INTERNATIONAL FEDERATION

100 1919-2019

THE COST OF DOING NOTHING

Appendix: Methodology

The International Federation of Red Cross and Red Crescent Societies (IFRC) is the world's largest volunteer–based humanitarian network. With our 190 member National Red Cross and Red Crescent Societies worldwide, we are in every community reaching 160.7 million people annually through long–term services and development programmes, as well as 110 million people through disaster response and early recovery programmes. We act before, during and after disasters and health emergencies to meet the needs and improve the lives of vulnerable people. We do so with impartiality as to nationality, race, gender, religious beliefs, class and political opinions.

Our strength lies in our volunteer network, our community–based expertise and our independence and neutrality. We work to improve humanitarian standards, as partners in development, and in response to disasters. We persuade decision-makers to act at all times in the interests of vulnerable people. The result: we enable healthy and safe communities, reduce vulnerabilities, strengthen resilience and foster a culture of peace around the world.

© International Federation of Red Cross and Red Crescent Societies, Geneva, 2019

Any part of this publication may be cited, copied, translated into other languages or adapted to meet local needs without prior permission from the International Federation of Red Cross and Red Crescent Societies, provided that the source is clearly stated.

Requests for commercial reproduction should be directed to the IFRC Secretariat at *secretariat@ifrc.org*

Chemin des Crêts 17
CH-1214
Switzerland

Telephone: +41 22 730 4222
Telefax: +41 22 730 4200
E-mail: *secretariat@ifrc.org*
Web site: *www.ifrc.org*

The cost of doing nothing.
Appendix: Methodology. 2019

1

PER CAPITA COSTS AND DISASTER AFFECT RATES

OVERVIEW

Per capita costs were calculated across two sets of data: costs of response within the IFRC system and costs of response within the UNOCHA Appeals system. The key sources for this analysis were IFRC GO (International Federation of Red Cross and Red Crescent Societies, 2019) and UNOCHA's FTS (United Nations Office for the Coordination of Humanitarian Affairs, 2019). The present-day share of populations affected by disasters was calculated based on a single core dataset: EM-DAT (Centre for Research on the Epidemiology of Disasters, 2019) .

PER CAPITA COST OF RESPONSE, IFRC

The primary source of data regarding the cost of humanitarian response within the IFRC system was IFRC GO, a public repository of more than 3,000 IFRC operations and appeals with data available back to 1919. The analysis examined the value of funds requested and number of individuals targeted for aid provided on a per-disaster basis by this repository. As the intention is to assess the actual financial need per capita targeted for aid, the value of requested funds was used in the calculation rather than the funded total of disaster response. Furthermore, research suggests that disaster response needs are chronically underfunded.

Classification of disasters (IFRC GO)

Disasters were disaggregated according to type, onset speed, and relation to climate change based on examined literature and authors' discretion (Development Initiatives, 2018; Webster, et al., 2008). Estimates of per capita IFRC costs were limited to disasters with a direct relationship to climate change (table 1). Disaster types were combined into broad classifications for ease of analysis within the model.

Earlier iterations of this analysis also disaggregated disasters by five-year time periods, country income groupings and by disaster types within regions. Each of these was discarded due to limitations in integrating into the Shock Waves Model.

Data cleaning and transformations

Data for events and values earlier than the year 2000 were removed, as were entries which contained no data for the number of targeted beneficiaries of aid or the amount of funding requested.

The numbers of individuals targeted in a disaster was transformed to an annualised value, such that calculated per capita costs are year-equivalent. This was achieved by multiplying the recorded time length of disaster occurrence and response in years by the number of individuals aided.

Currency

The IFRC GO value of requested funds is presented in current-year Swiss francs (CHF); for the purpose of analysis, these values were converted to constant 2018 price United States Dollars (USD).

The process of conversion consisted of deflating the current-year value to constant 2018 prices by Switzerland's implicit GDP price deflator, and then converting this value to USD by the official 2018 CHF/USD exchange rate. All conversion and deflation factors were sourced from the World Bank's DataBank (World Bank, 2019). Values for 2019 were considered as 2018 prices due to a lack of an available 2019 deflator. Disasters occurring over multiple years had price data deflated at the average rate across the period.

Table 1

USED IN MODEL	IFRC CLASSIFICATION	MODEL CLASSIFICATION	ONSET
Yes	Cyclone	Storm	Rapid
	Storm surge		
	Flood	Flood	
	Pluvial/Flash flood		
	Drought	Drought/food insecurity	Slow
	Food insecurity		
No	Biological Emergency		
	Chemical Emergency		
	Civil Unrest		
	Cold wave[1]		
	Complex Emergency		
	Earthquake		
	Epidemic		
	Fire		
	Heat wave[1]		
	Insect infestation		
	Landslide		
	Population Movement		
	Transport Accident		
	Tsunami		
	Volcanic eruption		
	Other		

An earlier iteration of the analysis explored the use of Purchasing Power Parities (PPPs) as the currency conversion approach. This approach was not utilised for the following reasons: 1) converting expressed in 2018 USD values allowed for the most direct comparison of present day needs with that of the future from a donor perspective; 2) PPPs are relatively obscure from the perspective of the audience of the final report; 3) the most recent year baseline year for PPPs is 2011—values expressed in PPPs were therefore not readily identifiable with present day costs.

Analysis

The average cost of humanitarian response per capita was calculated as the sum of per-disaster funds requested over the sum of per-disaster year-equivalent beneficiaries targeted. This analysis was split by disaster type and country income group. Country income groups were sourced from the World Bank DataBank.

Confidence intervals (90%) were calculated for each analytical mean through a bias-corrected and accelerated (BCa) bootstrap method (R=10,000).

An additional analysis focused on modelling the marginal cost of humanitarian need based on size of affected population was also explored but ultimately discarded. This is elaborated further at the end of this section.

[1] *While heat waves and cold waves are directly related to climate change, they were not used in this analysis because: 1) the IFRC database does not adequately include heat waves 2) cold waves are diminishing due to climate change and 3) neither event type is captured in the World Bank's Shock Waves model.*

Robustness: conflict-associated disasters

For robustness, it was checked whether disasters occurring within a conflict context had statistically significant differing costs of response per capita than disasters not associated with conflict.

Whether a disaster was associated with conflict was evaluated at a national level, by year. The presence of a conflict context was identified by authors' discretion based on data from the Aid Worker Security Database (Humanitarian Outcomes, 2019). In general, disasters occurring in countries which showed at least one aid worker affected by conflict in the same year were considered to be conflict-associated.

Analysis of the per capita cost of humanitarian response disaggregated by conflict and non-conflict contexts did not show a statistically significant difference. As a result, all data records were retained for the analysis.

Data limitations

The IFRC GO platform provides comprehensive documentation of allocations from IFRC's Disaster Relief Emergency Fund (DREFs) and Appeals covered by or requested by the IFRC secretariat. While it is open for wider reporting across the International Red Cross and Red Crescent Movement, in practice it does not yet capture a comprehensive picture of domestic responses by National Red Cross and Red Crescent Societies who are able to cover disaster response needs through direct fundraising. For example, the annual disaster response operations of the American Red Cross in the United States, a highly disaster-prone country, are not captured in this data set. This is the same for most disaster responses from National Societies located in high-income countries. Based on available data, the per capita needs in higher-income countries do not seem to have a higher degree of uncertainty as a result, but this cannot be entirely ruled out.

Results

Table 2

	IFRC COST OF RESPONSE 2000-TODAY (2018 PRICE USD)					
	n	**Funding requirement**	**Targeted for aid (number)**	**Mean**	**Lower CI (90%)**	**Upper CI (90%)**
Overall	706	1,662,684,019	68,908,687	24.13	17.01	31.52
Cyclone	116	380,264,789	10,090,411	37.69	20.88	50.18
Drought	54	261,956,298	11,104,792	23.59	17.80	33.17
Flood	462	632,070,581	20,484,126	30.86	22.81	39.11
Food Insecurity	45	367,670,090	26,372,017	13.94	7.19	35.96
Pluvial/Flash Flood	28	20,503,959	847,050	24.21	13.73	102.03
Low income	174	405,591,077	14,252,898	28.46	13.73	45.30
Lower middle income	290	835,992,324	45,688,072	18.30	11.71	25.84
Upper middle income	189	329,558,768	5,340,139	61.71	40.32	89.14
High income	34	70,770,542	1,370,747	51.63	43.48	74.44

PER CAPITA ESTIMATE OF HUMANITARIAN NEED, UNOCHA APPEALS

The primary source for costs to the wider humanitarian community was UNOCHA's FTS and Humanitarian Response Plans (HRPs); aggregated data on people targeted was UNOCHA's Humanitarian Data Exchange (United Nations Office for the Coordination of Humanitarian Affairs, 2019). Data contained within these sources include the total funding requested and number of individuals targeted on a per appeal basis. Disasters are not directly identified by type, but by locality and year. Comprehensive data was available for the years of 2011-2019, covering 232 annual appeals.

Data cleaning and transformations

Appeals which contained no data for either the number of targeted beneficiaries of aid or the amount of funding requested were removed.

The number of targeted beneficiaries of aid were assumed to be annual-equivalent values.

Currency

UNOCHA's FTS presents requested funding in current-year USD; for the purpose of analysis, these values were converted to constant 2018 price USD using the United States implicit GDP deflator.

An alternative deflation utilising the average OECD USD deflator was also completed, however the lack of required recent data for all constituent countries meant that this analysis was not utilised.

Analysis

The average cost of humanitarian response per capita was calculated as the sum of per-appeal requirements over the sum of per-appeal year-equivalent beneficiaries targeted.

Confidence intervals (90%) were calculated for the analytical mean through a bias-corrected and accelerated (BCa) bootstrap method (R=10,000).

Robustness: conflict-associated disasters

For robustness, we check whether appeals occurring within a conflict context have significantly differing costs of response per capita than disasters not associated with conflict.

Whether a disaster was associated with conflict was evaluated at a national level by year. The presence of a conflict context was identified by authors' discretion and data based on the Uppsala Conflict Data Program (Uppsala University, 2019).

Analysis of the per capita cost of humanitarian response disaggregated by conflict and non-conflict contexts showed a statistically significant difference, with conflict contexts reporting higher per capita costs. Conflict-associated disasters were therefore removed from the analysis.

Data limitations

Humanitarian Response Plans are generally defined on an annual basis, rather than in response to specific shocks. Although there is an occasional exception to this in the case of very large unanticipated needs, covered by Flash Appeals. The focus on annual planning cycles poses significant limitations to distinguishing disaster specific humanitarian need from wider forms of urgent need.

Results

Table 3

	UNOCHA APPEAL COST OF RESPONSE 2011-2019 (2018 USD)					
	n	**Funding requirement**	**Targeted for aid (number)**	**Mean**	**Lower CI (90%)**	**Upper CI (90%)**
Non-conflict	60	13,266,151,463	117,822,460	112.12	77.12	150.67
Conflict	172	160,131,760,852	623,404,660	256.34	227.23	294.98

SHARE OF PRESENT-DAY POPULATIONS AFFECTED BY DISASTERS

The primary source of data for the share of populations affected by disasters was the Centre for Research on the Epidemiology of Disasters' (CRED) Emergency events Database (EM-DAT). EM-DAT contains data on more than 22,000 disasters in the world from 1900 to the present day, including the estimated number of individuals affected by disasters.

Persons 'affected' by a disaster are those "requiring immediate assistance during a period of emergency, i.e. requiring basic survival needs such as food, water, shelter, sanitation and immediate medical assistance".

Data granularity is by country and by year.

Classification of disasters (EM-DAT)

Disaster types within the EM-DAT repository were classified and grouped according to match the model classifications (table 4).

Table 4

USED IN MODEL	EM-DAT CLASSIFICATION	MODEL CLASSIFICATION	ONSET
Yes	Storm	Storm	Rapid
	Flood	Flood	
	Drought	Drought/food insecurity	Slow

Data cleaning and transformations

Data for events and values earlier than the year 2009 were removed, as were entries which contained no data or zero for the number of individuals affected.

The numbers of individuals affected in a disaster was transformed to an annualised value, based on the recorded disaster length.

Analysis

The average share of populations affected by climate disasters was calculated by two methods to produce a lower and upper bound. The lower bound assumed that disasters occurring in the same year and country affected the same cohort of overall population—for example, a flood recorded as affecting 1,000 people and a storm affecting 5,000 people would return only 5,000 affected individuals overall. The upper bound assumed that disasters are always independent—in the previous example, the 1,000 individuals affected by the flood do not overlap with the 5,000 affected by the storm: 6,000 people were recorded as affected overall.

Shares of populations affected were calculated by disaster type for country income groups, per year. Population data were sourced from the World Bank DataBank. Country income groups were also sourced from the World Bank DataBank. Population-weighted means across the period 2008-2018 were then produced for each income group, by disaster type. Confidence intervals (90%) were calculated for the analytical means through a bias-corrected and accelerated (BCa) bootstrap method (R=10,000).

Results

Table 5

		SHARE OF POPULATION AFFECTED, ANNUAL AVERAGE			
		Complete overlap (lower bound)			
		Total affected (number)	Mean	Lower CI (90%)	Upper CI (90%)
Global	Overall	1,719,802,752	2.2%	1.3%	4.8%
	Drought	1,109,972,229	1.4%	0.5%	4.0%
	Flood	589,867,946	0.8%	0.5%	1.3%
	Storm	263,543,195	0.3%	0.2%	0.7%
	Wildfire	973,276	0.0%	0.0%	0.0%
Low income	Overall	71,298,813	0.9%	0.4%	2.3%
	Drought	63,050,000	0.8%	0.3%	2.1%
	Flood	5,405,341	0.1%	0.0%	0.1%
	Storm	4,992,191	0.1%	0.0%	0.2%
	Wildfire	-	0.0%	0.0%	0.0%
Lower middle income	Overall	901,340,052	2.9%	0.8%	9.0%
	Drought	691,034,094	2.2%	0.1%	8.3%
	Flood	163,193,503	0.5%	0.4%	0.7%
	Storm	88,999,148	0.3%	0.2%	0.5%
	Wildfire	409,664	0.0%	0.0%	0.0%
Upper middle income	Overall	642,024,361	2.4%	1.5%	3.7%
	Drought	355,877,000	1.3%	0.6%	2.7%
	Flood	405,467,251	1.5%	0.9%	2.8%
	Storm	78,136,359	0.3%	0.2%	0.5%
	Wildfire	17,473	0.0%	0.0%	0.0%
High income	Overall	105,139,526	0.8%	0.1%	2.8%
	Drought	11,135	0.0%	0.0%	0.0%
	Flood	15,801,851	0.1%	0.0%	0.4%
	Storm	91,415,497	0.7%	0.0%	2.8%
	Wildfire	546,139	0.0%	0.0%	0.0%

Table 5 (cont.)

		SHARE OF POPULATION AFFECTED, ANNUAL AVERAGE			
		No overlap (upper bound)			
		Total affected (number)	Mean	Lower CI (90%)	Upper CI (90%)
Global	Overall	2,117,082,444	2.7%	1.7%	5.2%
	Drought	1,110,198,229	1.4%	0.5%	4.0%
	Flood	671,142,675	0.9%	0.6%	1.4%
	Storm	334,753,788	0.4%	0.3%	0.7%
	Wildfire	987,752	0.0%	0.0%	0.0%
Low income	Overall	73,455,962	1.0%	0.4%	2.3%
	Drought	63,050,000	0.8%	0.3%	2.2%
	Flood	5,405,341	0.1%	0.0%	0.1%
	Storm	5,000,621	0.1%	0.0%	0.2%
	Wildfire	-	0.0%	0.0%	0.0%
Lower middle income	Overall	1,002,092,206	3.2%	1.1%	9.2%
	Drought	691,034,094	2.2%	0.1%	8.1%
	Flood	181,929,053	0.6%	0.4%	0.8%
	Storm	128,719,395	0.4%	0.3%	0.7%
	Wildfire	409,664	0.0%	0.0%	0.0%
Upper middle income	Overall	933,031,331	3.4%	2.2%	5.4%
	Drought	356,103,000	1.3%	0.6%	2.6%
	Flood	467,941,478	1.7%	1.0%	2.9%
	Storm	108,969,380	0.4%	0.2%	0.7%
	Wildfire	17,473	0.0%	0.0%	0.0%
High income	Overall	108,502,945	0.8%	0.2%	2.9%
	Drought	11,135	0.0%	0.0%	0.0%
	Flood	15,866,803	0.1%	0.0%	0.4%
	Storm	92,064,392	0.7%	0.0%	2.8%
	Wildfire	560,615	0.0%	0.0%	0.0%

ADDITIONAL NOTES; ALTERNATIVE APPROACHES

Marginal cost of need

Literature suggests that non-linear unit costing, specifically diminishing marginal unit costs, are used in planning the project costs of disaster response (Global Protection Cluster, 2019; Baker & Salway, 2016). Testing whether this occurs in the observed datasets requires observing the form of relationship between the number of individuals targeted in a disaster (I) and the total cost of need (C) per capita:

$$\Delta \frac{C}{I} = \Delta f(I) \tag{1}$$

Based on empirical observations of the datasets in question, both variables for individuals targeted and costs appear to be individually log-normally distributed; taking logs of each variable allows then an estimation of the following relationship (where a lowercase term represents the natural logarithm of the original):

$$c - i = \widehat{\beta_0} + (\widehat{\beta_1} - 1)i + \hat{u} \tag{2}$$

A Q-Q plot affirms that the residuals of this relationship $(\hat{u})$ are closely normally distributed. A Box-Cox plot also confirms that the lowest variance is observed for a log-log transformation. This relationship may be estimated by a simple ordinary least squares (OLS) regression.

Given $\widehat{U}$ is the estimated multiplicative error term, the back-transformed relationship is then:

$$\frac{C}{I} = \widehat{B_0}\, I^{\widehat{\beta_1} - 1}\, \widehat{U} \tag{3}$$

The marginal cost of need is then given by:

$$\Delta \frac{C}{I} = \left(\widehat{\beta_1} - 1\right) \widehat{B_0}\, I^{\widehat{\beta_1} - 2}\, \widehat{U} \tag{3}$$

As it is given that $\widehat{B_0},\ \widehat{U} > 0$, a value of $\widehat{\beta_1} < 1$ suggests a diminishing marginal cost relationship, a value of $\widehat{\beta_1} > 1$ suggests increasing marginal costs, and a value of $\widehat{\beta_1} = 1$ implies a linear (uniform) marginal cost of response.

While this methodology more accurately captures the efficiency gains associated with larger humanitarian response efforts, it was ultimately discarded due to challenges integrating this model into the Shock Waves Model. Specifically, this approach would require projecting the absolute size of future disasters in order to identify an appropriate per capita value of humanitarian need.

Table 6

		β_1	Lower CI (95%)	Upper CI (95%)	B_0	Lower CI (95%)	Upper CI (95%)
Low income	Cyclone	0.85	0.78	0.92	766	404	1,453
	Drought	0.68	0.50	0.85	5,282	731	38,178
	Flood	0.62	0.57	0.66	5,765	3,878	8,570
	Food Insecurity	0.56	0.45	0.67	10,826	3,355	34,929
	Pluvial/Flash Flood	0.61	0.49	0.74	4,994	1,476	16,901
Lower middle income	Cyclone	0.80	0.74	0.86	782	429	1,428
	Drought	0.77	0.65	0.88	997	293	3,398
	Flood	0.61	0.58	0.64	5,700	4,417	7,355
	Food Insecurity	0.58	0.46	0.70	4,628	1,294	16,555
	Pluvial/Flash Flood	0.66	0.52	0.80	4,950	1,734	14,135
Upper middle income	Cyclone	0.67	0.60	0.74	4,163	2,195	7,897
	Drought	0.59	0.47	0.70	5,890	2,137	16,236
	Flood	0.66	0.63	0.69	3,169	2,415	4,157
	Food Insecurity	0.86	0.32	1.40	579	1	494,093
	Pluvial/Flash Flood	0.74	0.69	0.80	1,901	1,236	2,923
High income	Cyclone	0.71	0.61	0.81	2,517	1,158	5,471
	Drought Flood Food Insecurity Pluvial/Flash Flood	0.70	0.61	0.79	2,196	995	4,850

Per capita economic damage

The humanitarian cost of disasters is not limited to the cost of emergency needs fulfilled by responding agencies; the economic costs of disaster, including damage to livestock, homes and property, are far greater. Investigating the full economic cost of disasters was undertaken by examining the CRED EM-DAT. The EM-DAT repository contains estimated values for total economic damage and numbers of individuals affected on a per-disaster basis.

It was ultimately regarded that this analysis was outside of the scope of the report.

Additional datasets

The following datasets were also explored for usage in this analysis but were ultimately determined not viable for analysis or outside of the scope of the report:

- IFRC Federation-wide Databank and Reporting System (FDRS)
- ACAPS
- Global Humanitarian Assistance Report 2018

2

EXPLORING THE IMPACT OF CLIMATE CHANGE ON INTERNATIONAL POST-DISASTER HUMANITARIAN NEEDS

APPROACH AND DEFINITIONS

In this study, we define the number of people in need of humanitarian support after a climate-related disaster as the people who are affected by a disaster (i.e., are in the area where a hazard takes place) and are too poor to be able to cope with and recover from the disaster without external (non-governmental) support. Here, the definition does not include all people who will receive support from their government, local authorities, or local charities – for instance thanks to well-functioning social protection systems or affordable insurance systems – but only those who need external help, provided by international agencies or NGOs. These people are referred to as "vulnerable people" in the rest of this note.

This definition is based on a large body of literature showing that poor people tend to be less able to cope with and recover from disasters, not only because their income is lower, but also because they have little savings, less access to financial instruments like emergency loans and insurance and are less covered by social protection systems and other government-managed tools (Hallegatte et al. 2016).

With this definition, the people in need of humanitarian support can be calculated using the following relationship:

$$Need = \frac{Vulnerable}{Population} \cdot Affected$$

With ***Affected*** the number of people exposed the hazard; Population the total population in a country, and ***Vulnerable***, the number of people vulnerable in the country. It is assumed that the likelihood of being affected by a hazard is independent of whether an individual is vulnerable to poverty or not. In some countries, exposure to natural hazards is positively correlated with poverty, especially for frequent urban floods and droughts. However, this correlation is far from universal and in some countries the correlation is negative (for instance where the richest places are coastal cities that are highly exposed to floods). Here, to simplify the analysis, it is assumed that exposure and poverty are independent.

Affected is directly taken from the EM-DAT database, and the fraction of affected population per country is taken as the average over the 2008-2018 period. It is assumed that this period represents the "current" climate conditions, even though a ten-year period is too short to include all possible events.

The definition of vulnerable people is classically based on the income or consumption level. Here, individuals are considered vulnerable if their income is below a certain threshold. It is assumed that people beyond this threshold have their own resources to cope with shock, either in the form of savings, insurance, ability to borrow, or support from friends, family, social networks, or formal governmental support systems.

There is a large literature on the threshold below which people are ***vulnerable to poverty,*** i.e. likely to fall in poverty if affected by a shock, and the threshold of $10 per day has been commonly used. The concept of people living below $10 a day being considered vulnerable is based on evidence that a considerable share of households living just above a given poverty line is vulnerable to falling below that line over time; see (World Bank 2015; López-Calva and Ortiz-Juarez 2014; Birdsall 2015; Ferreira et al. 2012). In other words, we assume that household income is an acceptable proxy for the capacity to cope with and recover from the shock. More work is needed to refine this vulnerability definition for the specific case of climate-related disasters, and to introduce other non-income-related determinant of resilience and vulnerability (On the difference between income and resilience, see a case study in Accra, Ghana, in Erman et al. 2018).

In the 134 countries covered by the World Bank Global Monitoring Database, with a total of 5.7 billion people, approximately 4.6 billion people are living below $10 per day today (in Parity of Purchasing Power US dollars).[2]

---

[2] ***More information can be find on*** *http://povertydata.worldbank.org/poverty/home/*. ***We did not extrapolate these results to the countries not included in the data base, which leads to underestimating most of the results.***

VULNERABLE PEOPLE, NOW AND IN THE FUTURE

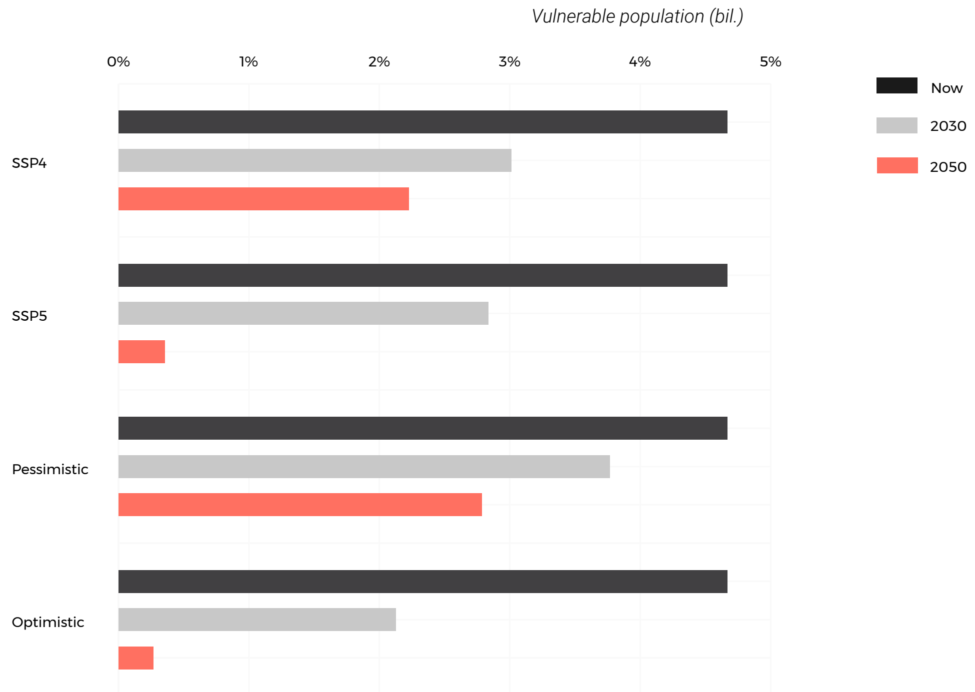
The number of vulnerable people is expected to evolve over time, as development and economic growth takes people beyond the $10/day thresholds. This change in income is used as a proxy for a broader improvement in people's socioeconomic status, with higher financial inclusion and better social protection systems that are expected to make people less dependent on external humanitarian support. However, how much development will reduce the number of people below $10/day in uncertain and depends on many socioeconomic trends and policy choices.

We explore how these numbers will change using two contrasted socioeconomic scenarios, the Shared Socioeconomic Pathways SSP4 and 5. The SSP5 describes a world of rapid economic growth, while SSP4 has a slower (and less inclusive) economic growth.

To determine how these aggregate scenarios affect the population below $10, we start by assuming that all households see the same change in income, following the GDP per capita in the country. In this case, the number of people below $10/day in 2030 lie between 2.8 and 3 billion in 2030 and between 350 million and 2.2 billion in 2050 (Figure 1). Note that there are big differences across countries: the population below $10/day is growing by 50% and 38% in Afghanistan and Madagascar by 2030, because population growth in the scenarios dominates the effect of economic growth.

However, growth can be more or less inclusive, and the distribution of income within countries may change over time too. It is challenging to determine the change in distribution that are achievable with different tools and instruments, and full modeling simulations (like in Hallegatte and Rozenberg 2017; Rao et al. 2019; Lakner et al. 2019) were not possible for the range of countries and the time horizon considered here. Here, for illustrative purposes only, we assume that the share of people below $10/day can decrease by 25% in every country in SSP5 in response to more inclusive growth patterns and dedicated poverty reduction policies, and that the same share can increase by 25% in SSP4 due to unequal growth trends.[3] In this case, the number of vulnerable people lies between 2.1 and 3.8 billion in 2030 and 280 million and 2.8 billion in 2050.

Figure 1: Vulnerable population now, in 2030, and in 2050, in four scenarios with a constant climate.



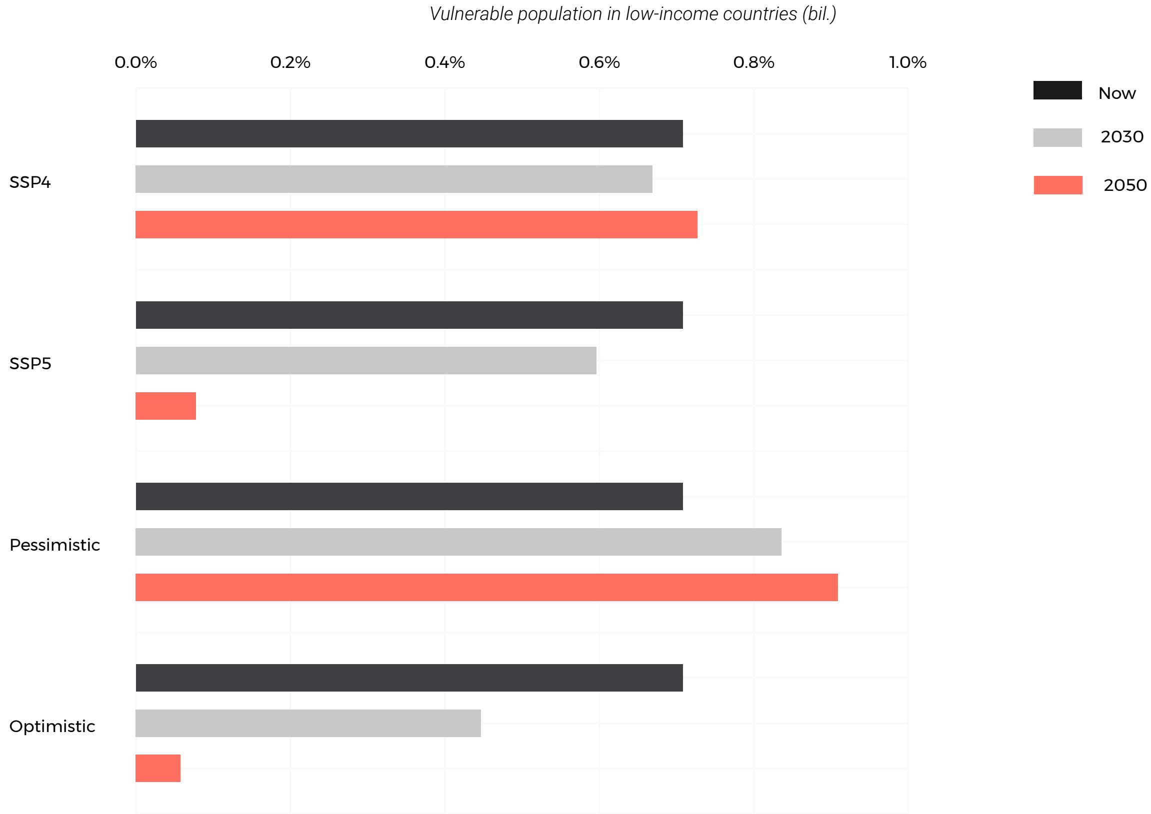
---

[3] *An obvious priority for further work is to replace this simple representation of changes in inequality by actual modeling, which would make it possible to connect the change in income distribution with explicit socio-economic trends or policy changes. It would also allow us to check that the assumptions used here are realistic.*

Note: Scenario 1 and 2 are the SSP4 and SSP5 with stable within-country distribution; Scenario 3 is SSP4 with a 25% increase in the share of vulnerable people within countries; Scenario 4 is SSP5 with a 25% decrease in the share of vulnerable people within countries.

Global trends can easily hide regional dynamics: in the two SSP4 scenarios (with fixed income distribution or slower growth for the poorest), the population below $10 is expected to stay stable or increase in today's low-income countries, while it decreases in the other categories (Figure 2). The effect is particularly strong in Sub-Saharan Africa, where most of the countries with increasing vulnerable populations can be found.

Figure 2: Same as Figure 1, but for low-income countries only



Climate change will affect the number of vulnerable people in each country by affecting people's income and consumption level, especially through impacts on agricultural income, food prices, and labour productivity. Based on the most recent estimates of the macroeconomic impact of climate change, the impact on GDP by 2030 and 2050 is expected to be around 1% (for 2030) and 3% (for 2050). These estimates are highly uncertain of course, as they are based on historical data and cannot include the possible effect of thresholds that have not been crossed already and do not include potential climate change tipping points.[4] And past studies have shown that even small impacts on GDP can have significant effect on poverty (Hallegatte et al. 2015). However, most estimates of the impact of climate change on the population in poverty (or, here, living below $10/day) suggest that the main driver will remain demography and economic growth, at least through 2050. In the absence of a simulation of the impact of climate change on the income distribution within countries going to 2050, and because of the uncertainty on the effects of climate change on GDP, this study does not consider the impact of climate change through the number of people living below our vulnerability threshold, making it more conservative.

In spite of this limit, the main message in this first exploration is that there is a large uncertainty in the number of vulnerable people in the future – due to uncertainty on future patterns of economic growth but also on future policies implemented to reduce poverty and make people more resilient, and on future climate change impacts. Even though stability in the global number of vulnerable people cannot be ruled out, we can expect a global decrease in this population by 2030 and 2050. At the same time, a demography-driven increase in vulnerable populations in low-income countries (especially in Sub-Saharan Africa) is likely by 2030.

[4] Including for instance the threshold on agricultural production (Schlenker and Lobell 2010; Schlenker and Roberts 2009) or on human physiology (Im, Pal, and Eltahir 2017).

HUMANITARIAN NEEDS, NOW AND IN THE FUTURE

When projecting humanitarian needs from now to 2030 or 2050, the impact of climate change will arise from two channels. First, climate change may slow down economic growth and affect income distribution within countries. As discussed earlier, this effect is expected to increase the number of vulnerable people, compared with a baseline estimate with constant climate.

Second, climate change will directly increase the fraction of the population affected by climate-related disasters every year. In the Shock Wave report, as a benchmark, two scenarios were used: one in which the fraction of the global population affected by a disaster each year increases from 1.4% to 2% because of the effect of climate change on the frequency, intensity, and geographic distribution of extreme weather events; and one in which it increases to 3%. These assumptions were based on a review of the literature on future climate-related disaster impacts, using scenarios without ambitious additional resilience and adaptation efforts (IPCC 2012; Bouwer 2013; H. Winsemius et al. 2015; H. C. Winsemius et al. 2013; Hallegatte et al. 2013). Overall, flood exposure is expected to increase in response to heavier rainfall and sea level rise; drought exposure is expected to increase, not only due to reduced average precipitation in some regions, but also increased evaporation with higher temperature. The future of hurricanes remains a debated question and future trends are likely to be different in different ocean basins, but there is an expectation of higher frequency of the most intense storms, with the coastal flood potential magnified by sea level rise. And heat waves are expected to increase very rapidly, with unprecedented heat episodes becoming increasingly frequent and reaching in some regions levels that are close to physiological limits.

Of course, the real increase will depend on the efforts and policies that will be made to reduce risks and adapt to climate change, and more pessimistic or optimistic scenarios are possible. Here, we explore future possible outcomes with four contrasted scenarios:

- A SSP4-based scenario, with slow growth and stable within-country distribution of income, with the global population affected by disaster annually growing from 1.4 to 2% per year 2030 and to 3% per year in 2050.
- A SSP5-based scenario, with rapid growth and stable within country distribution of income, and the global population affected by disaster annually growing from 1.4 to 2% per year 2030 and to 3% per year in 2050.
- A pessimistic scenario, based on SSP4 but with unbalanced growth, and the global population affected by disaster annually growing from 1.4 to 3% per year 2030 and to 5% per year in 2050. This scenario assumes little action to reduce risk exposure and rapid climate change, but is not the worst-case scenario, since it does not include any large-scale tipping point in the climate system and assumes continued growth in productivity leading to positive growth in GDP per capita in all countries in the world.
- An optimistic scenario, based on SSP5 but with inclusive growth, and the global population affected by disaster annually growing from 1.4 to 2% per year 2030 and to 3% per year in 2050.

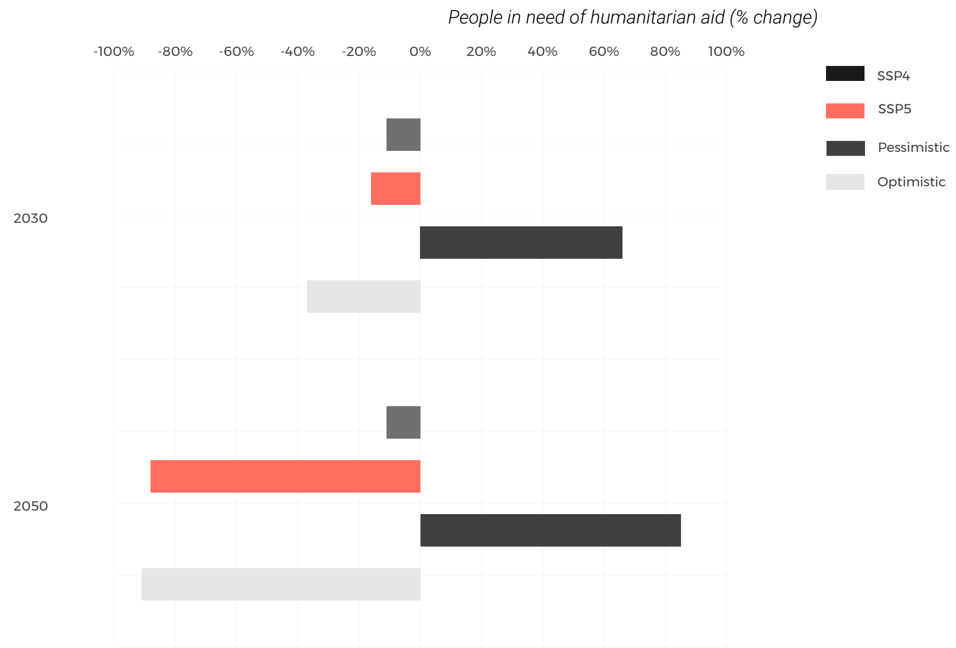
An obvious next step in this analysis is to consider country-per-country changes in exposure, since hazards are expected to increase or decrease differently in different regions of the world. And for large countries like India, China, Nigeria, or Brazil, working at the subnational level would be preferable.

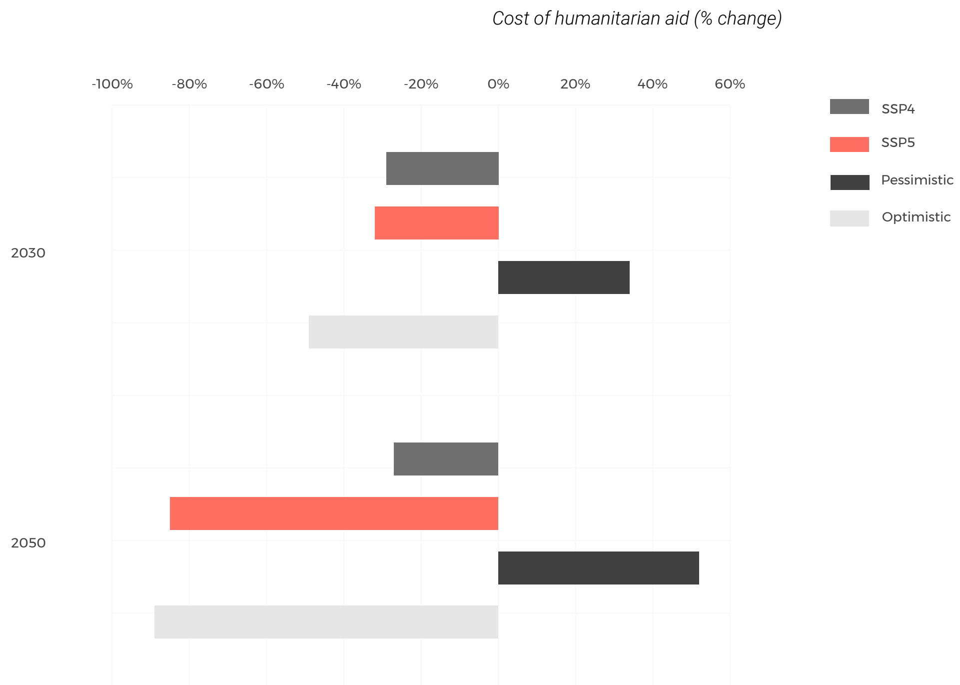
Also, the increase in people exposed is highly dependent on policies and adaptation measures. For instance, risk-sensitive land-use planning could make the fraction of people exposed to floods decrease (instead of increase as assumed here). And irrigation infrastructure can reduce the number of people affected by drought. Here, the estimates are used to illustrate the "cost of doing nothing"—that is, futures without ambitious adaptation and resilience actions.

In the two most optimistic scenarios, the need for external humanitarian support basically disappears by 2050, even if the number of people affected by disasters increases over time (Figure 3, upper panel). This is because countries and regions become increasingly self-sufficient as their income increases. Of course, this is based on extreme assumptions: rapid and inclusive economic growth, with a parallel improvement in the capacity and willingness of government and local actors to provide support to affected population, and limited climate change. The main message here is that it is possible to build realistic scenarios in which almost all countries can manage climate-related disasters on their own by 2050, even with climate change.[5]

In our most pessimistic scenario, the picture is very different: the number of people in need annually increases significantly by 2030 (+66%) and almost doubles by 2050 (+85%). In this scenario, economic growth is not fast enough to compensate for the effect of climate change on the number of people affected by natural hazards every year (and a significant but smaller demographic effect).

Figure 3: Change in the number of people in need of external humanitarian support (upper panel) and change in annual costs (bottom panel), in four scenarios: SSP4, SSP5, Pessimistic, and Optimistic.





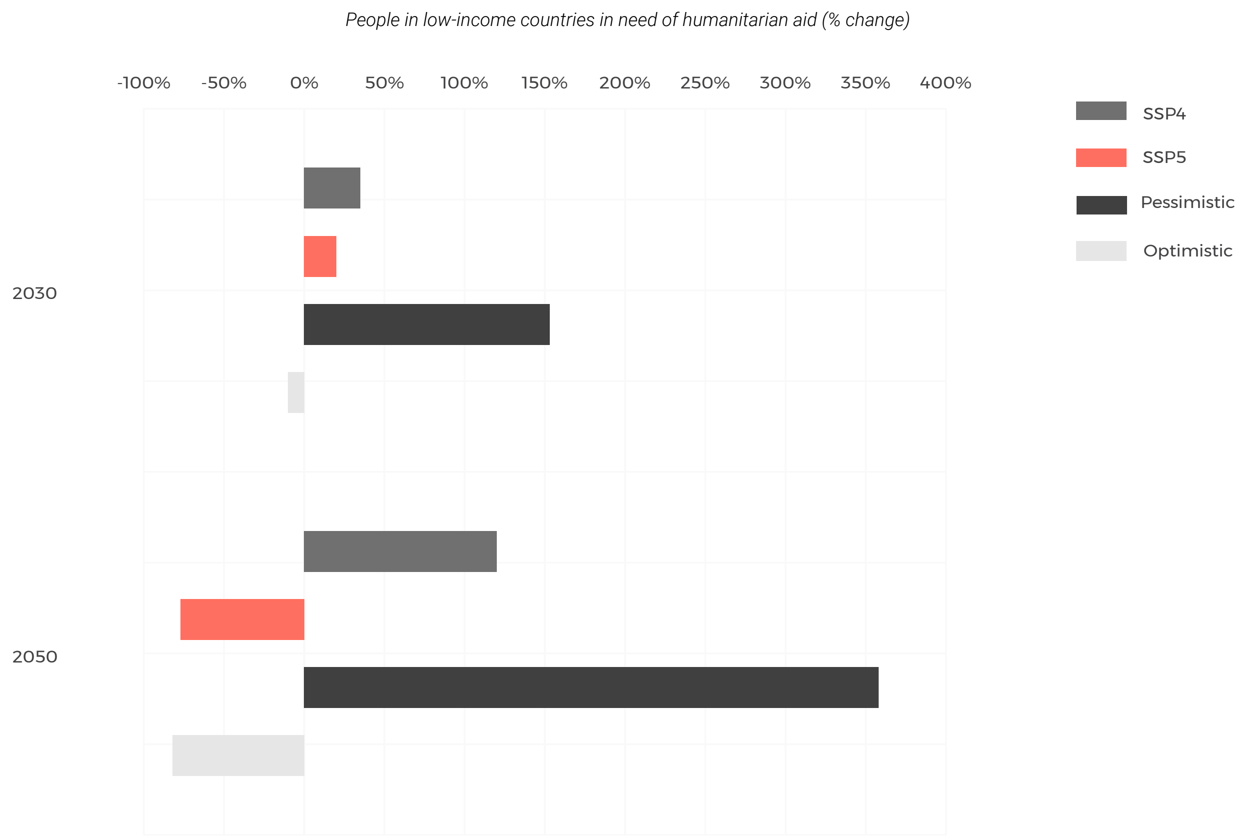
[5] The fact that they can manage does not mean that the costs of these disasters is not taking up a growing share of these countries' income, thereby strongly affecting the well-being of the population. Also, an important caveat is that the analysis does not consider the special situation of small islands and countries: even high-income countries can be unable to manage a disaster when 100% of the country population is affected at once, as illustrated by the recent events in the Caribbean.

The estimates for the population in need every year can be translated into cost estimates, using data on past interventions (Figure 3, bottom panel). Here, the cost of providing basic survival support to the population in need is estimated using IFRC data, aggregated per country income class. Average intervention costs are estimated at $28 in low-income countries, $18 in lower-middle income countries, $62 in upper-middle income countries, and $51 in high-income countries.[6] Of course, these numbers hide a large heterogeneity across situations. Also, they are assumed constant over time in the present study (see a discussion in the conclusion).

Assuming per capita costs remain constant in the future, total annual costs decrease in most scenarios (Figure 3, bottom panel). Across scenarios, costs tend to decrease faster (or increase more slowly) than the total number of people at risk, because of the distribution of people in need. In today's data, support costs are the highest in upper-middle income countries, and these countries are those where the vulnerable population is dropping the fastest. The decrease in upper-middle income countries dominates expected increases in low-income countries.

In the pessimistic scenario, however, there is a large increase, by 34% in 2030 and over 50% in 2050. Most of the increase takes place in low-income countries, where the increase in the number of people in need and in cost exceeds 350% in the pessimistic scenarios (Figure 4).

Figure 4: Same as Figure 3, but for low-income countries only.



[6] *These differences arise from differences in the cost of providing the same goods and services in different contexts, but also the fact that the goods and services provided are different across countries. A convergence over time in the costs and types of goods and services has not been considered here.*

THE IMPACT OF CLIMATE CHANGE

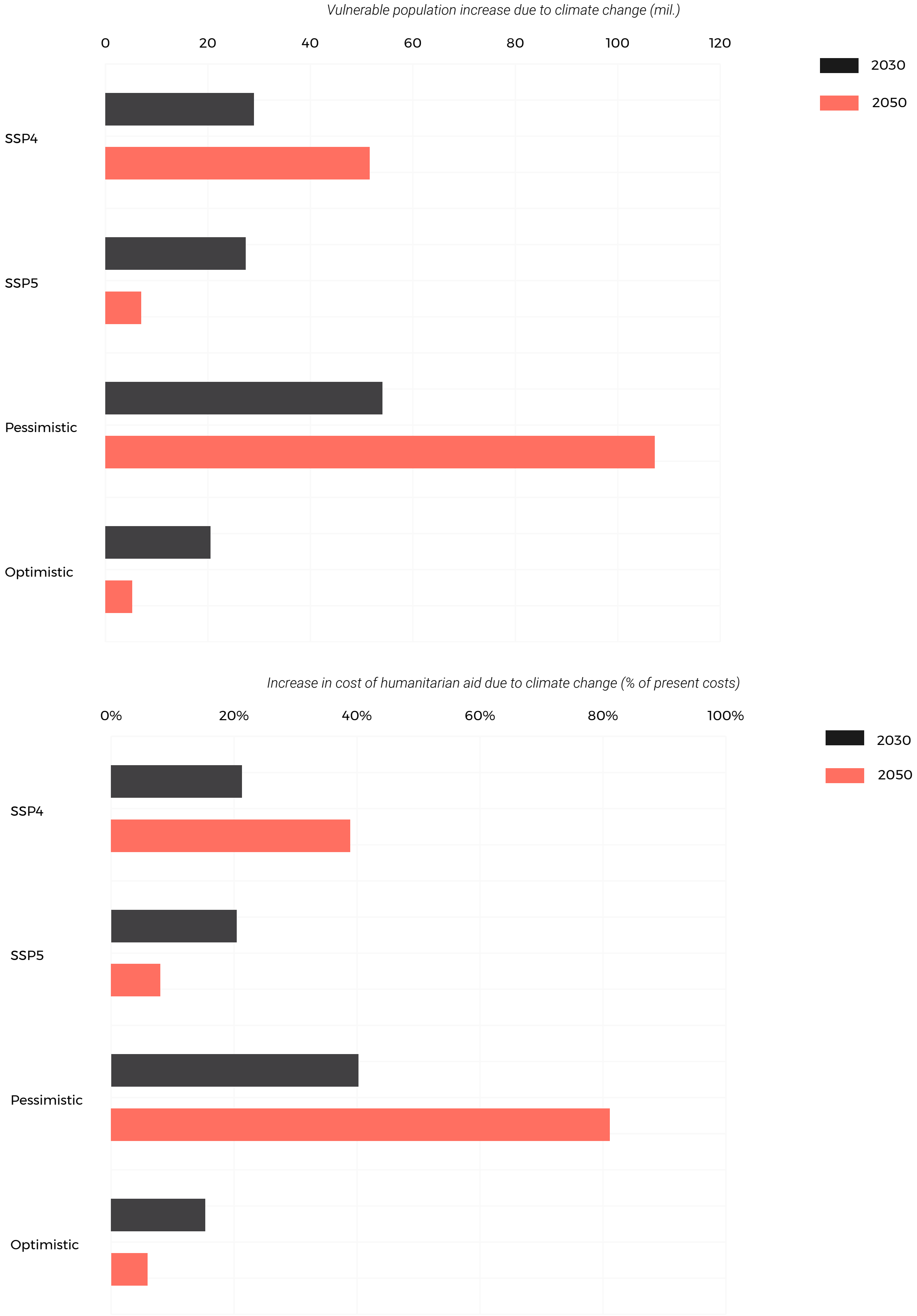
Figure 5 shows how climate change affects the number of people in need of humanitarian assistance due to climate-related disasters, and the corresponding increase in humanitarian cost (in relative terms[7]). The effect of climate change is driven by the change in the number of people affected every year, but the effect is mediated by the change in socioeconomic context.

While the increase in climate change impacts would translate into higher needs and higher costs in all baseline scenarios, the increase ranges from less than 20% in 2030 in our optimistic scenario (with rapid and inclusive economic growth and "only" 21 million more people in need in 2030) to almost 40% in 2030 in our most pessimistic case (slow and inequal development, with more than 50 million more people in need every year).

This result confirms many previous studies[8], and highlights the fact that the future socio-economic impacts of climate change depends as much on the socioeconomic context (especially poverty and the instruments people have to cope and adapt) as on the physical impacts of climate change themselves.

[7] Calculating the absolute cost in dollars is possible, starting from our estimate of the total "need" to support everybody today, which is around $3.8 billion per year. In this case, the most pessimistic scenario leads to an increase in financial needs of $1.5 billion in 2030 and $3 billion in 2050. However, due to the large uncertain and the many opportunity to reduce these costs through risk management policies, these numbers remain illustrative of the orders of magnitude, more than precise estimates of future costs.
[8] Such as (Hallegatte et al. 2015; O'Brien and Leichenko 2000; IPCC 2014; Kriegler et al. 2014).

Figure 5: Increase in population in need (upper panel) and annual humanitarian costs (bottom panel, in percent) in 2030 and 2050 in the four scenarios.



A SENSITIVITY ANALYSIS – USING A DIFFERENT VULNERABILITY LINE

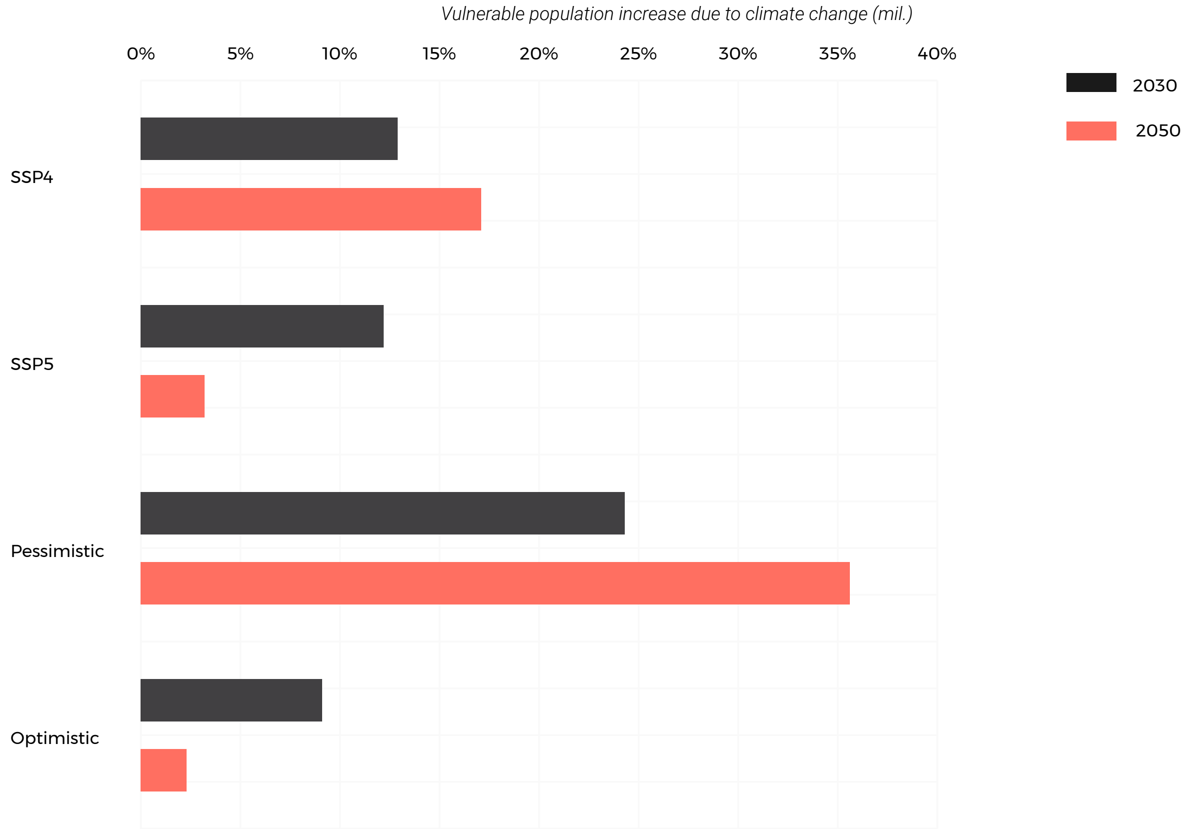
The use of different scenarios shows that results are highly sensitive to assumptions regarding socioeconomic growth and patterns. This sensitivity shows the opportunity of having good development patterns that take people out of poverty and vulnerability and make them more resilient. Particularly important is the assumption regarding the within-country distribution (seen for example in the different seen in Figure 1 between scenario one (SSP4) and three (Pessimistic). A first conclusion is thus that trends in inequality are as important as aggregate GDP growth (a point made for the future of poverty in Lakner et al. 2019, using assumptions on how the Gini will change over time). More work is therefore needed on the relationship between poverty, inequality, and vulnerability, so that the simple assumptions made in this analysis can be refined (and connected to policy options).

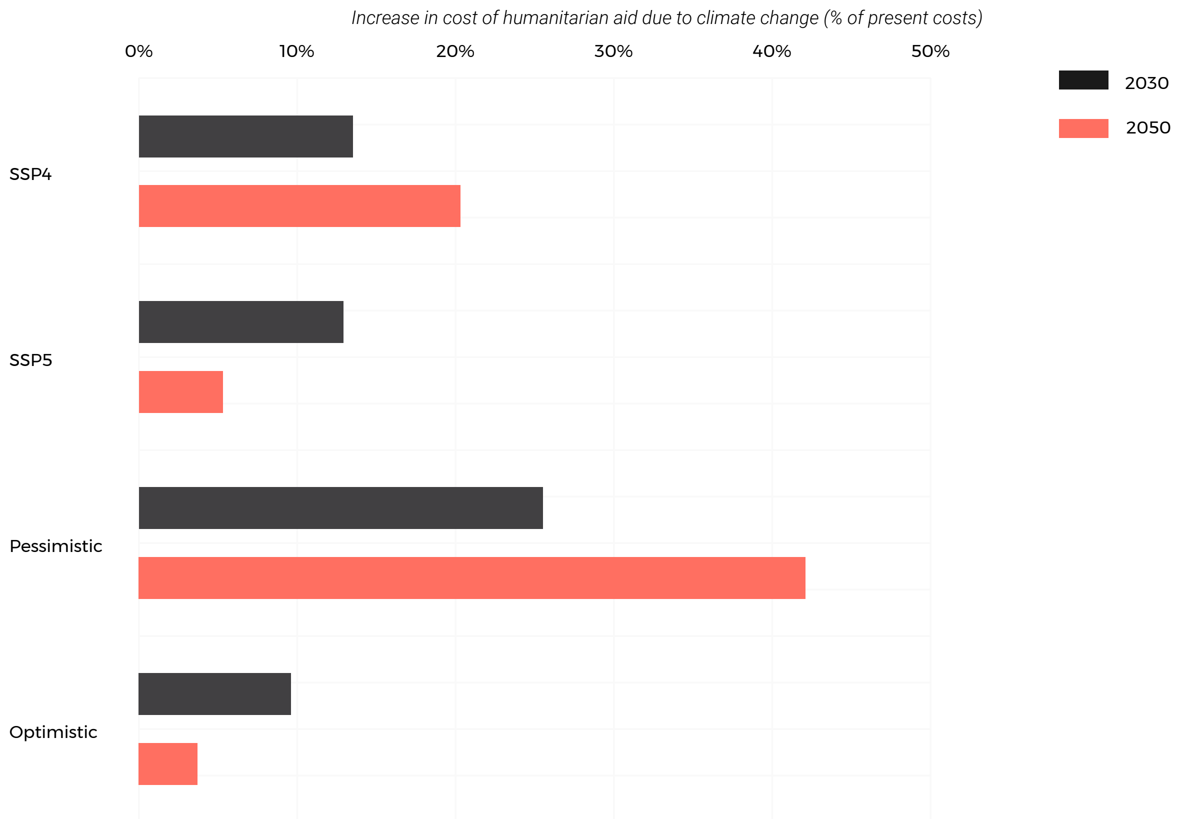
The choice of a $10 poverty line is somewhat subjective. The choice of the line depends indeed on objective factors, such as the income level at which people get access to emergency borrowing or insurance, or the income level at which people are able to save enough to deal with a shock. But it also depends on subjective choices, related to worldviews and policy choices, such as defining a level at which well-being impacts become unacceptable, triggering external assistance. Because of this subjectivity, we run the same analysis with a $6 line, as a sensitivity analysis.

Of course, using a $6 line instead of a $10 line reduces the number of people in need, and therefore current and future funding needs. Population today drops (in our sample of countries) from 4.7 to 3.6 billion people living in vulnerability (i.e. below the line). The number of people in need every year drops from 108 million to 85 million, and the total resources required to meet this need drop from $3.5 billion to $2.5 billion.

Using a $6 line instead of a $10 line does also change our results in terms of the relative impact of climate change (i.e. the change in impacts, compared with today's situation). We find that climate change makes an additional 10 to 25 million people vulnerable to poverty by 2030, and up to 36 million in 2050 in the pessimistic scenario. These numbers are smaller than with the $10/day line, as is the relative increase in cost: costs increase by 10 to 26% in 2030. Costs in 2050 are stationary in the optimistic scenario relative to today, and increase by up to 42% in the pessimistic scenario.

Figure 6: As in Figure 5, but with a $6/day vulnerability line





-

3

CONCLUSION

It's important to note that these estimates are mostly illustrative:

- The change in the population at risk of poverty depends on the socioeconomic scenario that is selected. More rapid and inclusive growth could easily make the population at risk decrease faster, but lower development (or localized economic or geopolitical crises) could increase this population. Also, the assumption used regarding the macroeconomic impacts of climate change (i.e. the impact on GDP growth) are quite conservative, explaining why climate change does not affect more significantly the share of the population at risk of poverty.
- The change in the number of people affected by a natural hazard every year depends on efforts to improve risk-informed land-use planning and other risk reduction measures and policies, from building dikes to protecting mangroves and wetlands. This not only helps to manage today's known risks but prevents the creation of future risks.
- These estimates are only looking at natural hazards. However, disasters and climate change often interact with stability and conflicts. Some studies suggest the existence of a link between disasters and violence, which is not accounted for the present studies.
- The cost of humanitarian support is highly dependent on the cost per person, which is very different across countries and cases and is assumed constant in these simulations. This cost depends on multiple factors, including (1) how much support people receive (the generosity of support); and (2) the transaction costs (the efficiency of support). Total costs could therefore be much higher than our estimates, for instance because support per capita is increased to ensure people do not experience long-lasting impacts on their physical and mental health, or much lower, for instance because new technologies help target people in need and provide support at a much lower cost.

In spite of their simplicity, these scenarios illustrate two important ideas.

First, rapid and inclusive development could make countries and population much better able to manage shocks, reducing the need for external humanitarian support. However, slow growth and increasing inequality could lead to a stable or even increasing population in need of externally-provided humanitarian support every year due to climate-related disasters. And even if the global population in need declines, an increase in low-income countries remains likely.

Second, the effect of climate change on the people in need of humanitarian support is expected to materialize through more intense and frequent disasters, more than through an increase in the vulnerable population. In pessimistic scenarios, the combination of slow and unequal growth with climate change impacts can lead to significant increases in annual cost of external humanitarian support. However, since this effect is largely driven by the number of affected people every year, it can be mitigated by adaptation and risk mitigation efforts and policy.

The good news is that the socioeconomic impacts of climate change – and the consequences on well-being – depend largely on the socioeconomic context in which physical impacts occur, and they can therefore be reduced by appropriate development and risk management policies.

Finally, the support costs per capita depend on the efficiency of the support, but also on political and ethical choices (how much do rich countries and people want to help others affected by disasters and unable to cope by themselves?). Changes in these factors can dominate the changes in the population in need and are likely to remain the main drivers of future humanitarian costs.

REFERENCES

Baker, J. & Salway, M., 2016. Development of a proposal for a methodology to cost inter-agency humanitarian response plans, s.l.: s.n.

Centre for Research on the Epidemiology of Disasters, 2019. EM-DAT The International Disaster Database. [Online] Available at: *https://emdat.be*

Development Initiatives, 2018. Global Humanitarian Assistance Report 2018, s.l.: s.n.

Global Protection Cluster, 2019. HRP Costing Methodology Options, s.l.: s.n.

Humanitarian Outcomes, 2019. Aid Worker Security Database. [Online] Available at: *https://aidworkersecurity.org*

International Federation of Red Cross and Red Crescent Societies, 2019. IFRC GO. [Online] Available at: *https://go.ifrc.org/*

United Nations Office for the Coordination of Humanitarian Affairs, 2019. Financial Tracking Service. [Online] Available at: *https://fts.unocha.org*

United Nations Office for the Coordination of Humanitarian Affairs, 2019. Humanitarian InSight. [Online] Available at: *https://hum-insight.info*

United Nations Office for the Coordination of Humanitarian Affairs, 2019. Humanitarian Response Plans. [Online] Available at: *https://unocha.org*

United Nations Office for the Coordination of Humanitarian Affairs, 2019. The Humanitarian Data Exchange. [Online] Available at: *https://humdata.org*

Uppsala University, 2019. Uppsala Conflict Data Program UCDP Conflict Database. [Online] Available at: *https://www.ucdp.uu.se/*

Webster, M. et al., 2008. The Humanitarian Costs Of Climate Change, s.l.: s.n.

World Bank, 2019. DataBank. [Online] Available at: *https://data.worldbank.org*

Birdsall, Nancy. 2015. "Does the Rise of the Middle Class Lock in Good Government in the Developing World?" The European Journal of Development Research 27 (2): 217–29. Available at: *https://doi.org/10.1057/ejdr.2015.6*.

Bouwer, Laurens M. 2013. "Projections of Future Extreme Weather Losses Under Changes in Climate and Exposure." Risk Analysis 33 (5): 915–30. Available at: *https://doi.org/10.1111/j.1539-6924.2012.01880.x*.

Erman, Alvina, Elliot Motte, Radhika Goyal, Akosua Asare, Shinya Takamatsu, Xiaomeng Chen, Silvia Malgioglio, Alexander Skinner, Nobuo Yoshida, and Stephane Hallegatte. 2018. The Road to Recovery: The Role of Poverty in the Exposure, Vulnerability and Resilience to Floods in Accra. Policy Research Working Papers. The World Bank. Available at: *https://doi.org/10.1596/1813-9450-8469*.

Ferreira, Francisco H. G., Julian Messina, Jamele Rigolini, Luis-Felipe López-Calva, Maria Ana Lugo, and Renos Vakis. 2012. Economic Mobility and the Rise of the Latin American Middle Class. The World Bank. Available at: *https://doi.org/10.1596/978-0-8213-9634-6*.

Hallegatte, Stephane, Mook Bangalore, Laura Bonzanigo, Marianne Fay, Tamaro Kane, Ulf Narloch, Julie Rozenberg, David Treguer, and Adrien Vogt-Schilb. 2015. Shock Waves: Managing the Impacts of Climate Change on Poverty. World Bank Publications. Available at: *https://doi.org/10.1596/978-1-4648-0673-5*.

Hallegatte, Stephane, Colin Green, Robert J. Nicholls, and Jan Corfee-Morlot. 2013. "Future Flood Losses in Major Coastal Cities." Nature Climate Change 3 (9): 802–6. Available at: *https://doi.org/10.1038/nclimate1979*.

Hallegatte, Stephane, and Julie Rozenberg. 2017. "Climate Change through a Poverty Lens." Nature Climate Change 7 (4): 250–56. Available at: *https://doi.org/10.1038/nclimate3253*.

Hallegatte, Stephane, Adrien Vogt-Schilb, Mook Bangalore, and Julie Rozenberg. 2016. Unbreakable: Building the Resilience of the Poor in the Face of Natural Disasters. The World Bank.
Available at: *https://doi.org/10.1596/978-1-4648-1003-9*.

Im, Eun-Soon, Jeremy S. Pal, and Elfatih A. B. Eltahir. 2017. "Deadly Heat Waves Projected in the Densely Populated Agricultural Regions of South Asia." Science Advances 3 (8): e1603322.
Available at: *https://doi.org/10.1126/sciadv.1603322*.

IPCC. 2012. "Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation: Summary for Policymakers : A Report of Working Groups I and II of the IPCC." Published for the Intergovernmental Panel on Climate Change.
Available at: *https://books.google.co.uk/books?id=zZ13MwEACAAJ*.

2014. "Livelihoods and Poverty." In Climate Change 2014: Impacts, Adaptation and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, 793–832. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press. Available at: *https://doi.org/10.1017/CBO9781107415379.018*.

Kriegler, Elmar, Jae Edmonds, Stéphane Hallegatte, Kristie L. Ebi, Tom Kram, Keywan Riahi, Harald Winkler, and Detlef P. van Vuuren. 2014. "A New Scenario Framework for Climate Change Research: The Concept of Shared Climate Policy Assumptions." Climatic Change 122 (3): 401–14.
Available at: *https://doi.org/10.1007/s10584-013-0971-5*.

Lakner, Christoph, Daniel Gerszon Mahler, Mario Negre, and Espen Beer Prydz. 2019. "How Much Does Reducing Inequality Matter for Global Poverty ?" Policy Research Working Paper Series, May.
Available at: *https://ideas.repec.org/p/wbk/wbrwps/8869.html*.

López-Calva, Luis F., and Eduardo Ortiz-Juarez. 2014. "A Vulnerability Approach to the Definition of the Middle Class." Journal of Economic Inequality 12 (1): 23–47.
Available at: *https://doi.org/10.1007/s10888-012-9240-5*.

O'Brien, Karen L., and Robin M. Leichenko. 2000. "Double Exposure: Assessing the Impacts of Climate Change within the Context of Economic Globalization." Global Environmental Change 10 (3): 221–32. Available at: *https://doi.org/10.1016/S0959-3780(00)00021-2*.

Rao, Narasimha D., Petra Sauer, Matthew Gidden, and Keywan Riahi. 2019. "Income Inequality Projections for the Shared Socioeconomic Pathways (SSPs)." Futures 105 (January): 27–39.
Available at: *https://doi.org/10.1016/J.FUTURES.2018.07.001*.

Schlenker, W., and M. J. Roberts. 2009. "Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change." Proceedings of the National Academy of Sciences 106 (37): 15594–98. Available at: *https://doi.org/10.1073/pnas.0906865106*.

Schlenker, W, and David B Lobell. 2010. "Robust Negative Impacts of Climate Change on African Agriculture." Environmental Research Letters 5 (1): 014010.
Available at: *https://doi.org/10.1088/1748-9326/5/1/014010*.

Winsemius, H. C., L. P. H. Van Beek, B. Jongman, P. J. Ward, and A. Bouwman. 2013. "A Framework for Global River Flood Risk Assessments." Hydrology and Earth System Sciences 17 (5): 1871–92.
Available at: *https://doi.org/10.5194/hess-17-1871-2013*.

Winsemius, Hessel, Brenden Jongman, Ted Veldkamp, Stéphane Hallegatte, and Mook Bangalore. 2015. "Disaster Risk and Poverty : Assessing the Global Exposure of the Poor to Floods and Droughts." In , 17:3225.

World Bank. 2015. A Measured Approach to Ending Poverty and Boosting Shared Prosperity: Concepts, Data, and the Twin Goals. World Bank Publications.

INTERNATIONAL FEDERATION

100 1919-2019

Climate Center