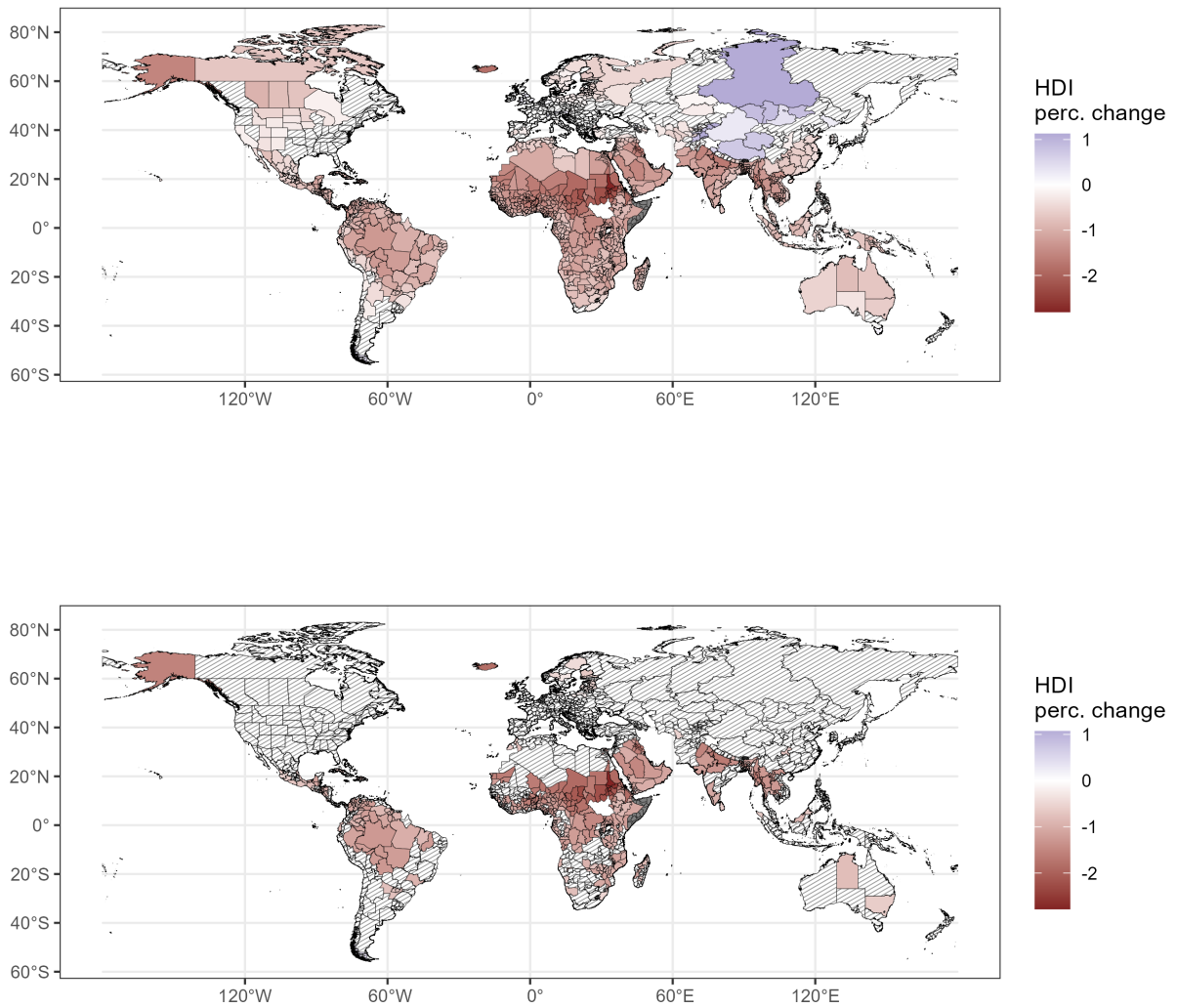


Figure A.30: HDI percentage change (median across models), in 2100, SSP245, either clustering damage functions errors by region (top panel) or by country (bottom panel).

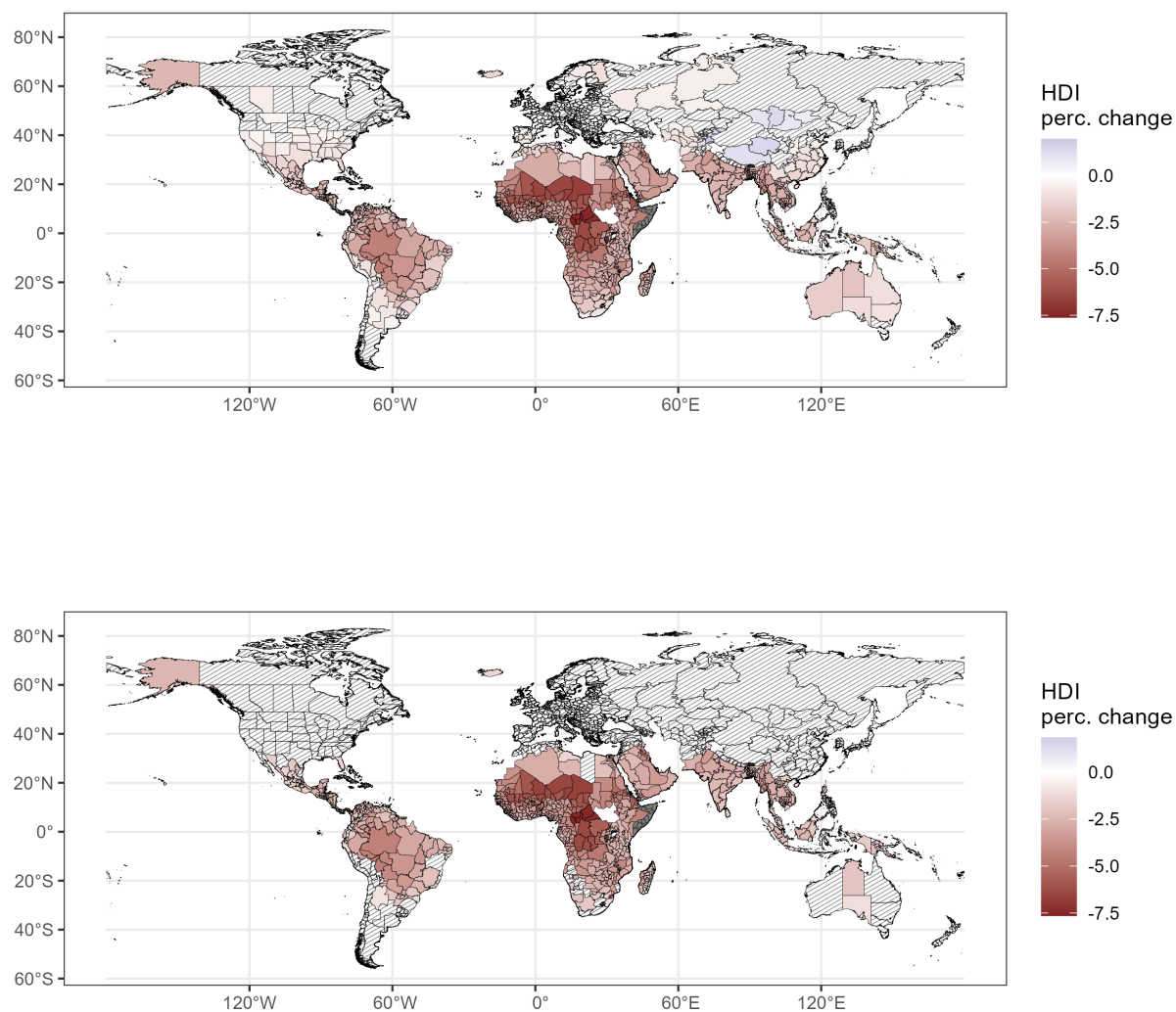


Figure A.31: HDI percentage change (median across models), in 2100, SSP370, either clustering damage functions errors by region (top panel) or by country (bottom panel).

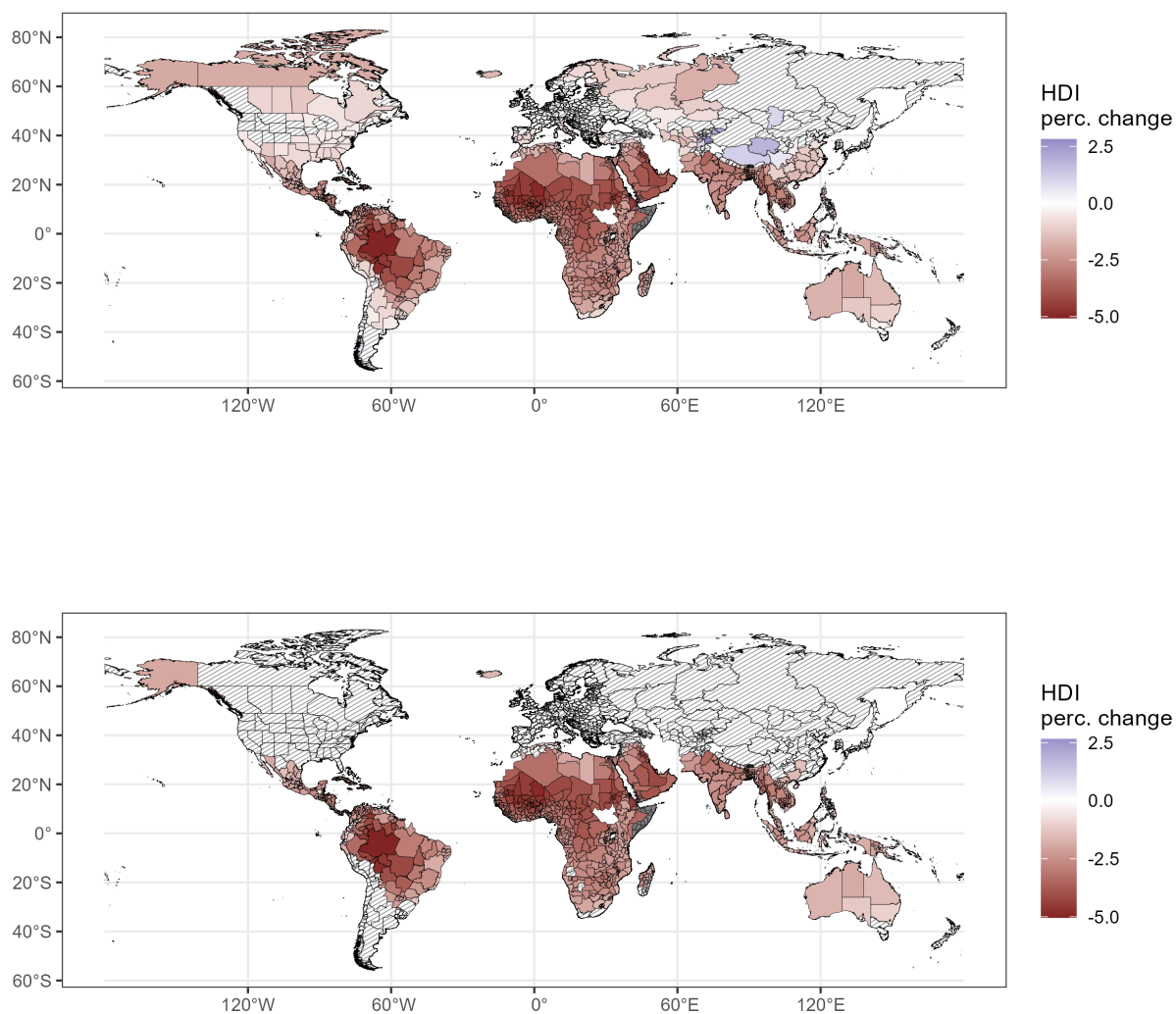
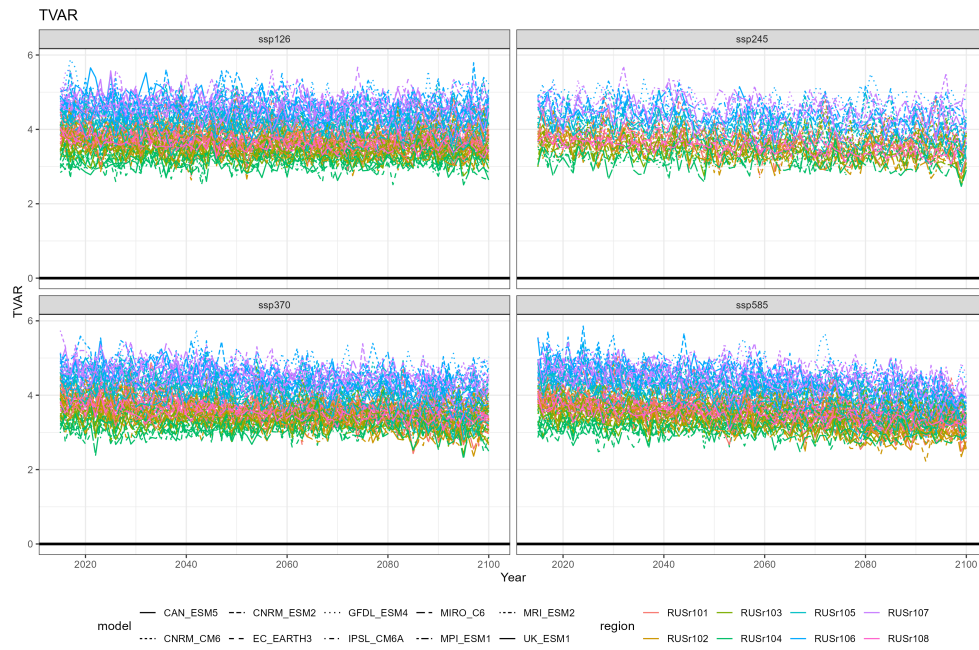
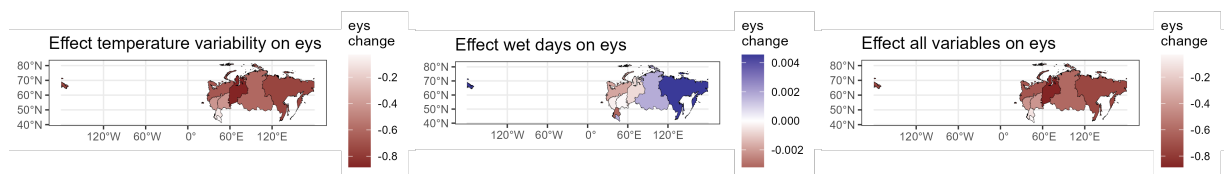


Figure A.32: HDI percentage change (median across models), in 2100, SSP585, either clustering damage functions errors by region (top panel) or by country (bottom panel).



(a) Temperature variability projected evolution by year, SSP, climate model in Russia.



(b) Expected years of schooling damage decomposition in Russia.

Figure A.33: Projected Temperature Variability evolution and its mean decomposed effect on Expected Years of Schooling in russian regions, focusing on SSP-3.70 in 2100.

Appendix B

B.4. Climate Emulator

B.4.1. Scope and Positioning

This supplementary material describes the trajectory-sensitive lookup-table (LUT) climate emulator used to map annual global mean surface temperature (GMST) anomaly pathways to regional climate indicator trajectories. We provide a mathematically explicit description of the core algorithm, including the window extraction rule, adaptive spline representation, matching objective, search domain, and regional-indicator retrieval layer.

B.4.2. Notation

Core Sets and Indices

Table B.12: Core notation for the emulator description.

Symbol	Meaning
$\mathcal{M}$	Set of climate models
$\mathcal{S}$	Set of emissions scenarios
$\mathcal{R}$	Set of spatial units (regions)
$i \in \{1, \dots, N\}$	Index along the target trajectory
$j \in \{0, \dots, W - 1\}$	Within-window offset
u	Candidate window start year in the lookup table
y	Calendar year returned by the emulator
W	Window size
$p = \lfloor W/2 \rfloor$	Target position within a window

Temperature and Indicator Objects

Let $\mathbf{g} = (g_1, \dots, g_N)$ denote the target annual GMST anomaly trajectory. For each climate model $m \in \mathcal{M}$, scenario $s \in \mathcal{S}$, and calendar year y , let $G_{m,s}(y)$ denote the annual GMST anomaly stored in the LUT.

For a target index i , define the fixed-length target window

$$\mathbf{g}_i^{(W)} = \text{Win}_W(\mathbf{g}, i) = (g_{i,0}^{(W)}, \dots, g_{i,W-1}^{(W)})$$

and for a candidate model-scenario-year triple (m, s, u) define the LUT window

$$\mathbf{G}_{m,s,u}^{(W)} = (G_{m,s}(u), \dots, G_{m,s}(u + W - 1))$$

Let

$$\mathbf{C}_{r,m,s,y} \in \mathbb{R}^9$$

denote the vector of annual regional climate indicators for region r , model m , scenario s , and year y .

Spline Representation

We define the adaptive spline degree as

$$k(W) = \min\{3, \max(1, W - 2)\}$$

For any window $\mathbf{z} \in \mathbb{R}^W$, let

$$\text{spl}_{k(W)}(\mathbf{z})$$

denote the interpolating univariate spline of degree $k(W)$ fitted on the discrete grid $\{0, \dots, W - 1\}$. Let

$$\boldsymbol{\alpha}(\mathbf{z})$$

be the spline coefficient vector and

$$\boldsymbol{\beta}(\mathbf{z})$$

the coefficient vector of the derivative spline.

Temporal Weights and Matching Loss

For center-weighted temporal matching, define

$$w_j^{(W,p,\lambda)} = \frac{\exp(-\lambda(j-p)^2/W)}{\sum_{\ell=0}^{W-1} \exp(-\lambda(\ell-p)^2/W)}, \quad j = 0, \dots, W-1$$

where $\lambda > 0$ is the concentration parameter controlling the strength of the center weighting.

The weighted temperature-window mismatch is

$$d_{\text{temp}}(\mathbf{g}_i^{(W)}, \mathbf{G}_{m,s,u}^{(W)}) = \sum_{j=0}^{W-1} w_j^{(W,p,\lambda)} \left| g_{i,j}^{(W)} - G_{m,s}(u+j) \right|$$

The gradient mismatch is

$$d_{\text{grad}}(\mathbf{g}_i^{(W)}, \mathbf{G}_{m,s,u}^{(W)}) = \left\| \boldsymbol{\beta}(\mathbf{g}_i^{(W)}) - \boldsymbol{\beta}(\mathbf{G}_{m,s,u}^{(W)}) \right\|_2$$

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The total matching loss is

$$L_i(m, s, u) = \omega_{\text{mag}} d_{\text{temp}} + \omega_{\text{grad}} d_{\text{grad}}$$

The selected analog is

$$(m_i^*, s_i^*, u_i^*) = \arg \min_{(m, s, u) \in \mathcal{A}_i} L_i(m, s, u)$$

where $\mathcal{A}_i$ denotes the admissible search set after applying the scenario and year restrictions active in a given run. The matched calendar year returned by the emulator is

$$y_i^* = u_i^* + p$$

and the matched regional-indicator vector is

$$\hat{\mathbf{C}}_{r,i} = \mathbf{C}_{r,m_i^*,s_i^*,y_i^*}$$

Throughout, we distinguish the candidate window start year u from the returned calendar year $y = u + p$. The search optimizes over window start years, whereas the retrieval layer consumes the aligned year corresponding to the target position within the matched window.

B.4.3. Algorithm Description

Overview

The emulator is designed to map arbitrary annual GMST anomaly trajectories to spatially resolved climate-indicator trajectories by querying a pre-computed lookup table of CMIP6 model outputs. Its intended use case is the analysis of novel warming pathways, particularly overshoot and return trajectories, for which Earth System Models do not provide a direct analog. Rather than interpolating within a high-dimensional climate field, our emulator searches observed model-scenario-year combinations to identify the analog window that most closely mirrors the target trajectory’s temperature level and short-run trend.

The method is trajectory-sensitive by construction. While single-year temperature matching is supported, our primary application relies on sequence-based matching over fixed-length windows. Because transient overshoot pathways are characterized not only by absolute warming but by whether the local system is actively warming, stabilizing, or cooling, the emulator evaluates candidates using a composite loss that balances temporally weighted temperature mismatch against derivative-spline coefficient divergence.

Lookup-Table Construction

The emulator operates across two linked archives. The first contains annual GMST anomaly trajectories for a collection of CMIP6 climate models and emissions scenarios. The second

contains annual regional climate indicators indexed by model, scenario, year, and spatial unit. The emulator identifies an optimal tuple (m_i^*, s_i^*, y_i^*) in the temperature archive and subsequently retrieves the corresponding regional indicator rows. This architecture links the archives via a common index, avoiding direct interpolation of the regional indicators themselves.

$$\begin{aligned}\mathcal{D}_{\text{temp}} &= \{G_{m,s}(y) : m \in \mathcal{M}, s \in \mathcal{S}, y \in \mathcal{Y}_{\text{temp}}\} \\ \mathcal{D}_{\text{ind}} &= \{\mathbf{C}_{r,m,s,y} : r \in \mathcal{R}, m \in \mathcal{M}, s \in \mathcal{S}, y \in \mathcal{Y}_{\text{ind}}\}\end{aligned}$$

The full emulator supports a wide range of scenarios (from `historical` to `ssp585`). Our configuration for this study restricts the set to `historical`, `ssp119`, `ssp126`, `ssp245`, `ssp370`, `ssp534`, and `ssp585`, looping across eight distinct CMIP6 models to comprehensively sample structural climate uncertainty.

The regional archive stores a nine-dimensional indicator vector summarizing annual mean conditions, variability, extremes, and drought parameters:

$$\mathbf{C}_{r,m,s,y} = (\text{PEXT}, \text{RR}, \text{TM}, \text{TVAR}, \text{WD}, \text{HW}, \text{RX}, \text{SPI}, \text{SPEI})_{r,m,s,y}$$

Target Trajectory Preprocessing

The emulator accepts target GMST anomalies as `float32` NumPy arrays. This preprocessing is deliberately minimal: the trajectory is treated as an exogenous path and is not detrended or smoothed prior to window extraction.

$$\begin{aligned}\mathbf{g} &= (g_1, \dots, g_N) \\ \tilde{g}_i &= g_i + \varepsilon_i, \quad \varepsilon_i \sim \mathcal{U}[-\sigma, \sigma] \quad \text{if noise injection is enabled.}\end{aligned}$$

If noise injection is enabled (`add_noise=True`), the emulator perturbs the target sequence additively with i.i.d. uniform noise. Reproducibility is strictly maintained by resetting random seeds (base seed 42) before each emulation call, ensuring that pre-processing noise and any random model selections remain deterministic within a given batch configuration.

B.4.4. Window Extraction and Boundary Handling

For sequence-based matching, the emulator constructs a fixed-length window around each target index i and evaluates that local trajectory against all admissible LUT candidates. The window length W remains constant across the entire target trajectory.

$$\begin{aligned}p &= \left\lfloor \frac{W}{2} \right\rfloor \\ \text{Win}_W(\mathbf{g}, i) &= (g_{i,0}^{(W)}, \dots, g_{i,W-1}^{(W)}) \\ g_{i,j}^{(W)} &= \tilde{g}_{\min\{\max(i-p+j, 1), N\}}\end{aligned}$$

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When W is odd, the window is perfectly centered. When W is even, it is right-centered. If a nominal window extends beyond the available trajectory bounds, the series is padded via edge replication. This robust padding ensures that boundary indices yield windows of identical length, allowing spline fitting to proceed without special-case logic.

Spline Representation and Pre-Computed Reference Windows

Whenever $W > 1$, the emulator augments the temperature LUT with a spline archive storing a compact representation of every valid sliding window. This archive is loaded lazily: if a valid spline file for the required model, window size, and spline degree exists, it is reused; otherwise, it is generated.

$$\begin{aligned} k(W) &= \min\{3, \max(1, W - 2)\} \\ (\boldsymbol{\alpha}_{m,s,u}, \boldsymbol{\beta}_{m,s,u}) &= \text{SplineCoeffs}\left(\mathbf{G}_{m,s,u}^{(W)}\right) \\ (\boldsymbol{\alpha}_i^{\text{tar}}, \boldsymbol{\beta}_i^{\text{tar}}) &= \text{SplineCoeffs}\left(\mathbf{g}_i^{(W)}\right) \end{aligned}$$

The implementation fits an interpolating univariate spline on the discrete support $\{0, \dots, W-1\}$. The adaptive rule ensures the spline order remains mathematically valid even for short windows. We extract both the primary coefficients ($\boldsymbol{\alpha}$) and derivative coefficients ($\boldsymbol{\beta}$), storing them in scenario-specific arrays within a compressed `.npz` archive.

Sequence-Matching Objective

For each target index i , the composite loss combines a temporally weighted temperature-window mismatch with a derivative-coefficient mismatch.

$$\begin{aligned} w_j^{(W,p,\lambda)} &= \frac{\exp(-\lambda(j-p)^2/W)}{\sum_{\ell=0}^{W-1} \exp(-\lambda(\ell-p)^2/W)} \\ d_{\text{temp},i}(m, s, u) &= \sum_{j=0}^{W-1} w_j^{(W,p,\lambda)} \left| g_{i,j}^{(W)} - G_{m,s}(u+j) \right| \\ d_{\text{grad},i}(m, s, u) &= \left\| \boldsymbol{\beta}_i^{\text{tar}} - \boldsymbol{\beta}_{m,s,u} \right\|_2 \\ L_i(m, s, u) &= \omega_{\text{mag}} d_{\text{temp},i}(m, s, u) + \omega_{\text{grad}} d_{\text{grad},i}(m, s, u) \end{aligned}$$

By default, we set $\omega_{\text{mag}} = 0.9$ and $\omega_{\text{grad}} = 0.1$. This configuration heavily prioritizes close agreement in absolute temperature while sufficiently penalizing analog windows that exhibit contradictory local trends.

Admissible Search Set and Selected Analog

The sequence matcher optimizes within a single model file at a time rather than jointly across all models.

$$\begin{aligned}
\tilde{m}_i &\in \mathcal{M}_{\text{act}} \\
\mathcal{A}_i(\tilde{m}_i) &= \left\{ (\tilde{m}_i, s, u) : s \in \mathcal{S}_{\text{act}}, u \in \mathcal{U}_{\tilde{m}_i, s, W}^{\text{valid}} \right\} \\
(s_i^*, u_i^*) &= \arg \min_{(\tilde{m}_i, s, u) \in \mathcal{A}_i(\tilde{m}_i)} L_i(\tilde{m}_i, s, u) \\
m_i^* &= \tilde{m}_i \\
y_i^* &= u_i^* + p \\
\hat{g}_i &= G_{m_i^*, s_i^*}(y_i^*)
\end{aligned}$$

The search is bounded by the year range 1950–2100. The matched GMST anomaly $\hat{g}_i$ is drawn directly from the original annual temperature series at year y_i^* , ensuring strict fidelity to the underlying ESM output.

Retrieval of Regional Climate Indicators

Once the optimal trajectory tuple is identified, the `get_country_projections()` wrapper retrieves the corresponding regional indicators.

$$\begin{aligned}
\hat{\mathbf{C}}_{r,i} &= \mathbf{C}_{r, m_i^*, s_i^*, y_i^*} \\
\hat{\mathbf{C}}_i &= \left\{ \hat{\mathbf{C}}_{r,i} : r \in \mathcal{R} \right\}
\end{aligned}$$

The algorithm applies a deterministic name-mapping to bridge short identifiers and full model names. It outputs a nested JSON dictionary mapping `gdlcode` to target-index-specific indicator arrays, preserving both the emulation metadata and the retrieved regional impacts.

B.4.5. Algorithms

B.4.6. Window Size Validation

Validation Framework

We evaluated the emulator’s sensitivity to the window size parameter W using the seven synthetic GMST anomaly pathways (Scenarios A-G) outlined in the primary text. All results reported below rely on spline-based matching $\forall W > 1$, reverting to standard temperature matching when $W = 1$.

Metrics

We benchmarked emulator performance across two orthogonal dimensions: *accuracy* (the fidelity of the temperature match) and *temporal consistency* (the physical plausibility of the matched-year sequence).

Accuracy metrics

Algorithm B.1 Pre-computation of spline representations for LUT windows

Require: Requested model files, window size W

```

1: Set spline degree  $k \leftarrow \min\{3, \max(1, W - 2)\}$ 
2: for each requested model file do
3:   if a valid spline archive for  $(W, k)$  already exists then
4:     Reuse the existing archive
5:   else
6:     for each scenario row in fixed file order do
7:       for each candidate start year  $u$  do
8:         Construct LUT window  $\mathbf{G}_{m,s,u}^{(W)}$ 
9:         if the window contains no missing values and the spline fit succeeds then
10:          Fit interpolating spline of degree  $k$  on positions  $\{0, \dots, W - 1\}$ 
11:          Store  $\alpha_{m,s,u}$ ,  $\beta_{m,s,u}$ , and start year  $u$ 
12:        end if
13:      end for
14:    end for
15:    Save the pre-computed arrays in a compressed spline archive
16:  end if
17: end for

```

- **Mean Squared Error (MSE).** The mean squared error between emulated and target temperatures, reported in $^{\circ}\text{C}^2$.
- **Fraction within 0.1 $^{\circ}\text{C}$.** The percentage of target timesteps where the matched anomaly deviates by less than 0.1 $^{\circ}\text{C}$.

Consistency metrics A physically coherent emulation of a warming trajectory should produce a monotonically increasing sequence of matched years $(y_1^*, \dots, y_N^*)$ and exhibit long, stable runs within a single emissions scenario $(s_1^*, \dots, s_N^*)$. Erratic jumps between distant years or divergent scenarios introduce spatial discontinuities in the downstream indicators, even if the absolute temperature match is tight. We quantify this via two complementary metrics:

- **Monotonicity violation rate.** The fraction of consecutive timestep pairs where the matched year reverses (decreases):

$$V_{\text{mono}} = \frac{1}{N-1} \sum_{i=2}^N \mathbf{1}[y_i^* < y_{i-1}^*]$$

- **Scenario switch rate.** The fraction of consecutive timestep pairs where the matched scenario changes:

$$V_{\text{switch}} = \frac{1}{N-1} \sum_{i=2}^N \mathbf{1}[s_i^* \neq s_{i-1}^*]$$

We define a composite inconsistency score $(V_{\text{mono}} + V_{\text{switch}})$ to evaluate the overarching accuracy-consistency trade-off.

Algorithm B.2 Sequence-based matching for one target index

Require: Target trajectory $\mathbf{g}$, target index i , window size W , weights $\omega_{\text{mag}}, \omega_{\text{grad}}$

- 1: Compute $p \leftarrow \lfloor W/2 \rfloor$
 - 2: Extract padded target window $\mathbf{g}_i^{(W)}$
 - 3: Fit target spline and compute derivative coefficients β_i^{tar}
 - 4: **if** the target spline fit fails **then**
 - 5: Fall back to single-year matching on the temperature at position p
 - 6: **end if**
 - 7: Select model $\tilde{m}_i$ according to the emulator configuration
 - 8: Initialize $L_i^* \leftarrow +\infty$
 - 9: **for** each admissible candidate $(\tilde{m}_i, s, u) \in \mathcal{A}_i(\tilde{m}_i)$ **do**
 - 10: Load candidate LUT window $\mathbf{G}_{\tilde{m}_i, s, u}^{(W)}$
 - 11: Compute $d_{\text{temp}, i}(\tilde{m}_i, s, u)$
 - 12: Compute $d_{\text{grad}, i}(\tilde{m}_i, s, u)$
 - 13: Compute $L_i(\tilde{m}_i, s, u)$
 - 14: **if** $L_i(\tilde{m}_i, s, u) < L_i^*$ **then**
 - 15: Update $(m_i^*, s_i^*, u_i^*) \leftarrow (\tilde{m}_i, s, u)$
 - 16: Update $L_i^* \leftarrow L_i(\tilde{m}_i, s, u)$
 - 17: **end if**
 - 18: **end for**
 - 19: Return matched year $y_i^* \leftarrow u_i^* + p$
 - 20: Return matched GMST $\hat{g}_i \leftarrow G_{m_i^*, s_i^*}(y_i^*)$
-

Results Table B.13 summarizes the accuracy and consistency metrics across window sizes $W \in \{1, 3, 5, 7, 9\}$, averaged over 56 emulation files per configuration.

Table B.13: Emulator accuracy and consistency metrics by window size. All values are means over emulation files (8 models $\times$ 7 scenarios). MSE is in $^\circ\text{C}^2$; %0.1 $^\circ\text{C}$ is the percentage of timesteps within 0.1 $^\circ\text{C}$ of the target.

W	Accuracy		Consistency		
	MSE	% 0.1 $^\circ\text{C}$	V_{mono}	V_{switch}	$V_{\text{mono}} + V_{\text{switch}}$
1	0.0001	100.0	0.377	0.417	0.794
3	0.0013	99.2	0.297	0.360	0.657
5	0.0025	96.0	0.291	0.269	0.560
7	0.0049	85.8	0.286	0.238	0.523
9	0.0058	82.9	0.292	0.215	0.507

Figure B.34 presents the Pareto frontier for the accuracy-consistency trade-off. Several dynamics emerge:

Accuracy is still exceptionally high at $W = 3$. While single-year matching ($W = 1$) guarantees near-perfect accuracy, extending the window to $W = 3$ preserves near-perfect fidelity. The root-mean-square error at $W = 3$ is approximately 0.036 $^\circ\text{C}$, and 99.2% of timesteps remain within 0.1 $^\circ\text{C}$ of the target.

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Consistency improves sharply at $W = 3$. Composite inconsistency drops from 0.794 to 0.657. By constraining target years to LUT windows with similar local trends, the $W = 3$ configuration reduces temporal reversals and supports longer, more stable runs within a single emissions pathway.

Diminishing returns beyond $W = 3$. Increasing the window to $W = 5$ further reduces inconsistency, but it also roughly doubles the MSE relative to $W = 3$ and lowers the fraction of timesteps within 0.1°C from 99.2% to 96.0%. Beyond $W = 7$, accuracy deteriorates much more strongly while consistency gains become comparatively modest.

Conclusion. We adopt $W = 3$ as the default window size for all analyses, as it represents the optimal trade-off between temporal coherence and strict temperature fidelity.

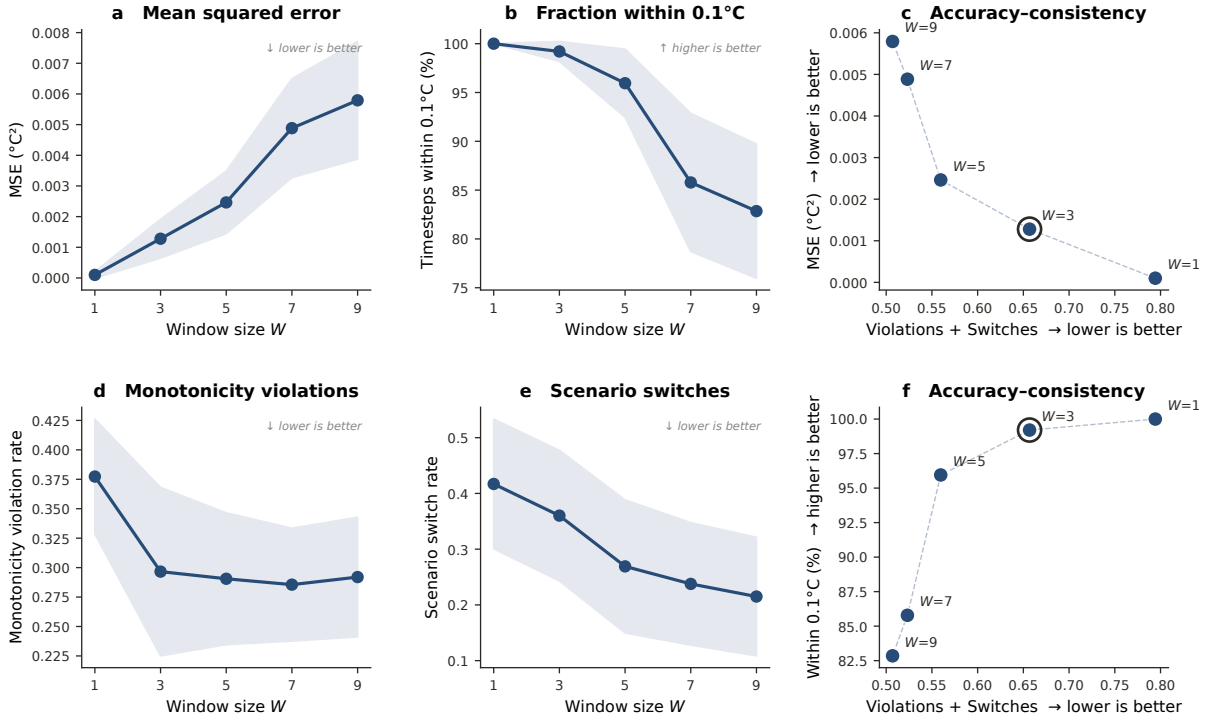


Figure B.34: Accuracy-consistency trade-off across window sizes $W \in \{1, 3, 5, 7, 9\}$. (a) Mean squared error of temperature matching (lower is better). (b) Fraction of timesteps with matched temperature within 0.1°C of the target (higher is better). (d) Monotonicity violation rate of the matched-year sequence (lower is better). (e) Scenario switch rate of the matched-scenario sequence (lower is better). (c, f) Accuracy-consistency Pareto frontier, with consistency (sum of monotonicity violations and scenario switches) on the x -axis and accuracy on the y -axis. The circled point marks $W = 3$. All values are averaged over emulation files (8 CMIP6 models $\times$ 7 synthetic scenarios).

B.4.7. Climate Indicators Validation

We provide distribution validation of emulated regional climate variables against original variables in ISIMIP in Figures B.37, B.38, B.40, B.39, B.41. Scenarios are here indicated with letters:

- A: 1.5→1.5
- B: 1.7→1.5
- C: 2→1.5
- D: 2.5→1.5
- E: 2→2
- F: 2.5→2
- G: 3→2.

For Heatwaves, we report the trimmed distribution (95%), as some ISIMIP values reach particularly extreme values. Overall, the distributions of the emulated variables match those of ISIMIP well. Lower values are generally dependent on the lower global mean temperatures reached by the scenarios used in this exercise compared to ISIMIP (Figures B.36, B.35).

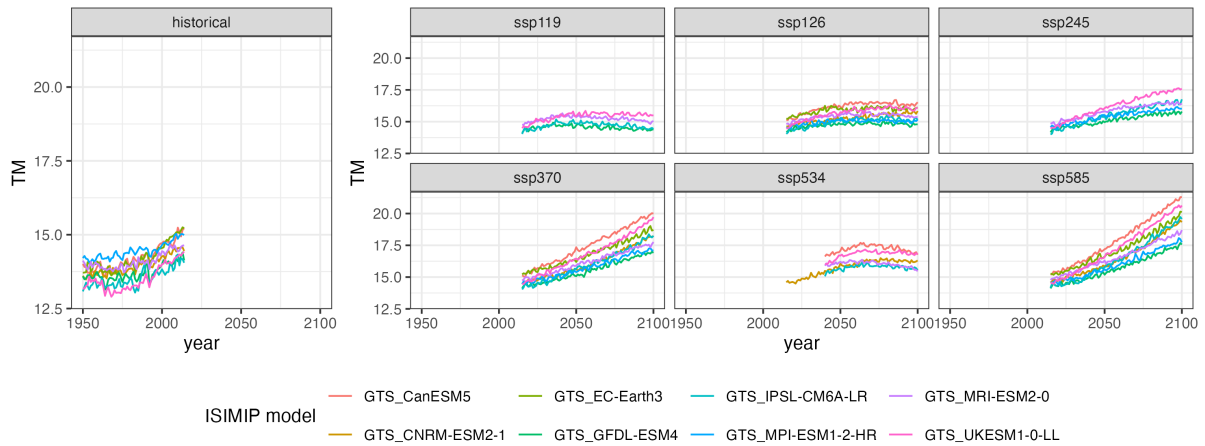


Figure B.35: ISIMIP-CMIP6 Global Mean Temperatures (°C) trajectories by scenario (SSPs combined with radiative forcing levels).

B.5. Impacts by Component

B.6. Pairwise Scenario Comparisons

To assess whether differences in projected peak damages and recovery rates across scenarios are statistically distinguishable, we conduct pairwise bootstrap difference tests for all model-scenario combinations. For each pair of scenarios and each climate model, the difference in the outcome metric between the two scenarios is computed draw-by-draw across the 1,000 bootstrap replicates, yielding a distribution of 1,000 pairwise differences per model. A difference is deemed statistically significant if the 90% bootstrap confidence interval of that model's pairwise distribution does not cross zero. Results are shown separately for each climate model, allowing assessment of whether

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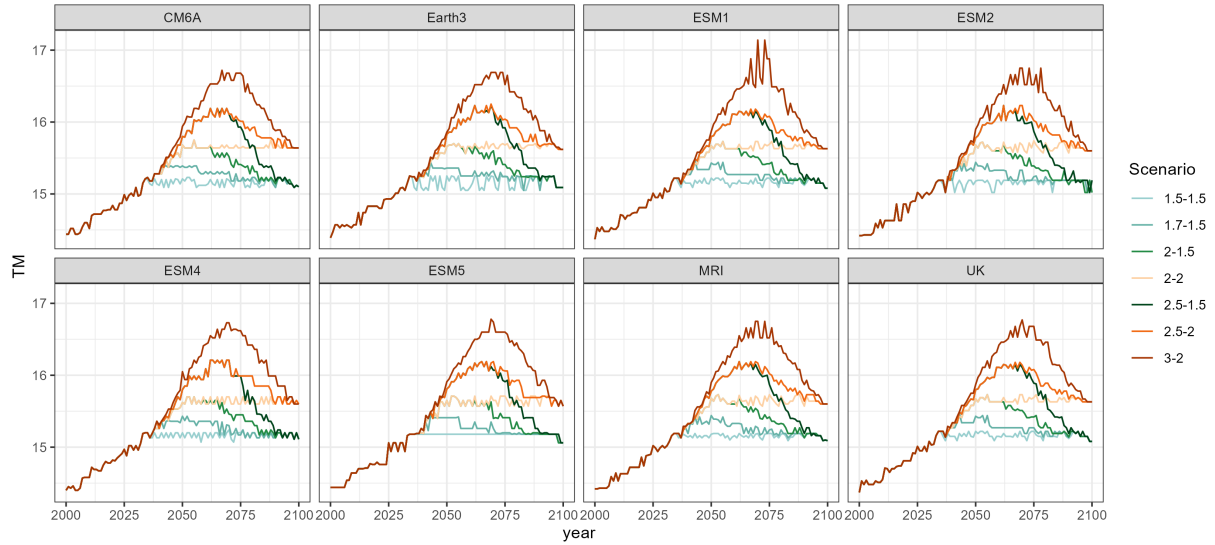


Figure B.36: Matched Global Mean Temperature ($^{\circ}\text{C}$) trajectories by model.

the direction and significance of scenario differences is consistent across the full model ensemble or driven by specific models.

Scenario pairs are grouped into three categories reflecting different dimensions of the overshoot design (Table 3.1):

- (i) *Same end-of-century temperature, different peak warming*: isolates the effect of peak magnitude on the overshoot pathway at fixed long-run stabilization level (1.5°C). Pairs: $1.7 \rightarrow 1.5$ vs $2 \rightarrow 1.5$; $1.7 \rightarrow 1.5$ vs $2.5 \rightarrow 1.5$; $2 \rightarrow 1.5$ vs $2.5 \rightarrow 1.5$.
- (ii) *Same peak warming, different end-of-century temperature*: isolates the effect of the cooling trajectory at fixed peak magnitude (2.5°C). Pair: $2.5 \rightarrow 1.5$ vs $2.5 \rightarrow 2$.
- (iii) *Both dimensions differ*: comparisons across both peak and end-of-century temperature simultaneously. Pairs: all remaining combinations involving one 1.5°C -target and one 2°C -target scenario.

Results for HDI are shown in Figure B.45; analogous figures for the three components are provided in Figures B.46, B.47, B.48.

B.7. Recovery by Component

B.8. Variance Decomposition of Projected Impacts and Recovery

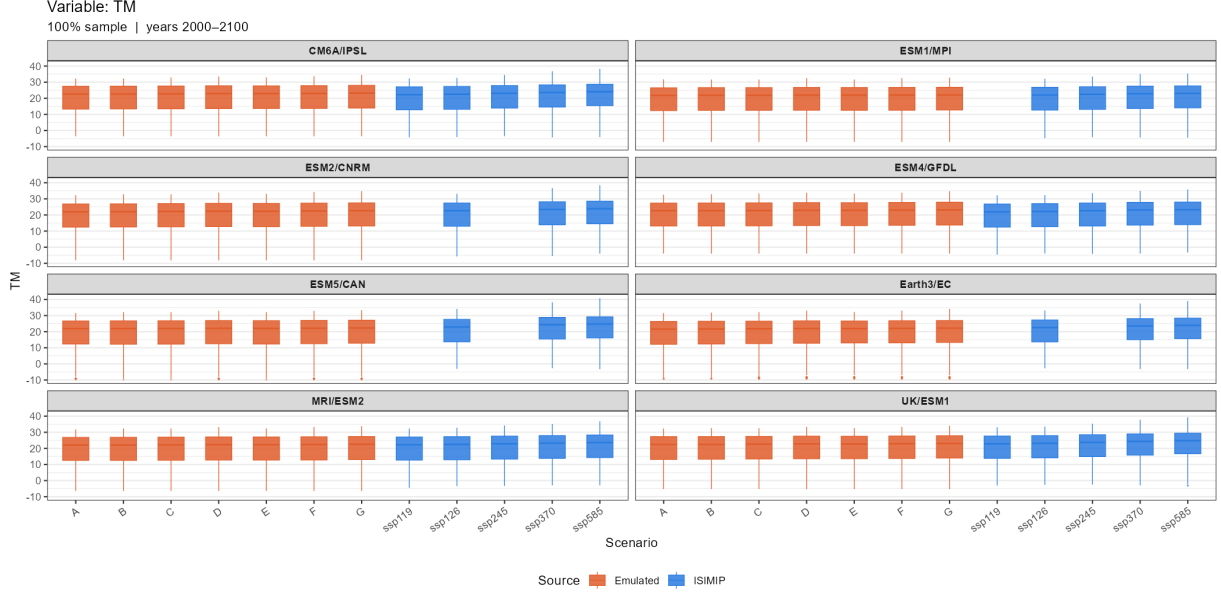


Figure B.37: Full distributions of Temperature ($^{\circ}\text{C}$) over 2000-2100 of emulated and original ISIMIP-CMIP6 regional climate data, by climate model, under available SSPs and our set of scenarios.

Sobol sensitivity analysis of recovery metrics

To formally quantify the relative contributions of empirical uncertainty in the estimated damage functions and structural uncertainty across climate models to the variance in recovery outcomes, we apply Sobol global sensitivity analysis (Saltelli et al., 2010a) to three scalar recovery metrics: the percentage of peak damages reversed by 2100 ($\rho\%$), the absolute recovery from peak to 2100 (ρ), and the cumulative HDI impact integrated over 2020–2100 (Δ^{cum}).

For each metric, scenario s , and HDI component, the scalar output is treated as a function of two inputs: (i) the bootstrap draw index $b \in \{1, \dots, 1000\}$, encoding parametric uncertainty in the impact functions; and (ii) the climate model index $m \in \{1, \dots, 10\}$, encoding structural model uncertainty. First-order Sobol indices S_i measure the fraction of output variance attributable to each input independently, and the second-order index S_{ij} captures the fraction attributable to their interaction. Indices are computed via quasi-random Sobol sampling ($N = 6,000$ samples) using the `sensobol` package (Puy et al., 2022a). The three indices are normalized to sum to unity after flooring negative values at zero, yielding shares of total explained variance.

Because $\rho\%$ and ρ are only defined for draws where peak damage is negative (i.e. where a genuine climate impact occurred at peak warming), bootstrap draws with non-negative peak impact are excluded from these two metrics. To preserve the independence of the two Sobol input dimensions without imputation, we restrict the analysis to bootstrap columns in which all retained climate models exhibit a genuine negative peak impact; only these fully valid draws enter the Sobol estimator. Climate models for which fewer than 25% of bootstrap draws show a genuine peak damage are excluded from the decomposition entirely. Scenarios for which fewer than 50 fully-valid bootstrap columns remain after these filters are omitted. The cumulative metric Δ^{cum} uses

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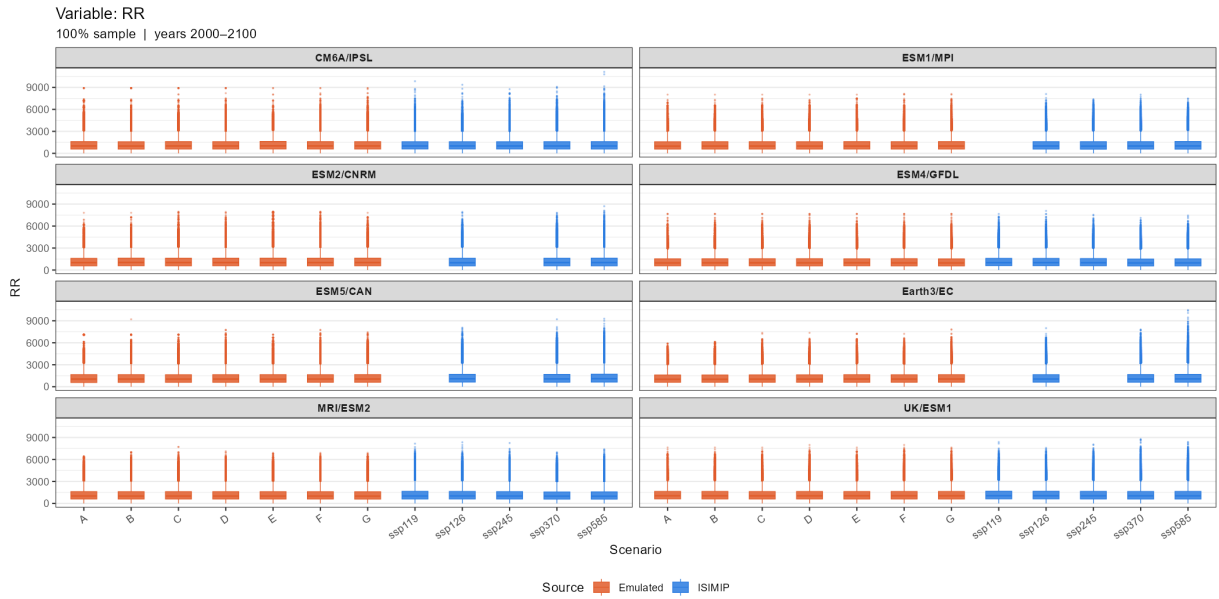


Figure B.38: Full distributions of Total Rainfall (mm) over 2000-2100 of emulated and original ISIMIP-CMIP6 regional climate data, by climate model, under available SSPs and our set of scenarios.

all bootstrap draws.

Figure B.54 shows the decomposition for all four HDI components across scenarios. The figure presents results for HDI, the income index, the education index, and the life expectancy index (rows), across the three recovery metrics (columns).

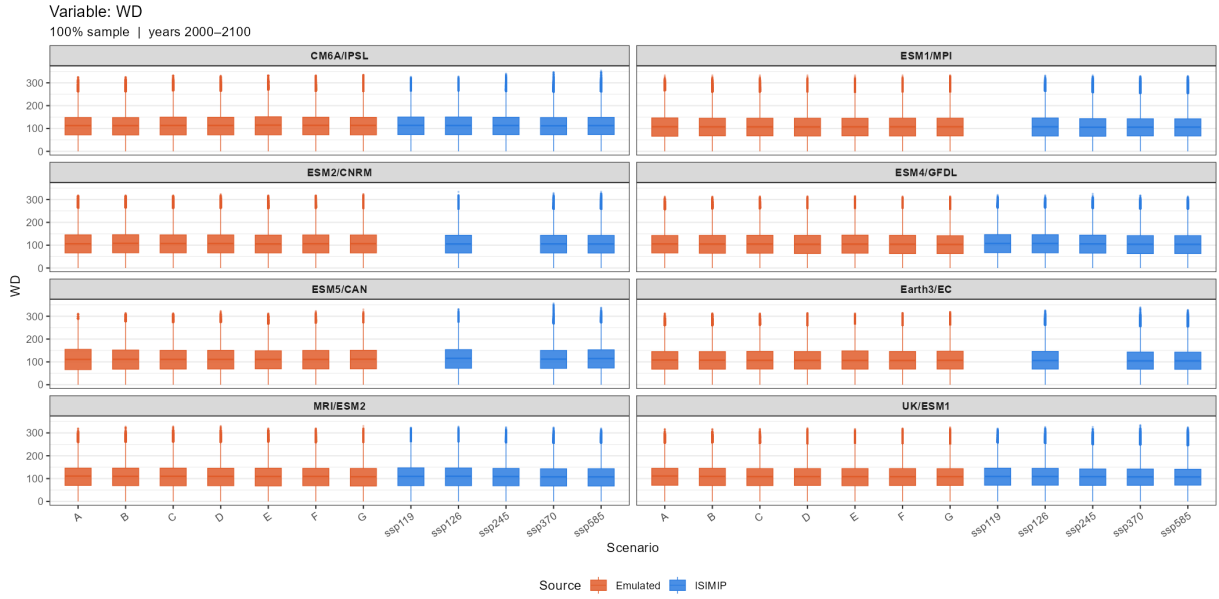


Figure B.39: Full distributions of Number of Wet Days over 2000-2100 of emulated and original ISIMIP-CMIP6 regional climate data, by climate model, under available SSPs and our set of scenarios.

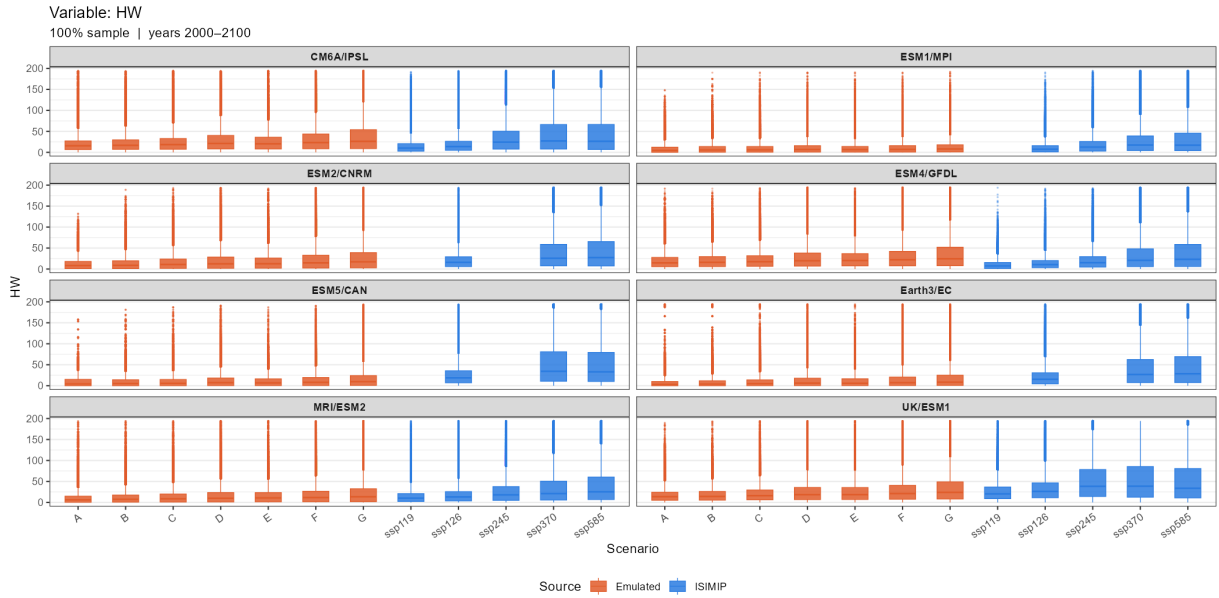


Figure B.40: Trimmed (at 95% quantiles) distributions of Heatwaves severity ($^{\circ}\text{C}$) over 2000-2100 of emulated and original ISIMIP-CMIP6 regional climate data, by climate model, under available SSPs and our set of scenarios.

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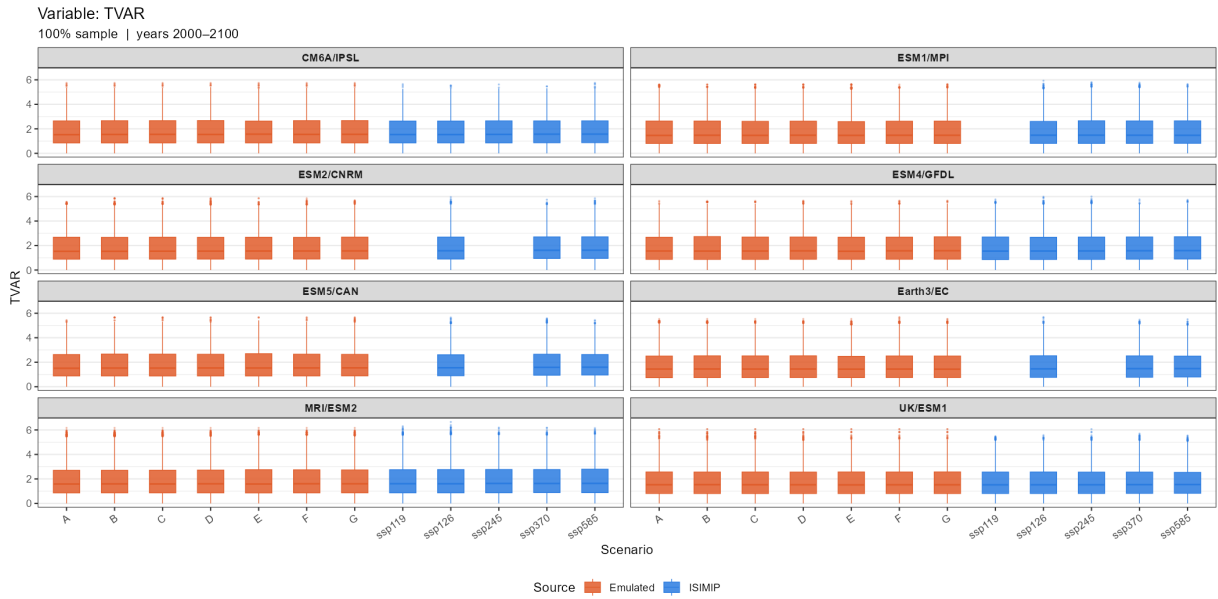


Figure B.41: Full distributions of Temperature Variability ($^{\circ}\text{C}$) over 2000–2100 of emulated and original ISIMIP-CMIP6 regional climate data, by climate model, under available SSPs and our set of scenarios.

Global climate impacts on Income Index (index change)

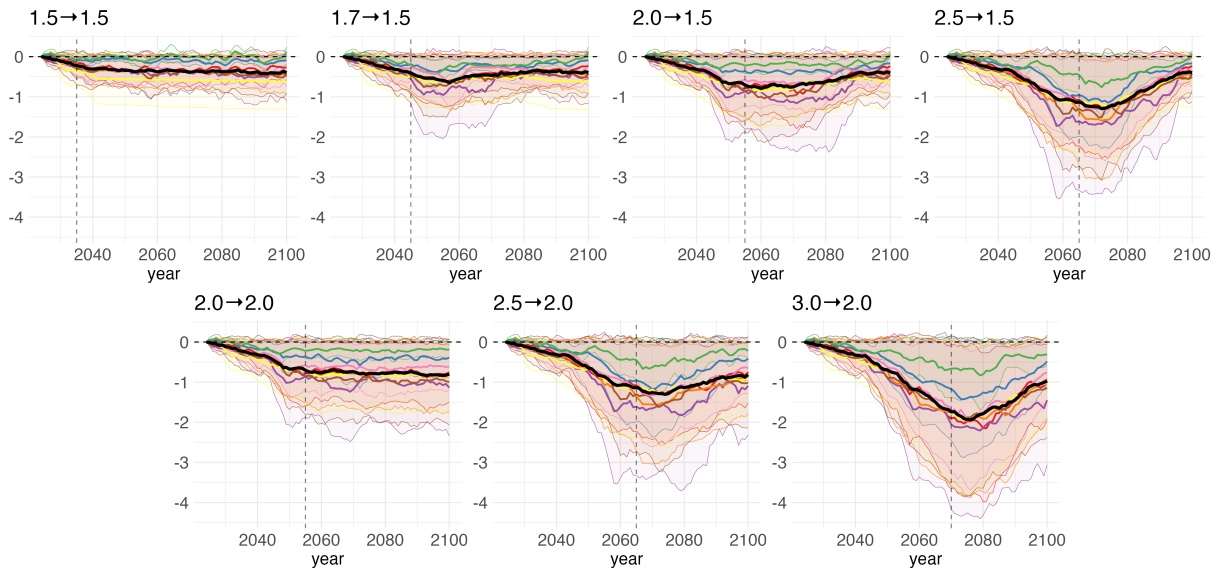


Figure B.42: Projected climate change impacts on global Income Index relative to a counterfactual baseline without climate change, in 2020–2100, under seven temperature overshoot scenarios labeled peak $^{\circ}\text{C}$ –end-of-century $^{\circ}\text{C}$). Coloured lines show individual climate model estimates; the black line shows the cross-model ensemble median; shaded ribbons indicate the 90% bootstrap interval. The vertical dashed line marks the year of peak warming for each scenario.

Global climate impacts on Education Index (index change)

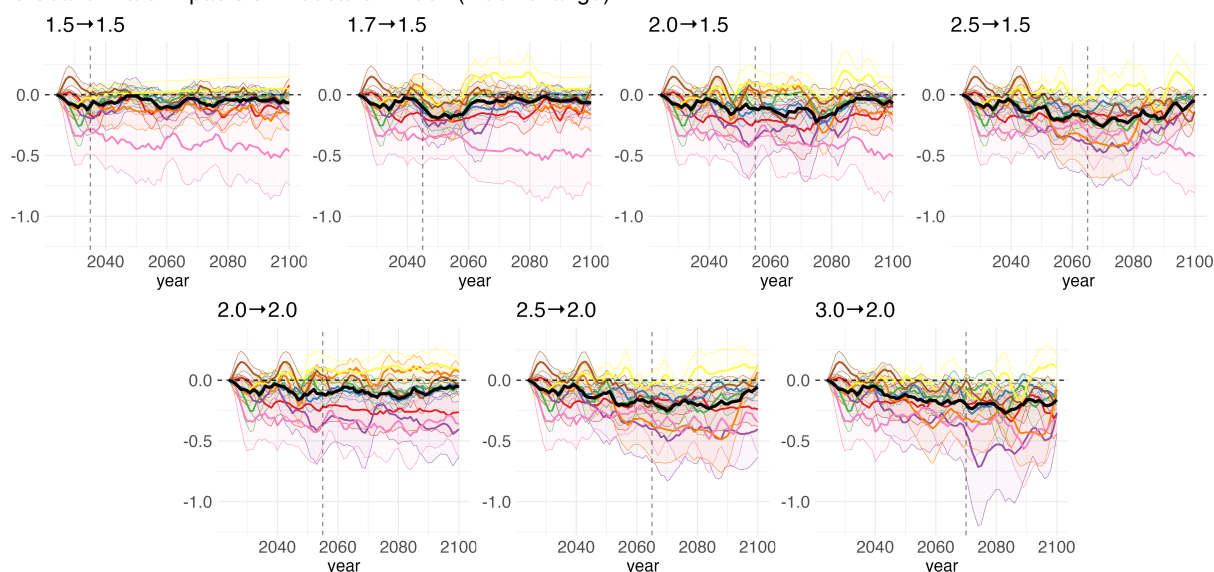


Figure B.43: Projected climate change impacts on global Education Index relative to a counterfactual baseline without climate change, in 2020–2100, under seven temperature overshoot scenarios labeled peak°C–end-of-century°C). Coloured lines show individual climate model estimates; the black line shows the cross-model ensemble median; shaded ribbons indicate the 90% bootstrap interval. The vertical dashed line marks the year of peak warming for each scenario.

Global climate impacts on Lifex Index (index change)

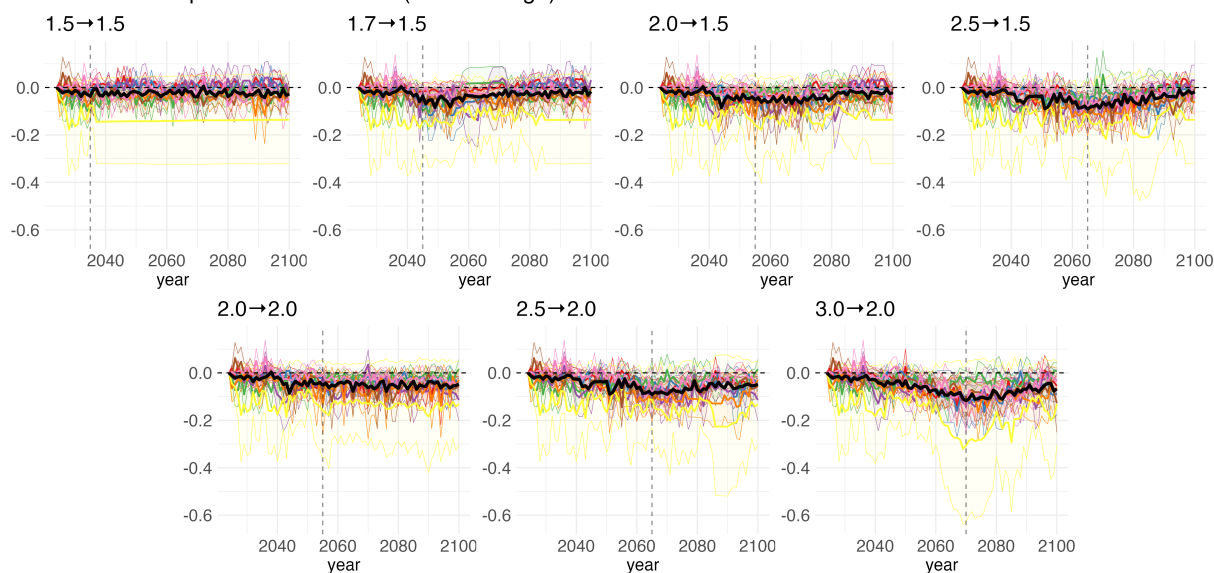


Figure B.44: Projected climate change impacts on global Lifex Index relative to a counterfactual baseline without climate change, in 2020–2100, under seven temperature overshoot scenarios labeled peak°C–end-of-century°C). Coloured lines show individual climate model estimates; the black line shows the cross-model ensemble median; shaded ribbons indicate the 90% bootstrap interval. The vertical dashed line marks the year of peak warming for each scenario.

Scenario pair comparisons — HDI

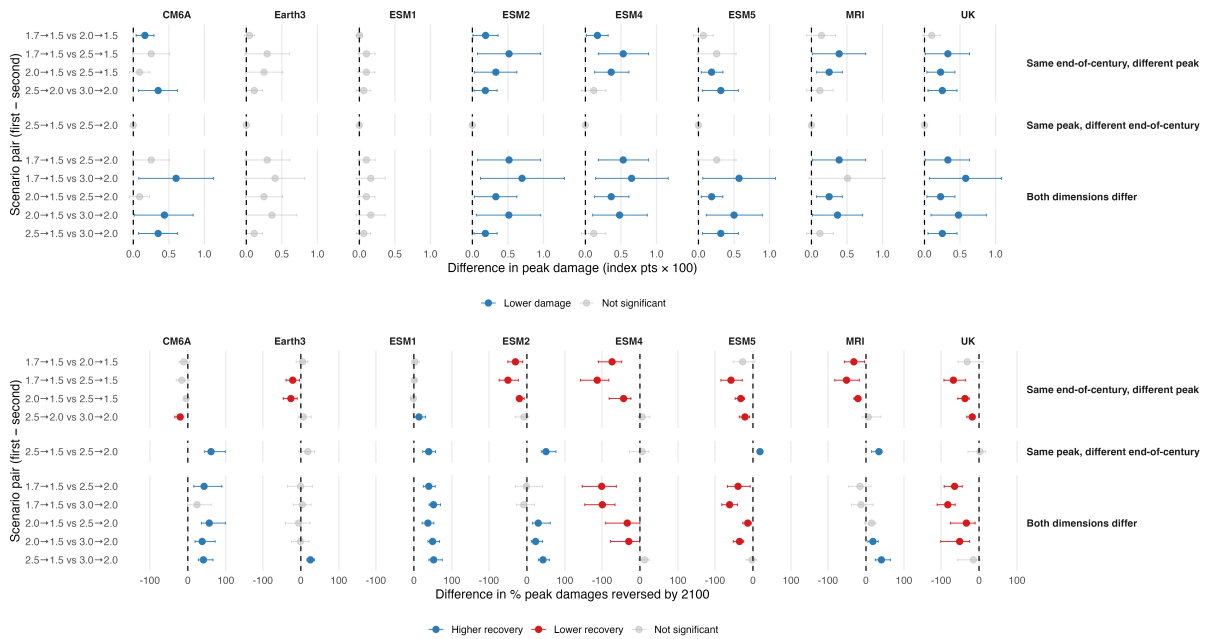


Figure B.45: Pairwise differences in projected peak climate damages and percentage of peak damages reversed by 2100, across selected pairs of temperature overshoot scenarios, for HDI. Comparisons are grouped into three categories: scenarios differing only in peak warming (same end-of-century temperature; top group), scenarios differing only in end-of-century temperature (same peak; middle group), and scenarios differing in both dimensions (bottom group). Points show the cross-model mean of bootstrap pairwise differences; horizontal bars indicate the 90% bootstrap confidence interval pooled across climate models. Scenarios are labeled peak°C–end-of-century°C. In the legend, Lower damage, Higher recovery, and Lower recovery refer to the first scenario of the considered pair.

Scenario pair comparisons — Income Index

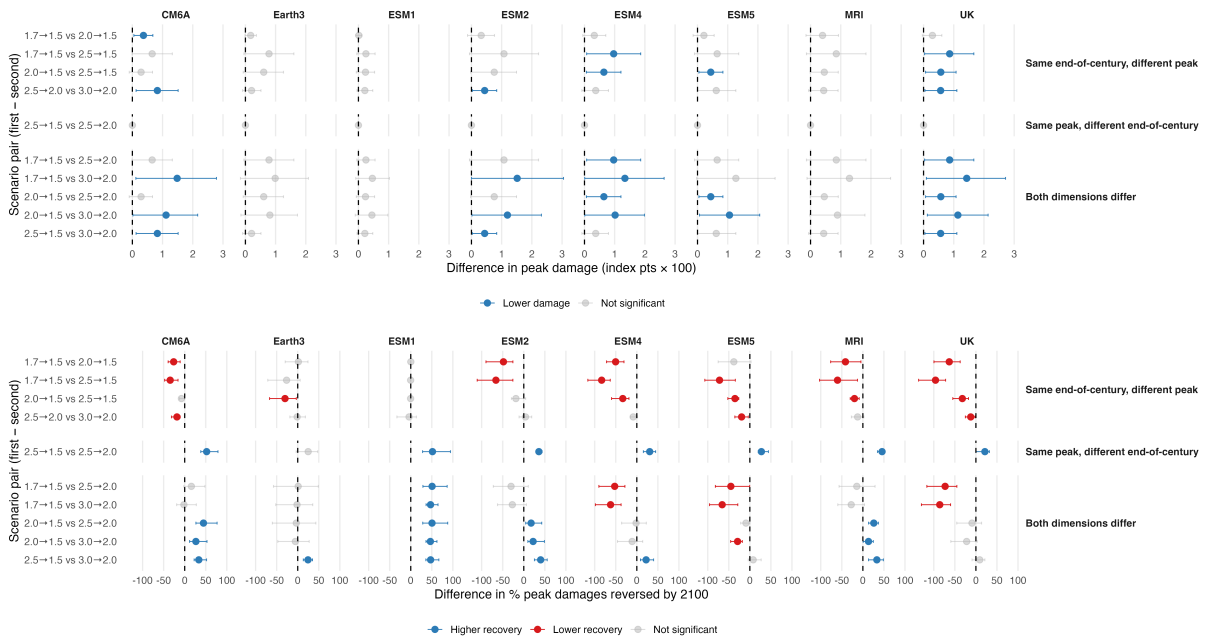


Figure B.46: Pairwise differences in projected peak climate damages and percentage of peak damages reversed by 2100, across selected pairs of temperature overshoot scenarios, for Income Index. Comparisons are grouped into three categories: scenarios differing only in peak warming (same end-of-century temperature; top group), scenarios differing only in end-of century temperature (same peak; middle group), and scenarios differing in both dimensions (bottom group). Points show the cross-model mean of bootstrap pairwise differences; horizontal bars indicate the 90% bootstrap confidence interval pooled across climate models. Scenarios are labeled peak°C–end-of-century°C. In the legend, Lower damage, Higher recovery, and Lower recovery refer to the first scenario of the considered pair.

Appendix B

Scenario pair comparisons — Life Expectancy Index

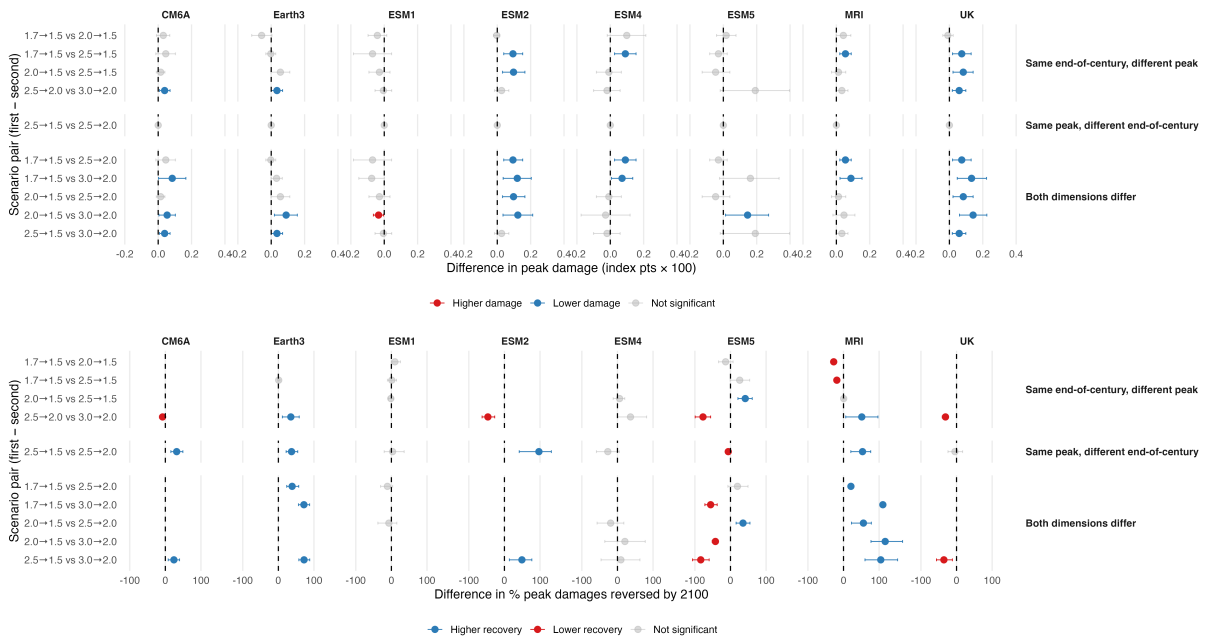


Figure B.47: Pairwise differences in projected peak climate damages and percentage of peak damages reversed by 2100, across selected pairs of temperature overshoot scenarios, for Lifex Index. Comparisons are grouped into three categories: scenarios differing only in peak warming (same end-of-century temperature; top group), scenarios differing only in end-of century temperature (same peak; middle group), and scenarios differing in both dimensions (bottom group). Points show the cross-model mean of bootstrap pairwise differences; horizontal bars indicate the 90% bootstrap confidence interval pooled across climate models. Scenarios are labeled peak°C–end-of-century°C. In the legend, Lower damage, Higher recovery, and Lower recovery refer to the first scenario of the considered pair.

Scenario pair comparisons — Education Index

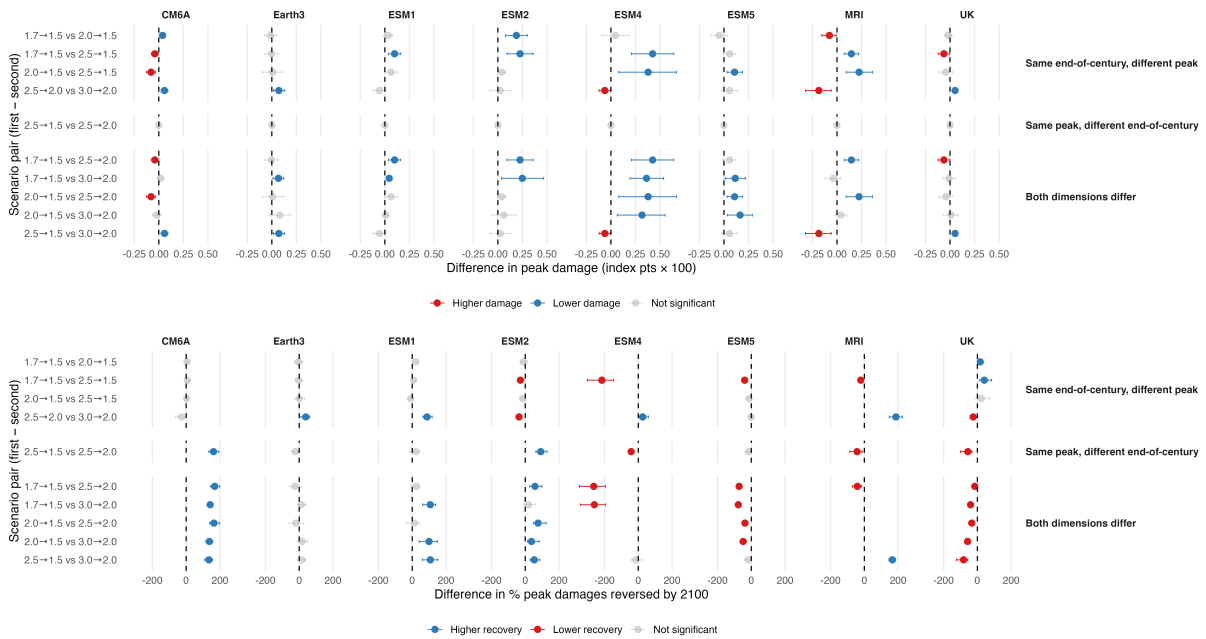


Figure B.48: Pairwise differences in projected peak climate damages and percentage of peak damages reversed by 2100, across selected pairs of temperature overshoot scenarios, for Edu Index. Comparisons are grouped into three categories: scenarios differing only in peak warming (same end-of-century temperature; top group), scenarios differing only in end-of century temperature (same peak; middle group), and scenarios differing in both dimensions (bottom group). Points show the cross-model mean of bootstrap pairwise differences; horizontal bars indicate the 90% bootstrap confidence interval pooled across climate models. Scenarios are labeled peak°C–end-of-century°C. In the legend, Lower damage, Higher recovery, and Lower recovery refer to the first scenario of the considered pair.

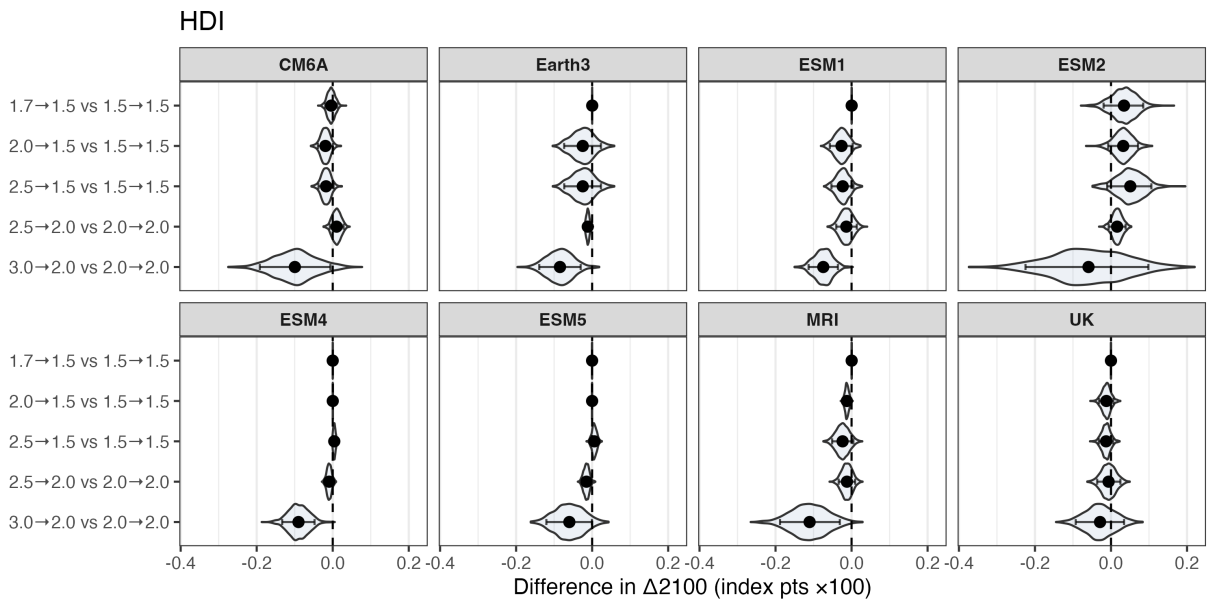


Figure B.49: Model-level uncertainty in projected overshoot impacts differences at the end of the century. Each panel displays results for an individual climate model. Violin plots show the bootstrap distribution of differences in projected end-of-century impacts ($\Delta 2100$) between overshoot trajectories and their corresponding stable climate references. Points denote model-specific mean differences and error bars show 90% bootstrap intervals (5th–95th percentiles). This representation separates within-model uncertainty (distribution width) from between-model variation (differences across panels), allowing assessment of the consistency of overshoot effects across climate models.

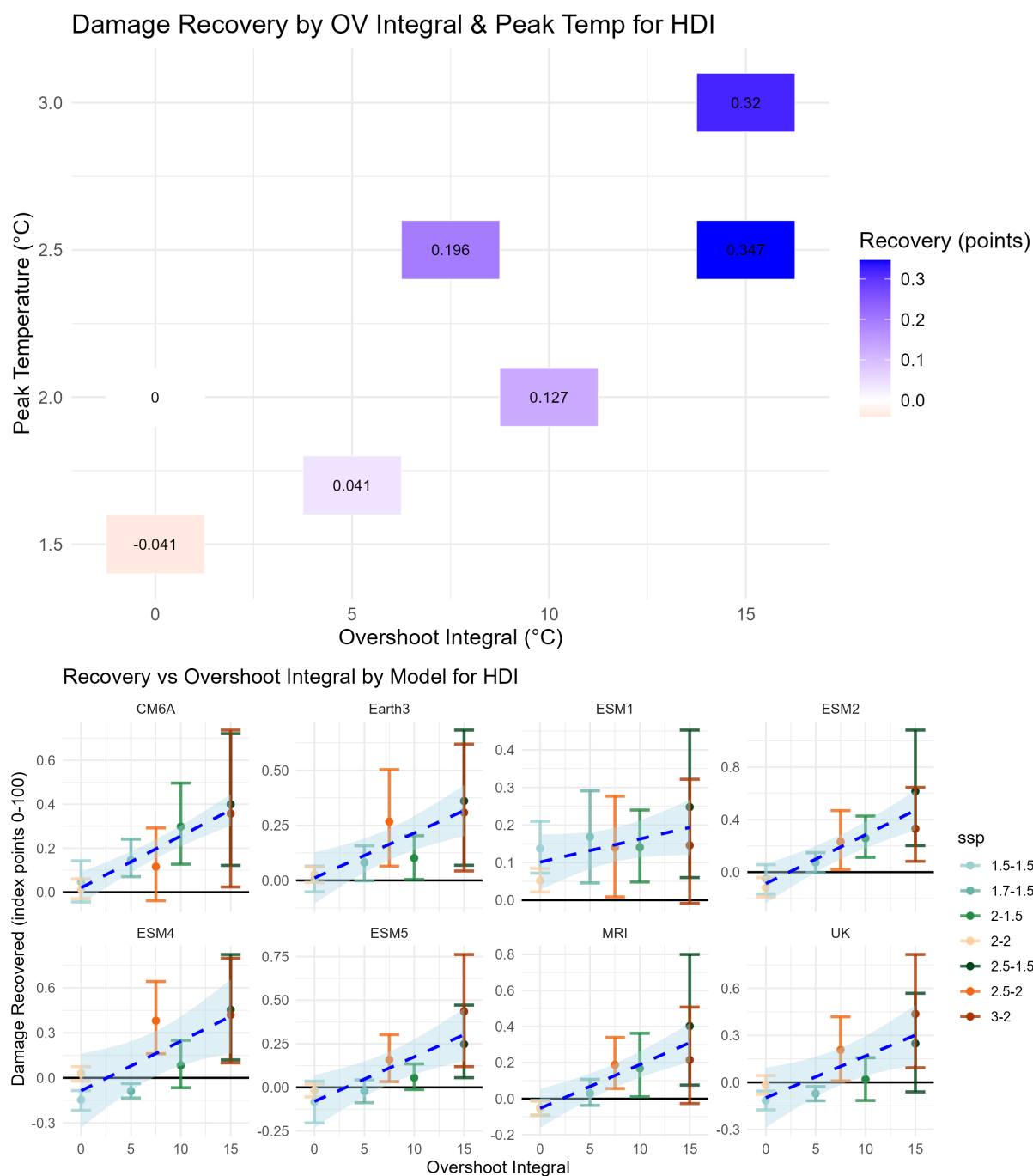


Figure B.50: Median absolute recovery of peak impacts for HDI, in relation to overshoot integral and peak temperature, pooled across models (top) and by model (bottom). The regression line in the bottom panel are fitted on the median recovery value between scenarios, by model.

Appendix B

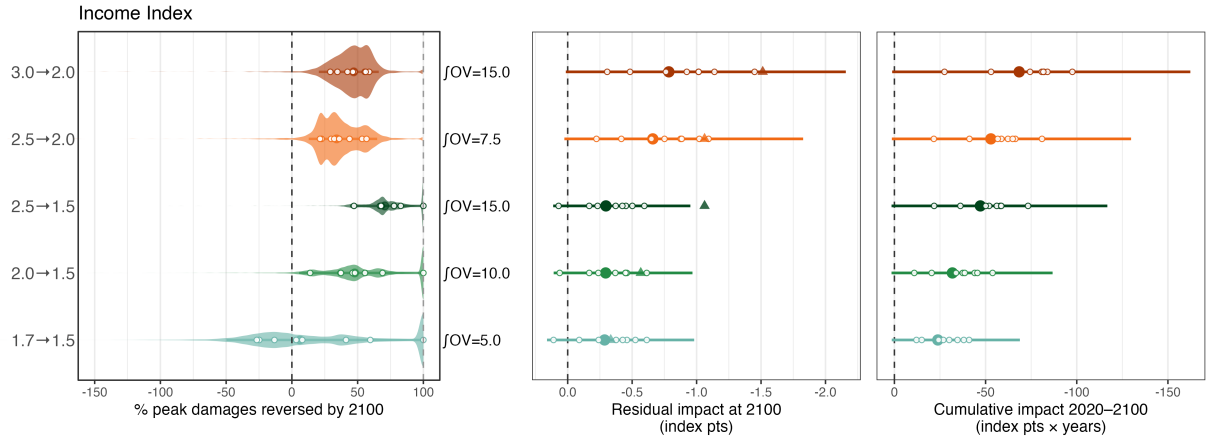


Figure B.51: Climate change impacts on global Income Index across temperature overshoot scenarios. *Left*: distribution of the percentage of peak damages reversed by 2100, pooled across climate models and bootstrap draws; the thick line and dot show the 90% confidence interval and median; open dots show individual climate model medians; the isolated mass at 100% represents draws where impacts are fully reversed by 2100 ($\delta_{2100} \geq 0$); the $\int OV$ annotation indicates the temperature overshoot integral ($^{\circ}\text{C}\cdot\text{years}$). *Centre*: residual impact at 2100 (index points $\times 100$); filled dot = pooled median with 90% CI; open dots = per-model medians; triangle = impact at peak warming for reference. *Right*: cumulative impact integrated over 2020–2100 (index points $\times$ years); filled dot = pooled median with 90% CI; open dots = per-model medians.

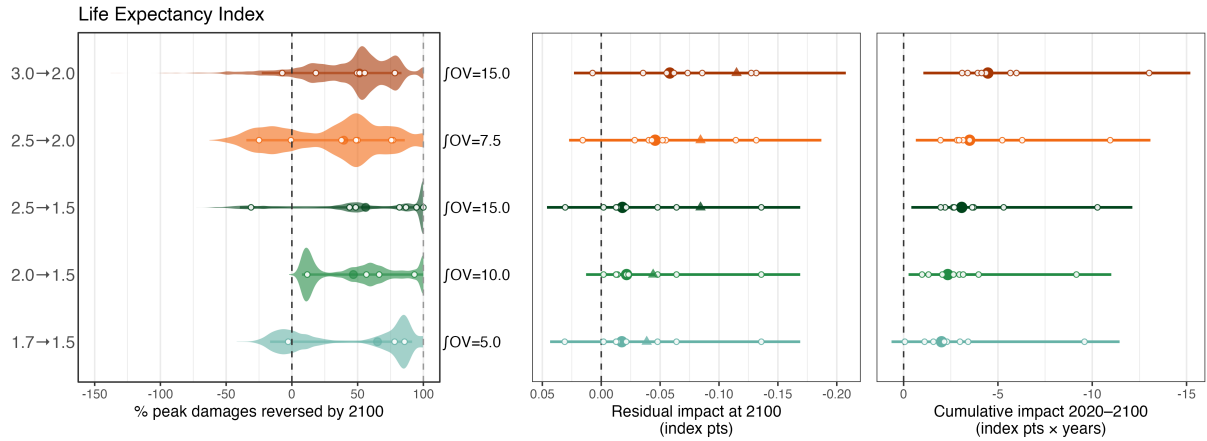


Figure B.52: Climate change impacts on global Lifex Index across temperature overshoot scenarios. *Left*: distribution of the percentage of peak damages reversed by 2100, pooled across climate models and bootstrap draws; the thick line and dot show the 90% confidence interval and median; open dots show individual climate model medians; the isolated mass at 100% represents draws where impacts are fully reversed by 2100 ($\delta_{2100} \geq 0$); the $\int OV$ annotation indicates the temperature overshoot integral ($^{\circ}\text{C}\cdot\text{years}$). *Centre*: residual impact at 2100 (index points $\times 100$); filled dot = pooled median with 90% CI; open dots = per-model medians; triangle = impact at peak warming for reference. *Right*: cumulative impact integrated over 2020–2100 (index points $\times$ years); filled dot = pooled median with 90% CI; open dots = per-model medians.

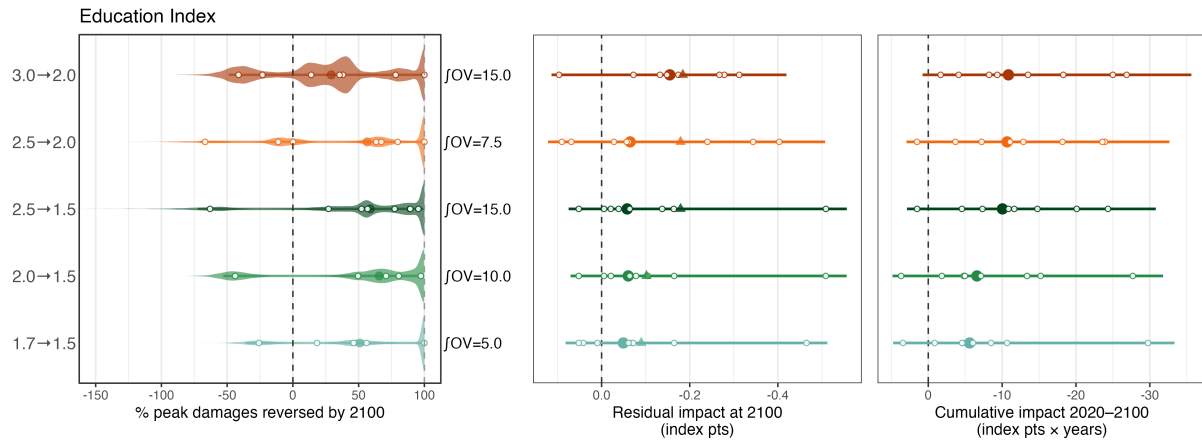


Figure B.53: Climate change impacts on global Income Index across temperature overshoot scenarios. *Left*: distribution of the percentage of peak damages reversed by 2100, pooled across climate models and bootstrap draws; the thick line and dot show the 90% confidence interval and median; open dots show individual climate model medians; the isolated mass at 100% represents draws where impacts are fully reversed by 2100 ($\delta_{2100} \geq 0$); the fOV annotation indicates the temperature overshoot integral ($^{\circ}\text{C}\cdot\text{years}$). *Centre*: residual impact at 2100 (index points $\times 100$); filled dot = pooled median with 90% CI; open dots = per-model medians; triangle = impact at peak warming for reference. *Right*: cumulative impact integrated over 2020–2100 (index points $\times$ years); filled dot = pooled median with 90% CI; open dots = per-model medians.

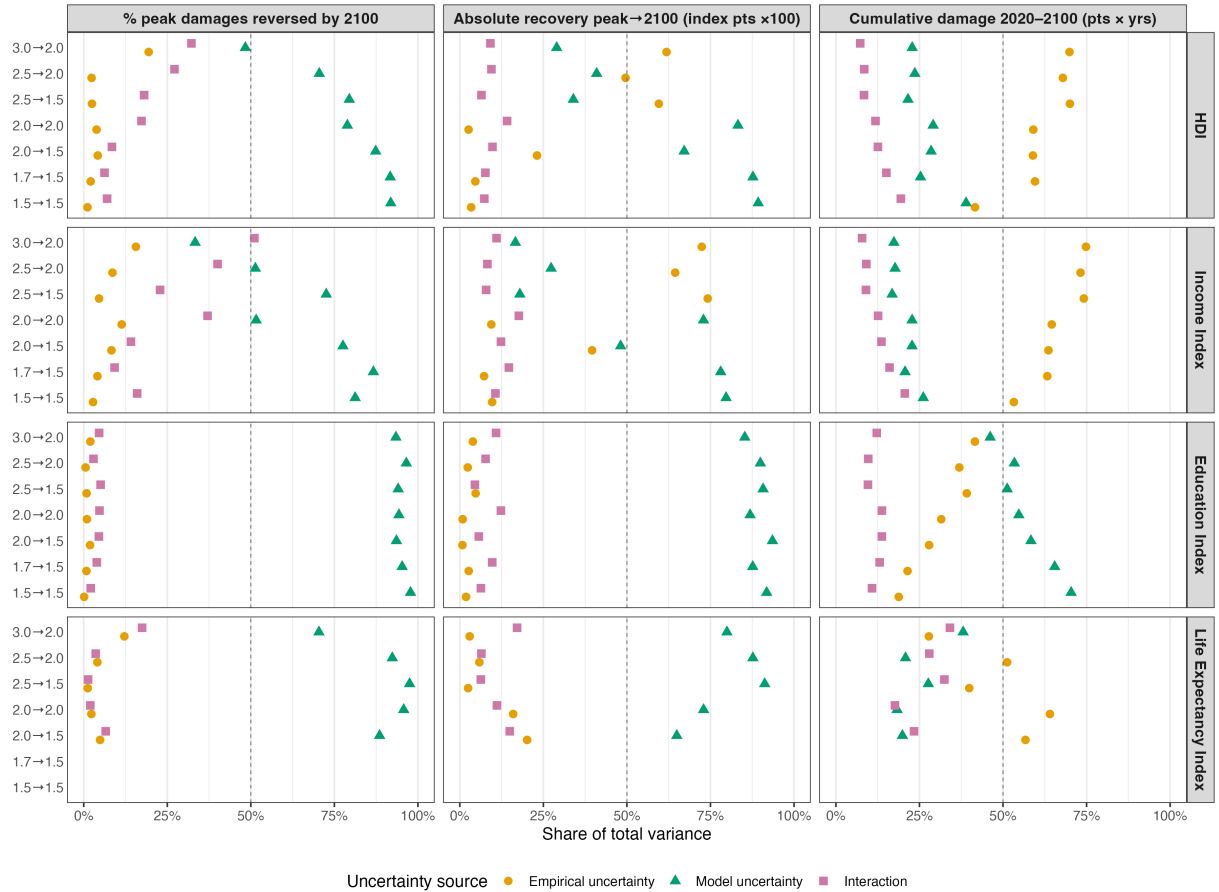


Figure B.54: Sobol sensitivity indices decomposing variance in three recovery metrics across temperature overshoot scenarios (labeled peak°C–end-of-century°C), for four human development indices (rows). Points show normalized first-order (S_i) Sobol indices for empirical uncertainty (bootstrap draws from the impact function; orange circles), climate model uncertainty (green triangles), and their second-order interaction term (purple squares). Recovery metrics are: percentage of peak damages reversed by 2100 (left); absolute recovery from peak to 2100 in index points ×100 (center); cumulative HDI impact integrated over 2020–2100 in index points × years (right).

Appendix C

C.9. Robustness for Empirical Models

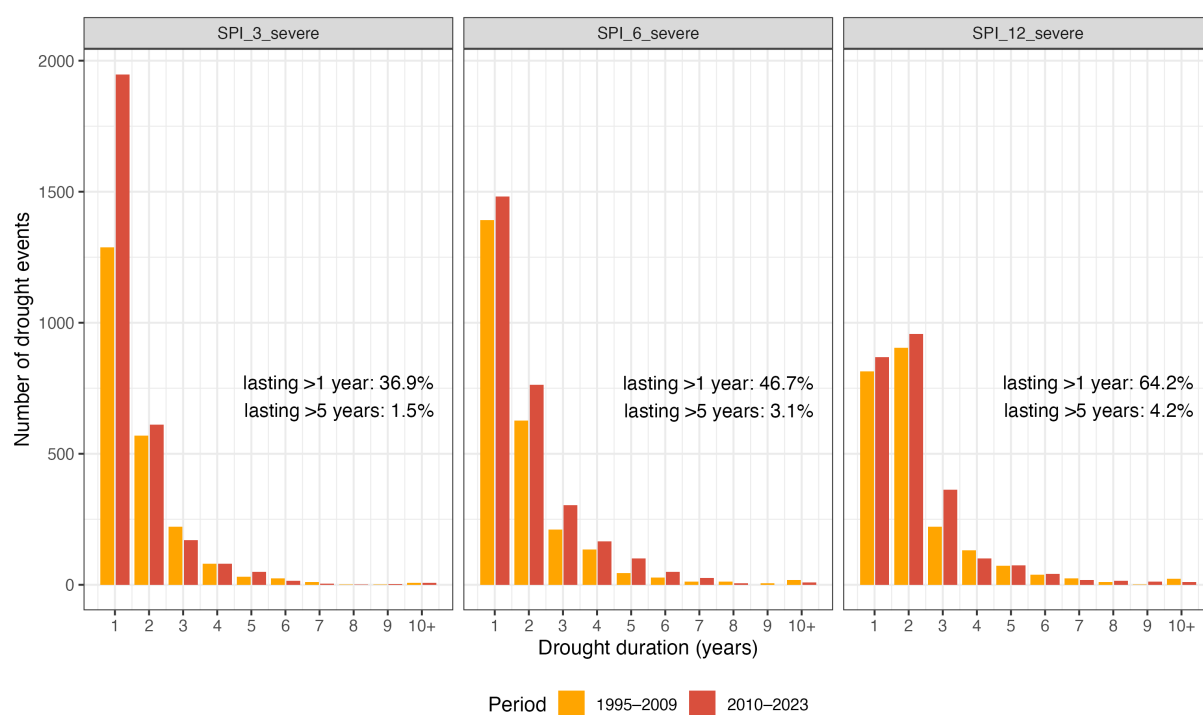


Figure C.55: Drought persistence in European Nuts3 regions for the SPI drought index, in 1995-2023.

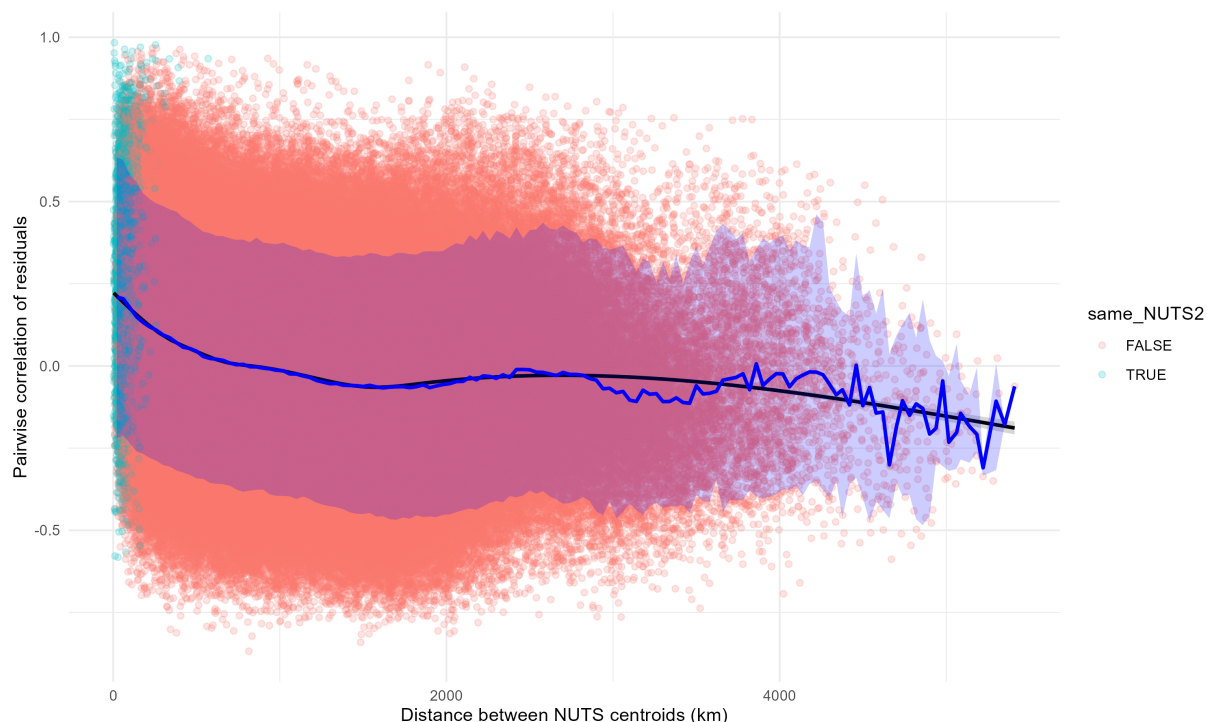


Figure C.56: Residuals correlation plot as a function of distance between NUTS3 centroids, for the GDP p.c - SPEI3 ARDL model.

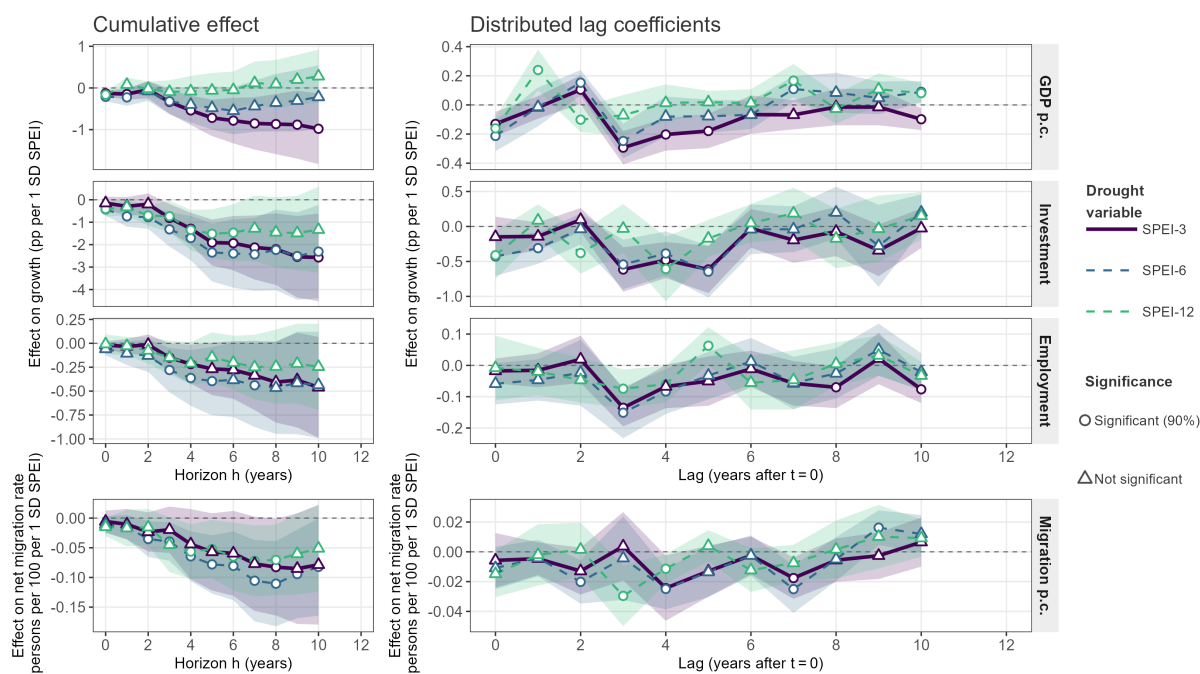


Figure C.57: ARDL model results for macroeconomic outcomes. Right-hand panels show the effect of a one-unit drought shock at each lag; left-hand panels show the cumulative effect under a persistent shock lasting 1-12 years. Standard errors are calculated following Conley (1999) to account for heteroskedasticity, temporal autocorrelation, and spatial autocorrelation between regions up to a distance of 500 km.

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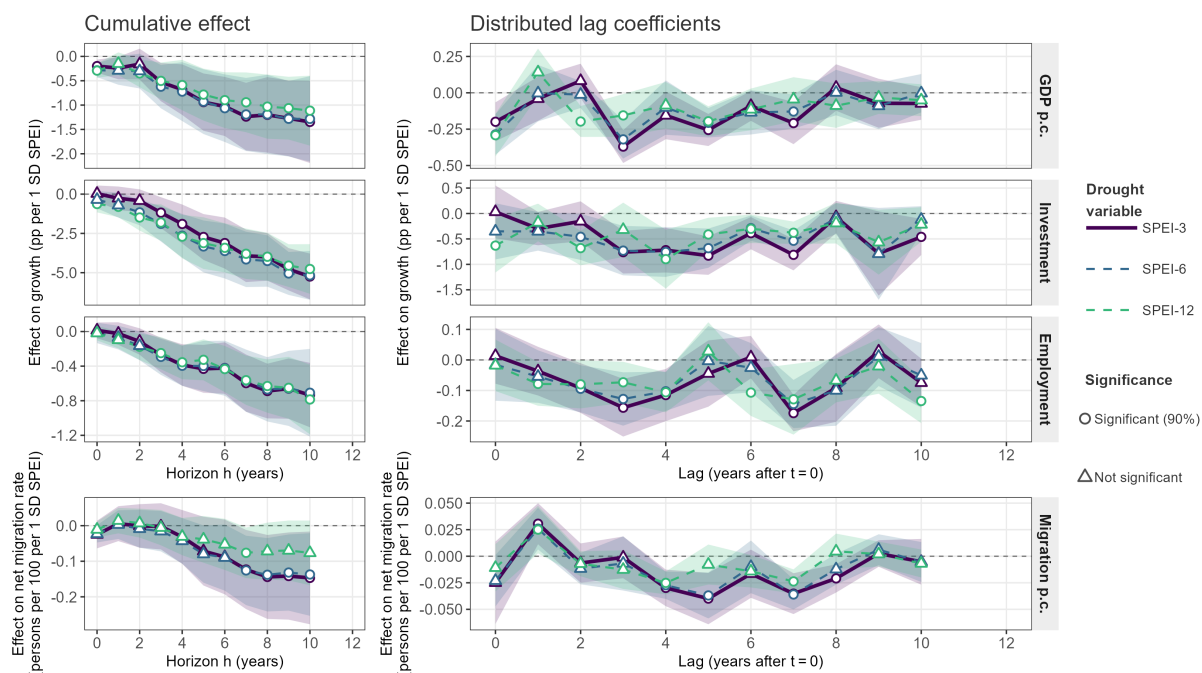


Figure C.58: ARDL model results for macroeconomic outcomes. Right-hand panels show the effect of a one-unit drought shock at each lag; left-hand panels show the cumulative effect under a persistent shock lasting 1-12 years. Standard errors are calculated following Conley (1999) to account for heteroskedasticity, temporal autocorrelation, and spatial autocorrelation between regions up to a distance of 500 km.

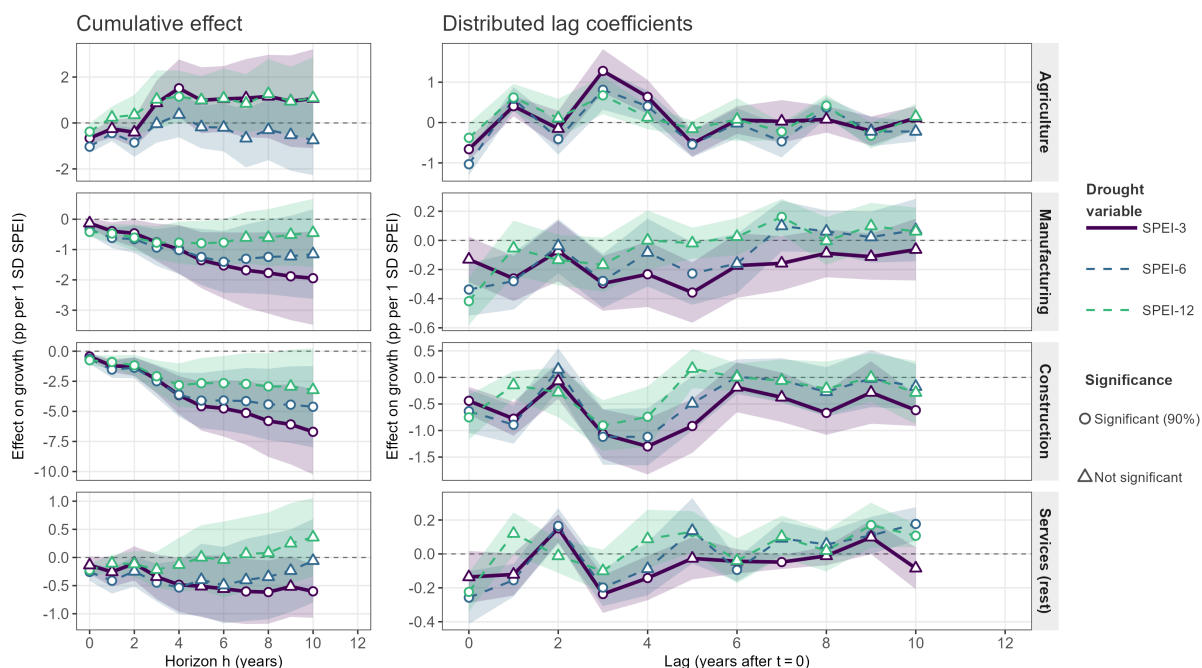


Figure C.59: ARDL model results for sectoral outputs (components of Gross Value Added). Right-hand panels show the effect of a one-unit severe drought shock at each lag; left-hand panels show the cumulative effect under a persistent shock lasting 1-12 years. Standard errors are calculated following Conley (1999) to account for heteroskedasticity, temporal autocorrelation, and spatial autocorrelation between regions up to a distance of 500 km.

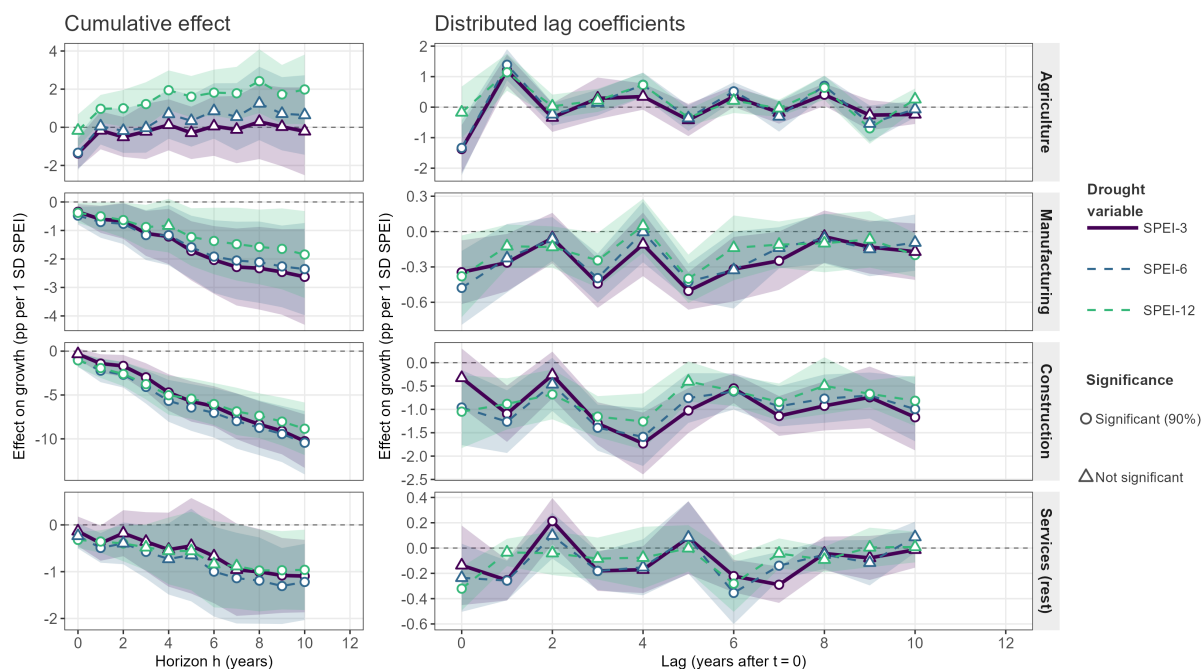


Figure C.60: ARDL model results for sectoral outputs (components of Gross Value Added). Right-hand panels show the effect of a one-unit severe drought shock at each lag; left-hand panels show the cumulative effect under a persistent shock lasting 1-12 years. Standard errors are calculated following Conley (1999) to account for heteroskedasticity, temporal autocorrelation, and spatial autocorrelation between regions up to a distance of 500 km.

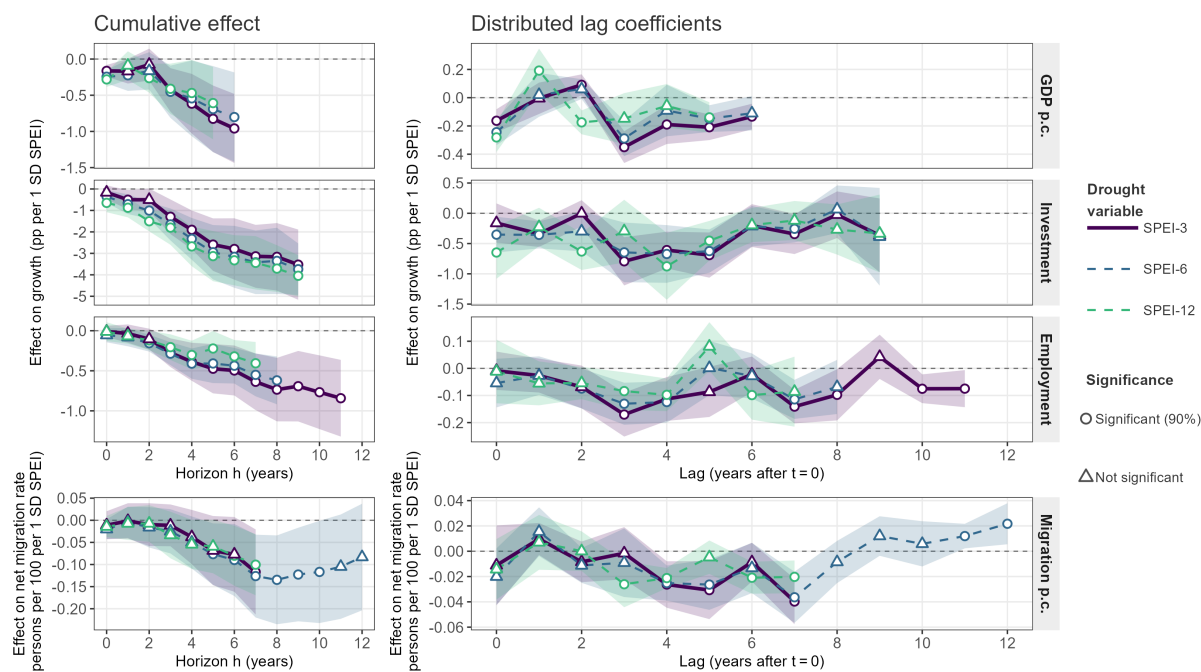


Figure C.61: ARDL model results for macroeconomic outcomes. Right-hand panels show the effect of a one-unit drought shock at each lag; left-hand panels show the cumulative effect under a persistent shock lasting 1-12 years. Standard errors are calculated following Conley (1999) to account for heteroskedasticity, temporal autocorrelation, and spatial autocorrelation between regions up to a distance of 500 km.

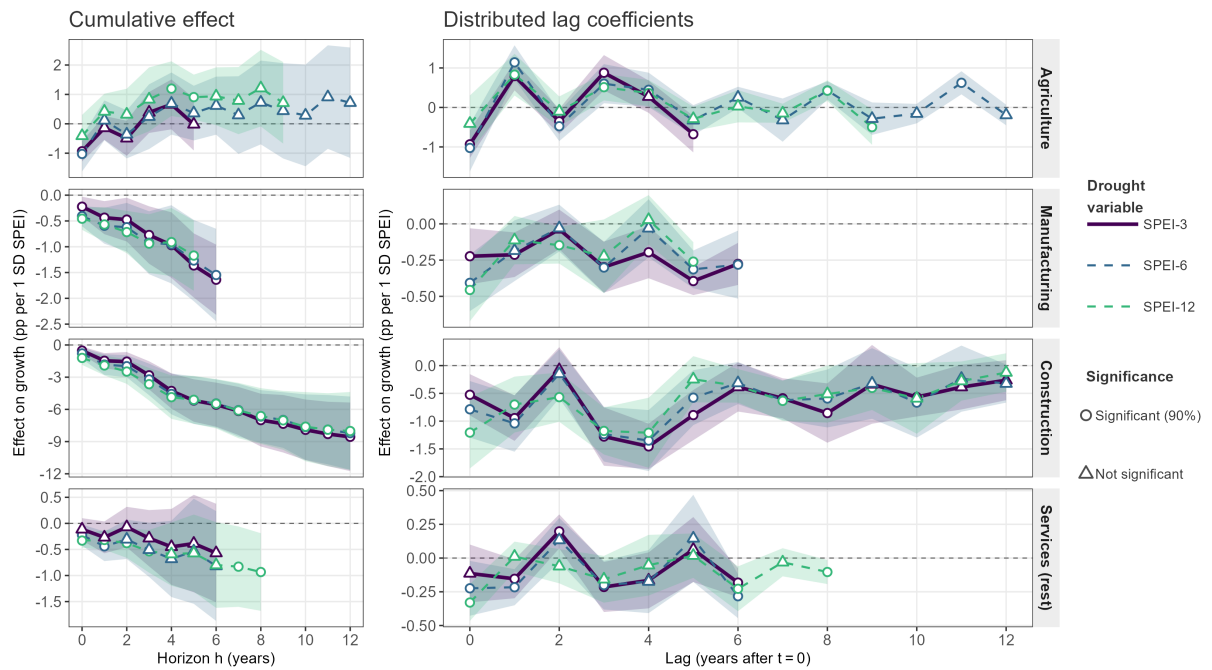


Figure C.62: ARDL model results for sectoral outputs (components of Gross Value Added). Right-hand panels show the effect of a one-unit drought shock at each lag; left-hand panels show the cumulative effect under a persistent shock lasting 1-12 years. Standard errors are calculated following Conley (1999) to account for heteroskedasticity, temporal autocorrelation, and spatial autocorrelation between regions up to a distance of 500 km.

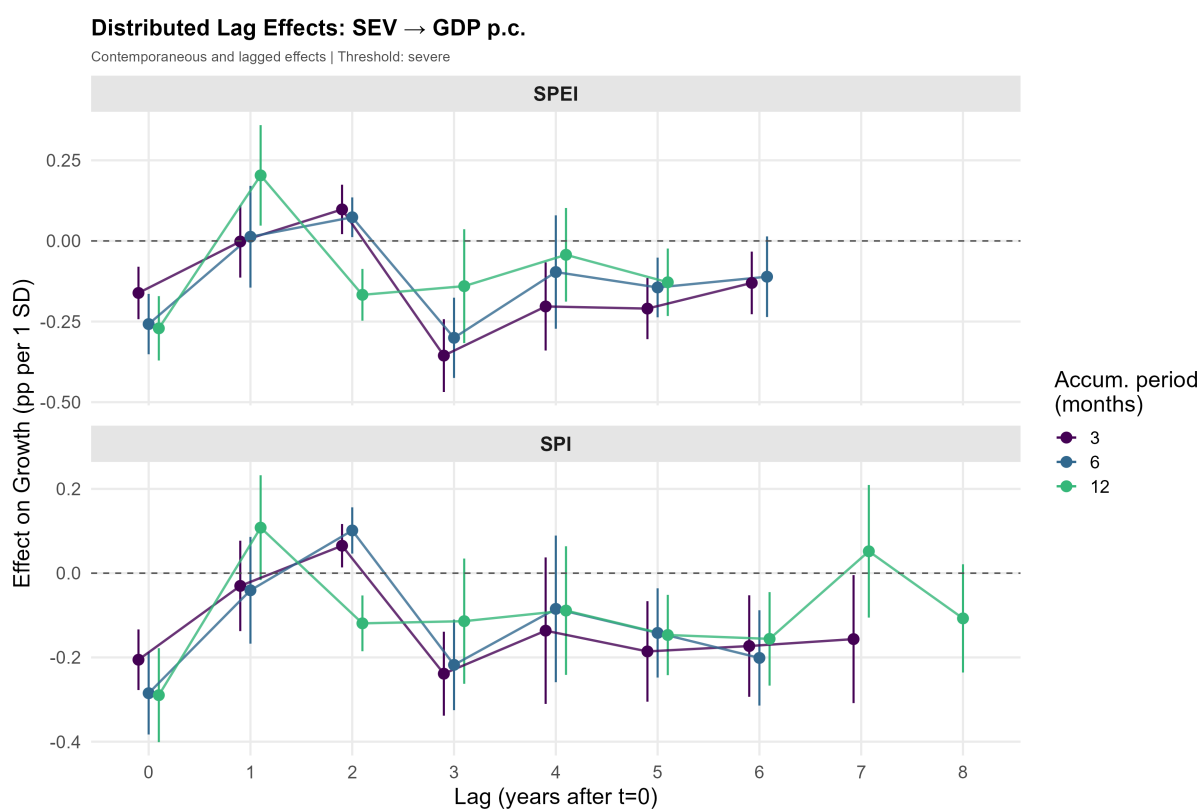


Figure C.63: ARDL model results for Gross Domestic Product Per Capita. Standard errors are calculated following Conley (1999) to account for heteroskedasticity, temporal autocorrelation, and spatial autocorrelation between regions up to a distance of 500 km.

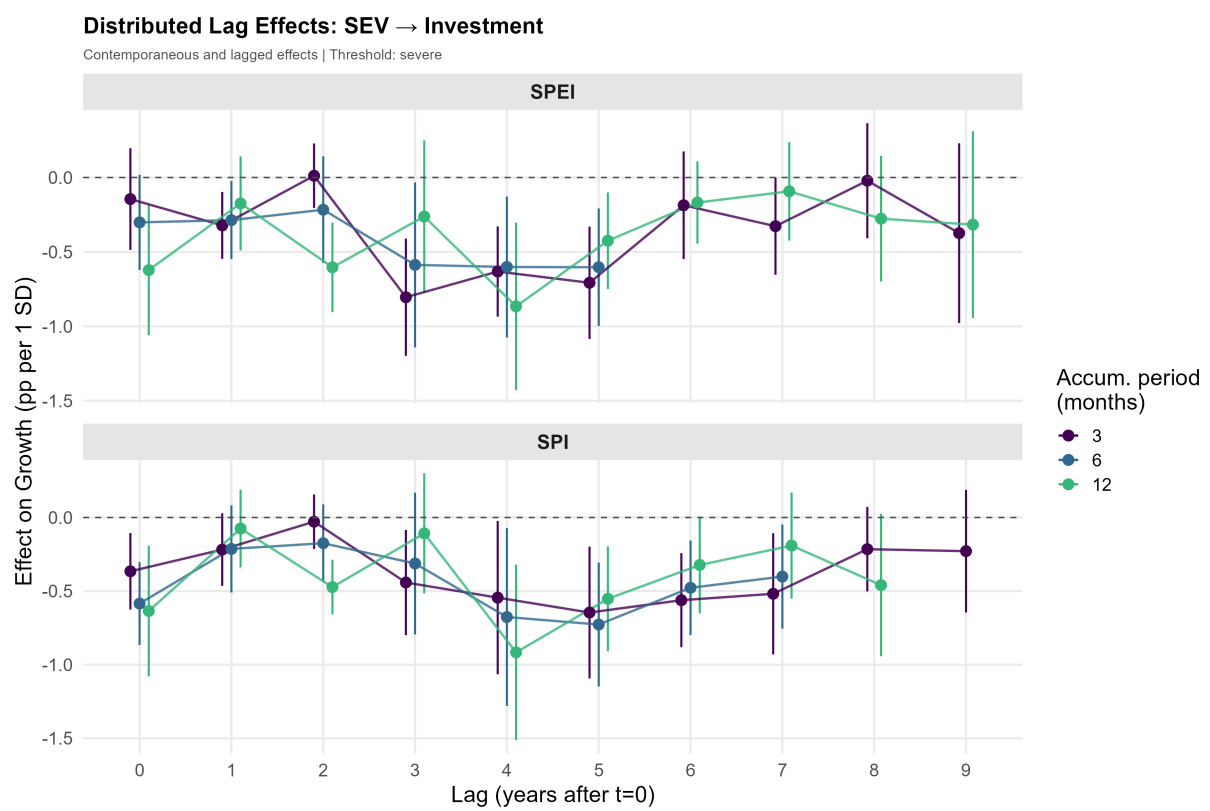


Figure C.64: ARDL model results for Investment. Standard errors are calculated following Conley (1999) to account for heteroskedasticity, temporal autocorrelation, and spatial autocorrelation between regions up to a distance of 500 km.

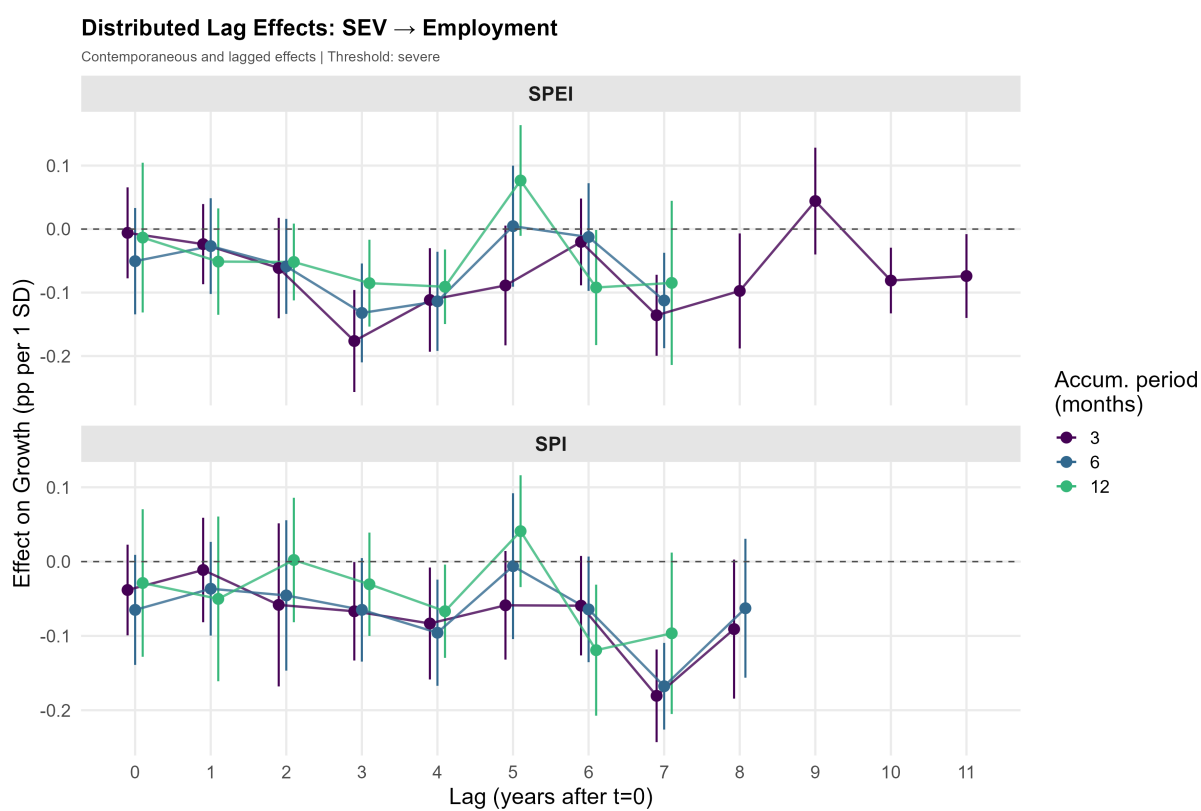


Figure C.65: ARDL model results for Employment. Standard errors are calculated following Conley (1999) to account for heteroskedasticity, temporal autocorrelation, and spatial autocorrelation between regions up to a distance of 500 km.

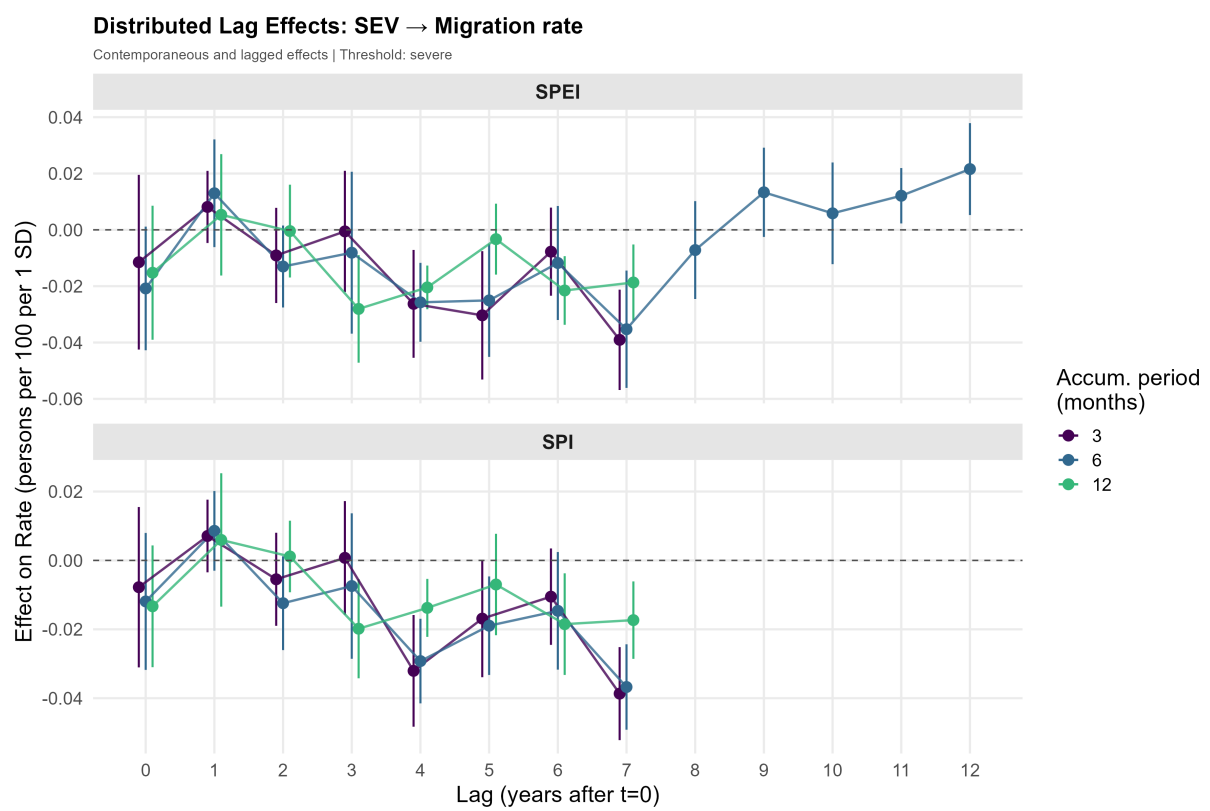


Figure C.66: ARDL model results for Migration Rate. Standard errors are calculated following Conley (1999) to account for heteroskedasticity, temporal autocorrelation, and spatial autocorrelation between regions up to a distance of 500 km.

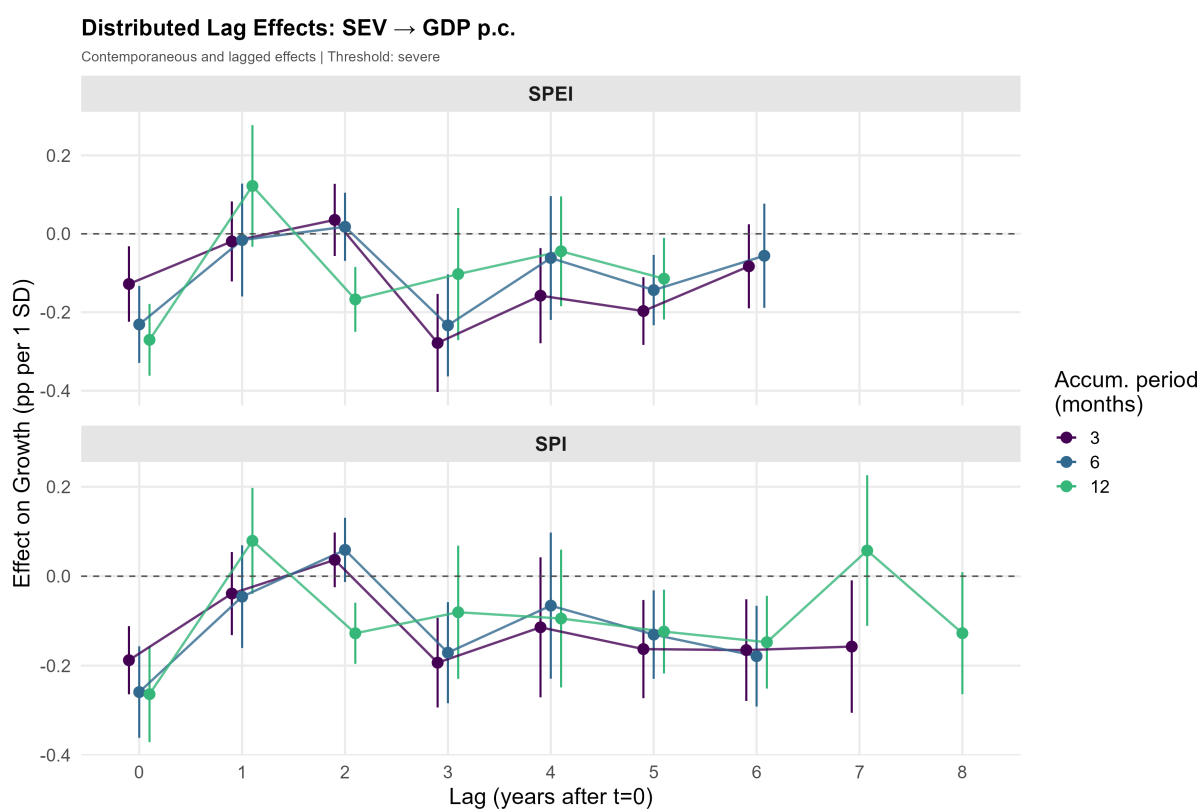


Figure C.67: ARDL model results for Gross Domestic Product Per Capita. Standard errors are calculated following Conley (1999) to account for heteroskedasticity, temporal autocorrelation, and spatial autocorrelation between regions up to a distance of 500 km. The underlying data here includes the UK and Turkey.

Appendix C

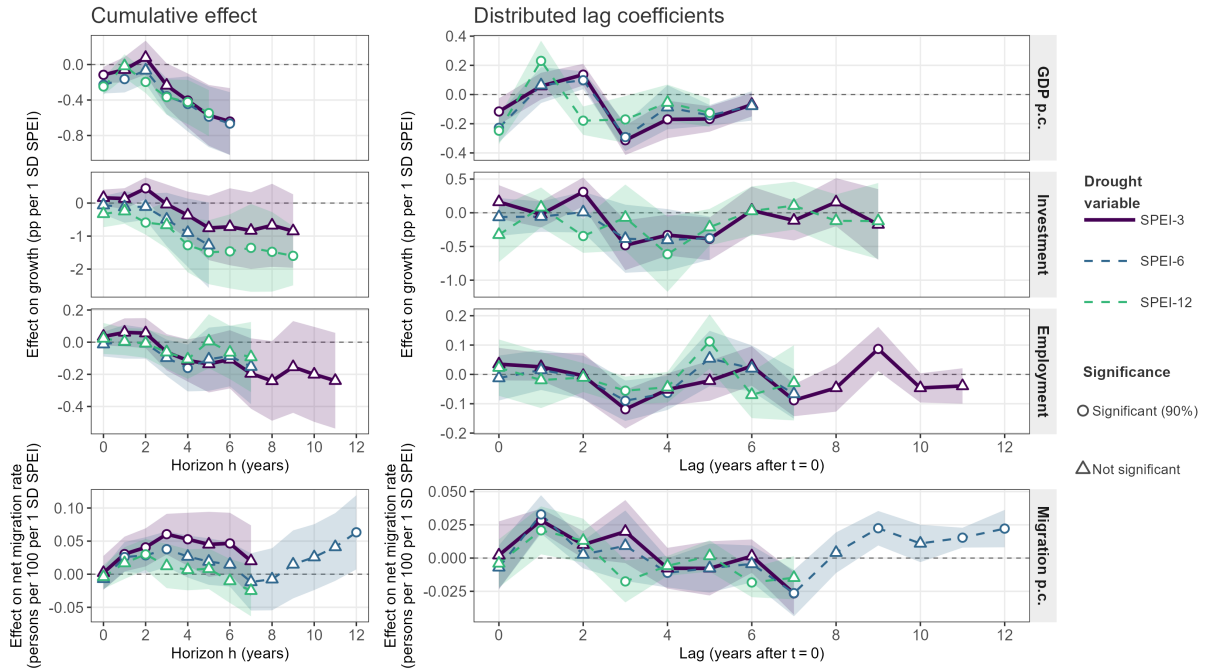


Figure C.68: ARDL model results for macroeconomic outcomes. Right-hand panels show the effect of a one-unit severe drought shock at each lag; left-hand panels show the cumulative effect under a persistent shock lasting 1-12 years. Standard errors are calculated following Conley (1999) to account for heteroskedasticity, temporal autocorrelation, and spatial autocorrelation between regions up to a distance of 500 km. Results for models with no regional time trends.

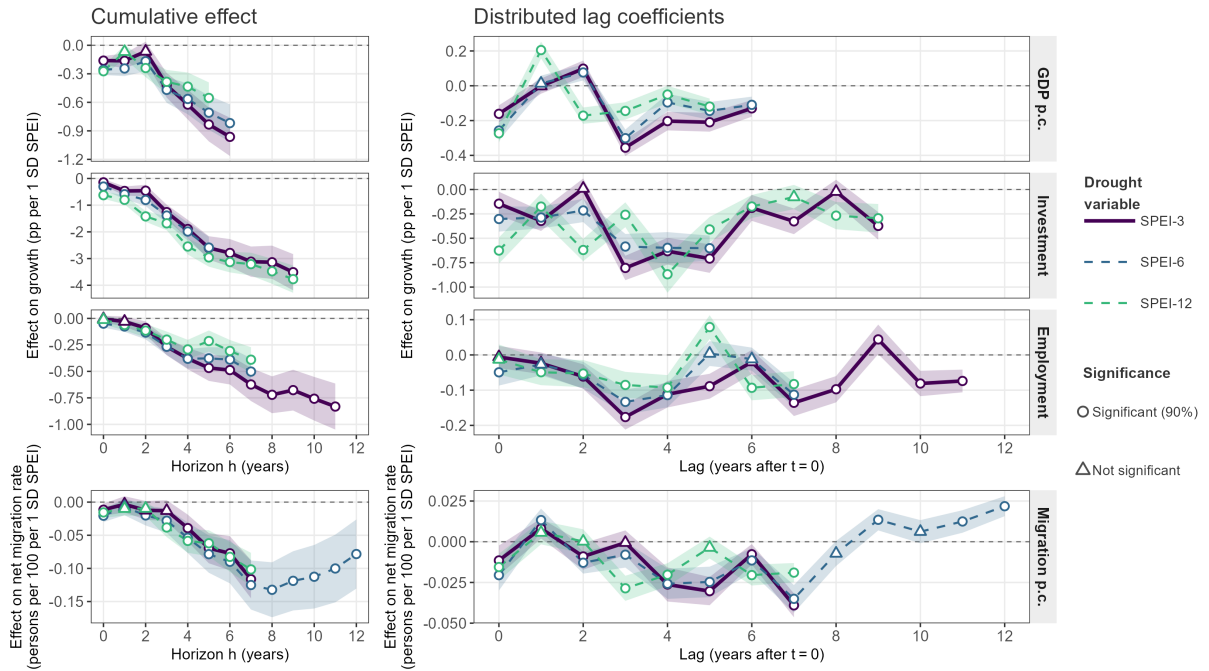


Figure C.69: ARDL model results for macroeconomic outcomes. Right-hand panels show the effect of a one-unit severe drought shock at each lag; left-hand panels show the cumulative effect under a persistent shock lasting 1-12 years. Standard errors are clustered by NUTS3.

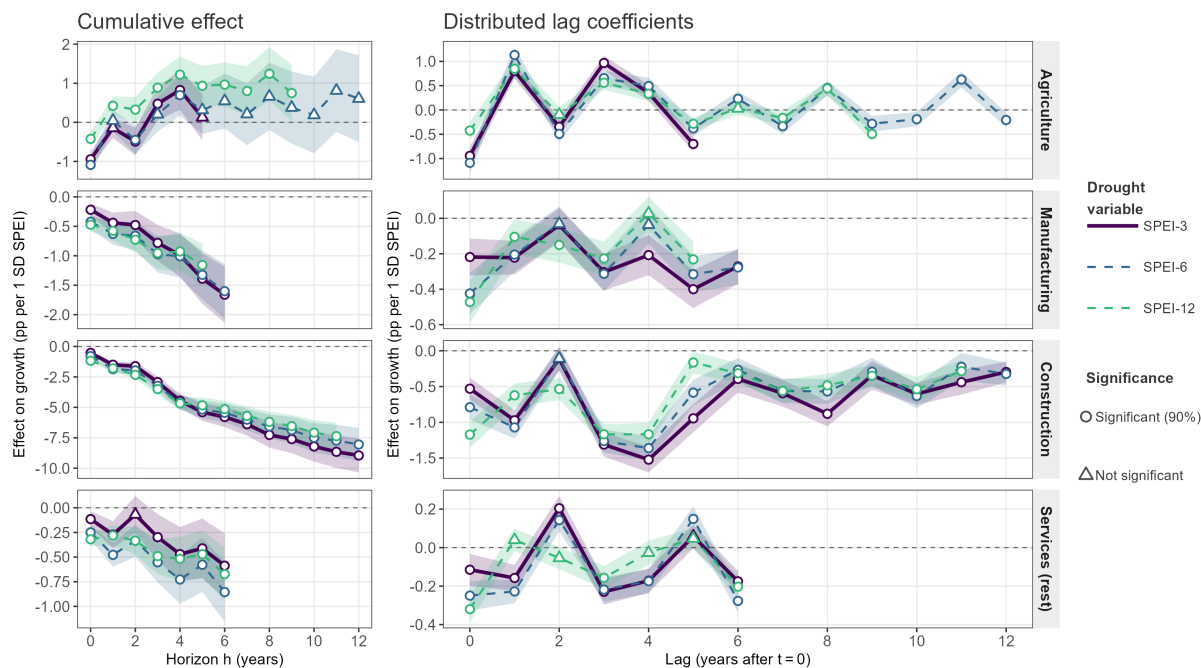


Figure C.70: ARDL model results for sectoral outputs (components of Gross Value Added). Right-hand panels show the effect of a one-unit severe drought shock at each lag; left-hand panels show the cumulative effect under a persistent shock lasting 1-12 years. Standard errors are clustered by NUTS3.

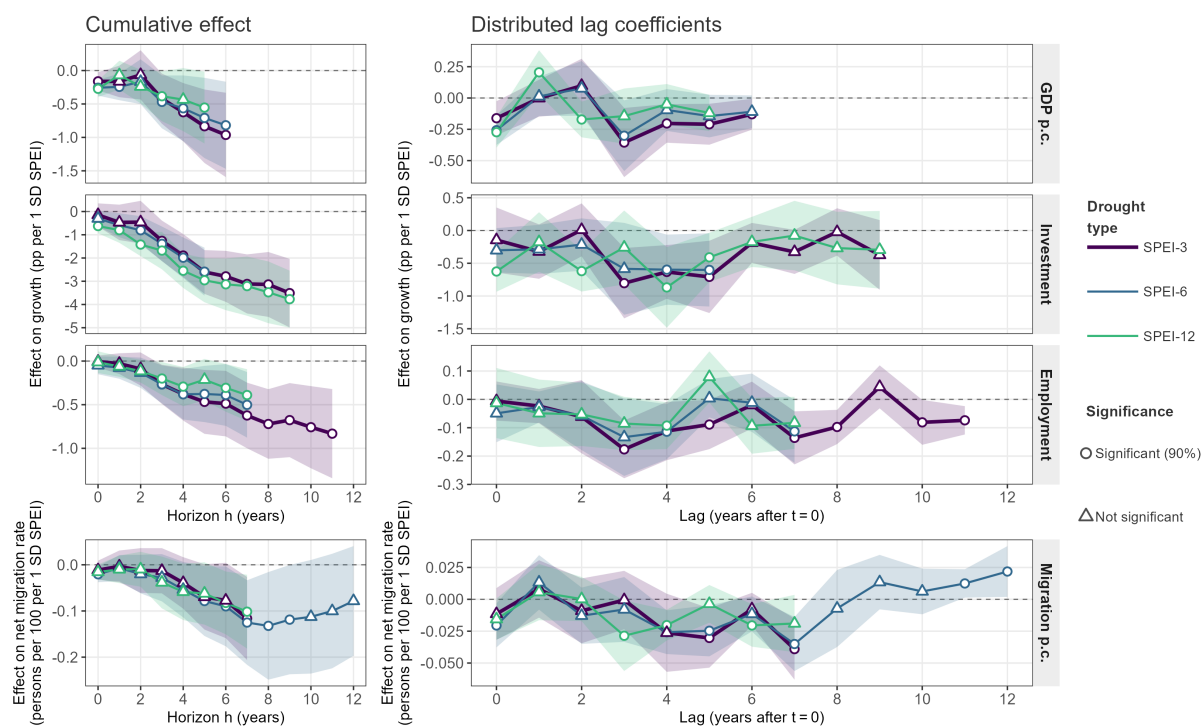


Figure C.71: ARDL model results for macroeconomic outcomes. Right-hand panels show the effect of a one-unit severe drought shock at each lag; left-hand panels show the cumulative effect under a persistent shock lasting 1-12 years. Standard errors are clustered following Driscoll and Kraay (1998).

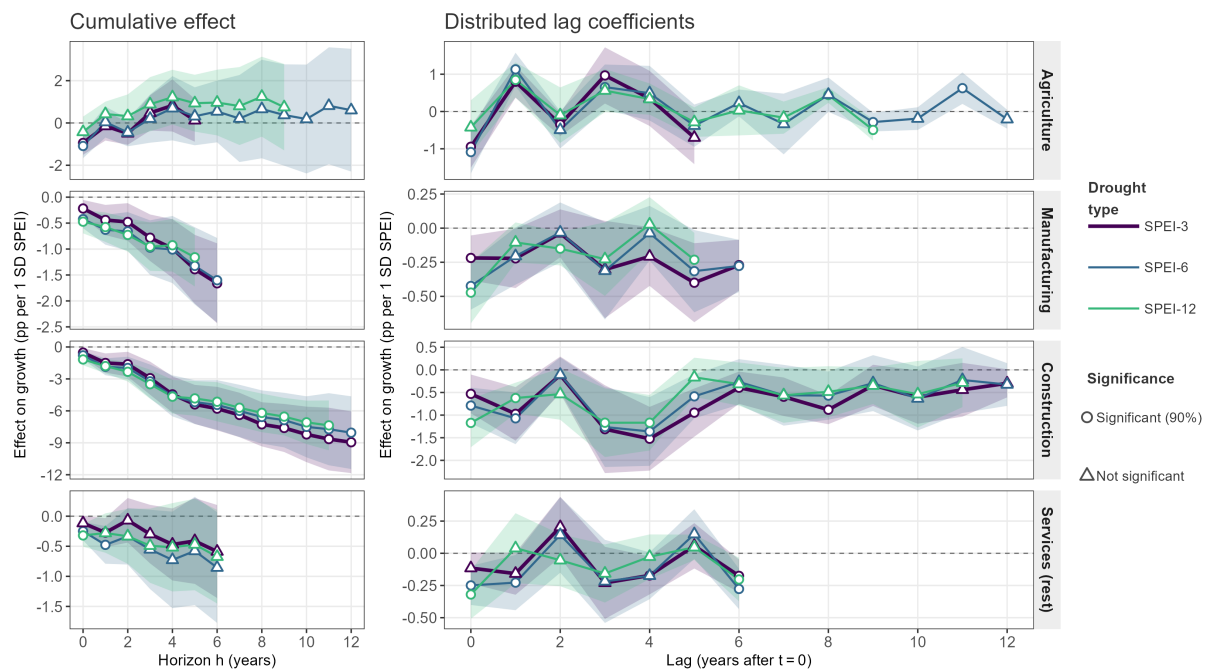


Figure C.72: ARDL model results for sectoral outputs (components of Gross Value Added). Right-hand panels show the effect of a one-unit severe drought shock at each lag; left-hand panels show the cumulative effect under a persistent shock lasting 1-12 years. Standard errors are clustered following Driscoll and Kraay (1998).

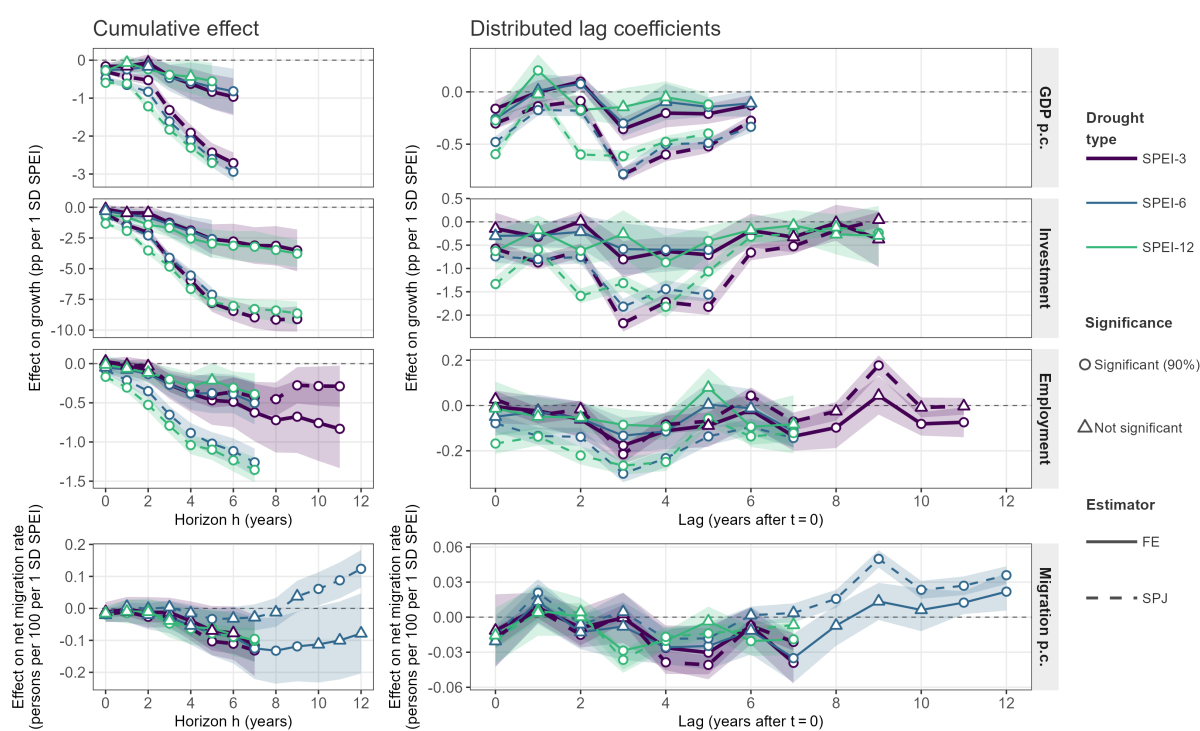


Figure C.73: ARDL and Split Panel Jackknife model results for macroeconomic outcomes. Right-hand panels show the effect of a one-unit severe drought shock at each lag; left-hand panels show the cumulative effect under a persistent shock lasting 1-12 years. Standard errors are calculated following Conley (1999) to account for heteroskedasticity, temporal autocorrelation, and spatial autocorrelation between regions up to a distance of 500 km..

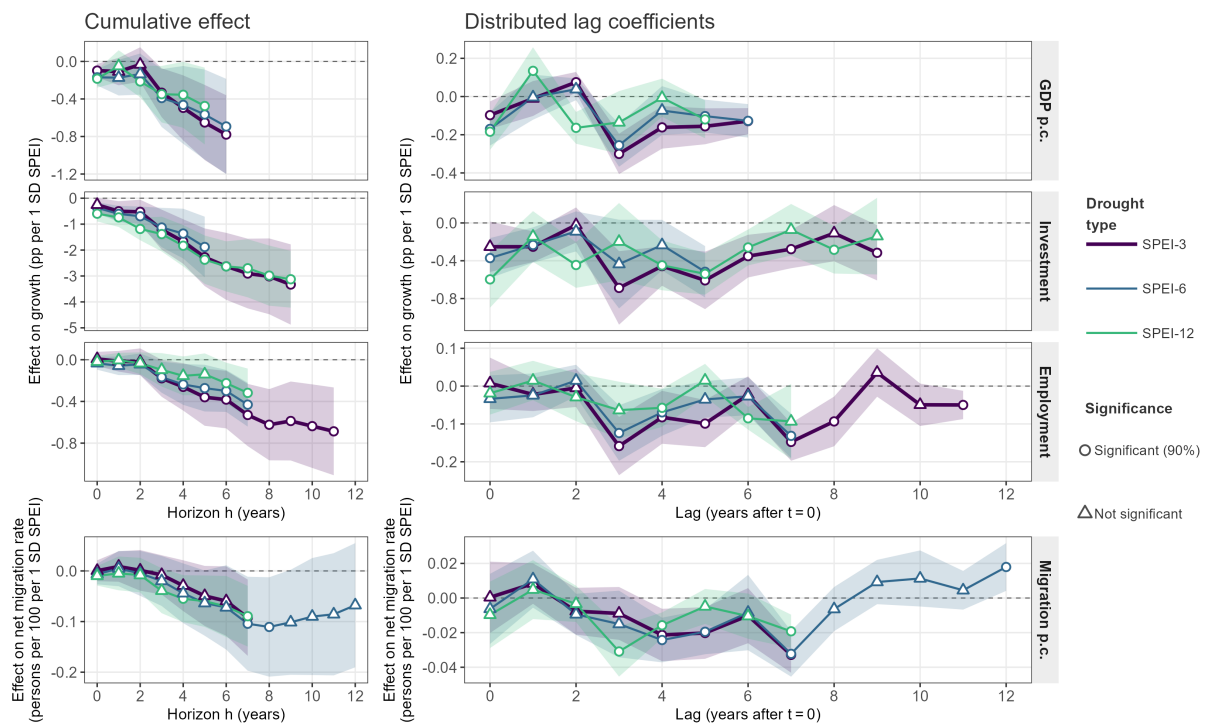


Figure C.74: ARDL model results for macroeconomic outcomes. Right-hand panels show the effect of a one-unit severe drought shock at each lag; left-hand panels show the cumulative effect under a persistent shock lasting 1-12 years. Standard errors are calculated following Conley (1999) to account for heteroskedasticity, temporal autocorrelation, and spatial autocorrelation between regions up to a distance of 500 km.. Outcomes distributions are trimmed below the 0.25 and over 0.75 inter-quartile ranges.

C.10. Storyline: the 2015-2018 European Drought Country Level Impacts

Table C.14: Country-level cumulative drought impacts (SPEI3) — event years 2015–2018. Cumulative drought impacts (SPEI3), 90% MC confidence intervals in brackets. Observed uncertainty: ARDL coefficient estimation. +2°C: additionally captures uncertainty across four climate models. See notes below table for row definitions.

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Albania	GDP p.c. (pp growth)	-1.14 [-1.68, -0.60]	-5.88 [-14.94, -0.34]
	<i>GDP loss (bn €)</i>	-0.1 [-0.2, -0.1]	-0.7 [-1.8, -0.0]
	<i>% of 2015 base</i>	-1.17 [-1.72, -0.61]	-6.02 [-15.05, -0.31]
	Investment (pp growth)	-4.47 [-6.88, -2.21]	-23.43 [-59.49, -1.37]
	<i>Investment loss (bn €)</i>	-0.1 [-0.2, -0.1]	-0.7 [-1.8, -0.0]
	<i>% of 2015 base</i>	-4.58 [-7.05, -2.27]	-23.99 [-59.91, -1.24]
	Employment (pp growth)	-1.09 [-1.72, -0.44]	-5.91 [-15.52, -0.28]
	<i>Employment loss (m persons)</i>	-0.01 [-0.02, -0.00]	-0.06 [-0.17, -0.00]
	<i>% of 2015 base</i>	-1.09 [-1.72, -0.44]	-5.91 [-15.53, -0.28]
	Migration p.c. [†] (pers./100)	-0.15 [-0.25, -0.03]	-0.87 [-2.35, -0.02]
Austria	GDP p.c. (pp growth)	-1.70 [-2.51, -0.90]	-3.77 [-7.81, -1.03]
	<i>GDP loss (bn €)</i>	-6.4 [-9.5, -3.4]	-14.1 [-29.2, -3.7]
	<i>% of 2015 base</i>	-1.72 [-2.54, -0.91]	-3.78 [-7.85, -1.00]
	Investment (pp growth)	-6.67 [-10.28, -3.30]	-14.65 [-31.16, -4.02]
	<i>Investment loss (bn €)</i>	-5.7 [-8.8, -2.8]	-12.4 [-26.2, -3.5]
	<i>% of 2015 base</i>	-6.70 [-10.33, -3.32]	-14.60 [-30.76, -4.14]
	Employment (pp growth)	-1.63 [-2.56, -0.65]	-3.56 [-7.81, -0.93]
	<i>Employment loss (m persons)</i>	-0.07 [-0.11, -0.03]	-0.15 [-0.33, -0.04]
	<i>% of 2015 base</i>	-1.64 [-2.58, -0.66]	-3.54 [-7.75, -0.94]
	Migration p.c. [†] (pers./100)	-0.22 [-0.37, -0.04]	-0.52 [-1.23, -0.04]
Belgium	GDP p.c. (pp growth)	-6.64 [-9.81, -3.50]	-9.12 [-15.33, -3.35]
	<i>GDP loss (bn €)</i>	-29.0 [-42.8, -15.3]	-41.3 [-69.8, -15.1]
	<i>% of 2015 base</i>	-6.39 [-9.43, -3.36]	-9.08 [-15.36, -3.33]
	Investment (pp growth)	-26.02 [-40.11, -12.90]	-35.28 [-60.45, -12.55]
	<i>Investment loss (bn €)</i>	-25.7 [-39.6, -12.7]	-36.3 [-62.5, -12.5]
	<i>% of 2015 base</i>	-24.84 [-38.29, -12.31]	-35.12 [-60.51, -12.13]
	Employment (pp growth)	-6.35 [-10.00, -2.54]	-8.69 [-15.50, -2.97]

(continued on next page)

| Appendix C

Table C.14: Country-level cumulative drought impacts (SPEI3) — event years 2015–2018. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Bulgaria	<i>Employment loss (m persons)</i>	-0.28 [-0.45, -0.11]	-0.40 [-0.71, -0.13]
	<i>% of 2015 base</i>	-6.14 [-9.67, -2.46]	-8.58 [-15.39, -2.88]
	Migration p.c. [†] (pers./100)	-0.85 [-1.46, -0.16]	-1.20 [-2.40, -0.12]
	GDP p.c. (pp growth)	-0.06 [-0.08, -0.03]	-2.73 [-12.59, -0.16]
	<i>GDP loss (bn €)</i>	-0.0 [-0.0, -0.0]	-1.6 [-7.6, -0.1]
	<i>% of 2015 base</i>	-0.03 [-0.05, -0.02]	-2.85 [-13.40, -0.11]
	Investment (pp growth)	-0.23 [-0.35, -0.11]	-11.28 [-50.11, -0.68]
	<i>Investment loss (bn €)</i>	-0.0 [-0.0, -0.0]	-1.3 [-5.6, -0.0]
	<i>% of 2015 base</i>	-0.15 [-0.22, -0.07]	-11.38 [-51.33, -0.45]
	Employment (pp growth)	-0.05 [-0.09, -0.02]	-3.08 [-13.02, -0.15]
	<i>Employment loss (m persons)</i>	-0.00 [-0.00, -0.00]	-0.11 [-0.46, -0.00]
	<i>% of 2015 base</i>	-0.04 [-0.07, -0.02]	-3.13 [-13.33, -0.14]
	Migration p.c. [†] (pers./100)	-0.01 [-0.01, -0.00]	-0.46 [-1.98, -0.01]
Croatia	GDP p.c. (pp growth)	-0.96 [-1.41, -0.50]	-3.52 [-8.35, -0.40]
	<i>GDP loss (bn €)</i>	-0.5 [-0.7, -0.2]	-1.7 [-3.9, -0.2]
	<i>% of 2015 base</i>	-0.94 [-1.39, -0.49]	-3.43 [-8.01, -0.50]
	Investment (pp growth)	-3.74 [-5.77, -1.86]	-13.80 [-33.20, -1.39]
	<i>Investment loss (bn €)</i>	-0.3 [-0.5, -0.2]	-1.3 [-3.0, -0.2]
	<i>% of 2015 base</i>	-3.59 [-5.53, -1.78]	-13.21 [-31.43, -1.66]
	Employment (pp growth)	-0.91 [-1.44, -0.37]	-3.41 [-8.63, -0.34]
	<i>Employment loss (m persons)</i>	-0.01 [-0.02, -0.01]	-0.05 [-0.13, -0.01]
	<i>% of 2015 base</i>	-0.91 [-1.44, -0.37]	-3.34 [-8.39, -0.38]
	Migration p.c. [†] (pers./100)	-0.12 [-0.21, -0.02]	-0.50 [-1.31, -0.02]
Cyprus	GDP p.c. (pp growth)	-0.05 [-0.07, -0.03]	-0.76 [-3.65, -0.05]
	<i>GDP loss (bn €)</i>	-0.0 [-0.0, -0.0]	-0.1 [-0.7, -0.0]
	<i>% of 2015 base</i>	-0.05 [-0.07, -0.03]	-0.76 [-3.65, -0.05]
	Investment (pp growth)	-0.19 [-0.29, -0.09]	-3.17 [-14.53, -0.20]
	<i>Investment loss (bn €)</i>	-0.0 [-0.0, -0.0]	-0.1 [-0.3, -0.0]
	<i>% of 2015 base</i>	-0.19 [-0.29, -0.09]	-3.17 [-14.53, -0.20]
	Employment (pp growth)	-0.05 [-0.07, -0.02]	-0.87 [-3.78, -0.05]

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Table C.14: Country-level cumulative drought impacts (SPEI3) — event years 2015–2018. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Czechia	<i>Employment loss (m persons)</i>	-0.00 [-0.00, -0.00]	-0.00 [-0.01, -0.00]
	<i>% of 2015 base</i>	-0.05 [-0.07, -0.02]	-0.87 [-3.78, -0.05]
	Migration p.c. [†] (pers./100)	-0.01 [-0.01, -0.00]	-0.13 [-0.57, -0.00]
	GDP p.c. (pp growth)	-5.32 [-7.85, -2.80]	-7.53 [-13.22, -2.52]
	<i>GDP loss (bn €)</i>	-10.5 [-15.5, -5.5]	-14.8 [-26.0, -4.8]
	<i>% of 2015 base</i>	-5.18 [-7.65, -2.73]	-7.30 [-12.85, -2.36]
	Investment (pp growth)	-20.82 [-32.10, -10.32]	-29.15 [-52.61, -9.43]
	<i>Investment loss (bn €)</i>	-10.1 [-15.6, -5.0]	-14.0 [-25.4, -4.2]
	<i>% of 2015 base</i>	-20.23 [-31.19, -10.03]	-28.00 [-50.67, -8.47]
	Employment (pp growth)	-5.08 [-8.00, -2.04]	-7.14 [-13.16, -2.23]
	<i>Employment loss (m persons)</i>	-0.26 [-0.41, -0.10]	-0.37 [-0.68, -0.11]
	<i>% of 2015 base</i>	-5.04 [-7.93, -2.02]	-7.08 [-13.19, -2.15]
	Migration p.c. [†] (pers./100)	-0.68 [-1.17, -0.13]	-1.00 [-2.10, -0.09]
Denmark	GDP p.c. (pp growth)	-1.93 [-2.85, -1.01]	-2.94 [-4.97, -1.05]
	<i>GDP loss (bn €)</i>	-5.2 [-7.7, -2.7]	-8.3 [-14.1, -2.9]
	<i>% of 2015 base</i>	-1.83 [-2.70, -0.96]	-2.90 [-4.96, -1.03]
	Investment (pp growth)	-7.55 [-11.64, -3.74]	-11.41 [-19.61, -4.00]
	<i>Investment loss (bn €)</i>	-3.9 [-6.0, -1.9]	-6.2 [-10.8, -2.0]
	<i>% of 2015 base</i>	-6.97 [-10.74, -3.45]	-11.08 [-19.32, -3.67]
	Employment (pp growth)	-1.84 [-2.90, -0.74]	-2.81 [-5.01, -0.95]
	<i>Employment loss (m persons)</i>	-0.05 [-0.08, -0.02]	-0.08 [-0.14, -0.02]
	<i>% of 2015 base</i>	-1.71 [-2.69, -0.68]	-2.72 [-4.89, -0.87]
	Migration p.c. [†] (pers./100)	-0.25 [-0.42, -0.05]	-0.39 [-0.78, -0.04]
Estonia	GDP p.c. (pp growth)	-1.30 [-1.91, -0.68]	-0.75 [-1.61, -0.17]
	<i>GDP loss (bn €)</i>	-0.3 [-0.4, -0.2]	-0.1 [-0.3, -0.0]
	<i>% of 2015 base</i>	-1.21 [-1.79, -0.64]	-0.58 [-1.24, -0.11]
	Investment (pp growth)	-5.07 [-7.82, -2.51]	-2.87 [-6.21, -0.63]
	<i>Investment loss (bn €)</i>	-0.2 [-0.4, -0.1]	-0.1 [-0.3, -0.0]
	<i>% of 2015 base</i>	-4.74 [-7.30, -2.35]	-2.24 [-4.77, -0.39]
	Employment (pp growth)	-1.24 [-1.95, -0.50]	-0.71 [-1.60, -0.15]

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| **Appendix C**

Table C.14: Country-level cumulative drought impacts (SPEI3) — event years 2015–2018. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Finland	<i>Employment loss (m persons)</i>	-0.01 [-0.01, -0.00]	-0.00 [-0.01, -0.00]
	<i>% of 2015 base</i>	-1.20 [-1.89, -0.48]	-0.64 [-1.45, -0.13]
	Migration p.c. [†] (pers./100)	-0.16 [-0.28, -0.03]	-0.10 [-0.22, -0.01]
	GDP p.c. (pp growth)	-0.89 [-1.31, -0.47]	-0.62 [-1.19, -0.21]
	<i>GDP loss (bn €)</i>	-1.9 [-2.8, -1.0]	-1.3 [-2.5, -0.4]
	<i>% of 2015 base</i>	-0.84 [-1.24, -0.44]	-0.58 [-1.14, -0.19]
	Investment (pp growth)	-3.48 [-5.36, -1.72]	-2.43 [-4.66, -0.87]
	<i>Investment loss (bn €)</i>	-1.6 [-2.4, -0.8]	-1.1 [-2.1, -0.4]
	<i>% of 2015 base</i>	-3.14 [-4.84, -1.55]	-2.17 [-4.28, -0.76]
	Employment (pp growth)	-0.85 [-1.34, -0.34]	-0.60 [-1.22, -0.17]
	<i>Employment loss (m persons)</i>	-0.02 [-0.03, -0.01]	-0.01 [-0.03, -0.00]
	<i>% of 2015 base</i>	-0.83 [-1.31, -0.33]	-0.59 [-1.21, -0.16]
	Migration p.c. [†] (pers./100)	-0.11 [-0.20, -0.02]	-0.09 [-0.19, -0.01]
France	GDP p.c. (pp growth)	-1.76 [-2.59, -0.92]	-4.48 [-10.08, -1.08]
	<i>GDP loss (bn €)</i>	-37.8 [-55.8, -19.9]	-103.8 [-244.9, -22.6]
	<i>% of 2015 base</i>	-1.61 [-2.38, -0.85]	-4.43 [-10.44, -0.97]
	Investment (pp growth)	-6.88 [-10.61, -3.41]	-17.61 [-40.12, -3.96]
	<i>Investment loss (bn €)</i>	-30.4 [-46.9, -15.1]	-83.5 [-199.1, -16.8]
	<i>% of 2015 base</i>	-6.32 [-9.75, -3.13]	-17.37 [-41.39, -3.49]
	Employment (pp growth)	-1.68 [-2.64, -0.67]	-4.45 [-10.43, -0.96]
	<i>Employment loss (m persons)</i>	-0.43 [-0.68, -0.17]	-1.19 [-2.84, -0.24]
	<i>% of 2015 base</i>	-1.56 [-2.46, -0.63]	-4.31 [-10.34, -0.88]
	Migration p.c. [†] (pers./100)	-0.22 [-0.39, -0.04]	-0.63 [-1.58, -0.04]
Germany	GDP p.c. (pp growth)	-6.34 [-9.35, -3.33]	-7.71 [-12.91, -2.79]
	<i>GDP loss (bn €)</i>	-211.2 [-311.8, -111.1]	-258.5 [-435.5, -91.9]
	<i>% of 2015 base</i>	-6.30 [-9.29, -3.31]	-7.71 [-12.98, -2.74]
	Investment (pp growth)	-24.82 [-38.25, -12.30]	-29.86 [-50.62, -11.89]
	<i>Investment loss (bn €)</i>	-163.6 [-252.2, -81.1]	-198.6 [-336.9, -77.5]
	<i>% of 2015 base</i>	-24.28 [-37.42, -12.03]	-29.47 [-49.99, -11.50]
	Employment (pp growth)	-6.06 [-9.54, -2.43]	-7.35 [-12.66, -2.69]

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Table C.14: Country-level cumulative drought impacts (SPEI3) — event years 2015–2018. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Greece	<i>Employment loss (m persons)</i>	-2.61 [-4.11, -1.04]	-3.17 [-5.47, -1.16]
	<i>% of 2015 base</i>	-6.05 [-9.52, -2.42]	-7.35 [-12.67, -2.70]
	Migration p.c. [†] (pers./100)	-0.81 [-1.39, -0.15]	-1.02 [-2.01, -0.10]
	GDP p.c. (pp growth)	-1.43 [-2.11, -0.75]	-5.52 [-15.98, -1.57]
	<i>GDP loss (bn €)</i>	-2.6 [-3.9, -1.4]	-10.2 [-28.5, -3.1]
	<i>% of 2015 base</i>	-1.50 [-2.21, -0.79]	-5.87 [-16.37, -1.76]
	Investment (pp growth)	-5.61 [-8.64, -2.78]	-22.16 [-63.63, -6.81]
	<i>Investment loss (bn €)</i>	-1.1 [-1.7, -0.5]	-4.1 [-11.7, -1.3]
	<i>% of 2015 base</i>	-5.68 [-8.76, -2.82]	-21.32 [-60.27, -6.62]
	Employment (pp growth)	-1.37 [-2.15, -0.55]	-5.80 [-16.54, -1.33]
	<i>Employment loss (m persons)</i>	-0.06 [-0.10, -0.02]	-0.26 [-0.72, -0.06]
	<i>% of 2015 base</i>	-1.41 [-2.23, -0.57]	-5.93 [-16.68, -1.40]
	Migration p.c. [†] (pers./100)	-0.18 [-0.32, -0.03]	-0.82 [-2.51, -0.06]
Hungary	GDP p.c. (pp growth)	-0.45 [-0.66, -0.23]	-4.39 [-11.33, -0.03]
	<i>GDP loss (bn €)</i>	-0.4 [-0.6, -0.2]	-5.1 [-13.3, -0.0]
	<i>% of 2015 base</i>	-0.32 [-0.47, -0.17]	-4.14 [-10.81, -0.02]
	Investment (pp growth)	-1.75 [-2.69, -0.87]	-17.01 [-44.70, -0.11]
	<i>Investment loss (bn €)</i>	-0.4 [-0.6, -0.2]	-4.6 [-11.9, -0.0]
	<i>% of 2015 base</i>	-1.35 [-2.08, -0.67]	-16.13 [-42.20, -0.08]
	Employment (pp growth)	-0.43 [-0.67, -0.17]	-4.05 [-11.14, -0.03]
	<i>Employment loss (m persons)</i>	-0.01 [-0.02, -0.01]	-0.16 [-0.45, -0.00]
	<i>% of 2015 base</i>	-0.32 [-0.50, -0.13]	-3.81 [-10.44, -0.02]
	Migration p.c. [†] (pers./100)	-0.06 [-0.10, -0.01]	-0.62 [-1.74, -0.00]
Ireland	GDP p.c. (pp growth)	-1.22 [-1.79, -0.64]	-1.93 [-3.78, -0.64]
	<i>GDP loss (bn €)</i>	-4.2 [-6.2, -2.2]	-5.7 [-10.5, -2.0]
	<i>% of 2015 base</i>	-1.49 [-2.20, -0.78]	-2.00 [-3.73, -0.72]
	Investment (pp growth)	-4.76 [-7.34, -2.36]	-7.35 [-14.49, -2.79]
	<i>Investment loss (bn €)</i>	-4.4 [-6.7, -2.2]	-5.6 [-10.6, -2.3]
	<i>% of 2015 base</i>	-6.06 [-9.35, -3.00]	-7.87 [-14.70, -3.19]
	Employment (pp growth)	-1.16 [-1.83, -0.47]	-1.77 [-3.72, -0.56]

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| **Appendix C**

Table C.14: Country-level cumulative drought impacts (SPEI3) — event years 2015–2018. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Italy	<i>Employment loss (m persons)</i>	-0.03 [-0.04, -0.01]	-0.04 [-0.08, -0.01]
	<i>% of 2015 base</i>	-1.29 [-2.03, -0.52]	-1.86 [-3.86, -0.58]
	Migration p.c. [†] (pers./100)	-0.15 [-0.27, -0.03]	-0.24 [-0.52, -0.02]
	GDP p.c. (pp growth)	-1.45 [-2.14, -0.76]	-3.99 [-7.89, -1.15]
	<i>GDP loss (bn €)</i>	-24.3 [-35.8, -12.8]	-74.0 [-147.2, -19.9]
	<i>% of 2015 base</i>	-1.38 [-2.04, -0.73]	-4.21 [-8.37, -1.13]
	Investment (pp growth)	-5.69 [-8.77, -2.82]	-15.59 [-30.83, -4.89]
	<i>Investment loss (bn €)</i>	-15.3 [-23.6, -7.6]	-47.2 [-94.3, -13.9]
	<i>% of 2015 base</i>	-5.28 [-8.14, -2.62]	-16.25 [-32.48, -4.78]
	Employment (pp growth)	-1.39 [-2.19, -0.56]	-3.85 [-8.11, -1.15]
	<i>Employment loss (m persons)</i>	-0.33 [-0.52, -0.13]	-0.96 [-2.03, -0.29]
	<i>% of 2015 base</i>	-1.36 [-2.14, -0.55]	-3.97 [-8.37, -1.18]
	Migration p.c. [†] (pers./100)	-0.18 [-0.32, -0.04]	-0.55 [-1.21, -0.05]
Latvia	GDP p.c. (pp growth)	-3.84 [-5.67, -2.02]	-3.98 [-7.09, -1.49]
	<i>GDP loss (bn €)</i>	-1.2 [-1.8, -0.6]	-1.3 [-2.3, -0.5]
	<i>% of 2015 base</i>	-4.46 [-6.58, -2.34]	-4.64 [-8.52, -1.68]
	Investment (pp growth)	-15.04 [-23.18, -7.45]	-15.49 [-27.63, -6.34]
	<i>Investment loss (bn €)</i>	-1.0 [-1.6, -0.5]	-1.1 [-1.9, -0.4]
	<i>% of 2015 base</i>	-17.45 [-26.90, -8.65]	-18.06 [-33.20, -7.13]
	Employment (pp growth)	-3.67 [-5.78, -1.47]	-3.82 [-7.07, -1.36]
	<i>Employment loss (m persons)</i>	-0.04 [-0.06, -0.01]	-0.04 [-0.07, -0.01]
	<i>% of 2015 base</i>	-3.94 [-6.20, -1.58]	-4.09 [-7.65, -1.42]
	Migration p.c. [†] (pers./100)	-0.49 [-0.85, -0.09]	-0.54 [-1.11, -0.06]
Lithuania	GDP p.c. (pp growth)	-2.66 [-3.93, -1.40]	-3.04 [-5.55, -1.11]
	<i>GDP loss (bn €)</i>	-1.2 [-1.7, -0.6]	-1.3 [-2.5, -0.5]
	<i>% of 2015 base</i>	-2.75 [-4.06, -1.45]	-3.15 [-5.83, -1.17]
	Investment (pp growth)	-10.42 [-16.06, -5.16]	-11.64 [-22.15, -4.95]
	<i>Investment loss (bn €)</i>	-0.9 [-1.3, -0.4]	-1.0 [-1.9, -0.4]
	<i>% of 2015 base</i>	-10.72 [-16.53, -5.31]	-11.99 [-23.09, -4.92]
	Employment (pp growth)	-2.54 [-4.00, -1.02]	-2.78 [-5.41, -0.97]

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Table C.14: Country-level cumulative drought impacts (SPEI3) — event years 2015–2018. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Luxembourg	<i>Employment loss (m persons)</i>	-0.03 [-0.05, -0.01]	-0.04 [-0.07, -0.01]
	<i>% of 2015 base</i>	-2.57 [-4.05, -1.03]	-2.81 [-5.49, -0.99]
	Migration p.c. [†] (pers./100)	-0.34 [-0.59, -0.06]	-0.39 [-0.78, -0.04]
	GDP p.c. (pp growth)	-9.20 [-13.58, -4.84]	-10.87 [-18.38, -4.11]
	<i>GDP loss (bn €)</i>	-5.4 [-7.9, -2.8]	-6.3 [-10.7, -2.4]
	<i>% of 2015 base</i>	-9.20 [-13.58, -4.84]	-10.87 [-18.38, -4.11]
	Investment (pp growth)	-36.04 [-55.55, -17.86]	-42.02 [-70.09, -16.28]
	<i>Investment loss (bn €)</i>	-3.7 [-5.6, -1.8]	-4.3 [-7.1, -1.7]
	<i>% of 2015 base</i>	-36.04 [-55.55, -17.86]	-42.02 [-70.09, -16.28]
	Employment (pp growth)	-8.80 [-13.85, -3.52]	-10.36 [-18.34, -3.61]
	<i>Employment loss (m persons)</i>	-0.04 [-0.06, -0.01]	-0.04 [-0.07, -0.01]
	<i>% of 2015 base</i>	-8.80 [-13.85, -3.52]	-10.36 [-18.34, -3.61]
	Migration p.c. [†] (pers./100)	-1.17 [-2.02, -0.22]	-1.42 [-2.80, -0.14]
Malta	GDP p.c. (pp growth)	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
	<i>GDP loss (bn €)</i>	0.0 [0.0, 0.0]	0.0 [0.0, 0.0]
	<i>% of 2015 base</i>	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
	Investment (pp growth)	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
	<i>Investment loss (bn €)</i>	0.0 [0.0, 0.0]	0.0 [0.0, 0.0]
	<i>% of 2015 base</i>	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
	Employment (pp growth)	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
	<i>Employment loss (m persons)</i>	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
	<i>% of 2015 base</i>	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
	Migration p.c. [†] (pers./100)	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
Montenegro	GDP p.c. (pp growth)	-0.07 [-0.10, -0.04]	-3.87 [-13.43, -0.09]
	<i>GDP loss (bn €)</i>	-0.0 [-0.0, -0.0]	-0.2 [-0.6, -0.0]
	<i>% of 2015 base</i>	-0.07 [-0.10, -0.04]	-3.87 [-13.43, -0.09]
	Investment (pp growth)	-0.27 [-0.42, -0.14]	-15.51 [-53.48, -0.35]
	<i>Investment loss (bn €)</i>	-0.0 [-0.0, -0.0]	-0.1 [-0.4, -0.0]
	<i>% of 2015 base</i>	-0.27 [-0.42, -0.14]	-15.51 [-53.48, -0.35]
	Employment (pp growth)	-0.07 [-0.11, -0.03]	-3.95 [-13.90, -0.07]

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| **Appendix C**

Table C.14: Country-level cumulative drought impacts (SPEI3) — event years 2015–2018. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
N. Macedonia	<i>Employment loss (m persons)</i>	-0.00 [-0.00, -0.00]	-0.01 [-0.03, -0.00]
	<i>% of 2015 base</i>	-0.07 [-0.11, -0.03]	-3.95 [-13.90, -0.07]
	Migration p.c. [†] (pers./100)	-0.01 [-0.02, -0.00]	-0.60 [-2.11, -0.00]
	GDP p.c. (pp growth)	-0.03 [-0.05, -0.02]	-4.31 [-16.46, -0.05]
	<i>GDP loss (bn €)</i>	-0.0 [-0.0, -0.0]	-0.4 [-1.7, -0.0]
	<i>% of 2015 base</i>	-0.03 [-0.04, -0.01]	-4.33 [-16.65, -0.05]
	Investment (pp growth)	-0.13 [-0.20, -0.06]	-17.49 [-65.55, -0.19]
	<i>Investment loss (bn €)</i>	-0.0 [-0.0, -0.0]	-0.4 [-1.5, -0.0]
	<i>% of 2015 base</i>	-0.10 [-0.16, -0.05]	-17.62 [-66.29, -0.20]
	Employment (pp growth)	-0.03 [-0.05, -0.01]	-4.58 [-17.04, -0.04]
	<i>Employment loss (m persons)</i>	-0.00 [-0.00, -0.00]	-0.04 [-0.14, -0.00]
	<i>% of 2015 base</i>	-0.03 [-0.04, -0.01]	-4.62 [-17.52, -0.05]
	Migration p.c. [†] (pers./100)	-0.00 [-0.01, -0.00]	-0.69 [-2.59, -0.00]
	GDP p.c. (pp growth)	-1.66 [-2.46, -0.88]	-2.79 [-4.95, -0.83]
	<i>GDP loss (bn €)</i>	-11.8 [-17.4, -6.2]	-20.6 [-36.8, -5.8]
Netherlands	<i>% of 2015 base</i>	-1.54 [-2.27, -0.81]	-2.69 [-4.80, -0.76]
	Investment (pp growth)	-6.52 [-10.05, -3.23]	-10.76 [-19.32, -3.05]
	<i>Investment loss (bn €)</i>	-9.7 [-15.0, -4.8]	-16.9 [-30.6, -4.6]
	<i>% of 2015 base</i>	-5.84 [-9.01, -2.90]	-10.16 [-18.37, -2.79]
	Employment (pp growth)	-1.59 [-2.51, -0.64]	-2.63 [-4.85, -0.72]
	<i>Employment loss (m persons)</i>	-0.14 [-0.21, -0.05]	-0.23 [-0.42, -0.06]
	<i>% of 2015 base</i>	-1.54 [-2.43, -0.62]	-2.60 [-4.79, -0.70]
	Migration p.c. [†] (pers./100)	-0.21 [-0.37, -0.04]	-0.37 [-0.77, -0.03]
	GDP p.c. (pp growth)	-1.94 [-2.86, -1.02]	-1.88 [-3.59, -0.75]
	<i>GDP loss (bn €)</i>	-4.8 [-7.1, -2.5]	-4.8 [-9.0, -1.9]
Norway	<i>% of 2015 base</i>	-1.85 [-2.74, -0.98]	-1.83 [-3.46, -0.72]
	Investment (pp growth)	-7.59 [-11.70, -3.76]	-7.44 [-14.29, -3.16]
	<i>Investment loss (bn €)</i>	-4.1 [-6.3, -2.0]	-4.0 [-7.9, -1.7]
	<i>% of 2015 base</i>	-7.11 [-10.96, -3.52]	-7.01 [-13.67, -2.92]
	Employment (pp growth)	-1.85 [-2.92, -0.74]	-1.89 [-3.71, -0.62]

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Table C.14: Country-level cumulative drought impacts (SPEI3) — event years 2015–2018. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Poland	<i>Employment loss (m persons)</i>	-0.05 [-0.08, -0.02]	-0.05 [-0.10, -0.02]
	<i>% of 2015 base</i>	-1.79 [-2.82, -0.72]	-1.84 [-3.62, -0.60]
	Migration p.c. [†] (pers./100)	-0.25 [-0.43, -0.05]	-0.26 [-0.56, -0.03]
	GDP p.c. (pp growth)	-2.79 [-4.12, -1.47]	-4.47 [-8.43, -1.28]
	<i>GDP loss (bn €)</i>	-13.9 [-20.5, -7.3]	-21.6 [-39.6, -6.8]
	<i>% of 2015 base</i>	-3.08 [-4.54, -1.62]	-4.78 [-8.78, -1.51]
	Investment (pp growth)	-10.94 [-16.86, -5.42]	-17.37 [-33.26, -5.55]
	<i>Investment loss (bn €)</i>	-10.5 [-16.1, -5.2]	-16.1 [-30.0, -5.6]
	<i>% of 2015 base</i>	-11.97 [-18.45, -5.93]	-18.40 [-34.24, -6.37]
	Employment (pp growth)	-2.67 [-4.20, -1.07]	-4.27 [-8.57, -1.32]
	<i>Employment loss (m persons)</i>	-0.43 [-0.68, -0.17]	-0.69 [-1.37, -0.21]
	<i>% of 2015 base</i>	-2.72 [-4.28, -1.09]	-4.32 [-8.56, -1.35]
	Migration p.c. [†] (pers./100)	-0.36 [-0.61, -0.07]	-0.61 [-1.33, -0.05]
Portugal	GDP p.c. (pp growth)	-2.35 [-3.46, -1.23]	-5.99 [-12.01, -2.06]
	<i>GDP loss (bn €)</i>	-3.9 [-5.7, -2.0]	-10.9 [-22.6, -3.6]
	<i>% of 2015 base</i>	-1.97 [-2.91, -1.04]	-5.53 [-11.53, -1.82]
	Investment (pp growth)	-9.19 [-14.17, -4.56]	-23.53 [-47.83, -8.93]
	<i>Investment loss (bn €)</i>	-2.5 [-3.9, -1.3]	-7.0 [-14.7, -2.5]
	<i>% of 2015 base</i>	-8.11 [-12.51, -4.02]	-22.50 [-46.93, -7.89]
	Employment (pp growth)	-2.24 [-3.53, -0.90]	-5.98 [-12.43, -1.83]
	<i>Employment loss (m persons)</i>	-0.10 [-0.15, -0.04]	-0.27 [-0.56, -0.08]
	<i>% of 2015 base</i>	-2.13 [-3.36, -0.85]	-5.83 [-12.21, -1.79]
	Migration p.c. [†] (pers./100)	-0.30 [-0.52, -0.06]	-0.83 [-1.89, -0.08]
Romania	GDP p.c. (pp growth)	-0.31 [-0.46, -0.16]	-3.23 [-11.75, -0.13]
	<i>GDP loss (bn €)</i>	-0.4 [-0.5, -0.2]	-5.1 [-19.4, -0.1]
	<i>% of 2015 base</i>	-0.20 [-0.29, -0.10]	-2.73 [-10.39, -0.08]
	Investment (pp growth)	-1.21 [-1.87, -0.60]	-13.03 [-46.76, -0.46]
	<i>Investment loss (bn €)</i>	-0.2 [-0.3, -0.1]	-4.3 [-16.9, -0.1]
	<i>% of 2015 base</i>	-0.49 [-0.75, -0.24]	-9.67 [-38.04, -0.17]
	Employment (pp growth)	-0.30 [-0.47, -0.12]	-3.40 [-12.15, -0.11]

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| **Appendix C**

Table C.14: Country-level cumulative drought impacts (SPEI3) — event years 2015–2018. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Serbia	<i>Employment loss (m persons)</i>	-0.03 [-0.04, -0.01]	-0.29 [-1.04, -0.01]
	<i>% of 2015 base</i>	-0.31 [-0.49, -0.12]	-3.44 [-12.19, -0.11]
	Migration p.c. [†] (pers./100)	-0.04 [-0.07, -0.01]	-0.51 [-1.85, -0.01]
	GDP p.c. (pp growth)	-0.03 [-0.04, -0.02]	-3.86 [-10.85, -0.06]
	<i>GDP loss (bn €)</i>	-0.0 [-0.0, -0.0]	-1.8 [-4.7, -0.0]
	<i>% of 2015 base</i>	-0.03 [-0.04, -0.02]	-4.14 [-11.07, -0.07]
	Investment (pp growth)	-0.12 [-0.18, -0.06]	-15.21 [-42.95, -0.23]
	<i>Investment loss (bn €)</i>	-0.0 [-0.0, -0.0]	-1.1 [-3.0, -0.0]
	<i>% of 2015 base</i>	-0.12 [-0.18, -0.06]	-16.47 [-44.08, -0.24]
	Employment (pp growth)	-0.03 [-0.05, -0.01]	-3.76 [-11.21, -0.06]
	<i>Employment loss (m persons)</i>	-0.00 [-0.00, -0.00]	-0.12 [-0.36, -0.00]
	<i>% of 2015 base</i>	-0.03 [-0.04, -0.01]	-3.74 [-11.20, -0.05]
	Migration p.c. [†] (pers./100)	-0.00 [-0.01, -0.00]	-0.57 [-1.70, -0.00]
Slovakia	GDP p.c. (pp growth)	-1.64 [-2.42, -0.86]	-5.47 [-13.07, -0.36]
	<i>GDP loss (bn €)</i>	-1.8 [-2.7, -1.0]	-5.1 [-11.7, -0.4]
	<i>% of 2015 base</i>	-2.12 [-3.12, -1.11]	-5.86 [-13.53, -0.41]
	Investment (pp growth)	-6.43 [-9.91, -3.19]	-21.06 [-51.59, -1.25]
	<i>Investment loss (bn €)</i>	-1.8 [-2.8, -0.9]	-4.7 [-11.1, -0.3]
	<i>% of 2015 base</i>	-8.66 [-13.34, -4.29]	-22.52 [-52.95, -1.43]
	Employment (pp growth)	-1.57 [-2.47, -0.63]	-4.98 [-12.80, -0.31]
	<i>Employment loss (m persons)</i>	-0.04 [-0.06, -0.02]	-0.12 [-0.29, -0.01]
	<i>% of 2015 base</i>	-1.76 [-2.76, -0.70]	-5.13 [-12.99, -0.32]
	Migration p.c. [†] (pers./100)	-0.21 [-0.36, -0.04]	-0.75 [-1.97, -0.02]
Slovenia	GDP p.c. (pp growth)	-0.75 [-1.10, -0.39]	-2.58 [-6.43, -0.38]
	<i>GDP loss (bn €)</i>	-0.3 [-0.4, -0.2]	-1.1 [-2.7, -0.2]
	<i>% of 2015 base</i>	-0.70 [-1.03, -0.37]	-2.60 [-6.48, -0.40]
	Investment (pp growth)	-2.93 [-4.51, -1.45]	-10.15 [-25.48, -1.34]
	<i>Investment loss (bn €)</i>	-0.2 [-0.3, -0.1]	-0.8 [-2.0, -0.1]
	<i>% of 2015 base</i>	-2.82 [-4.35, -1.40]	-10.32 [-25.92, -1.42]
	Employment (pp growth)	-0.71 [-1.12, -0.29]	-2.51 [-6.65, -0.32]

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Table C.14: Country-level cumulative drought impacts (SPEI3) — event years 2015–2018. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Spain	<i>Employment loss (m persons)</i>	-0.01 [-0.01, -0.00]	-0.02 [-0.06, -0.00]
	<i>% of 2015 base</i>	-0.69 [-1.09, -0.28]	-2.54 [-6.74, -0.33]
	Migration p.c. [†] (pers./100)	-0.10 [-0.16, -0.02]	-0.37 [-1.01, -0.01]
	GDP p.c. (pp growth)	-2.17 [-3.20, -1.14]	-7.69 [-17.46, -2.23]
	<i>GDP loss (bn €)</i>	-25.6 [-37.8, -13.5]	-88.8 [-205.3, -24.6]
	<i>% of 2015 base</i>	-2.23 [-3.30, -1.18]	-7.75 [-17.92, -2.15]
	Investment (pp growth)	-8.50 [-13.10, -4.21]	-30.33 [-69.53, -9.51]
	<i>Investment loss (bn €)</i>	-18.4 [-28.3, -9.1]	-64.9 [-152.7, -19.4]
	<i>% of 2015 base</i>	-8.76 [-13.50, -4.34]	-30.92 [-72.72, -9.24]
	Employment (pp growth)	-2.07 [-3.27, -0.83]	-7.63 [-18.07, -2.11]
	<i>Employment loss (m persons)</i>	-0.39 [-0.62, -0.16]	-1.43 [-3.42, -0.39]
	<i>% of 2015 base</i>	-2.11 [-3.33, -0.85]	-7.68 [-18.38, -2.08]
	Migration p.c. [†] (pers./100)	-0.28 [-0.48, -0.05]	-1.09 [-2.75, -0.10]
Sweden	GDP p.c. (pp growth)	-2.13 [-3.15, -1.12]	-2.47 [-4.19, -1.03]
	<i>GDP loss (bn €)</i>	-9.9 [-14.6, -5.2]	-11.3 [-18.9, -4.8]
	<i>% of 2015 base</i>	-2.21 [-3.25, -1.16]	-2.52 [-4.22, -1.06]
	Investment (pp growth)	-8.36 [-12.88, -4.14]	-9.62 [-16.66, -4.14]
	<i>Investment loss (bn €)</i>	-8.9 [-13.8, -4.4]	-10.1 [-17.1, -4.5]
	<i>% of 2015 base</i>	-8.59 [-13.24, -4.26]	-9.70 [-16.42, -4.30]
	Employment (pp growth)	-2.04 [-3.21, -0.82]	-2.37 [-4.15, -0.84]
	<i>Employment loss (m persons)</i>	-0.10 [-0.16, -0.04]	-0.12 [-0.20, -0.04]
	<i>% of 2015 base</i>	-2.06 [-3.24, -0.83]	-2.38 [-4.18, -0.85]
	Migration p.c. [†] (pers./100)	-0.27 [-0.47, -0.05]	-0.33 [-0.67, -0.04]
Switzerland	GDP p.c. (pp growth)	-3.74 [-5.53, -1.97]	-6.00 [-12.20, -1.65]
	<i>GDP loss (bn €)</i>	-24.3 [-35.9, -12.8]	-38.3 [-77.0, -10.8]
	<i>% of 2015 base</i>	-3.88 [-5.72, -2.04]	-6.09 [-12.26, -1.72]
	Investment (pp growth)	-14.66 [-22.60, -7.27]	-23.48 [-48.30, -7.18]
	<i>Investment loss (bn €)</i>	-25.5 [-39.3, -12.7]	-40.1 [-81.6, -12.6]
	<i>% of 2015 base</i>	-15.18 [-23.40, -7.52]	-23.84 [-48.55, -7.47]
	Employment (pp growth)	-3.58 [-5.63, -1.43]	-5.85 [-12.60, -1.78]

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| Appendix C

Table C.14: Country-level cumulative drought impacts (SPEI3) — event years 2015–2018. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
	<i>Employment loss (m persons)</i>	-0.18 [-0.28, -0.07]	-0.29 [-0.62, -0.09]
	<i>% of 2015 base</i>	-3.66 [-5.76, -1.46]	-5.94 [-12.69, -1.82]
	Migration p.c. [†] (pers./100)	-0.48 [-0.82, -0.09]	-0.83 [-1.91, -0.07]

[†] Migration p.c. in persons per 100 inhabitants; all other pp rows are percentage-point growth. Loss rows in bn € (GDP, investment) or millions of persons (employment). % rows express loss as % of group 2015 base.

C.11. Storyline: the 2022 European Drought

Table C.15: Macro-region cumulative drought impacts (SPEI3) — event year 2022 (UN M49 macro-region classification). Cumulative drought impacts (SPEI3), 90% MC confidence intervals in brackets. Observed uncertainty: ARDL coefficient estimation. +2°C: additionally captures uncertainty across four climate models. See notes below table for row definitions.

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Europe	GDP p.c. (pp growth)	-1.35 [-2.02, -0.73]	-2.33 [-4.35, -0.95]
	<i>GDP loss (bn €)</i>	-202.6 [-302.9, -109.7]	-340.3 [-619.8, -142.1]
	<i>% of 2015 base</i>	-1.44 [-2.15, -0.78]	-2.41 [-4.40, -1.01]
	Investment (pp growth)	-5.25 [-7.91, -2.36]	-8.63 [-16.76, -3.33]
	<i>Investment loss (bn €)</i>	-154.1 [-232.4, -69.3]	-249.0 [-469.9, -96.7]
	<i>% of 2015 base</i>	-5.38 [-8.11, -2.42]	-8.69 [-16.40, -3.37]
	Employment (pp growth)	-1.28 [-2.10, -0.56]	-2.21 [-4.53, -0.79]
	<i>Employment loss (m persons)</i>	-2.65 [-4.34, -1.16]	-4.58 [-9.48, -1.63]
	<i>% of 2015 base</i>	-1.26 [-2.06, -0.55]	-2.18 [-4.50, -0.77]
	Migration p.c. [†] (pers./100)	-0.18 [-0.32, -0.05]	-0.31 [-0.59, -0.07]
Northern	GDP p.c. (pp growth)	-0.16 [-0.24, -0.09]	-0.31 [-0.86, -0.08]
	<i>GDP loss (bn €)</i>	-1.9 [-2.9, -1.0]	-4.6 [-13.4, -0.9]
	<i>% of 2015 base</i>	-0.12 [-0.18, -0.06]	-0.29 [-0.84, -0.06]
	Investment (pp growth)	-0.61 [-0.92, -0.27]	-1.11 [-3.23, -0.29]
	<i>Investment loss (bn €)</i>	-1.5 [-2.3, -0.7]	-3.2 [-10.1, -0.7]
	<i>% of 2015 base</i>	-0.42 [-0.63, -0.19]	-0.90 [-2.81, -0.19]
	Employment (pp growth)	-0.15 [-0.24, -0.07]	-0.28 [-0.90, -0.07]
	<i>Employment loss (m persons)</i>	-0.02 [-0.04, -0.01]	-0.05 [-0.16, -0.01]

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Table C.15: Macro-region cumulative drought impacts (SPEI3) — event year 2022. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Western	% of 2015 base	-0.14 [-0.23, -0.06]	-0.27 [-0.91, -0.06]
	Migration p.c. [†] (pers./100)	-0.02 [-0.04, -0.01]	-0.04 [-0.12, -0.01]
	GDP p.c. (pp growth)	-1.77 [-2.65, -0.96]	-2.78 [-4.84, -1.21]
	GDP loss (bn €)	-126.4 [-189.1, -68.5]	-205.8 [-369.0, -86.1]
	% of 2015 base	-1.58 [-2.37, -0.86]	-2.58 [-4.62, -1.08]
	Investment (pp growth)	-6.88 [-10.38, -3.09]	-10.36 [-18.64, -4.16]
	Investment loss (bn €)	-101.7 [-153.4, -45.7]	-159.8 [-295.7, -63.2]
	% of 2015 base	-6.02 [-9.09, -2.71]	-9.47 [-17.51, -3.75]
	Employment (pp growth)	-1.68 [-2.75, -0.73]	-2.66 [-5.06, -1.00]
	Employment loss (m persons)	-1.47 [-2.41, -0.64]	-2.35 [-4.58, -0.87]
	% of 2015 base	-1.57 [-2.57, -0.68]	-2.51 [-4.89, -0.93]
	Migration p.c. [†] (pers./100)	-0.24 [-0.41, -0.06]	-0.37 [-0.70, -0.09]
	GDP p.c. (pp growth)	-0.68 [-1.02, -0.37]	-1.38 [-3.31, -0.39]
	GDP loss (bn €)	-6.5 [-9.7, -3.5]	-13.8 [-32.3, -3.8]
Eastern	% of 2015 base	-0.59 [-0.88, -0.32]	-1.25 [-2.92, -0.34]
	Investment (pp growth)	-2.65 [-4.00, -1.19]	-5.01 [-12.48, -1.45]
	Investment loss (bn €)	-5.8 [-8.7, -2.6]	-11.9 [-27.9, -3.3]
	% of 2015 base	-2.39 [-3.60, -1.07]	-4.91 [-11.52, -1.36]
	Employment (pp growth)	-0.65 [-1.06, -0.28]	-1.26 [-3.48, -0.33]
	Employment loss (m persons)	-0.23 [-0.38, -0.10]	-0.48 [-1.37, -0.12]
	% of 2015 base	-0.59 [-0.97, -0.26]	-1.22 [-3.45, -0.31]
	Migration p.c. [†] (pers./100)	-0.09 [-0.16, -0.02]	-0.18 [-0.45, -0.03]
	GDP p.c. (pp growth)	-1.63 [-2.43, -0.88]	-2.94 [-5.32, -1.22]
	GDP loss (bn €)	-67.6 [-101.0, -36.6]	-113.3 [-199.7, -48.9]
Southern	% of 2015 base	-2.05 [-3.07, -1.11]	-3.44 [-6.07, -1.49]
	Investment (pp growth)	-6.31 [-9.52, -2.84]	-10.94 [-20.48, -4.21]
	Investment loss (bn €)	-45.0 [-67.9, -20.3]	-73.2 [-132.4, -28.5]
	% of 2015 base	-7.94 [-11.98, -3.57]	-12.90 [-23.36, -5.03]
	Employment (pp growth)	-1.54 [-2.52, -0.67]	-2.81 [-5.53, -1.02]
	Employment loss (m persons)	-0.92 [-1.50, -0.40]	-1.65 [-3.23, -0.60]
	% of 2015 base	-1.64 [-2.68, -0.72]	-2.95 [-5.77, -1.07]

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Table C.15: Macro-region cumulative drought impacts (SPEI3) — event year 2022. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
	Migration p.c. [†] (pers./100)	-0.22 [-0.38, -0.06]	-0.39 [-0.75, -0.09]

[†] Migration p.c. in persons per 100 inhabitants; all other pp rows are percentage-point growth. Loss rows in bn€ (GDP, investment) or millions of persons (employment). % rows express loss as % of group 2015 base.

Table C.16: Country-level cumulative drought impacts (SPEI3) — event year 2022. Cumulative drought impacts (SPEI3), 90% MC confidence intervals in brackets. Observed uncertainty: ARDL coefficient estimation. +2°C: additionally captures uncertainty across four climate models. See notes below table for row definitions.

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Albania	GDP p.c. (pp growth)	-1.23 [-1.84, -0.66]	-2.84 [-6.60, -0.96]
	<i>GDP loss (bn €)</i>	-0.2 [-0.3, -0.1]	-0.4 [-0.9, -0.1]
	<i>% of 2015 base</i>	-1.44 [-2.16, -0.78]	-3.09 [-6.99, -1.09]
	Investment (pp growth)	-4.76 [-7.19, -2.14]	-10.27 [-24.92, -3.34]
	<i>Investment loss (bn €)</i>	-0.2 [-0.3, -0.1]	-0.3 [-0.8, -0.1]
	<i>% of 2015 base</i>	-5.60 [-8.45, -2.52]	-11.21 [-26.39, -3.78]
	Employment (pp growth)	-1.16 [-1.90, -0.51]	-2.60 [-6.96, -0.83]
	<i>Employment loss (m persons)</i>	-0.01 [-0.02, -0.01]	-0.03 [-0.07, -0.01]
	<i>% of 2015 base</i>	-1.17 [-1.91, -0.51]	-2.61 [-6.96, -0.83]
	Migration p.c. [†] (pers./100)	-0.17 [-0.29, -0.04]	-0.37 [-0.89, -0.08]
Austria	GDP p.c. (pp growth)	-0.10 [-0.15, -0.05]	-0.76 [-2.57, -0.06]
	<i>GDP loss (bn €)</i>	-0.3 [-0.5, -0.2]	-2.8 [-9.6, -0.2]
	<i>% of 2015 base</i>	-0.09 [-0.14, -0.05]	-0.76 [-2.59, -0.06]
	Investment (pp growth)	-0.39 [-0.59, -0.18]	-2.61 [-9.71, -0.22]
	<i>Investment loss (bn €)</i>	-0.3 [-0.5, -0.1]	-2.2 [-8.4, -0.2]
	<i>% of 2015 base</i>	-0.36 [-0.54, -0.16]	-2.60 [-9.82, -0.21]
	Employment (pp growth)	-0.10 [-0.16, -0.04]	-0.65 [-2.71, -0.06]
	<i>Employment loss (m persons)</i>	-0.00 [-0.01, -0.00]	-0.03 [-0.12, -0.00]
	<i>% of 2015 base</i>	-0.09 [-0.15, -0.04]	-0.65 [-2.73, -0.06]
	Migration p.c. [†] (pers./100)	-0.01 [-0.02, -0.00]	-0.10 [-0.35, -0.01]
Belgium	GDP p.c. (pp growth)	-3.78 [-5.65, -2.05]	-4.64 [-7.25, -2.38]
	<i>GDP loss (bn €)</i>	-15.9 [-23.8, -8.6]	-20.4 [-31.9, -10.3]

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Table C.16: Country-level cumulative drought impacts (SPEI3) — event year 2022. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Bulgaria	% of 2015 base	-3.51 [-5.25, -1.90]	-4.49 [-7.02, -2.27]
	Investment (pp growth)	-14.67 [-22.13, -6.60]	-17.56 [-27.39, -7.59]
	Investment loss (bn €)	-14.3 [-21.6, -6.4]	-17.7 [-27.5, -7.7]
	% of 2015 base	-13.86 [-20.92, -6.24]	-17.07 [-26.61, -7.41]
	Employment (pp growth)	-3.58 [-5.86, -1.56]	-4.54 [-7.58, -1.81]
	Employment loss (m persons)	-0.16 [-0.26, -0.07]	-0.20 [-0.34, -0.08]
	% of 2015 base	-3.41 [-5.59, -1.49]	-4.43 [-7.45, -1.77]
	Migration p.c. [†] (pers./100)	-0.51 [-0.88, -0.13]	-0.62 [-1.13, -0.19]
	GDP p.c. (pp growth)	-0.15 [-0.22, -0.08]	-1.43 [-5.33, -0.14]
	GDP loss (bn €)	-0.1 [-0.1, -0.0]	-0.7 [-2.7, -0.1]
	% of 2015 base	-0.09 [-0.14, -0.05]	-1.23 [-4.80, -0.09]
	Investment (pp growth)	-0.58 [-0.87, -0.26]	-4.74 [-20.13, -0.47]
	Investment loss (bn €)	-0.0 [-0.1, -0.0]	-0.5 [-2.2, -0.0]
	% of 2015 base	-0.42 [-0.64, -0.19]	-4.57 [-19.90, -0.38]
	Employment (pp growth)	-0.14 [-0.23, -0.06]	-1.20 [-5.62, -0.12]
	Employment loss (m persons)	-0.00 [-0.01, -0.00]	-0.04 [-0.19, -0.00]
Croatia	% of 2015 base	-0.11 [-0.18, -0.05]	-1.13 [-5.41, -0.10]
	Migration p.c. [†] (pers./100)	-0.02 [-0.03, -0.01]	-0.18 [-0.72, -0.01]
	GDP p.c. (pp growth)	-0.38 [-0.58, -0.21]	-1.84 [-3.25, -0.29]
	GDP loss (bn €)	-0.2 [-0.3, -0.1]	-1.0 [-1.8, -0.2]
	% of 2015 base	-0.44 [-0.66, -0.24]	-2.03 [-3.60, -0.33]
	Investment (pp growth)	-1.49 [-2.25, -0.67]	-7.00 [-12.85, -1.28]
	Investment loss (bn €)	-0.2 [-0.3, -0.1]	-0.7 [-1.3, -0.2]
	% of 2015 base	-2.06 [-3.10, -0.92]	-7.57 [-13.66, -1.68]
	Employment (pp growth)	-0.36 [-0.60, -0.16]	-1.78 [-3.53, -0.27]
	Employment loss (m persons)	-0.01 [-0.01, -0.00]	-0.03 [-0.06, -0.00]
Cyprus	% of 2015 base	-0.38 [-0.63, -0.17]	-1.86 [-3.70, -0.28]
	Migration p.c. [†] (pers./100)	-0.05 [-0.09, -0.01]	-0.24 [-0.52, -0.03]
	GDP p.c. (pp growth)	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
	GDP loss (bn €)	0.0 [0.0, 0.0]	0.0 [0.0, 0.0]
	% of 2015 base	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]

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| **Appendix C**

Table C.16: Country-level cumulative drought impacts (SPEI3) — event year 2022. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
	Investment (pp growth)	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
	<i>Investment loss (bn</i>	0.0 [0.0, 0.0]	0.0 [0.0, 0.0]
	€)		
	% of 2015 base	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
	Employment (pp growth)	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
	<i>Employment loss (m</i>	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
	persons)		
	% of 2015 base	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
	Migration p.c. [†]	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
	(pers./100)		
Czechia	GDP p.c. (pp growth)	-0.47 [-0.71, -0.26]	-0.75 [-1.54, -0.21]
	<i>GDP loss (bn €)</i>	-0.8 [-1.2, -0.4]	-1.2 [-2.6, -0.3]
	% of 2015 base	-0.39 [-0.58, -0.21]	-0.61 [-1.28, -0.16]
	Investment (pp growth)	-1.84 [-2.77, -0.83]	-2.78 [-5.82, -0.72]
	<i>Investment loss (bn</i>	-0.7 [-1.1, -0.3]	-1.1 [-2.4, -0.3]
	€)		
	% of 2015 base	-1.46 [-2.20, -0.65]	-2.23 [-4.72, -0.54]
	Employment (pp growth)	-0.45 [-0.73, -0.20]	-0.70 [-1.62, -0.19]
	<i>Employment loss (m</i>	-0.02 [-0.04, -0.01]	-0.03 [-0.08, -0.01]
	persons)		
	% of 2015 base	-0.43 [-0.71, -0.19]	-0.66 [-1.55, -0.17]
	Migration p.c. [†]	-0.06 [-0.11, -0.02]	-0.10 [-0.24, -0.02]
	(pers./100)		
Denmark	GDP p.c. (pp growth)	-0.36 [-0.55, -0.20]	-0.97 [-2.56, -0.20]
	<i>GDP loss (bn €)</i>	-0.8 [-1.1, -0.4]	-2.7 [-7.9, -0.4]
	% of 2015 base	-0.26 [-0.40, -0.14]	-0.96 [-2.76, -0.15]
	Investment (pp growth)	-1.41 [-2.13, -0.64]	-3.45 [-9.67, -0.84]
	<i>Investment loss (bn</i>	-0.5 [-0.8, -0.2]	-1.8 [-5.6, -0.3]
	€)		
	% of 2015 base	-0.94 [-1.42, -0.42]	-3.22 [-9.95, -0.57]
	Employment (pp growth)	-0.35 [-0.57, -0.15]	-0.87 [-2.70, -0.18]
	<i>Employment loss (m</i>	-0.01 [-0.01, -0.00]	-0.02 [-0.08, -0.00]
	persons)		
	% of 2015 base	-0.27 [-0.44, -0.12]	-0.82 [-2.71, -0.14]
	Migration p.c. [†]	-0.05 [-0.09, -0.01]	-0.13 [-0.34, -0.02]
	(pers./100)		
Estonia	GDP p.c. (pp growth)	-0.35 [-0.52, -0.19]	-0.69 [-2.25, -0.01]
	<i>GDP loss (bn €)</i>	-0.1 [-0.2, -0.1]	-0.2 [-0.7, -0.0]
	% of 2015 base	-0.42 [-0.63, -0.23]	-0.86 [-2.83, -0.01]
	Investment (pp growth)	-1.36 [-2.04, -0.61]	-2.40 [-8.48, -0.04]

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Table C.16: Country-level cumulative drought impacts (SPEI3) — event year 2022. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Finland	<i>Investment loss (bn €)</i>	-0.1 [-0.1, -0.0]	-0.2 [-0.6, -0.0]
	<i>% of 2015 base</i>	-1.62 [-2.45, -0.73]	-2.95 [-10.67, -0.03]
	Employment (pp growth)	-0.33 [-0.54, -0.14]	-0.60 [-2.37, -0.01]
	<i>Employment loss (m persons)</i>	-0.00 [-0.00, -0.00]	-0.00 [-0.02, -0.00]
	<i>% of 2015 base</i>	-0.35 [-0.58, -0.15]	-0.64 [-2.59, -0.01]
	Migration p.c. [†] (pers./100)	-0.05 [-0.08, -0.01]	-0.09 [-0.30, -0.00]
	GDP p.c. (pp growth)	-0.16 [-0.24, -0.09]	-0.15 [-0.49, -0.03]
	<i>GDP loss (bn €)</i>	-0.5 [-0.7, -0.3]	-0.4 [-1.3, -0.1]
	<i>% of 2015 base</i>	-0.21 [-0.32, -0.11]	-0.18 [-0.58, -0.03]
	Investment (pp growth)	-0.62 [-0.94, -0.28]	-0.50 [-1.84, -0.08]
	<i>Investment loss (bn €)</i>	-0.4 [-0.6, -0.2]	-0.3 [-1.1, -0.1]
	<i>% of 2015 base</i>	-0.84 [-1.27, -0.38]	-0.63 [-2.19, -0.11]
	Employment (pp growth)	-0.15 [-0.25, -0.07]	-0.13 [-0.51, -0.02]
	<i>Employment loss (m persons)</i>	-0.00 [-0.01, -0.00]	-0.00 [-0.01, -0.00]
	<i>% of 2015 base</i>	-0.18 [-0.29, -0.08]	-0.14 [-0.56, -0.02]
	Migration p.c. [†] (pers./100)	-0.02 [-0.04, -0.01]	-0.02 [-0.07, -0.00]
France	GDP p.c. (pp growth)	-2.02 [-3.02, -1.09]	-3.51 [-5.92, -1.50]
	<i>GDP loss (bn €)</i>	-42.0 [-62.9, -22.8]	-76.2 [-133.6, -31.1]
	<i>% of 2015 base</i>	-1.79 [-2.68, -0.97]	-3.25 [-5.70, -1.33]
	Investment (pp growth)	-7.83 [-11.81, -3.52]	-13.16 [-22.80, -5.29]
	<i>Investment loss (bn €)</i>	-33.4 [-50.4, -15.0]	-58.4 [-104.5, -23.3]
	<i>% of 2015 base</i>	-6.94 [-10.47, -3.12]	-12.14 [-21.73, -4.85]
	Employment (pp growth)	-1.91 [-3.13, -0.83]	-3.38 [-6.24, -1.26]
	<i>Employment loss (m persons)</i>	-0.49 [-0.80, -0.21]	-0.88 [-1.65, -0.32]
	<i>% of 2015 base</i>	-1.78 [-2.91, -0.78]	-3.21 [-6.01, -1.17]
	Migration p.c. [†] (pers./100)	-0.27 [-0.47, -0.07]	-0.46 [-0.88, -0.12]
Germany	GDP p.c. (pp growth)	-1.87 [-2.79, -1.01]	-2.63 [-4.83, -1.12]
	<i>GDP loss (bn €)</i>	-58.9 [-88.0, -31.9]	-85.2 [-159.0, -35.3]
	<i>% of 2015 base</i>	-1.76 [-2.63, -0.95]	-2.54 [-4.74, -1.05]
	Investment (pp growth)	-7.24 [-10.92, -3.26]	-9.79 [-18.59, -3.81]

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| **Appendix C**

Table C.16: Country-level cumulative drought impacts (SPEI3) — event year 2022. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Greece	<i>Investment loss (bn €)</i>	-45.5 [-68.7, -20.5]	-62.7 [-121.4, -23.9]
	<i>% of 2015 base</i>	-6.76 [-10.20, -3.04]	-9.31 [-18.02, -3.54]
	Employment (pp growth)	-1.77 [-2.89, -0.77]	-2.50 [-5.05, -0.96]
	<i>Employment loss (m persons)</i>	-0.74 [-1.22, -0.32]	-1.06 [-2.16, -0.40]
	<i>% of 2015 base</i>	-1.73 [-2.83, -0.75]	-2.46 [-5.01, -0.94]
	Migration p.c. [†] (pers./100)	-0.25 [-0.44, -0.07]	-0.35 [-0.68, -0.09]
	GDP p.c. (pp growth)	-0.11 [-0.17, -0.06]	-1.33 [-3.69, -0.36]
	<i>GDP loss (bn €)</i>	-0.2 [-0.3, -0.1]	-2.7 [-6.9, -0.9]
	<i>% of 2015 base</i>	-0.11 [-0.17, -0.06]	-1.56 [-3.93, -0.50]
	Investment (pp growth)	-0.43 [-0.65, -0.19]	-4.67 [-13.93, -1.23]
	<i>Investment loss (bn €)</i>	-0.1 [-0.1, -0.0]	-0.9 [-2.6, -0.2]
	<i>% of 2015 base</i>	-0.39 [-0.60, -0.18]	-4.48 [-13.40, -1.20]
	Employment (pp growth)	-0.11 [-0.17, -0.05]	-1.19 [-3.89, -0.30]
	<i>Employment loss (m persons)</i>	-0.00 [-0.01, -0.00]	-0.06 [-0.17, -0.01]
	<i>% of 2015 base</i>	-0.10 [-0.17, -0.05]	-1.27 [-3.97, -0.35]
	Migration p.c. [†] (pers./100)	-0.02 [-0.03, -0.00]	-0.17 [-0.50, -0.03]
Hungary	GDP p.c. (pp growth)	-1.11 [-1.67, -0.60]	-2.18 [-4.42, -0.70]
	<i>GDP loss (bn €)</i>	-0.9 [-1.4, -0.5]	-2.4 [-5.4, -0.6]
	<i>% of 2015 base</i>	-0.75 [-1.12, -0.41]	-1.96 [-4.41, -0.47]
	Investment (pp growth)	-4.32 [-6.52, -1.94]	-8.07 [-16.85, -2.66]
	<i>Investment loss (bn €)</i>	-1.0 [-1.5, -0.4]	-2.1 [-4.7, -0.6]
	<i>% of 2015 base</i>	-3.42 [-5.16, -1.54]	-7.41 [-16.72, -2.12]
	Employment (pp growth)	-1.05 [-1.73, -0.46]	-2.04 [-4.60, -0.60]
	<i>Employment loss (m persons)</i>	-0.03 [-0.05, -0.01]	-0.08 [-0.20, -0.02]
	<i>% of 2015 base</i>	-0.77 [-1.26, -0.34]	-1.85 [-4.60, -0.44]
	Migration p.c. [†] (pers./100)	-0.15 [-0.26, -0.04]	-0.29 [-0.65, -0.06]
Ireland	GDP p.c. (pp growth)	0.00 [0.00, 0.00]	-0.01 [-0.02, -0.00]
	<i>GDP loss (bn €)</i>	0.0 [0.0, 0.0]	-0.0 [-0.0, -0.0]
	<i>% of 2015 base</i>	0.00 [0.00, 0.00]	-0.00 [-0.01, -0.00]
	Investment (pp growth)	0.00 [0.00, 0.00]	-0.03 [-0.06, -0.01]

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Table C.16: Country-level cumulative drought impacts (SPEI3) — event year 2022. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Italy	<i>Investment loss (bn €)</i>	0.0 [0.0, 0.0]	-0.0 [-0.0, -0.0]
	<i>% of 2015 base</i>	0.00 [0.00, 0.00]	-0.01 [-0.03, -0.00]
	Employment (pp growth)	0.00 [0.00, 0.00]	-0.01 [-0.02, -0.00]
	<i>Employment loss (m persons)</i>	0.00 [0.00, 0.00]	-0.00 [-0.00, -0.00]
	<i>% of 2015 base</i>	0.00 [0.00, 0.00]	-0.01 [-0.01, -0.00]
	Migration p.c. [†] (pers./100)	0.00 [0.00, 0.00]	-0.00 [-0.00, -0.00]
	GDP p.c. (pp growth)	-2.06 [-3.09, -1.12]	-3.25 [-5.63, -1.40]
	<i>GDP loss (bn €)</i>	-43.0 [-64.3, -23.3]	-66.0 [-113.4, -28.6]
	<i>% of 2015 base</i>	-2.44 [-3.65, -1.32]	-3.75 [-6.45, -1.63]
	Investment (pp growth)	-8.01 [-12.08, -3.60]	-12.16 [-21.49, -4.81]
	<i>Investment loss (bn €)</i>	-27.1 [-40.9, -12.2]	-40.3 [-71.0, -16.0]
	<i>% of 2015 base</i>	-9.34 [-14.09, -4.20]	-13.89 [-24.45, -5.49]
	Employment (pp growth)	-1.95 [-3.20, -0.85]	-3.12 [-5.86, -1.17]
	<i>Employment loss (m persons)</i>	-0.52 [-0.86, -0.23]	-0.82 [-1.54, -0.31]
	<i>% of 2015 base</i>	-2.15 [-3.52, -0.94]	-3.39 [-6.33, -1.27]
	Migration p.c. [†] (pers./100)	-0.28 [-0.48, -0.07]	-0.43 [-0.81, -0.11]
Latvia	GDP p.c. (pp growth)	0.00 [0.00, 0.00]	-0.05 [-0.23, 0.00]
	<i>GDP loss (bn €)</i>	0.0 [0.0, 0.0]	-0.0 [-0.0, 0.0]
	<i>% of 2015 base</i>	0.00 [0.00, 0.00]	-0.03 [-0.15, 0.00]
	Investment (pp growth)	0.00 [0.00, 0.00]	-0.16 [-0.85, 0.00]
	<i>Investment loss (bn €)</i>	0.0 [0.0, 0.0]	-0.0 [-0.0, 0.0]
	<i>% of 2015 base</i>	0.00 [0.00, 0.00]	-0.11 [-0.58, 0.00]
	Employment (pp growth)	0.00 [0.00, 0.00]	-0.04 [-0.24, 0.00]
	<i>Employment loss (m persons)</i>	0.00 [0.00, 0.00]	-0.00 [-0.00, 0.00]
	<i>% of 2015 base</i>	0.00 [0.00, 0.00]	-0.04 [-0.21, 0.00]
	Migration p.c. [†] (pers./100)	0.00 [0.00, 0.00]	-0.01 [-0.03, 0.00]
Lithuania	GDP p.c. (pp growth)	-0.48 [-0.72, -0.26]	-0.55 [-1.06, -0.23]
	<i>GDP loss (bn €)</i>	-0.2 [-0.3, -0.1]	-0.2 [-0.4, -0.1]
	<i>% of 2015 base</i>	-0.43 [-0.64, -0.23]	-0.49 [-0.94, -0.21]
	Investment (pp growth)	-1.86 [-2.81, -0.84]	-2.03 [-4.02, -0.73]

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| **Appendix C**

Table C.16: Country-level cumulative drought impacts (SPEI3) — event year 2022. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Luxembourg	<i>Investment loss (bn €)</i>	-0.1 [-0.2, -0.1]	-0.2 [-0.3, -0.1]
	<i>% of 2015 base</i>	-1.72 [-2.60, -0.78]	-1.88 [-3.67, -0.69]
	Employment (pp growth)	-0.45 [-0.74, -0.20]	-0.52 [-1.12, -0.20]
	<i>Employment loss (m persons)</i>	-0.01 [-0.01, -0.00]	-0.01 [-0.02, -0.00]
	<i>% of 2015 base</i>	-0.46 [-0.76, -0.20]	-0.53 [-1.12, -0.20]
	Migration p.c. [†] (pers./100)	-0.06 [-0.11, -0.02]	-0.07 [-0.15, -0.02]
	GDP p.c. (pp growth)	-4.13 [-6.17, -2.24]	-4.88 [-7.55, -2.46]
	<i>GDP loss (bn €)</i>	-2.4 [-3.6, -1.3]	-2.8 [-4.4, -1.4]
	<i>% of 2015 base</i>	-4.13 [-6.17, -2.24]	-4.88 [-7.55, -2.46]
	Investment (pp growth)	-16.02 [-24.16, -7.20]	-18.44 [-28.68, -7.77]
	<i>Investment loss (bn €)</i>	-1.6 [-2.5, -0.7]	-1.9 [-2.9, -0.8]
	<i>% of 2015 base</i>	-16.02 [-24.16, -7.20]	-18.44 [-28.68, -7.77]
	Employment (pp growth)	-3.91 [-6.40, -1.71]	-4.74 [-7.89, -1.95]
	<i>Employment loss (m persons)</i>	-0.02 [-0.03, -0.01]	-0.02 [-0.03, -0.01]
Malta	<i>% of 2015 base</i>	-3.91 [-6.40, -1.71]	-4.74 [-7.89, -1.95]
	Migration p.c. [†] (pers./100)	-0.56 [-0.97, -0.15]	-0.65 [-1.17, -0.20]
	GDP p.c. (pp growth)	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
	<i>GDP loss (bn €)</i>	0.0 [0.0, 0.0]	0.0 [0.0, 0.0]
	<i>% of 2015 base</i>	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
	Investment (pp growth)	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
	<i>Investment loss (bn €)</i>	0.0 [0.0, 0.0]	0.0 [0.0, 0.0]
	<i>% of 2015 base</i>	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
	Employment (pp growth)	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
	<i>Employment loss (m persons)</i>	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
Montenegro	<i>% of 2015 base</i>	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
	Migration p.c. [†] (pers./100)	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
	GDP p.c. (pp growth)	0.00 [0.00, 0.00]	-0.33 [-1.48, 0.00]
	<i>GDP loss (bn €)</i>	0.0 [0.0, 0.0]	-0.0 [-0.1, 0.0]
	<i>% of 2015 base</i>	0.00 [0.00, 0.00]	-0.33 [-1.48, 0.00]
	Investment (pp growth)	0.00 [0.00, 0.00]	-1.05 [-5.60, 0.00]

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Table C.16: Country-level cumulative drought impacts (SPEI3) — event year 2022. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
N. Macedonia	<i>Investment loss (bn €)</i>	0.0 [0.0, 0.0]	-0.0 [-0.0, 0.0]
	<i>% of 2015 base</i>	0.00 [0.00, 0.00]	-1.05 [-5.60, 0.00]
	Employment (pp growth)	0.00 [0.00, 0.00]	-0.26 [-1.56, 0.00]
	<i>Employment loss (m persons)</i>	0.00 [0.00, 0.00]	-0.00 [-0.00, 0.00]
	<i>% of 2015 base</i>	0.00 [0.00, 0.00]	-0.26 [-1.56, 0.00]
	Migration p.c. [†] (pers./100)	0.00 [0.00, 0.00]	-0.04 [-0.20, 0.00]
	GDP p.c. (pp growth)	-0.02 [-0.03, -0.01]	-1.33 [-5.14, -0.04]
	<i>GDP loss (bn €)</i>	-0.0 [-0.0, -0.0]	-0.1 [-0.5, -0.0]
	<i>% of 2015 base</i>	-0.01 [-0.02, -0.01]	-1.32 [-5.24, -0.02]
	Investment (pp growth)	-0.08 [-0.13, -0.04]	-4.43 [-19.40, -0.16]
	<i>Investment loss (bn €)</i>	-0.0 [-0.0, -0.0]	-0.1 [-0.4, -0.0]
	<i>% of 2015 base</i>	-0.04 [-0.07, -0.02]	-4.36 [-19.77, -0.08]
	Employment (pp growth)	-0.02 [-0.03, -0.01]	-1.11 [-5.42, -0.03]
	<i>Employment loss (m persons)</i>	-0.00 [-0.00, -0.00]	-0.01 [-0.04, -0.00]
Netherlands	<i>% of 2015 base</i>	-0.01 [-0.02, -0.01]	-1.09 [-5.39, -0.02]
	Migration p.c. [†] (pers./100)	-0.00 [-0.01, -0.00]	-0.17 [-0.69, -0.00]
	GDP p.c. (pp growth)	-0.31 [-0.46, -0.17]	-0.65 [-1.45, -0.22]
	<i>GDP loss (bn €)</i>	-1.9 [-2.8, -1.0]	-4.2 [-9.8, -1.3]
	<i>% of 2015 base</i>	-0.25 [-0.37, -0.13]	-0.55 [-1.28, -0.17]
	Investment (pp growth)	-1.20 [-1.81, -0.54]	-2.36 [-5.46, -0.83]
	<i>Investment loss (bn €)</i>	-1.4 [-2.0, -0.6]	-2.9 [-7.0, -0.9]
	<i>% of 2015 base</i>	-0.81 [-1.22, -0.37]	-1.71 [-4.21, -0.56]
	Employment (pp growth)	-0.29 [-0.48, -0.13]	-0.60 [-1.52, -0.18]
	<i>Employment loss (m persons)</i>	-0.02 [-0.04, -0.01]	-0.05 [-0.13, -0.01]
Norway	<i>% of 2015 base</i>	-0.27 [-0.44, -0.12]	-0.57 [-1.47, -0.17]
	Migration p.c. [†] (pers./100)	-0.04 [-0.07, -0.01]	-0.08 [-0.19, -0.02]
	GDP p.c. (pp growth)	-0.09 [-0.13, -0.05]	-0.17 [-0.41, -0.04]
	<i>GDP loss (bn €)</i>	-0.2 [-0.3, -0.1]	-0.4 [-0.9, -0.1]
	<i>% of 2015 base</i>	-0.07 [-0.11, -0.04]	-0.14 [-0.33, -0.03]
	Investment (pp growth)	-0.34 [-0.51, -0.15]	-0.63 [-1.56, -0.17]

(*continued on next page*)

| **Appendix C**

Table C.16: Country-level cumulative drought impacts (SPEI3) — event year 2022. *(continued)*

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Poland	<i>Investment loss (bn €)</i>	-0.2 [-0.2, -0.1]	-0.3 [-0.7, -0.1]
	<i>% of 2015 base</i>	-0.26 [-0.40, -0.12]	-0.49 [-1.23, -0.13]
	Employment (pp growth)	-0.08 [-0.13, -0.04]	-0.16 [-0.43, -0.03]
	<i>Employment loss (m persons)</i>	-0.00 [-0.00, -0.00]	-0.00 [-0.01, -0.00]
	<i>% of 2015 base</i>	-0.07 [-0.12, -0.03]	-0.14 [-0.38, -0.03]
	Migration p.c. [†] (pers./100)	-0.01 [-0.02, -0.00]	-0.02 [-0.06, -0.00]
	GDP p.c. (pp growth)	-0.51 [-0.77, -0.28]	-0.76 [-1.81, -0.15]
	<i>GDP loss (bn €)</i>	-2.1 [-3.1, -1.1]	-3.1 [-7.5, -0.6]
	<i>% of 2015 base</i>	-0.46 [-0.69, -0.25]	-0.68 [-1.66, -0.14]
	Investment (pp growth)	-1.99 [-3.00, -0.89]	-2.75 [-6.84, -0.55]
	<i>Investment loss (bn €)</i>	-1.6 [-2.4, -0.7]	-2.2 [-5.5, -0.4]
	<i>% of 2015 base</i>	-1.79 [-2.70, -0.80]	-2.47 [-6.28, -0.48]
	Employment (pp growth)	-0.48 [-0.79, -0.21]	-0.69 [-1.91, -0.14]
	<i>Employment loss (m persons)</i>	-0.08 [-0.12, -0.03]	-0.11 [-0.30, -0.02]
Portugal	<i>% of 2015 base</i>	-0.48 [-0.78, -0.21]	-0.67 [-1.89, -0.13]
	Migration p.c. [†] (pers./100)	-0.07 [-0.12, -0.02]	-0.10 [-0.25, -0.01]
	GDP p.c. (pp growth)	-0.48 [-0.71, -0.26]	-1.61 [-3.24, -0.50]
	<i>GDP loss (bn €)</i>	-0.9 [-1.4, -0.5]	-3.1 [-6.1, -1.0]
	<i>% of 2015 base</i>	-0.48 [-0.72, -0.26]	-1.58 [-3.09, -0.53]
	Investment (pp growth)	-1.85 [-2.79, -0.83]	-5.95 [-12.37, -1.69]
	<i>Investment loss (bn €)</i>	-0.6 [-0.9, -0.3]	-1.8 [-3.8, -0.6]
	<i>% of 2015 base</i>	-1.81 [-2.74, -0.82]	-5.90 [-12.12, -1.81]
	Employment (pp growth)	-0.45 [-0.74, -0.20]	-1.56 [-3.47, -0.41]
	<i>Employment loss (m persons)</i>	-0.02 [-0.03, -0.01]	-0.07 [-0.16, -0.02]
Romania	<i>% of 2015 base</i>	-0.44 [-0.72, -0.19]	-1.54 [-3.42, -0.42]
	Migration p.c. [†] (pers./100)	-0.06 [-0.11, -0.02]	-0.21 [-0.50, -0.04]
	GDP p.c. (pp growth)	-0.84 [-1.26, -0.46]	-2.29 [-5.72, -0.56]
	<i>GDP loss (bn €)</i>	-1.6 [-2.4, -0.9]	-4.9 [-11.5, -1.4]
	<i>% of 2015 base</i>	-0.85 [-1.27, -0.46]	-2.65 [-6.17, -0.74]
	Investment (pp growth)	-3.26 [-4.92, -1.47]	-8.22 [-21.59, -2.37]

(continued on next page)

Table C.16: Country-level cumulative drought impacts (SPEI3) — event year 2022. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Serbia	<i>Investment loss (bn €)</i>	-1.5 [-2.3, -0.7]	-4.8 [-11.1, -1.5]
	<i>% of 2015 base</i>	-3.39 [-5.12, -1.53]	-10.75 [-24.86, -3.39]
	Employment (pp growth)	-0.80 [-1.30, -0.35]	-2.09 [-6.03, -0.49]
	<i>Employment loss (m persons)</i>	-0.07 [-0.11, -0.03]	-0.18 [-0.52, -0.04]
	<i>% of 2015 base</i>	-0.81 [-1.32, -0.35]	-2.15 [-6.12, -0.52]
	Migration p.c. [†] (pers./100)	-0.11 [-0.20, -0.03]	-0.30 [-0.77, -0.05]
	GDP p.c. (pp growth)	-0.18 [-0.27, -0.10]	-1.58 [-4.33, -0.18]
	<i>GDP loss (bn €)</i>	-0.1 [-0.1, -0.0]	-0.7 [-1.9, -0.1]
	<i>% of 2015 base</i>	-0.15 [-0.22, -0.08]	-1.63 [-4.33, -0.15]
	Investment (pp growth)	-0.71 [-1.07, -0.32]	-5.61 [-16.36, -0.77]
	<i>Investment loss (bn €)</i>	-0.0 [-0.1, -0.0]	-0.4 [-1.1, -0.0]
	<i>% of 2015 base</i>	-0.60 [-0.91, -0.27]	-5.91 [-16.25, -0.68]
	Employment (pp growth)	-0.17 [-0.28, -0.08]	-1.41 [-4.57, -0.17]
	<i>Employment loss (m persons)</i>	-0.01 [-0.01, -0.00]	-0.05 [-0.15, -0.01]
	<i>% of 2015 base</i>	-0.19 [-0.31, -0.08]	-1.41 [-4.62, -0.17]
Slovakia	Migration p.c. [†] (pers./100)	-0.02 [-0.04, -0.01]	-0.20 [-0.58, -0.02]
	GDP p.c. (pp growth)	-1.61 [-2.40, -0.87]	-2.13 [-4.29, -0.49]
	<i>GDP loss (bn €)</i>	-1.1 [-1.6, -0.6]	-1.4 [-2.9, -0.3]
	<i>% of 2015 base</i>	-1.23 [-1.85, -0.67]	-1.67 [-3.40, -0.37]
	Investment (pp growth)	-6.23 [-9.41, -2.80]	-7.97 [-16.66, -1.77]
	<i>Investment loss (bn €)</i>	-1.0 [-1.4, -0.4]	-1.2 [-2.6, -0.3]
	<i>% of 2015 base</i>	-4.58 [-6.92, -2.06]	-5.94 [-12.54, -1.28]
	Employment (pp growth)	-1.52 [-2.49, -0.66]	-1.99 [-4.56, -0.45]
	<i>Employment loss (m persons)</i>	-0.03 [-0.05, -0.01]	-0.04 [-0.09, -0.01]
	<i>% of 2015 base</i>	-1.34 [-2.19, -0.58]	-1.78 [-4.13, -0.39]
Slovenia	Migration p.c. [†] (pers./100)	-0.22 [-0.38, -0.06]	-0.29 [-0.67, -0.04]
	GDP p.c. (pp growth)	-1.60 [-2.39, -0.86]	-2.26 [-3.92, -1.00]
	<i>GDP loss (bn €)</i>	-0.8 [-1.1, -0.4]	-1.0 [-1.8, -0.5]
	<i>% of 2015 base</i>	-1.84 [-2.75, -1.00]	-2.50 [-4.21, -1.14]
	Investment (pp growth)	-6.19 [-9.34, -2.79]	-8.50 [-14.85, -3.37]

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Table C.16: Country-level cumulative drought impacts (SPEI3) — event year 2022. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
Spain	<i>Investment loss (bn €)</i>	-0.5 [-0.8, -0.2]	-0.7 [-1.2, -0.3]
	<i>% of 2015 base</i>	-6.85 [-10.34, -3.08]	-9.14 [-15.76, -3.76]
	Employment (pp growth)	-1.51 [-2.47, -0.66]	-2.16 [-4.15, -0.85]
	<i>Employment loss (m persons)</i>	-0.02 [-0.03, -0.01]	-0.02 [-0.04, -0.01]
	<i>% of 2015 base</i>	-1.64 [-2.68, -0.72]	-2.29 [-4.28, -0.91]
	Migration p.c. [†] (pers./100)	-0.22 [-0.37, -0.06]	-0.30 [-0.60, -0.08]
	GDP p.c. (pp growth)	-1.81 [-2.70, -0.98]	-3.36 [-6.07, -1.46]
	<i>GDP loss (bn €)</i>	-22.4 [-33.5, -12.1]	-41.0 [-73.2, -18.3]
	<i>% of 2015 base</i>	-1.96 [-2.93, -1.06]	-3.58 [-6.39, -1.60]
	Investment (pp growth)	-7.01 [-10.58, -3.15]	-12.49 [-23.22, -4.78]
	<i>Investment loss (bn €)</i>	-16.4 [-24.7, -7.4]	-28.7 [-53.0, -11.0]
	<i>% of 2015 base</i>	-7.81 [-11.78, -3.51]	-13.67 [-25.26, -5.25]
	Employment (pp growth)	-1.71 [-2.80, -0.75]	-3.21 [-6.31, -1.19]
	<i>Employment loss (m persons)</i>	-0.33 [-0.55, -0.15]	-0.62 [-1.21, -0.23]
	<i>% of 2015 base</i>	-1.79 [-2.93, -0.78]	-3.33 [-6.50, -1.25]
	Migration p.c. [†] (pers./100)	-0.24 [-0.42, -0.06]	-0.44 [-0.85, -0.11]
Sweden	GDP p.c. (pp growth)	-0.06 [-0.09, -0.03]	-0.18 [-0.59, -0.02]
	<i>GDP loss (bn €)</i>	-0.2 [-0.3, -0.1]	-0.7 [-2.2, -0.1]
	<i>% of 2015 base</i>	-0.05 [-0.07, -0.03]	-0.15 [-0.50, -0.01]
	Investment (pp growth)	-0.22 [-0.34, -0.10]	-0.62 [-2.23, -0.06]
	<i>Investment loss (bn €)</i>	-0.2 [-0.3, -0.1]	-0.5 [-1.8, -0.0]
	<i>% of 2015 base</i>	-0.16 [-0.25, -0.07]	-0.47 [-1.73, -0.04]
	Employment (pp growth)	-0.05 [-0.09, -0.02]	-0.15 [-0.62, -0.02]
	<i>Employment loss (m persons)</i>	-0.00 [-0.00, -0.00]	-0.01 [-0.03, -0.00]
	<i>% of 2015 base</i>	-0.05 [-0.08, -0.02]	-0.14 [-0.58, -0.02]
	Migration p.c. [†] (pers./100)	-0.01 [-0.01, -0.00]	-0.02 [-0.08, -0.00]
Switzerland	GDP p.c. (pp growth)	-0.80 [-1.19, -0.43]	-2.21 [-4.16, -0.58]
	<i>GDP loss (bn €)</i>	-4.9 [-7.4, -2.7]	-14.1 [-26.7, -3.6]
	<i>% of 2015 base</i>	-0.78 [-1.17, -0.42]	-2.24 [-4.25, -0.57]
	Investment (pp growth)	-3.10 [-4.68, -1.39]	-8.29 [-15.80, -2.49]

(*continued on next page*)

Table C.16: Country-level cumulative drought impacts (SPEI3) — event year 2022. (*continued*)

Group	Variable	Observed [90% CI]	+2°C [90% CI]
	<i>Investment loss (bn</i>	-5.1 [-7.7, -2.3]	-14.1 [-27.2, -4.1]
	€)		
	<i>% of 2015 base</i>	-3.04 [-4.59, -1.37]	-8.41 [-16.19, -2.42]
	Employment (pp growth)	-0.76 [-1.24, -0.33]	-2.10 [-4.39, -0.51]
	<i>Employment loss (m</i>	-0.03 [-0.06, -0.02]	-0.10 [-0.21, -0.02]
	persons)		
	<i>% of 2015 base</i>	-0.71 [-1.16, -0.31]	-2.09 [-4.38, -0.48]
	Migration p.c. [†]	-0.11 [-0.19, -0.03]	-0.29 [-0.63, -0.05]
	(pers./100)		

[†] Migration p.c. in persons per 100 inhabitants; all other pp rows are percentage-point growth. Loss rows in bn€ (GDP, investment) or millions of persons (employment). % rows express loss as % of group 2015 base.

GDP p.c. — drought severity & cumulative impact

SEV | SPEI-3 | severe | event: 2022

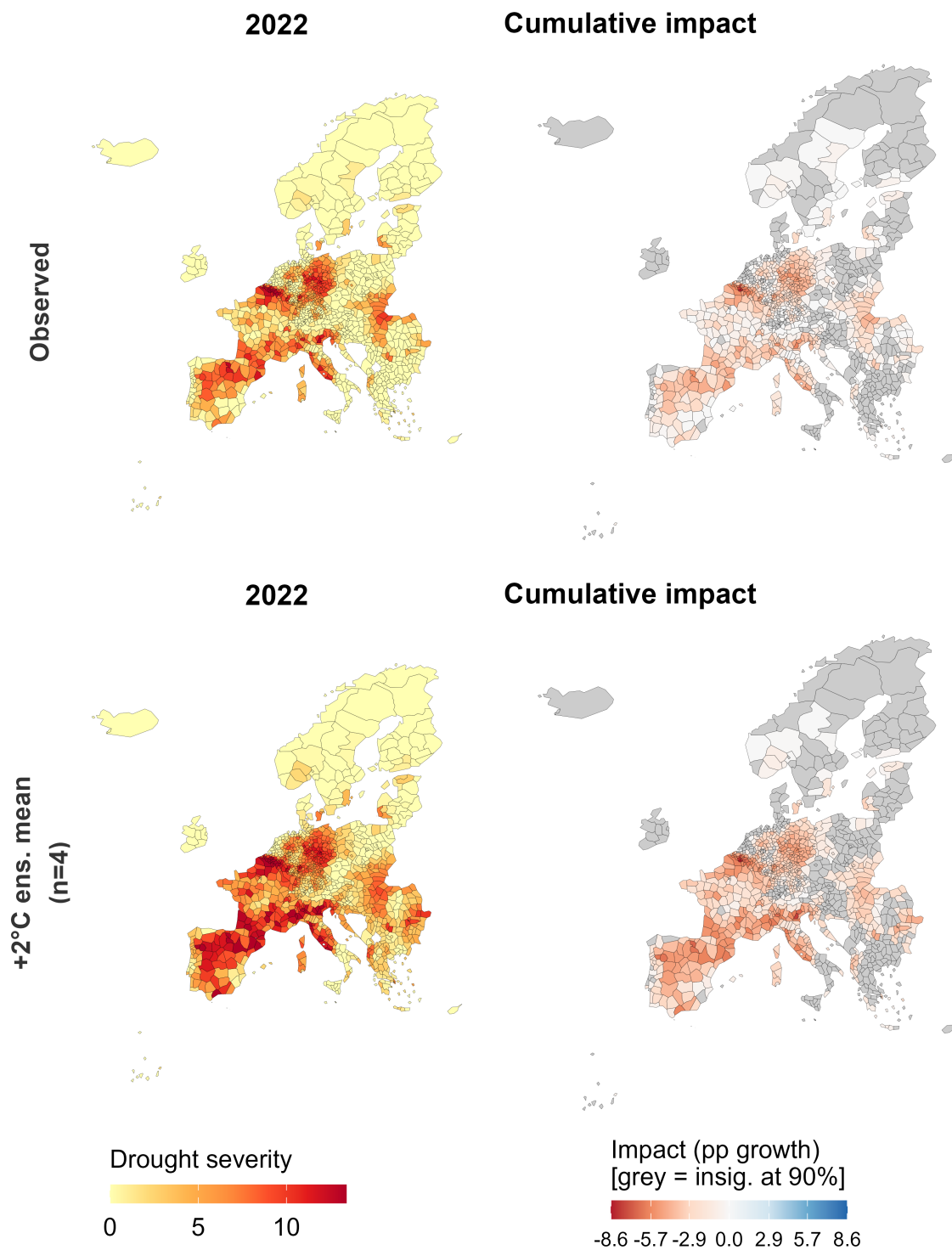


Figure C.75: SPEI-3 storyline for the 2022 drought event. We report cumulative impacts on GDP per capita growth, integrated over the full response horizon (lag selected by BIC: 6 years for SPEI-3). Grey regions are insignificant at the 90% level."

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