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The Present-Day Poverty Consequences of Climate Change

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Parallel Session 5A Climate Change, Land Inequality and Urban/ Rural Gaps
Time Slot: Friday, October 3, 10:30-12:30 PM

The Present-Day Poverty Consequences of Climate Change

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Abstract

This paper quantifies the impact of climate change on global extreme poverty by linking climate-induced GDP shocks to poverty outcomes. Using global GDP, poverty, and climate data from 1960-2024, we estimate that climate change added up to 95 million people to extreme poverty, with nearly 80 million still affected today. While excess poverty is projected to increase, reaching approximately 100 million by 2050 under a low-emissions scenario (RCP2.6) and over 140 million under a high-emissions scenario (RCP8.5), most of the total impact has already materialized. The burden falls disproportionately on Sub-Saharan Africa and the poorest households, who face welfare losses many times larger than the richest. Our findings highlight the dual role of economic growth as both a driver of resilience and a source of emissions. Future poverty reduction depends on fostering rapid, inclusive growth alongside pro-poor adaptation strategies.

Keywords: Climate change, global poverty, income inequality, economic growth

JEL codes: Q54, I32, O44, D63

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Introduction

Rapid economic growth in the 20th and 21st centuries has lifted billions out of extreme poverty, defined as living with less than $3 per day (Foster ⓡ et al. 2024). Further economic growth remains essential for continued improvements in global living standards. At the same time, this economic expansion has produced greenhouse gas emissions and global warming, which in turn is causing rising economic damages. Most of today's extreme poor live in countries that have contributed little to the global stock of emissions but disproportionately suffer the impacts of climate shocks, as these countries are less well equipped to adapt and protect vulnerable populations from climate shocks while they are projected to experience more intense warming.

A handful of studies have projected the impact of climate shocks on global poverty (Moyer et al. 2023; Jafino et al. 2020; Hallegatte and Rozenberg 2017; Crespo Cuaresma et al. 2018), using a variety of modelling and estimation approaches and relying on the Shared Socioeconomic Pathways (SSPs) to model future socioeconomic development under different climate change scenarios. The projections vary depending on the assumptions about future GDP growth, inequality, and global warming, ranging between 3 and 132 million additional extreme poor due to climate change. Relatedly, there is a large and growing literature on the projected impacts of climate shocks and global warming on global GDP (Nath et al. 2024; Newell et al. 2021; Burke et al. 2015; Kotz et al. 2024; Waidelich et al. 2024; Bilal and Känzig 2024). These studies have developed and improved a set of methods to identify the impact of climate change by linking year-on-year changes (shocks) in temperature and other climate variables to changes in GDP. Yet another related set of studies has documented the impact of increasing temperatures and precipitation anomalies on countries' levels of inequality (Palagi et al. 2022; Gilli et al. 2024).

Here, we employ the latest methods from the latter two streams of literature to compute the impact of climate shocks on global poverty. This approach is advantageous as changes in GDP are highly predictive of changes in poverty levels (Mahler et al. 2022). We contribute to the literature by quantifying the *historical* and *present-day* impacts of climate change on global poverty. The world has already experienced substantial global warming, with global mean surface temperatures averaging 1.6C above pre-industrial levels in 2024. Anchoring our estimates in historical weather and GDP data reduces the uncertainty related to predicted weather, socioeconomic, and inequality realizations and the sensitivity to different parameter values and simulation approaches to which existing results on the poverty impact of climate shocks are subject.

Results

We use country-year poverty data from the World Bank's Poverty and Inequality Platform, which contains poverty headcounts and headcount rates for 170 countries (World Bank 2025), and country-year GDP data from the World Bank's World Development Indicators for 211 economies for the years 1960-2024. To capture temperature and precipitation during the same period, we use ERA5 data. To construct a counterfactual temperature and precipitation distribution reflecting what could have materialized in the absence of any anthropogenic emissions, we rely on data from the Coupled Model Intercomparison Project Phase 6 (CMIP6), and in particular the 'hist-nat' simulations. These simulations model temperature and precipitation since 1870 without anthropogenic emissions and are designed to study and attribute human-made climatic changes (Gillett et al. 2016).

Our approach relies on the close empirical relationship between a country's GDP per capita and its per-capita consumption levels, which, in turn, define the poverty rate: a 1% change in GDP has been shown to lead to a 0.7% change in consumption on average (Prydz et al. 2022; Wollburg et al. 2023). Thus, to assess the impact of climate change on global poverty, we estimate how the change in GDP attributed to climate change affects poverty levels in each country and year.

In the first step, we run a country- and year-fixed effects regression model of GDP on a range climate variables, including temperature changes, total precipitation, extreme precipitation, and annual number of wet days, following the approach taken in two recent studies (Kotz et al. 2024; Waidelich et al. 2024).

The country-level GDP shocks we obtain from this model are translated into average consumption shocks. To assess poverty impacts, we account for how these shocks are distributed across the income distribution, since identical average shocks can have different poverty effects depending on how the shock affects different income groups differentially. We follow the approaches of Gilli et al. (2024) for temperature-related inequality effects and Palagi et al. (2022) for precipitation-related inequality effects. The resulting distributionally adjusted consumption shocks are then used to calculate poverty changes.

Between 1980 and 2024, climate change added up to 95 million people to global extreme poverty at its peak. Figure 1 shows that the number of additional poor rose steeply from 1980 to 2010, reaching 95 million, before stagnating and beginning to decline after 2020. This trajectory reflects two offsetting forces: while climate-related economic damages have continued to increase, rising incomes have reduced the share of people living near the extreme poverty line, meaning that a given climate shock now pushes fewer people into poverty.

We decompose the overall impact of climate change on poverty into an income effect (i.e. the change in poverty due to the aggregate shock to GDP) and a distributional effect (i.e. the change in poverty due to the inequality effects of the climate shocks). Of the 79 million added poor in 2024, 60 million were due to the income effect and 19 million due to the distributional effect.

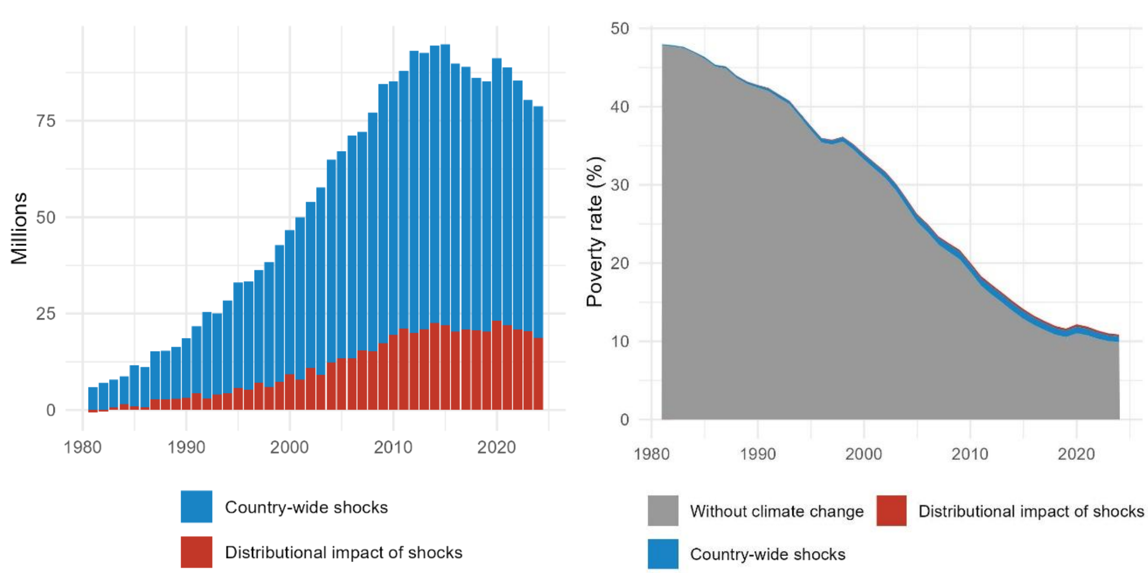
Global poverty has reduced significantly in the analysis period thanks to strong global GDP growth and despite climate damages. In 1980, over 2 billion people were in extreme poverty compared to 808 million in 2024 (World Bank 2024). Our results suggest that, without climate change, global extreme poverty headcount would instead be 729 million, implying a global extreme poverty rate of 8.9% instead of 9.9% (Figure 1, panel B). 39 million (50%) of added extreme poor due to climate shocks are in Sub-Saharan Africa as of 2024, and this incidence is still increasing. In South Asia, the incremental poverty headcount due to climate shocks peaked at 39 million in 2014, but has since reduced rapidly, to 16 million in 2024, suggesting that robust growth has offset the impact of climate shocks (Figure A.2).

Climate damages have affected richer and poorer households differently. The welfare (consumption) shock to the richest 10% of the global income distribution has been small at 0.5% in 2024 (Figure 2, panel A), compared to a reduction in welfare (consumption) of 6% for the poorest

10% globally, reflecting that poorer countries suffered greater economic damages and that, within countries, poorer household were disproportionately affected (Figure 2, panel B).

Figure 1. Impact of climate change on poverty 1981-2024

A. Millions of added extreme poor B. Global extreme poverty rate



We next extend our approach to predict the number of additional poor due to climate shocks until 2050 under two different emissions scenarios: Representative Concentration Pathway (RCP) 2.6 (a low-emissions, immediate mitigation scenario consistent with limiting warming to below 2 °C by 2100, in line with the Paris Agreement), and RCP 8.5 (a high-emissions scenario implying approximately 4-5 °C and assuming no significant mitigation).

Under RCP2.6, excess poverty due to climate shocks increases to peak at 105 million in 2043 before slightly decreasing to 98 million in 2050 (Figure 3, panel A), implying a global extreme poverty rate of 7.2%, a percentage point higher than without climate shocks (Figure 3, panel B). Under RCP8.5, it grows steadily to reach 141 million in 2050 (7.6%). In both cases, extreme poverty will be concentrated in Sub-Saharan Africa, accounting for 87% (Figure A.4).

Figure 2. Global distributional welfare changes due to climate change

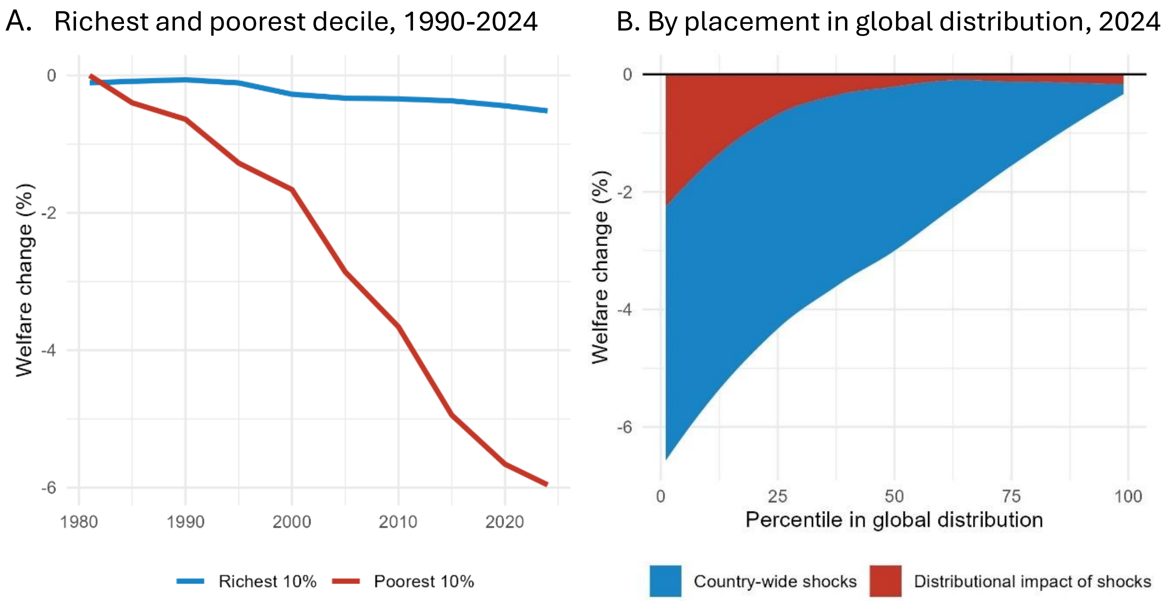
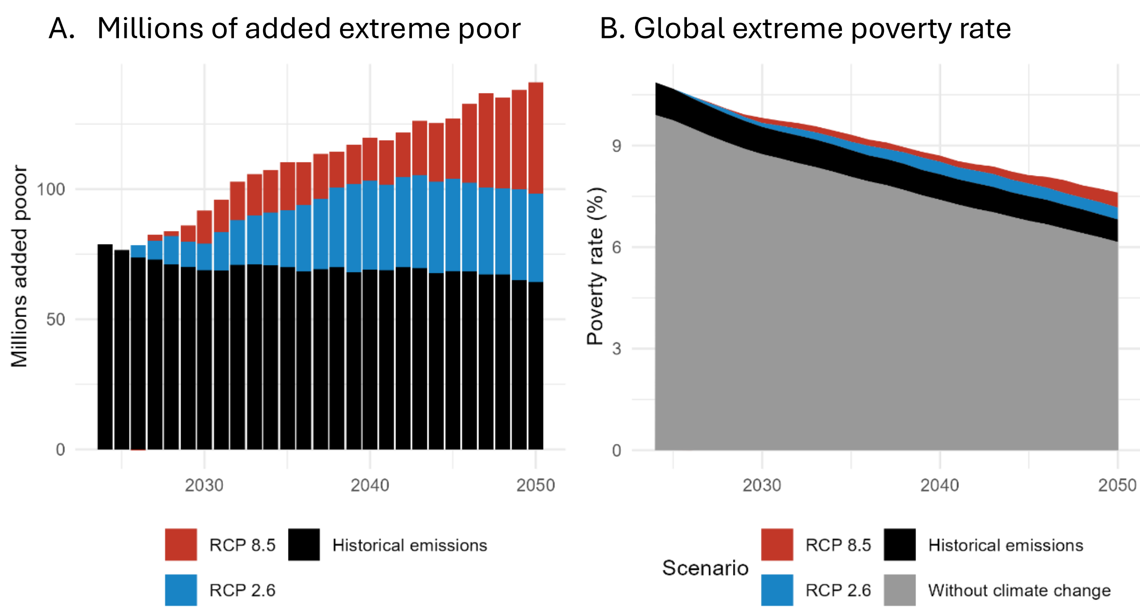


Figure 3. Projected impact of climate change on poverty 2025-2050



Discussion

Our research builds on recent advancements in the literature on climate impacts on GDP and inequality to present new estimates of the historical, present-day, and projected future impacts of climate change on extreme poverty.

Since 1980, climate shocks have added up to 95 million people to global extreme poverty, with nearly 80 million still affected in 2024. These historical losses are comparable in scale to those projected over coming decades: excess poverty is expected to persist at about 60 million even if emissions ceased immediately, rise to around 100 million by 2050 under a low-emissions pathway, and exceed 140 million under a high-emissions scenario. The burden is unevenly distributed. Sub-Saharan Africa now accounts for half of the climate-induced poor, while South Asia has reduced its exposure through rapid growth. Within countries, the poorest households have absorbed the largest shocks, with welfare losses an order of magnitude greater than those of the richest.

The past three decades of large-scale poverty reduction were driven primarily by broad-based economic growth, and this growth has been necessarily emissions intensive. Economic growth remains a highly effective way to build resilience and protect against climate-induced poverty, because it lifts households above subsistence and so reduces their vulnerability to poverty. Today's low-income countries, many in Sub-Saharan Africa, have contributed little to today's stock of emissions but remain highly exposed to climate shocks. For these countries, the central policy challenge is therefore to foster growth that is both rapid and inclusive, while advancing pro-poor adaptation strategies that reduce the sensitivity of living standards to climate shocks. In terms of protecting the poor, growing sooner and faster is likely to lead to the most significant improvements in resilience.

Our main results are only for extreme poverty ($3/day), a narrow bare-minimum definition of poverty, most relevant in low-income countries. For middle-income countries, moderate poverty ($8.30/day) is considered a more appropriate minimum welfare standard. The projected impacts of climate shocks on moderate poverty are considerably more severe: under a low-emission scenario, excess poverty is projected at 330 million and at 498 million under a high-emission scenario (Figure A.3).

Knowledge and data gaps remain in terms of the impacts of climate shocks on poverty. Some recent studies have used sub-national GDP and poverty data for the analysis of climate damages (Dang et al. 2024; Kotz et al. 2024); this approach however suffers from severe data limitations, especially in low-income countries, which raises important questions about its external validity. Another area relates to directly estimating the impact of climate variables on welfare and poverty rather than assessing the impact indirectly through climate-induced shocks to GDP. Here, too, data limitations hinder the use of optimal econometrical estimation techniques. Finally, future research should more explicitly model the trade-offs that low-income countries face between economic growth, inequality, and adaptation, under different climate change scenarios.

Methods

Climate data

Our measures of observed weather data series are extracted from ERA5, a global reanalysis product spanning 1940 to the present (Hersbach et al. 2020). To estimate counterfactual climate conditions without anthropogenic influence, we use the *hist-nat* simulations from the Coupled Model Intercomparison Project (CMIP) (Gillett et al. 2016b) and extract CMIP *historical* data (simulations of actual climate conditions). All CMIP datasets consist of ensemble medians, and are processed to derive five key climate indicators: mean temperature ($\bar{T}$), temperature variability ($\tilde{T}$), seasonal temperature difference ($\hat{T}$), total precipitation (P), total number of wet days (WD), and total extreme precipitation (XP).

Day-to-day temperature variability is calculated as follows:

$$\tilde{T}_{i,j,t} = \frac{1}{12}\sum_{m=1}^{12}\sqrt{\left(\frac{1}{D_m}\sum_{d=1}^{D_m}\left(T_{i,j,d,m,t} - \bar{T}_{i,j,m,t}\right)^2\right)}$$

Where $T_{i,j,d,m,t}$ denotes temperature in each year t, month m, day d, latitude i and longitude j. The term $\bar{T}_{i,j,m,t}$ is the mean temperature in month m. D_m is the number of days in month m.

Seasonal temperature difference is defined as inter-annual difference between the maximum and minimum average monthly temperature:

$$\hat{T}_{i,j,t} = \max_m \bar{T}_{i,j,m,t} - \min_m \bar{T}_{i,j,m,t}$$

The number of wet days can be written as:

$$WD_{i,j,t} = \sum_{d=1}^{365} I(P_{i,j,t,d} > 1)$$

Where indicator function I is equal to 1 if daily precipitation ($P_{i,j,t,d}$) is above 1mm, 0 otherwise.

Extreme precipitation is calculated as:

$$XP_{i,j,t} = \sum_{d=1}^{365} P_{i,j,t,d} \times I(P_{i,j,t,d} > P_{i,j}^{99.9})$$

Where indicator function I is equal to 1 if daily precipitation ($P_{i,j,t,d}$) is above the 99.9th percentile of a historical reference period (1950-1980).

The indicators were subsequently averaged within each country. To ensure that climate estimates reflect actual exposure, a set of population weights were computed, using data from the Global Human Settlement Layer (GHSL) (Schiavina et al. 2023). As this dataset ranges from 1975 to 2020, for the pre-1975 period, population weights are linearly extrapolated back to 1950, ensuring that no country is assigned a total population below 1,000. This was done to prevent unrealistic projections and extreme distortions of relative weights when some weights become 0. Since the population data was often at 10-year intervals, linear interpolation is applied between these years. Finally, for countries too small to encompass an entire grid point, climate indicators were linearly interpolated at the territory's centroid, without any population weighting.

While it is plausible to directly use the CMIP hist-nat series as a counterfactual, we take an additional step to ensure that the factual and counterfactual series differ solely in their climate signal. This approach eliminates the influence of high-frequency variability or noise around climate trends, which may confound the estimation of GDP shocks. For each climate indicator C in year t and country i, we first compute the difference between the historical and hist-nat CMIP series:

$$C_{it}^{diff} = C_{it}^{hist-nat} - C_{it}^{hist}$$

This captures the signal from anthropogenic climate change in the CMIP data, but also contains the variations around the trends of both series. To isolate climate trends, we fit locally weighted regressions of C_{it}^{diff} on a yearly time trend for each country in turn. As the historical CMIP data only reaches 2015, we extrapolate to 2025 by keeping the 2015 value constant. Finally, we calculate the counterfactual by adding the smoothed estimates of C_{it}^{diff} to the observed ERA5 factual series.

In addition, we extract climate projections from two CMIP Shared Socioeconomic Pathways (SSPs) that reflect contrasting trajectories of future climate change: SSP1-2.6 and SSP5-8.5. These SSPs correspond to the lowest and highest emissions scenarios until 2050. SSP1-2.6 reflects a sustainable development scenario in which global warming is likely to remain at 1.5°C relative to the 1850–1990 baseline, while SSP5-8.5 assumes continued fossil-fuel driven development, resulting in a projected warming of nearly 5°C above the baseline in 2100 (Lee et al. 2023).

Once the SSP data are extracted, we compute ensemble medians and derive the same set of indicators as previously described for the historical data. As they are derived from climate models and directly used as future observations in our analysis, these indicators are bias-adjusted using a change-factor method (Tabor and Williams 2010). Effectively, the simulated series at each grid point is adjusted by the difference between the mean observed and mean simulated values over a reference period. In line with Waidelich et al. (2024), the reference period spans 1950 to 1990 Formally, we can write:

$$I_{i,j,t}^{bc} = I_{i,j,t} + (\overline{I}_{i,j}^{era5} - \overline{I}_{i,j}^{ref})$$

Where $I_{i,j,t}^{bc}$ denotes the bias-corrected indicator at latitude i, longitude j, and year t. $\overline{I}_{i,j}^{era5}$ is mean observed indicator in the reference period, and $\overline{I}_{i,j}^{ref}$ is the mean simulated indicator in the reference period. For the future SSP data, reference period means ($\overline{I}_{i,j}^{ref}$) are taken from historical simulations. The number of wet days were bounded between 0 and 365.

Welfare data

The welfare data come from the World Bank's Poverty and Inequality Platform (PIP). PIP contains more than 2000 welfare distributions from household surveys from around 170 countries and is used for reporting on poverty and inequality for the United Nations' Sustainable Development Goals. Household surveys are available irregularly in many countries, so PIP interpolates and extrapolates distributions such that there is a distribution for every country and every year from 1990-2024 (World Bank 2025). For some countries, mostly high-income countries and countries in Latin America, the welfare distributions reflect measures of disposable income. For the remainder of countries, they reflect the monetized value of consumption. All welfare distributions are denominated in purchasing power parity adjusted 2021 U.S. dollars. We use a version of PIP data that adjusts for within-country comparability breaks in how welfare is measured (Mahler et al. 2025). To make the data faster to work with, we collapse each country-year distribution to 1000 points.

We use country-year GDP data from the World Bank's World Development Indicators for 211 economies for the years 1960-2024. Future growth data were extracted from the World Economic Outlook (WEO) database, and consist of series running from 2025 to 2030. To extend these projections to the future, we simulate a range of potential future growth paths using parameters from Müller et al. (2022). Our central projection is defined as the median of those simulated scenarios.

Counterfactual welfare distributions

To simulate what welfare distributions could have looked like in the absence of climate change, we proceed in two steps.

Impact of climate channels on GDP. First, we estimate the impact of the five climate channels described above on GDP per capita. We use the specification from Kotz, Levermann, and Wenz 2024, which predicts log GDP per capita in country c, in year t as

$$\begin{aligned}\Delta lngdp_{c,t} = \gamma_c + \alpha_t + k_c t \\ &+ \sum_{L=0}^{N}\left(\beta_{1,L}\Delta\bar{T}_{c,t-L} + \beta_{2,L}\Delta\bar{T}_{c,t-L} * \bar{T}_c\right) + \sum_{L=0}^{N}\left(\beta_{3,L}\Delta\tilde{T}_{c,t-L} + \beta_{4,L}\Delta\tilde{T}_{c,t-L} * \hat{T}_c\right) \\ &+ \sum_{L=0}^{N}\left(\beta_{5,L}\Delta P_{c,t-L} + \beta_{6,L}\Delta P_{c,t-L} * P_c\right) + \sum_{L=0}^{N}\left(\beta_{7,L}\Delta WD_{c,t-L} + \beta_{8,L}\Delta WD_{c,t-L} * WD_c\right) \\ &+ \sum_{L=0}^{N}\left(\beta_{9,L}\Delta XP_{c,t-L} + \beta_{10,L}\Delta XP_{c,t-L} * \bar{T}_c\right) + \varepsilon_{c,t}\end{aligned}$$

Here γ_c are country fixed effects, α_t are year fixed effects, and $k_c t$ is a country-year specific linear time trend. L indicates lagged terms, allowing for past weather shocks to influence GDP in later years. Kotz, Levermann, and Wenz (2024) do not find evidence that the climate shocks last more than 10 years, a finding we replicate on our data.

Once coefficients are estimated for each country using the observed weather data from ERA5, we predict the shock to GDP in a given year under both the factual scenario, and the counterfactual scenario, which consisted of weather data constructed from CMIP simulations as described above. The GDP shock from climate change we calculate as the difference between the two. Hence, the

GDP shock experienced for a country in a given year is $\Delta lngdp_{c,t}(ERA5) - \Delta lngdp_{c,t}(CMIP)$. For any year, we calculate the cumulative shock a country experienced since 1961 at year t,

$$\Delta lngdp_{c,t}^{*} = \sum_{\tau=1961}^{t} [\Delta lngdp_{c,\tau}(ERA5) - \Delta lngdp_{c,\tau}(CMIP)]$$

This approach only works until 2024. To estimate future GDP shocks from climate change, we rely on the CMIP SSP projections. To estimate the compounded GDP shocks towards 2050, we continue the compounded GDP shocks from 1960-2024 and compound them further to 2050.

For five small island economies where we lack the data to implement our approach above, we impute growth shocks using a regression-based approach with latitude as a predictor. Shocks in GDP generally map 1-1 to shocks to disposable income, but only 70% to consumption in line with prior estimates (Prydz et al. 2022; Wollburg et al. 2023). That is, GDP growth passes through at a rate1 for countries using income and 0.7 for countries using consumption. We apply these passthrough rates (*p*) for our counterfactual estimate of mean welfare in the absence of climate change, $\mu_{c,t}^{cf}$:

$$\mu_{c,t}^{cf} = \frac{\mu_{c,t}}{1 + p_c * \Delta lngdp_{c,t}^{*}}$$

Impact of climate channels on inequality. The welfare shocks of climate change are unlikely to accrue to all equally. To model the impact of mean temperature increases on inequality, we use the within-country income elasticity of damages, which was developed by Dennig et al. (2015), and is given by $d_q \propto \left(y_q^{cf}\right)^{\vartheta}$. Here ϑ is the elasticity, d_q is the damage experienced by quantile q, and y_q^{cf} is the counterfactual income in the absence of climate impacts. If $\vartheta = 1$, then damages are proportional to welfare levels (i.e. not changing inequality), if $\vartheta < 1$ it falls disproportionately on the poor and if $\vartheta > 1$ it falls disproportionately on the rich. Gilli et al. (2024) estimate this elasticity and find it to be 0.64 for countries that experience damages in mean income due to temperature increases (nearly all countries) and indistinguishable from 1 for countries that experience gains in mean income from temperature increases (a few countries with very cold temperatures). We apply this elasticity to change the distribution of the growth shock coming from mean temperature increases while keeping the total damages for the country unchanged.

This elasticity only accounts for distributional changes due to temperature increases. To model the impact of the other climate channels on inequality, we rely on Palagi et al. (2022), who find that the impact of precipitation anomalies on inequality depends on the agricultural intensity and initial yearly precipitation. They find that countries with high agricultural intensity and high annual precipitation see large declines in the income share held by the bottom 50%. For countries with high-agricultural intensity but low yearly precipitation, more rainfall increases the income share of the bottom 50%. For countries with low agricultural intensity, the impact of annual changes to precipitation on inequality is modest. We use their empirical estimates to model how the income share of the bottom 50% changes as a result of the growth shocks coming from precipitation (and daily temperature variation).

A change in the share of the bottom 50% can materialize in many ways, depending on whether the very poorest suffer the most, if the biggest losses accrue in the second poorest quantile etc. To model how the change in the share of the bottom 50% materializes across the welfare distribution, we apply a convex growth incidence curve (Lakner et al. 2022), which means that the largest proportional losses are felt at the very bottom. This, we think, is consistent with the findings of Palagi et al. (2022), which are stronger for inequality measures very sensitive to the welfare of the bottom.

Appendix

Figure A.3. Impact of climate change on moderate poverty ($8.30 poverty line), 1981-2024

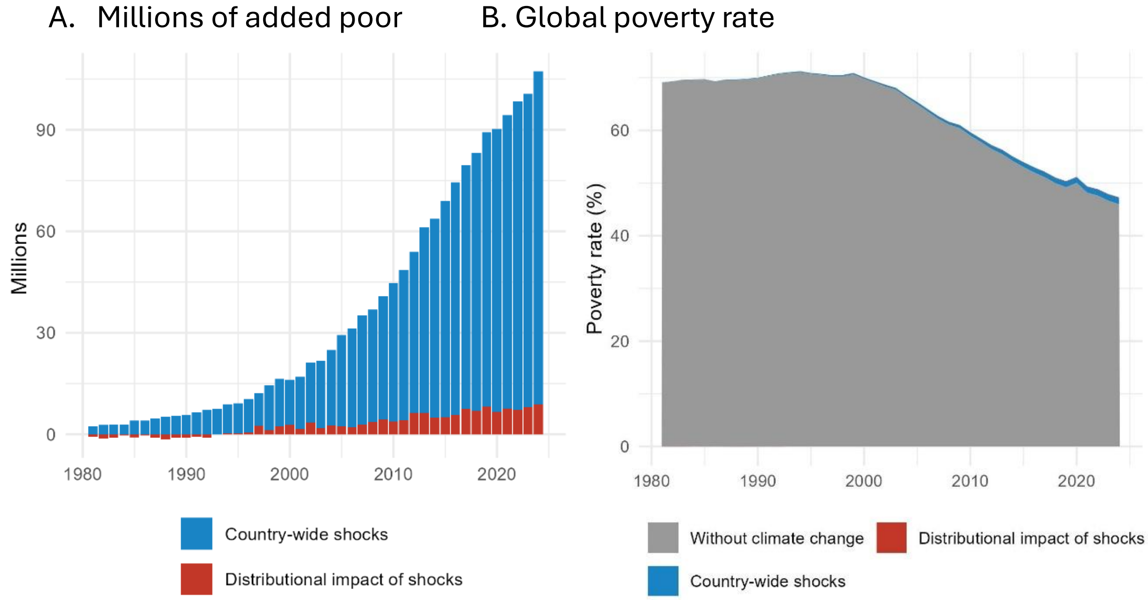


Figure A1.2. Additional poor attributed to climate change, by region and poverty line

Figure A.3. Future impact of climate change on moderate poverty ($8.30 poverty line), 1981-2024

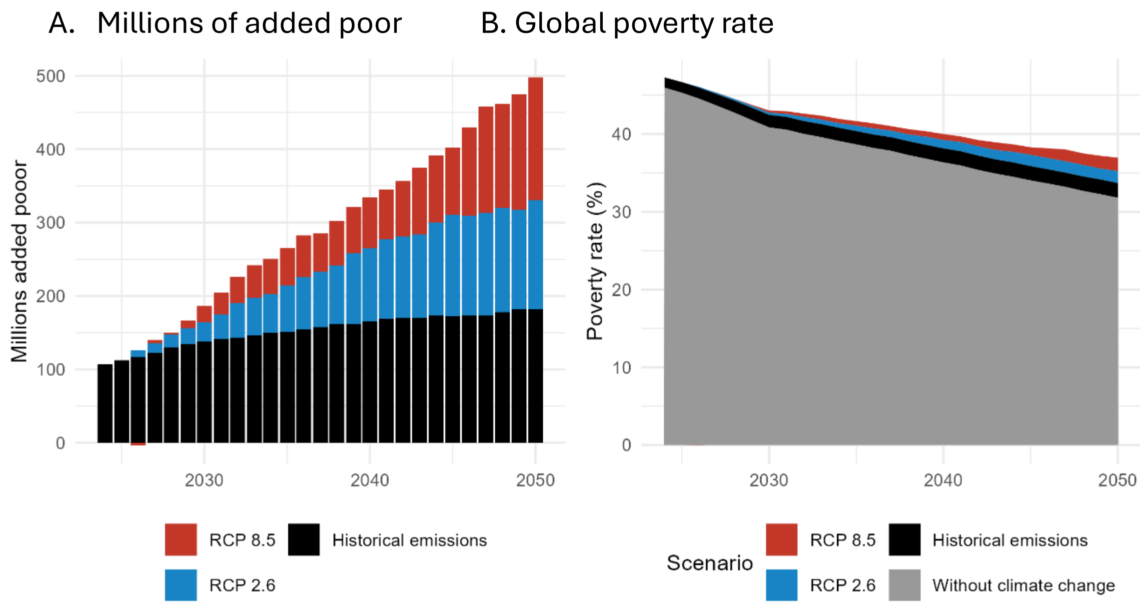
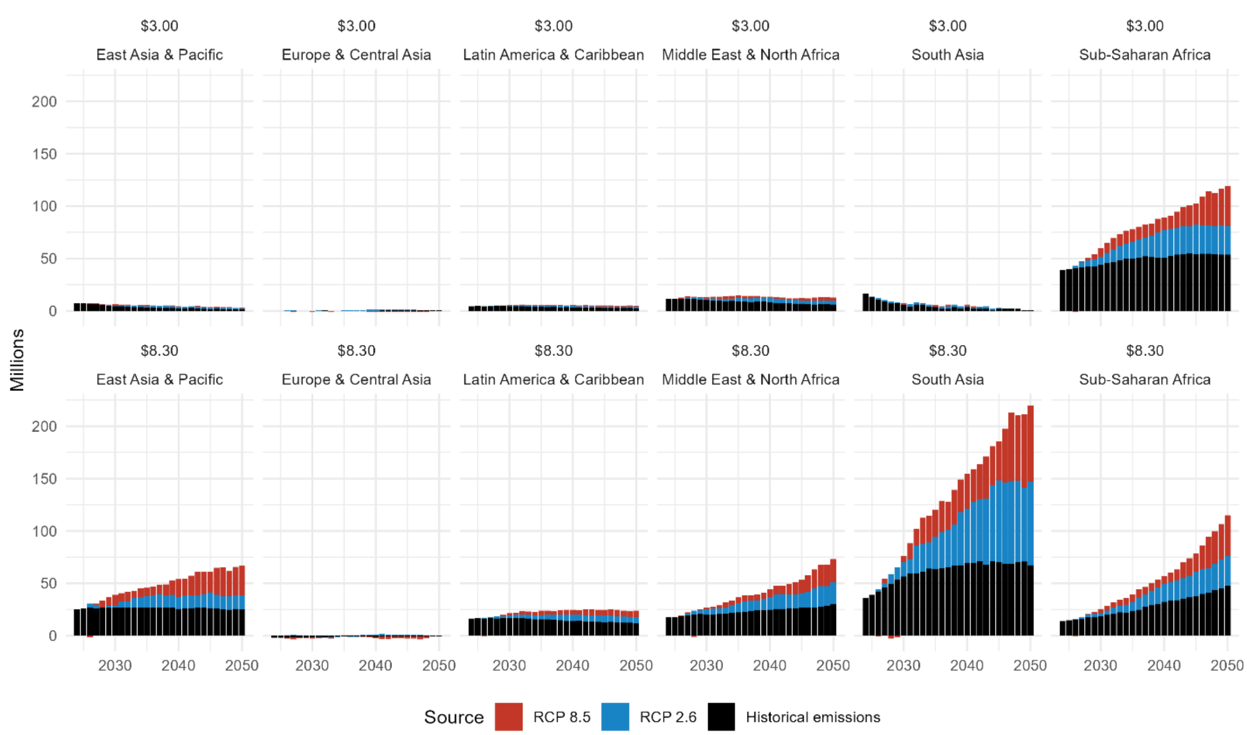


Figure A.4. Future additional poor attributed to climate change, by region and poverty line



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