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Revised Estimates of the Impact of Climate Change on Extreme Poverty by 2030

Bramka Arga Jafino

Brian Walsh

Julie Rozenberg

Stephane Hallegatte



WORLD BANK GROUP

Climate Change Group

&

Global Facility for Disaster Reduction and Recovery

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Abstract

Thousands of scenarios are used to provide updated estimates for the impacts of climate change on extreme poverty in 2030. The range of the number of people falling into poverty due to climate change is between 32 million and 132 million in most scenarios. These results are commensurate with available estimates for the global poverty increase due to COVID-19. Socioeconomic drivers play a major role: optimistic baseline scenarios (rapid and inclusive growth with universal access to basic services in 2030) halve poverty

impacts compared with the pessimistic baselines. Health impacts (malaria, diarrhea, and stunting) and the effect of food prices are responsible for most of the impact. The effect of food prices is the most important factor in Sub-Saharan Africa, while health effects, natural disasters, and food prices are all important in South Asia. These results suggest that accelerated action to boost resilience is urgent, and the COVID-19 recovery packages offer opportunities to do so.

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Revised Estimates of the Impact of Climate Change on Extreme Poverty by 2030*

Bramka Arga Jafino¹, Brian Walsh², Julie Rozenberg³, and Stephane Hallegatte³

¹Delft University of Technology

²Global Facility for Disaster Risk and Recovery, The World Bank

³The World Bank

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1 Introduction

It is widely recognized that climate change will disproportionately affect poorer countries (Mendelsohn, Dinar, & Williams, 2006; Tol, 2009; Bathiany, Dakos, Scheffer, & Lenton, 2018; Dell, Jones, & Olken, 2008), and poorer individuals within countries (Skoufias, Rabassa, & Olivieri, 2011; Hertel, 2016; Dennig, Budolfson, Fleurbaey, Siebert, & Socolow, 2015). Here, we provide a new assessment of the future impacts of climate change on extreme poverty by 2030, updating previous work (Rozenberg & Hallegatte, 2015; Hallegatte & Rozenberg, 2017) using the most recent available household surveys from the World Bank’s Global Monitoring Database. This assessment is done at the household level, using a bottom-up approach to explore the compounding effects of future socioeconomic development and changing climatic and environmental conditions.

Because of the uncertainty in future socioeconomic change and future climate change impacts (see Table 1), we use an exploratory modeling approach to create tens of thousands of scenarios for the next 10 years. The main idea behind this approach is to understand the consequences of various combinations of uncertainties to the system of interest (Bankes, Walker, & Kwakkel, 2013; Kwakkel & Haasnoot, 2019). The approach is mainly used for exploration, rather than prediction. Here, we do not provide a “best-guess” for the future impacts of climate change on poverty, but instead provide a range of possible impacts, and explore the influence of various relevant drivers and uncertainties. These factors include population growth, education, structural economic shifts, food prices, and health issues, among others.

Table 1: List of uncertain factors driving socioeconomic development and poverty and considered in this analysis.

| Category | Parameter |
|------------------------|-----------------------------------|
| Socioeconomic - SSP | Population growth |
| | Age structure |
| | Average productivity growth |
| | Education attainment |
| | Labor participation |
| Socioeconomic - Others | Fraction of skilled labor |
| | Sectoral share of employment |
| | Sectoral productivity growth |
| | Redistribution and pension |
| Climate change | Income premium of skilled workers |
| | Severity of impacts |

We find that rapid and inclusive development is necessary to reduce climate change vulnerability, consistent with previous findings. In particular, we show that climate change may have significant impacts on global poverty incidence in this decade, possibly pulling more than 100 million people into poverty by 2030. We identify the most important factors and uncertainties in each region, highlighting differential vulnerability priorities for action. Finally, the paper concludes with a discussion of the impact of the COVID-19 crisis on our estimates, and the importance of COVID-19 recoveries that contribute to the long-term resilience of populations against shocks and stresses, including climate change.

2 Methodology

The model used for this analysis is based on the model developed for the 2015 World Bank report, *Shock Waves: Managing the Impacts of Climate Change on Poverty* (Hallegatte et al., 2015; Rozenberg & Hallegatte, 2015; Hallegatte & Rozenberg, 2017). The model represents the impacts of climate change on household incomes to estimate the implications for poverty and inequality. The bottom-up approach, considering impacts on individual households, complements top-down analyses based on integrated assessment models (Dellink, Lanzi, & Chateau, 2019) or econometric estimates (Burke, Hsiang, & Miguel,

2015). It provides aggregate results that are similar but makes it possible to consider explicitly differential vulnerabilities for people with different socioeconomic status.

We start from household surveys using the latest vintage of the World Bank Global Monitoring Database, an aggregation and harmonization of country-level household surveys. The household surveys used here were made at different dates for different countries, but all are before the COVID-19 pandemic (cf. Appendix 1). The analysis covers 86 countries representing 64 percent of the total poor population. To provide a global estimate, the simulated poverty headcount is scaled up in accordance with the fraction of missing population in each region.

In each country, the population is described by a set of representative households, with their demographic information, education level, sectoral employment, and consumption or income level (here consumption and income are considered interchangeable). Each household has a *weight* that measures its importance and representativeness of the entire population.

First, we create scenarios for the future income distribution of households in each country in 2030, without accounting for climate change impacts. We factor in possible changes to demography, education, labor force participation, economic structure (share of population employed in various sectors), productivity (for skilled and unskilled labor), and redistribution (through pensions and social protection). We explore a range of possible futures for these factors and combine them to generate hundreds of scenarios representing a wide range of plausible socioeconomic development pathways for each country.

In practice, we first manipulate the weight of each household to match demographic and macroeconomic projections detailed in one of the five Shared Socioeconomic Pathways (SSPs). The SSPs describe plausible future changes in demographics, human development, economies, institutions, technologies, and the environment (O'Neill et al., 2014, 2017; Samir & Lutz, 2017). Within each country, representative weights of the households are adjusted so that the population matches SSP projections in terms of population size and composition (including for instance the number of children and education level of household members).

Following previous work (Rozenberg & Hallegatte, 2015; Hallegatte & Rozenberg, 2017), we consider two socioeconomic scenarios: SSP4 and SSP5. The SSP5 scenario is optimistic regarding economic growth and poverty reduction, with rapid growth, declining inequality, universal access to basic infrastructure services by 2030, and relatively slow population growth. Due to these shifts, this scenario forecasts a rapid decrease in the number of people living below the extreme poverty line by 2030. In the SSP4 scenario, by contrast, the population is growing faster with slow improvement in education levels, economic growth is also slower and more unequal. As a result, extreme poverty decreases much less and can even be stagnating (or increasing in number of people, since population is growing fast).

The SSP scenarios do not prescribe every dimension of future development, and our approach probes these unconstrained dimensions to understand the drivers of extreme poverty within countries and regions. Most importantly, the SSPs do not specify the relative sizes of the agriculture, services, and manufacturing sectors within each country's economy. We allow these parameters to fluctuate randomly within a wide range of possible outcomes.

Then, we adjust the income of each household based on assumption on future productivity gains in each of sectors, and for skilled and unskilled labor. Similarly, we adjust income for changes in social protection and pension systems, again allowing them to vary within bounds calibrated on historical values.

In practice, we apply a numerical sampling approach where we pseudo-randomly generate the value of parameters within a range based on historical data. For instance, we look at the value and change in the share of employment in agriculture in the past 20 years to determine a range of possible change in agriculture employment in a country in 2030 (see Rozenberg and Hallegatte (2015) for further details).

We generate 500 scenarios per country using the Latin Hypercube Sampling method (Kwakkel, 2017) where we fluctuate independently values for the various parameters characterizing each scenario. Combining this with the two SSP scenarios, we generate 1,000 baseline scenarios of future socioeconomic and demographic change for each country. Latin Hypercube Sampling ensures that each parameter is represented evenly across the entire scenarios, thus resulting in a wide and extensive coverage of the uncertainty space (McKay, Beckman, & Conover, 1979; Kasprzyk, Nataraj, Reed, & Lempert, 2013). Each

parameter is determined independently, and some scenarios may be considered extremely unlikely or even implausible (e.g., quick increase in skill premium in one sector and rapid drop in others). However, past history suggests that what is considered implausible can become possible, and we prioritize here the largest coverage of possible futures over the internal consistency of the scenarios.

Finally, we introduce climate change in these baselines by adjusting income levels based on quantified estimates of the impact of climate change. We specifically model the impacts of climate change directly on the income and real consumption of the representative households. Five climate change impact channels are accounted for in the model:

1. Impact on agricultural productivity and prices, with consequences for agricultural incomes. The impacts on incomes and poverty depend on agricultural productivity and the fraction of the population working in agriculture. The impact varies across regions and across different assumptions of climate change impacts (Havlík et al., 2015).
2. The impact of climate change on food prices (same as #1), and the consequences of this for consumers. The impact on poverty depends on the fraction of household expenditures dedicated to food consumption. Regional differences in fraction of expenditure used for purchasing foods are also accounted (World Bank, 2016).
3. Change in exposure to and losses from natural disasters. We consider four kinds of hazards: cyclones, storm surges, floods, and droughts. We focus on direct economic losses while disregarding loss of lives as well as second order and other indirect losses (Hallegatte et al., 2015; Hallegatte, Bangalore, & Vogt-Schilb, 2016). It is also important to note that we consider here only the changes in natural disasters, not the impact of pre-climate-change hazards. It has been estimated that the current (i.e. around 2015) distribution of natural hazards pushes 26 million people into extreme poverty every year (Hallegatte, Vogt-Schilb, Bangalore, & Rozenberg, 2017), but they are not included in this analysis, which focuses on the incremental impact of man-made climate change.
4. The impact of climate change on labor productivity, particularly outdoor workers, thus reducing their annual income.
5. The impact of climate change on child stunting, malaria, and diarrhea. The impact of malaria and diarrhea is modelled through combinations of cost of treatment, number of days out of work, and number of occurrences per year, whereas the impact of stunting is modeled through reduction in the individual’s lifelong earnings. The spatial distribution, prevalence, and incidence of these diseases are anticipated to change in the future due to climate change (Lloyd, Kovats, & Chalabi, 2011; Kolstad & Johansson, 2011; Caminade et al., 2014).

Taking these climate channels into account, we adjust the income and prices to reflect the impacts of climate change on households, and thus derive the impact on poverty at a national level. We consider two qualitative levels (“high” and “low”) of climate impacts, to represent the uncertainty on the physical impacts of climate change (e.g., the response of agricultural yields, or the implications on flood frequencies and intensities) and local adaptation policies (e.g., improvement in flood control infrastructure). Note that the two levels of climate change impacts do not represent the effect of climate change mitigation policies and their impact on carbon emissions: the inertia of the climate system means that climate policies do not influence climate change magnitude before 2050 (with the exception of policies targeting short-lived climate pollutants, but these effects are not considered here).

Furthermore, we simulate impacts of each channel individually, as well as impacts of all channels simultaneously. Therefore, we have in total 12 climate change scenarios (5 individual channels and 1 simultaneous impact scenario, and two severity assumptions). Combining this with the baseline scenarios, we end up with 12,000 scenarios for each country.

To create global scenarios, we have to combine the country scenarios. It is impossible to consider all possible combinations, so we create global scenarios by sampling the country results. We create 10,000 global baselines by randomly selecting baselines in each country and added low climate change impacts and high climate change impacts in each of them (for a total of 30,000 global scenarios). As for the

individual drivers of development, these global scenarios assume independence across countries, which (again) prioritizes the broadest possible exploration of possible futures, but leads to the inclusion of unlikely scenarios (e.g., where agriculture productivity grows very quickly in some countries but declines in others, which would assume some technological disconnection across countries).

3 Results

3.1 Future poverty without climate change

We first explore the number of people in extreme poverty in 2030 in the baseline scenarios (i.e., without climate change). Figure 1 shows the distribution of extreme poverty incidence in 2030 across the 1,000 baseline scenarios per country. These distributions are to be used carefully because each scenario represents a possible future, but they are not equally likely. However, we do not attribute any “probability” to these scenarios so that the figures in this section should be considered as histograms and not as probability distributions.

On average across the scenarios, there are 313.5 million people in extreme poverty in 2030. While this number is substantially lower than the poverty headcount in 2015, which amounts to 736 million people (World Bank, 2018), it is still far from the zero extreme poverty target. In most scenarios, the Sub-Saharan Africa region contributes the largest number of poor people (224.4 million people on average), followed by South Asia (30.6 million people on average), East Asia and Pacific (11.8 million people on average), and Latin America and Caribbean (1.9 million people on average).

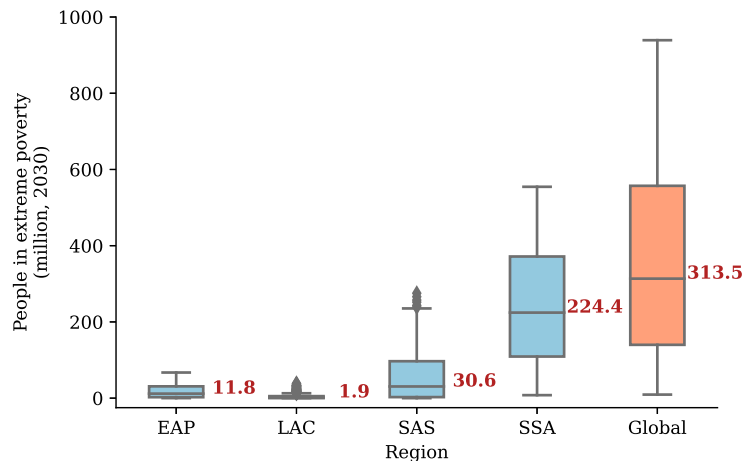


Figure 1: People in extreme poverty, without climate change in 2030

Figure 1 also shows that the total number of people in extreme poverty exceeds 590 million in more than 250 scenarios. There are therefore many futures among our scenarios in which extreme poverty remains close to its current levels. These scenarios tend to be associated with the SSP4, which assumes high population growth and slow progress in education and productivity.

On the other hand, there are also 250 scenarios with fewer than 170 million poor people. In the best-case scenario there are only 9.3 million people in extreme poverty globally. This shows that approaching the eradication of extreme poverty by 2030 requires all our assumptions to be among the most optimistic, confirming that this objective is very ambitious at this point. Introducing the impacts of COVID-19 would make this objective even more difficult to achieve.

3.2 Climate change impacts on extreme poverty

We now turn our attention to the poverty headcount under scenarios where all climate impact channels are simultaneously included. Figure 2a shows the distribution of the number of additional people falling

into extreme poverty due to climate change by 2030.

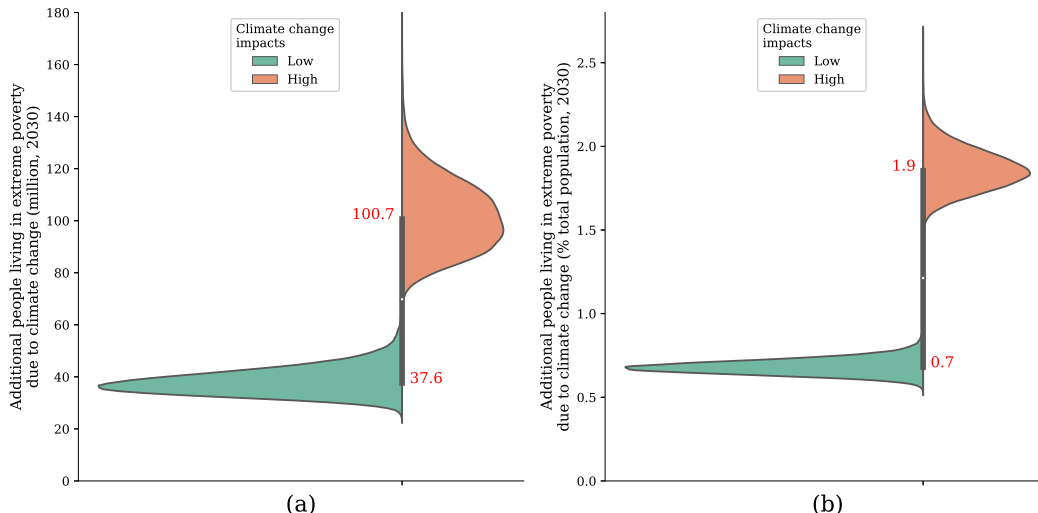


Figure 2: People pushed to extreme poverty due to all climate impact channels in 2030, (a) absolute number, (b) percentage of total population

In scenarios with the more pessimistic assumptions on future impacts of climate change, on average 100.7 million people are pushed into extreme poverty due to the effects of climate change. In more optimistic scenarios regarding climate change impacts, this number is reduced to 37.6 million. Figure 2b shows poverty incidence as a fraction of the total population. Within the high climate change scenarios, on average 1.9% of the total population would be pushed into poverty, whereas within the low climate change scenarios only 0.7% of the total population would become poor.

Figure 2a also shows that the high climate change scenarios have a wider distribution range of additional poverty headcount compared to the low climate change scenarios. In 95% of total cases within the high climate change scenarios, the poverty headcounts are between 81.6 million and 124 million people (a range of 42 million). Meanwhile, 95% of total cases within the low climate change scenarios have a smaller range of 16.7 million (i.e., between 31.1 million and 47.8 million). As is often the case, there is a larger uncertainty about the worst-case scenarios than the best-case scenarios.

The number of people falling into extreme poverty due to climate change varies across regions (see Figure 3).¹ The regions where climate change is expected to push the most people into poverty are Sub-Saharan Africa and South Asia, confirming previous results. Under high climate change scenarios, the numbers of people pushed into extreme poverty in Sub-Saharan Africa, South Asia, East Asia & Pacific, and Latin America & Caribbean are 39.7 million, 35.7 million, 7.5 million, and 5.8 million people respectively. More optimistic climate impact assumptions (i.e., low climate change scenarios) reduce the additional poverty headcount to less than half of the numbers in the more pessimistic climate impact assumptions.

When looking at absolute numbers, regions with relatively lower poverty headcount in baseline scenarios (i.e., East Asia & Pacific and Latin America & Caribbean, see Figure 1) also have fewer number of people pushed into poverty due to climate change. However, the figure changes when we look at relative terms by comparing the poverty headcounts in Figure 1 and in Figure 3 (see Table 2). Compared to baseline scenarios (i.e., no climate change), the high climate change scenarios increase the average poverty headcount by almost 64% in East Asia & Pacific, by more than 100% in South Asia, and by a staggering amount of more than 300% in Latin America & Caribbean. In Latin America & Caribbean, extreme

¹We include only regions with substantial coverage of poor countries in this region-level analysis. The available and workable survey data for some regions, such as Europe and Central Asia, are limited to only countries within the high income and upper middle income categories, where the international extreme poverty line is not the most relevant measure for poverty.

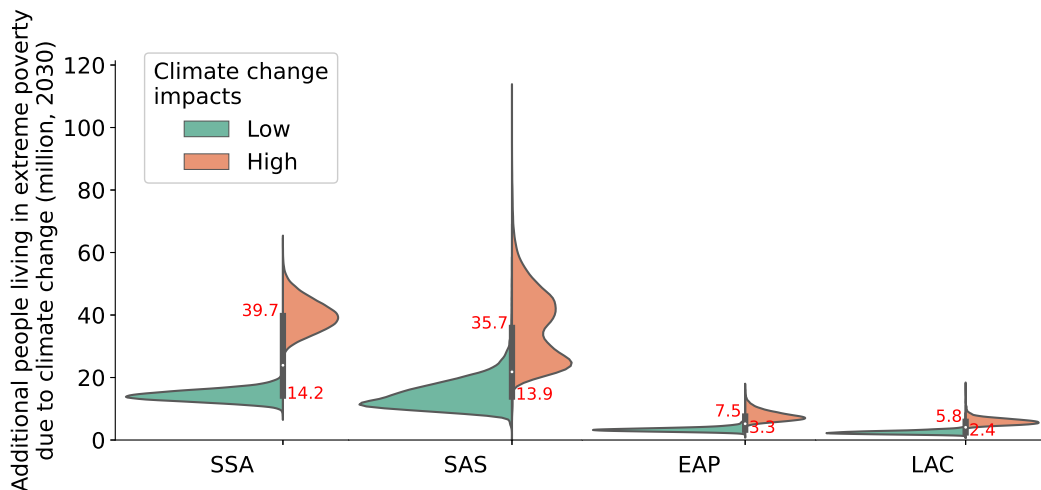


Figure 3: Regional breakdown of people pushed to extreme poverty in 2030

poverty is by and large eradicated by 2030 in most scenarios, so even a relatively small absolute increase in poverty due to climate change has a major relative effect. On the other hand, Sub-Saharan Africa experiences an increase in average poverty headcount of “only” around 17.5%. This is simply due to the larger denominator (i.e., number of people in extreme poverty in the baseline scenarios) in the poorest regions of the world.

Table 2: Summary of poverty headcount based on different scenarios. Numbers in climate change scenarios are additional headcount from the baseline scenario

| | Baseline (million people) | High climate change (million people) | Low climate change (million people) | High climate change (increase from baseline) | Low climate change (increase from baseline) |
|-----|------------------------------|--|---|--|---|
| EAP | 11.8 | 7.5 | 3.3 | 63.6% | 28% |
| LAC | 1.9 | 5.8 | 2.4 | 305% | 126.3% |
| SAS | 30.6 | 35.7 | 13.9 | 116.7% | 45.5% |
| SSA | 224.4 | 39.7 | 14.2 | 17.7% | 6.3% |

3.3 Impacts of individual channels

We now explore the effect of individual climate impact channels to extreme poverty (see Figure 4). On average, the health channel leads to the largest increase in poverty headcount. This channel pushes more than 44 million people into extreme poverty in the high climate impact scenarios. Even with a less stringent climate impact assumptions, 25 million people are still pushed into poverty due to impacts on health.

The health channel includes the increasing prevalence of child stunting, malaria, and diarrhea, three diseases which commonly affect low income households and trap them in poverty (Andres, Briceño, Chase, & Echenique, 2017; Lloyd et al., 2011; Organization, 2014). This result emphasizes the need for better access to health care, including better health care supply (with trained staff and appropriate equipment) and universal healthcare coverage. Health policy is therefore one of the most important adaptation policies to reduce the vulnerability of poor and near-poor households. More context-specific public health interventions such as subsidizing bed nets and antimalarial drugs along with context-based

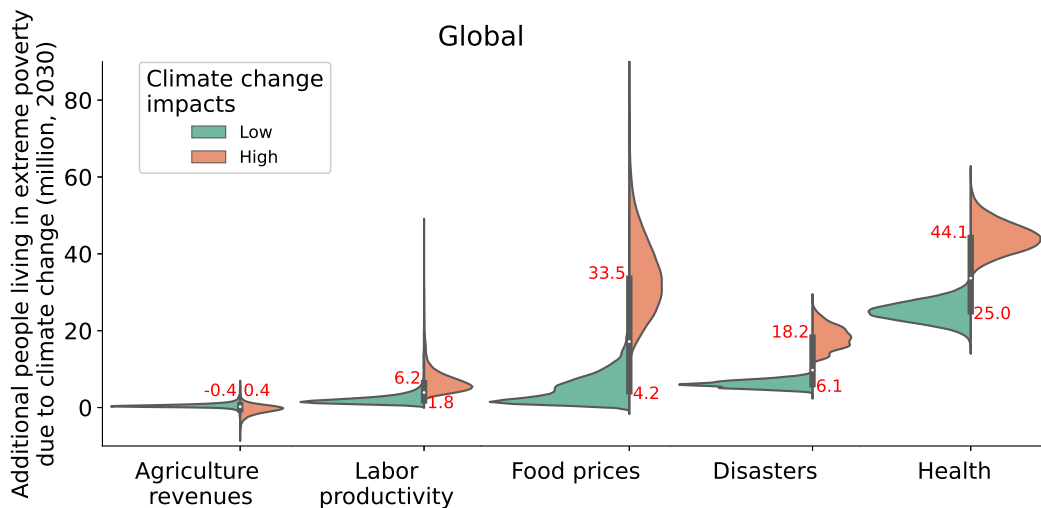


Figure 4: Impacts of individual channel to the number of people falling into extreme poverty in 2030. Highlighted red numbers are the median of the distribution

incentives are also another adaptation approach to minimize climate-induced health impacts to the poor (Cohen & Dupas, 2010; Cohen, Dupas, & Schaner, 2015).

The food prices channel is the second most influential channel for extreme poverty, with additional poverty headcounts of 33.5 million people in high climate impact scenarios. The impacts of this channel, however, are substantially reduced by almost 90% to only 4.2 million additional poor people in a less stringent climate impact assumption.

This large drop can be explained by the difference in projected food prices between high and low climate impact scenarios as reported in (Havlík et al., 2015). Under SSP4, for example, the South Asia region experiences increases of 7.7% and 3.3% in food prices under high and low climate impact scenarios, respectively — hence a difference of 4.4% between the two climate scenarios. The price increase difference is even larger in Sub-Saharan Africa, with 7.1% increase and 0.74% increase under high and low climate impact scenarios, respectively — a staggering difference of 6.36%. While the actual impacts of climate change to food prices are subject to large uncertainty and vary greatly across regions (Havlík et al., 2015; Osborne, Rose, & Wheeler, 2013), it is widely accepted that improvement in agricultural technologies and adjustment of management practices could dampen climate-induced agricultural shocks (Osborne et al., 2013; Leclère, Jayet, & de Noblet-Ducoudré, 2013; Nelson et al., 2014), hence a potential efficient intervention for reducing global poverty.

Climate-driven increase in disaster incidence and decrease in labor productivity also contribute to extreme poverty although only to a lesser degree. The impacts of natural disasters, however, are still huge with 18.2 million people pushed into extreme poverty in high climate impact scenarios. Within the low climate impact assumption, natural disasters push even more people (i.e., 6.1 million) into poverty compared to food prices. It is important to remember that the impact of natural disasters in this study is only the incremental change due to man-made climate change and needs to be added to the effect of today’s natural disasters on poverty, which is already very significant (Hallegatte et al. 2017).

The most dominant channel varies by region (see Table 3). Food prices have the largest influence for the South Asia and Sub-Saharan Africa regions but play a more marginal role in East Asia & Pacific and Latin America & Caribbean. There are two factors that can explain this result. First, Sub-Saharan Africa and South Asia experience a substantially higher increase in food prices due to climate change compared to East Asia & Pacific and Latin America & Caribbean. Under SSP4 and high climate impact scenarios, Havlik et al (2015) project food prices increases of 7.1% and 7.7% in Sub-Saharan Africa and South Asia, respectively. East Asia & Pacific and Latin America & Caribbean, on the other hand, experience only a 3.4% 1.4% increase in food prices. Second, purchasing foods occupies a larger share of daily expenditure

for poorer households. Having a relatively higher income per capita to begin with, countries in East Asia & Pacific as well as in Latin America & Caribbean are therefore less vulnerable to increase in food prices.

Table 3: Impacts of individual channel in each region under the high climate impact scenarios

| | Agri revenues | Labor productivity | Food prices | Disasters | Health | Dominant channel |
|-----|---------------|--------------------|-------------|-----------|--------|------------------|
| EAP | -0.05 | 0.30 | 1.67 | 1.32 | 5.65 | Health |
| LAC | -0.02 | 0.07 | 0.23 | 1.38 | 4.73 | Health |
| SAS | -0.30 | 2.60 | 17.90 | 12.31 | 17.85 | Food prices |
| SSA | -1.73 | 4.48 | 35.79 | 2.75 | 10.12 | Food prices |

Additional poverty headcount in richer regions, in this case East Asia & Pacific and Latin America & Caribbean, is more influenced by the increasing prevalence of diseases. Households in these regions are rich enough to absorb shocks from increase in food prices, which affect everybody in a relatively similar way. But they are still vulnerable to health shocks (and disasters) that tend to affect a small and concentrated fraction of the population but with impacts that can be massive for a given household.

In addition, it is also important to note that some regions see one channel dominating all others, while others are affected by multiple issues equally. In Sub-Saharan Africa, our results suggest that the absolute priority should be food security, and to a lesser extent health. In South Asia, on the other hand, the impact of food prices, disasters, and health shocks are almost equal, suggesting the need for a multi-prong approach.

3.4 Socioeconomic development and climate vulnerability

We now look at how different assumptions regarding socioeconomic development (i.e., the baselines) affect climate change vulnerability in terms of people pushed into extreme poverty.

To do so, we select — in each country — two sets of scenarios from the 1000 baseline scenarios (i.e., scenarios of socioeconomic and demographic changes, but without climate change). The first set of scenarios is termed the *pessimistic* baselines. Here, we select the 100 baseline scenarios with the highest poverty rates. These baseline scenarios have global poverty rates between 14% and 15.5%. The second set of scenarios, the *optimistic* baselines, consists of the 100 scenarios with the lowest poverty rates. The *optimistic* baseline has global poverty rates in the 2.8% and 3.8% range. The *optimistic* baseline can be seen as a future with rapid and inclusive socioeconomic development, which can be achieved among others through pro-poor policies (they are aligned with the World Bank objective of reducing extreme poverty below 3% of the global population by 2030).

Climate change vulnerability in terms of people falling into extreme poverty is recalculated for the two sets of baselines (see Figure 5). In the worst-case combination — with pessimistic baselines and high climate change impacts — climate change impacts make more than 130 million people fall in poverty by 2030.

Within the high climate change impact scenarios, rapid and inclusive development (i.e., the optimistic baseline) can reduce climate change vulnerability by almost 50% (from 131.5 million people on average to 67.7 million people on average). Although smaller, a noticeable effect of rapid and inclusive development is still evident under the low climate change scenarios, with almost 25% reduction in vulnerability (from 42 million to 32.2 million people). These results confirm previous findings which show that rapid development is an effective strategy to reduce climate vulnerability and is a strong determinant of a society’s adaptive capacity (Hallegatte & Rozenberg, 2017; Leichenko & Silva, 2014; Eakin, Lemos, & Nelson, 2014; Barnes et al., 2020).

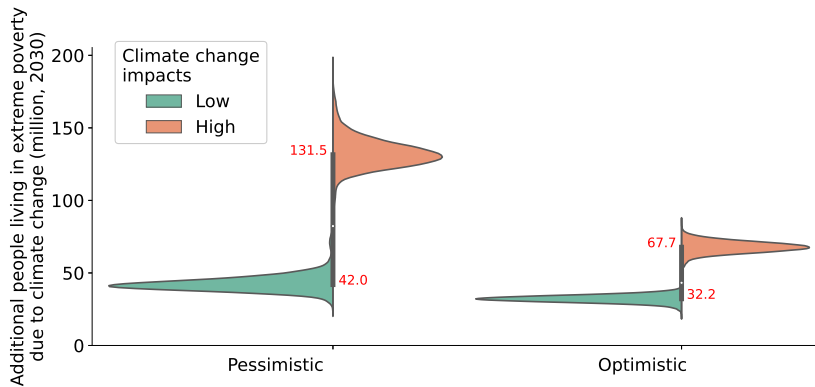


Figure 5: Effect of socioeconomic development to the number of people falling into extreme poverty in 2030

4 Discussion and conclusion

Building upon the methodology developed in (Hallegatte et al., 2015; Rozenberg & Hallegatte, 2015; Hallegatte & Rozenberg, 2017), this study uses household survey data from the 2020 Global Monitoring Database to update climate-driven poverty projections for 2030.

Several similarities in results compared to projections from a previous study (Hallegatte & Rozenberg, 2017) can be observed. For example, we find that health impacts are the dominant channel in most scenarios, pushing the largest number of people into extreme poverty. Impacts through increased food prices are the most uncertain ones (i.e., widest range of distribution), and could have an effect on poverty even bigger than health impacts in the most pessimistic cases.

Under the high climate change impact scenarios, we find that climate-driven increase in prevalence of diseases on average leads to 44 million people falling into extreme poverty. This projection is slightly higher than the previous projection (around 30 million people), although it is still within a similar order of magnitude.

This analysis does more than updating previous results and provides further results. For instance, we explore the dominant climate change impact channel in each region. Health impacts are particularly important in relatively richer regions (East Asia & Pacific and Latin America & Caribbean), while impacts of food prices dominate in poorer regions (South Asia and Sub-Saharan Africa). This is because the impacts through health shocks (and disasters) are concentrated on a fraction of the population and can therefore push people into poverty even if their income would be relatively high without climate change impacts. Impacts on poverty through food prices, in contrast, affect mostly people near poverty who spend a large share of their income on food. In the richest regions, even poor people are rich enough to manage the expected rise in food prices without falling into extreme poverty (which does not mean that they are not affected: increased food prices would reduce their real consumption).

Several differences compared to the previous study (Hallegatte & Rozenberg, 2017) are also observed. First, this study projects a higher climate vulnerability, in terms of increase in poverty headcount, compared with previous work. For example, under the worst case scenario (high climate change impact and pessimistic baseline), this study projects that on average there will be 131.5 million people pushed into extreme poverty whereas the previous projection was 122 million. Second, rapid and inclusive development has a slightly smaller effect, although still substantial, on reduction of climate change impacts. In the previous study, the optimistic baseline reduces climate change impacts by 86%, while this study shows that the optimistic baseline reduces the impacts by only 50%.

This discrepancy can be attributed to a different selection of the 'optimistic' and 'pessimistic' baseline (termed prosperity and poverty scenarios in the previous study). While the previous study uses only one representative scenario for the optimistic baseline and one for the pessimistic baseline, this study uses a set of scenarios for characterizing the two baselines. Despite the differences, the main message is still

the same: rapid and inclusive development can be seen as an adaptation in itself since it substantially reduces climate change impacts on poverty.

We do not attribute a probability to the realization of our optimistic or pessimistic baselines. However, the COVID-19 pandemic obviously changes the plausibility of the pessimistic baselines: while a stagnation of extreme poverty incidence could have been considered particularly pessimistic only one year ago, it is now estimated that the COVID-19 crisis could push 71 million people into extreme poverty in 2020 under the baseline scenario and 100 million under the downside scenario (World Bank, 2020). And COVID-19 leaves most countries with high debt levels and less resources to invest in development, poverty reduction, and access to health care and infrastructure services. A slower reduction in extreme poverty between now and 2030 would translate into a larger share of the global population with extreme vulnerability to climate change impacts. The COVID-19 pandemic is therefore contributing to future climate change impacts.

At the same time, governments have responded forcefully to the COVID-19 crisis with major investments in social protection (Gentilini, Almenfi, Orton, & Dale, 2020), and large-scale recovery packages.² These responses offer opportunities to boost the future resilience of the population, for instance with improved social protection and health coverage for the poorest (Bodewig & Hallegatte, 2020), or with investments in landscape and ecosystems that contribute to resilience (Hallegatte & Hammer, 2020).

In the next months and years, it will be critical to ensure that all synergies are captured between the response to COVID-19 (and the global economic crisis it has triggered) and anticipated climate change impacts. This study shows that the likely short-term impacts of climate change on poverty (32 million to 132 million additional people in extreme poverty by 2030) are of the same orders of magnitude as the impacts of COVID-19 (71 million to 100 million additional people in extreme poverty). There is utmost urgency to act to protect people affected by the COVID-19 crisis and restore the historical trend toward the eradication of extreme poverty, but doing so is possible only by factoring in future climate change impacts and the need to provide all individuals, and especially the poorest, with the capacity and resources to adapt to them.

References

- Andres, L., Briceno, B., Chase, C., & Echenique, J. A. (2017). Sanitation and externalities: evidence from early childhood health in rural india. *Journal of Water, Sanitation and Hygiene for Development*, 7(2), 272–289.
- Bankes, S., Walker, W. E., & Kwakkel, J. H. (2013). Exploratory modeling and analysis. In S. I. Gass & M. C. Fu (Eds.), *Encyclopedia of operations research and management science* (pp. 532–537). Boston, MA: Springer US. doi: 10.1007/978-1-4419-1153-7_314
- Barnes, M. L., Wang, P., Cinner, J. E., Graham, N. A., Guerrero, A. M., Jasny, L., ... Zamborain-Mason, J. (2020). Social determinants of adaptive and transformative responses to climate change. *Nature Climate Change*.
- Bathiany, S., Dakos, V., Scheffer, M., & Lenton, T. M. (2018). Climate models predict increasing temperature variability in poor countries. *Science advances*, 4(5), eaar5809.
- Bodewig, C., & Hallegatte, S. (2020). *Building back better after covid-19: How social protection can help countries prepare for the impacts of climate change, development and a changing climate*. Retrieved 2020-08-15, from <https://blogs.worldbank.org/climatechange/building-back-better-after-covid-19-how-social-protection-can-help-countries-prepare>
- Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, 527(7577), 235–239.

²<https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19>

- Caminade, C., Kovats, S., Rocklöv, J., Tompkins, A. M., Morse, A. P., Colón-González, F. J., . . . Lloyd, S. J. (2014). Impact of climate change on global malaria distribution. *Proceedings of the National Academy of Sciences*, *111*(9), 3286–3291.
- Cohen, J., & Dupas, P. (2010). Free distribution or cost-sharing? evidence from a randomized malaria prevention experiment. *Quarterly journal of Economics*, *125*(1), 1.
- Cohen, J., Dupas, P., & Schaner, S. (2015). Price subsidies, diagnostic tests, and targeting of malaria treatment: evidence from a randomized controlled trial. *American Economic Review*, *105*(2), 609–45.
- Dell, M., Jones, B. F., & Olken, B. A. (2008). *Climate change and economic growth: Evidence from the last half century* (Tech. Rep.). Cambridge, Massachusetts: National Bureau of Economic Research.
- Dellink, R., Lanzi, E., & Chateau, J. (2019). The sectoral and regional economic consequences of climate change to 2060. *Environmental and Resource Economics*, *72*(2), 309–363.
- Dennig, F., Budolfson, M. B., Fleurbaey, M., Siebert, A., & Socolow, R. H. (2015). Inequality, climate impacts on the future poor, and carbon prices. *Proceedings of the National Academy of Sciences*, *112*(52), 15827–15832.
- Eakin, H. C., Lemos, M. C., & Nelson, D. R. (2014). Differentiating capacities as a means to sustainable climate change adaptation. *Global Environmental Change*, *27*, 1–8.
- Gentilini, U., Almenfi, M., Orton, I., & Dale, P. (2020). *Social protection and jobs responses to covid-19*. World Bank, Washington, DC.
- Hallegatte, S., Bangalore, M., Bonzanigo, L., Fay, M., Kane, T., Narloch, U., . . . Vogt-Schilb, A. (2015). *Shock waves: managing the impacts of climate change on poverty*. The World Bank.
- Hallegatte, S., Bangalore, M., & Vogt-Schilb, A. (2016). *Assessing socioeconomic resilience to floods in 90 countries*. The World Bank. doi: 10.1596/1813-9450-7663
- Hallegatte, S., & Hammer, S. (2020). *Think ahead: For a sustainable recovery for covid-19. development and a changing climate*. Retrieved 2020-08-15, from <https://blogs.worldbank.org/climatechange/thinking-ahead-sustainable-recovery-covid-19-coronavirus>
- Hallegatte, S., & Rozenberg, J. (2017). Climate change through a poverty lens. *Nature Climate Change*, *7*(4), 250–256.
- Hallegatte, S., Vogt-Schilb, A., Bangalore, M., & Rozenberg, J. (2017). *Unbreakable: building the resilience of the poor in the face of natural disasters*. World Bank. Retrieved from <https://openknowledge.worldbank.org/handle/10986/25335>
- Havlík, P., Valin, H., Gusti, M., Schmid, E., Leclère, D., Forsell, N., . . . Obersteiner, M. (2015). *Climate change impacts and mitigation in the developing world: An integrated assessment of the agriculture and forestry sectors*. The World Bank. Retrieved from <https://elibrary.worldbank.org/doi/abs/10.1596/1813-9450-7477> doi: 10.1596/1813-9450-7477
- Hertel, T. W. (2016). Food security under climate change. *Nature Climate Change*, *6*(1), 10–13.
- Kasprzyk, J. R., Nataraj, S., Reed, P. M., & Lempert, R. J. (2013). Many objective robust decision making for complex environmental systems undergoing change. *Environmental Modelling & Software*, *42*, 55–71.
- Kolstad, E. W., & Johansson, K. A. (2011). Uncertainties associated with quantifying climate change impacts on human health: a case study for diarrhea. *Environmental Health Perspectives*, *119*(3), 299–305.

- Kwakkel, J. H. (2017). The exploratory modeling workbench: An open source toolkit for exploratory modeling, scenario discovery, and (multi-objective) robust decision making. *Environmental Modelling & Software*, *96*, 239 - 250. doi: 10.1016/j.envsoft.2017.06.054
- Kwakkel, J. H., & Haasnoot, M. (2019). Supporting dmdu: A taxonomy of approaches and tools. In V. A. W. J. Marchau, W. E. Walker, P. J. T. M. Bloemen, & S. W. Popper (Eds.), *Decision making under deep uncertainty: From theory to practice* (pp. 355–374). Cham: Springer International Publishing. doi: 10.1007/978-3-030-05252-2_15
- Leclère, D., Jayet, P.-A., & de Noblet-Ducoudré, N. (2013). Farm-level autonomous adaptation of european agricultural supply to climate change. *Ecological Economics*, *87*, 1 - 14. doi: 10.1016/j.ecolecon.2012.11.010
- Leichenko, R., & Silva, J. A. (2014). Climate change and poverty: vulnerability, impacts, and alleviation strategies. *Wiley Interdisciplinary Reviews: Climate Change*, *5*(4), 539–556.
- Lloyd, S. J., Kovats, R. S., & Chalabi, Z. (2011). Climate change, crop yields, and undernutrition: development of a model to quantify the impact of climate scenarios on child undernutrition. *Environmental health perspectives*, *119*(12), 1817–1823.
- McKay, M. D., Beckman, R. J., & Conover, W. J. (1979). Comparison of three methods for selecting values of input variables in the analysis of output from a computer code. *Technometrics*, *21*(2), 239–245. doi: 10.1080/00401706.1979.10489755
- Mendelsohn, R., Dinar, A., & Williams, L. (2006). The distributional impact of climate change on rich and poor countries. *Environment and development economics*, 159–178.
- Nelson, G. C., Valin, H., Sands, R. D., Havlík, P., Ahammad, H., Deryng, D., ... Willenbockel, D. (2014). Climate change effects on agriculture: Economic responses to biophysical shocks. *Proceedings of the National Academy of Sciences*, *111*(9), 3274–3279. doi: 10.1073/pnas.1222465110
- Organization, W. H. (2014). *Quantitative risk assessment of the effects of climate change on selected causes of death, 2030s and 2050s* [Publications]. Author.
- Osborne, T., Rose, G., & Wheeler, T. (2013). Variation in the global-scale impacts of climate change on crop productivity due to climate model uncertainty and adaptation. *Agricultural and Forest Meteorology*, *170*, 183–194.
- O’Neill, B. C., Kriegler, E., Ebi, K. L., Kemp-Benedict, E., Riahi, K., Rothman, D. S., ... others (2017). The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Global Environmental Change*, *42*, 169–180.
- O’Neill, B. C., Kriegler, E., Riahi, K., Ebi, K. L., Hallegatte, S., Carter, T. R., ... van Vuuren, D. P. (2014). A new scenario framework for climate change research: the concept of shared socioeconomic pathways. *Climatic change*, *122*(3), 387–400.
- Rozenberg, J., & Hallegatte, S. (2015). *The impacts of climate change on poverty in 2030 and the potential from rapid, inclusive, and climate-informed development* (Tech. Rep. No. WPS7483). The World Bank. Retrieved 2016-03-08, from <http://documents.worldbank.org/curated/en/2015/11/25257367/impacts-climate-change-poverty-2030-potential-rapid-inclusive-climate-informed-development>
- Samir, K., & Lutz, W. (2017). The human core of the shared socioeconomic pathways: Population scenarios by age, sex and level of education for all countries to 2100. *Global Environmental Change*, *42*, 181–192.
- Skoufias, E., Rabassa, M., & Olivieri, S. (2011). *The poverty impacts of climate change: a review of the evidence*. The World Bank.

Tol, R. S. (2009). The economic effects of climate change. *Journal of economic perspectives*, 23(2), 29–51.

World Bank. (2016). *Global consumption database*. World Bank.

World Bank. (2018). *Poverty and shared prosperity 2018 : Piecing together the poverty puzzle*. Washington, D.C.: World Bank Group. Retrieved from <http://documents.worldbank.org/curated/en/104451542202552048/Poverty-and-Shared-Prosperity-2018-Piecing-Together-the-Poverty-Puzzle>

World Bank. (2020). *Pandemic, recession: The global economy in crisis. global economic prospect*.

Appendix 1

The table below shows the household survey year for each country included the analysis.

| No | Country | Survey year |
|----|---------|-------------|
| 1 | AGO | 2018 |
| 2 | AUT | 2018 |
| 3 | BDI | 2013 |
| 4 | BEL | 2018 |
| 5 | BEN | 2015 |
| 6 | BFA | 2014 |
| 7 | BGD | 2016 |
| 8 | BGR | 2018 |
| 9 | BIH | 2011 |
| 10 | BOL | 2018 |
| 11 | BRA | 2018 |
| 12 | BTN | 2017 |
| 13 | BWA | 2015 |
| 14 | CHE | 2018 |
| 15 | CIV | 2015 |
| 16 | CMR | 2014 |
| 17 | COD | 2012 |
| 18 | COL | 2018 |
| 19 | COM | 2013 |
| 20 | CRI | 2018 |
| 21 | CYP | 2018 |
| 22 | CZE | 2018 |
| 23 | DNK | 2018 |
| 24 | DOM | 2018 |
| 25 | ECU | 2018 |
| 26 | ESP | 2018 |
| 27 | EST | 2018 |
| 28 | ETH | 2015 |
| 29 | FIN | 2018 |
| 30 | FRA | 2018 |
| 31 | GBR | 2017 |
| 32 | GHA | 2016 |
| 33 | GRC | 2018 |
| 34 | GTM | 2014 |
| 35 | HND | 2018 |
| 36 | HRV | 2018 |

| | | |
|----|-----|------|
| 37 | HUN | 2018 |
| 38 | IDN | 2016 |
| 39 | IRL | 2017 |
| 40 | IRQ | 2012 |
| 41 | ISL | 2016 |
| 42 | ITA | 2018 |
| 43 | JOR | 2010 |
| 44 | KAZ | 2017 |
| 45 | LAO | 2012 |
| 46 | LKA | 2016 |
| 47 | LSO | 2017 |
| 48 | LTU | 2018 |
| 49 | LUX | 2018 |
| 50 | LVA | 2018 |
| 51 | MAR | 2013 |
| 52 | MEX | 2018 |
| 53 | MKD | 2017 |
| 54 | MMR | 2015 |
| 55 | MNG | 2016 |
| 56 | MOZ | 2014 |
| 57 | MRT | 2014 |
| 58 | NER | 2014 |
| 59 | NGA | 2009 |
| 60 | NIC | 2014 |
| 61 | NOR | 2018 |
| 62 | PAK | 2015 |
| 63 | PAN | 2018 |
| 64 | PER | 2018 |
| 65 | PHL | 2015 |
| 66 | PNG | 2009 |
| 67 | POL | 2018 |
| 68 | PRT | 2018 |
| 69 | ROU | 2018 |
| 70 | SDN | 2009 |
| 71 | SLB | 2013 |
| 72 | SLE | 2018 |
| 73 | SLV | 2018 |
| 74 | SVK | 2017 |
| 75 | SWE | 2018 |
| 76 | SWZ | 2016 |
| 77 | TCD | 2011 |
| 78 | TGO | 2015 |
| 79 | THA | 2017 |
| 80 | TLS | 2014 |
| 81 | TZA | 2018 |
| 82 | UGA | 2016 |
| 83 | URY | 2018 |
| 84 | VNM | 2016 |
| 85 | VUT | 2010 |
| 86 | ZMB | 2015 |
