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Model and Methods for Estimating the Number of People Living in Extreme Poverty Because of the Direct Impacts of Natural Disasters

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Abstract

Natural disasters have an impact on poverty through many different channels—economic growth, health, schooling, behaviors—that are difficult to quantify. It is nonetheless possible to assess the short-term impacts of income losses. A counterfactual scenario is built of what people's income would be in developing countries in the absence of natural disasters. This scenario uses surveys of 1.4 million households in 89 countries. Depending on where they live and work, what they consume, and the nature of their vulnerability, the additional income that each household in the survey could earn every year on average in the absence of natural disasters is calculated. The analysis concludes that if all disasters could be prevented next year, 26 million fewer people would be in extreme poverty—that is, living on less than $1.90 a day. A systematic analysis of the uncertainty suggests that this impact could lie between 7 million if all the most optimistic assumptions are combined, and 77 million if we retain only the most pessimistic assumptions.

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1. Introduction

Natural disasters have an impact on poverty through many different channels (economic growth, health, schooling, behaviors) that are difficult to quantify. It is nonetheless possible to assess a fraction of the full effect. Here, we quantify the short-term impacts that natural disasters have on poverty through people's income when they are hit.

To do so, in this study we built a counterfactual scenario of what people's income would be today in the developing world in the absence of natural disasters. This scenario is based on the same methodology as in Rozenberg and Hallegatte (2015) and the *Shock Waves* report (Hallegatte et al. 2016).

It uses household surveys of 1.4 million households, which are representative of 1.2 billion households and 4.4 billion people in 89 developing countries.[1] The household surveys were formatted for the GIDD model, using the I2D2 database (Osorio-Rodarte, Cruz, and Bussolo 2015). Here we used an updated version of the database, harmonized in 2012, and using 2011PPP USD for household income. Therefore, we use 1.90 USD 2011PPP per day as a threshold for extreme poverty in this study.

Depending on where they live and work, what they consume, and the nature of their vulnerability, we calculated the additional income that each household in the survey could earn every year on average in the absence of natural disasters. We then assess the average number that are living today with less than $1.90 per day only because they have been affected by a disaster.

2. Estimating income for farmers and nonfarmers

The model first attributes one of the following mutually exclusive categories to each person in the household surveys database: (1) agriculture worker; (2) manufacturing worker; (3) services worker; (4) adult not in the labor force; (5) elderly (above 65 years old); (6) child (under 15 years old).

These categories are of course adaptable depending on the information available in the survey and the objective of the study. Here the main objective is to differentiate farmers from the rest of the workers because some disasters will affect their income differently.

The database only gives an aggregated estimate of income at the household level, and does not provide individual income data. Since droughts affect differently the income of farmers and of consumers, we estimate the income of each category of people in the database. We calculate the number of people in household *j* who belong to each category (cat_i^j) and we estimate current households' revenue using these categorical predictors (with weighted linear least squares). Note that

[1] Afghanistan, Angola, Albania, Argentina, Azerbaijan, Burundi, Burkina Faso, Bangladesh, Bosnia and Herzegovina, Belize, Bolivia, Brazil, Bhutan, Botswana, China, Côte d'Ivoire, Cameroon, Cabo Verde, Costa Rica, Dominican Republic, Ecuador, Arab Republic of Egypt, Ethiopia, Micronesia, Gabon, Georgia, Ghana, Guinea, Gambia, Guatemala, Guyana, Honduras, Haiti, Hungary, Indonesia, India, Jamaica, Kenya, Kyrgyz Republic, Cambodia, Lao People's Democratic Republic, Lebanon, Liberia, Sri Lanka, Morocco, Moldova, Madagascar, Mexico, Macedonia, Mongolia, Mozambique, Mauritania, Mauritius, Malawi, Namibia, Niger, Nigeria, Nicaragua, Nepal, Pakistan, Panama, Peru, Philippines, Papua New Guinea, Paraguay, Rwanda, Senegal, Solomon Islands, Sierra Leone, El Salvador, Serbia, São Tomé and Príncipe, Suriname, Swaziland, Syrian Arab Republic, Chad, Togo, Thailand, Tajikistan, Turkmenistan, Tunisia, Tanzania, Uganda, Ukraine, República Bolivariana de Venezuela, Vietnam, Republic of Yemen, South Africa, Zambia.

we exclude children ($\alpha_6 = 0$) as they should not contribute to the family income, and that there is no intercept in the formula:

$$Y_j = \sum_{i=1}^{5} \alpha_i \, cat_i^j + \varepsilon_j$$

where ε_j is an error term that depends on the household.

For most countries, the α_i are all positive as expected and – since there is no intercept – they can be interpreted as the average per capita income brought to the household by each category of people. In some countries $\alpha_7 < 0 \text{ or } \alpha_8 < 0$ in the regression, suggesting that people unable to work (category 7) or the elderly (category 8) may reduce the income of other household members, possibly due to caretaking obligations. In these cases, however, we force $\alpha_7 = 0 \text{ or } \alpha_8 = 0$ and we re-estimate the other α_i.

The per-capita revenue in each household *j* can therefore be expressed as:

$$y_j(t_0) = \frac{\sum_{i=1}^{5} \alpha_i \,(t_0) * cat_i^j}{\sum_{i=1}^{6} cat_i^j} + \varepsilon_j(t_0)$$

3. The impact of natural disasters

We model the impact of the following six natural disasters on people's income: cyclones, storm surges, tsunamis, floods, droughts, earthquakes. The share of people affected by each event is calculated based on data from GAR (for earthquakes, tsunamis, cyclones and storm surges) and GLOFRIS (for floods and drought). The impact on people's income is the same as for the resilience indicator, for each country. We represent the vulnerability bias between poor and non-poor households but no exposure bias.

For each natural disaster, we model each event, in each country, independently. For floods we have data for events with return periods between 5 and 1,000 years. For droughts, we have events with return periods of 5, 25, 50 and 100 years. For cyclones, storm surges, earthquakes, and tsunamis, we model events with return periods between 2 and 1,500 years. The assumption that each event can only happen alone and once every year means that we underestimate the real impact.

All events but droughts are modeled as a shock on income for affected households, during the year of the event.

It is first necessary to select affected households. In order to avoid exposure bias, all households in the country are duplicated, i.e. affected households are "created" similar to the existing ones while the weight of existing households is reduced. The weights of affected and unaffected households are adjusted to reflect the share of people affected and to keep the total number of people in the country unchanged. This method avoids a random selection of households, which would require running the scenarios many times. The income of affected households is then changed using the vulnerabilities calculated for the resilience indicator. Those differ for the poorest 20% and the rest of the population.

The impact of droughts is modeled through two channels: a shock on the income of farmers and a shock on food prices for consumers. The vulnerability of poverty reduction to food price hikes has already been demonstrated, for instance in (Ivanic and Martin 2008; Ivanic, Martin, and Zaman

2012; Hertel, Burke, and Lobell 2010; Devarajan et al. 2013). An increase in food prices reduces households' available income, but especially consumption of the poor who spend a large share of their income on food products. The impact in our scenarios depends on the fraction of food expenditure in total expenditure, which decreases with the income level of the household (Figure 1).

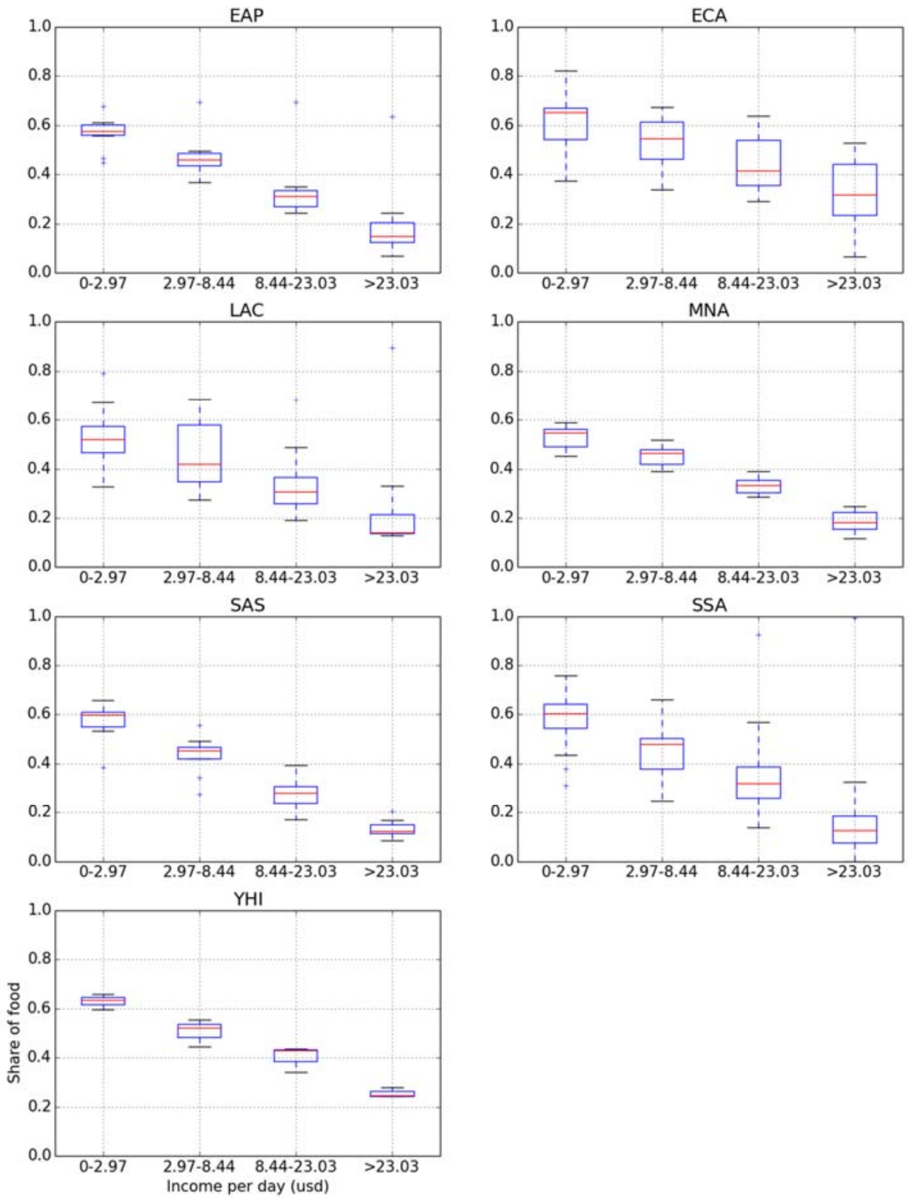

Figure 1 Share of food in total consumption, for each World Bank region and different income categories. Source: The World Bank Global Consumption Database.

In practice, to model the impact of a drought we change the income of the farmers affected by the drought (using the same method as for other disasters, but considering farmers only) and we rescale the (real) income of some households according to the change in food prices, accounting for the share of food in the household budget (which decreases with income, see Figure 1). The number of people who will suffer from higher food prices when a drought affects a farmer is uncertain. For a medium scenario we assume that for each farmer affected, 50 people will suffer from higher food prices.

For each disaster type and each event, there is uncertainty on the impacts. We therefore build three different scenarios, which are described in Table 1.

Table 1 Low, medium and high values for the impact of disasters

	Low	Medium	High
Vulnerability to floods, storm surges, cyclones, earthquakes, tsunamis	Medium -30%	Combination of the USGS PAGER building inventory and simple vulnerability curves	Medium +30%
Exposure to storm surges, cyclones, earthquakes, tsunamis	Medium -30%	GAR	Medium +30%
Exposure to floods	Medium -30%	GLOFRIS	Medium +30%
Exposure to drought	Medium -30%	GLOFRIS	Medium +30%
Impact of droughts on farmers' income	0	10	20%
Number of people affected by higher food prices for each farmer affected by a drought	Medium -30%	50	Medium +30%
Impact of drought on local food prices	10%	55%	100%

Table 2 Reconstruction time after disasters by return period and for the three scenarios

	Return period			
Scenarios	0-10	10-100	100-500	>500
Low	0.5	1	2	3
Medium	1	2	3	5
High	3	3	5	10

Note that we are building a counterfactual scenario in which disasters never hit, starting from surveys in which households' income factors in the impacts of disasters. We therefore apply positive shocks on households, i.e. we *increase* the income of each household when they are affected by a disaster, to reverse current disasters' effects on people's income.

The effect of natural disasters generally lasts more than a year. To simplify, we assume that the economy goes back to normal linearly during a "reconstruction" time that depends on the return period (Table 2). Here again we build three scenarios that account for the uncertainty around reconstruction times. For each event, therefore, we estimate the total impact (over time) by multiplying the yearly impact by N/2 (where N is the reconstruction time).

The impact of each event is represented in Figure 2, with the number of people in poverty because of an event multiplied by the probability of this event.

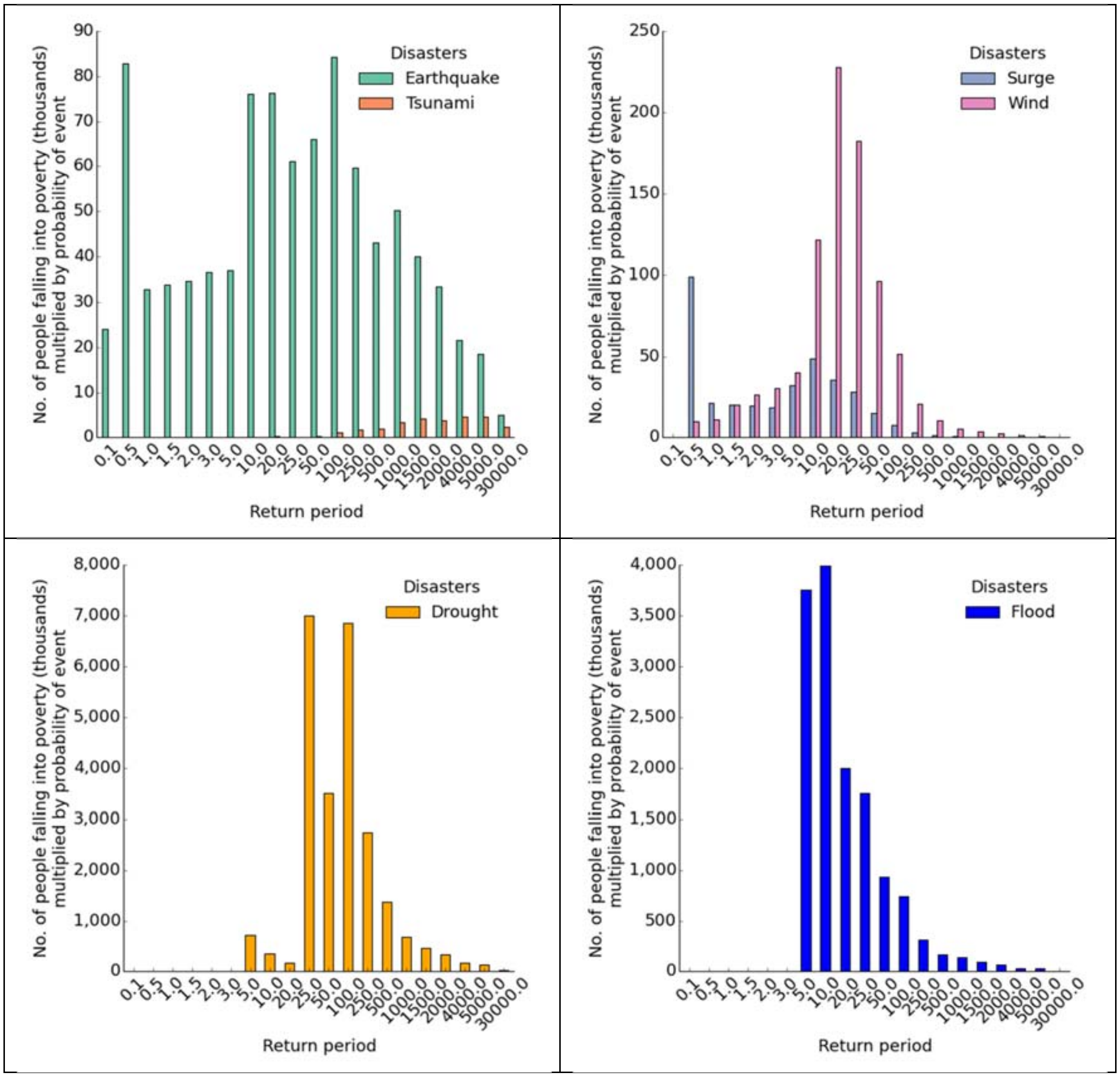

Figure 2 Number of people falling back into extreme poverty multiplied by the probability of the event, for all return periods. Reconstruction time is taken into account in these results.

The results reveal a difference in order of magnitude between the impacts of, on the one hand, earthquakes, storm surges, tsunamis and cyclones, and, on the other hand, floods and droughts. Events like rare earthquakes and tsunamis can push many people into poverty when they occur (1,000-year return period earthquakes push 27 million people into extreme poverty around the globe when they occur, and 50 million if reconstruction time is taken into account), but their probability of occurrence is very low, leading to relatively small impacts on average every year. In addition to that, frequent earthquakes cause very little damage. This result is illustrated in Figure 2 where the impact of an earthquake, on average every year, is the same whether it is a high-frequency low-impact event or a low-frequency high impact event.

On the other hand, floods and droughts can have significant impacts on poverty, even with small and frequent events. The biggest impact on average for floods is due to small events that happen every five or ten years (Figure 2). For droughts, the most dangerous events are the ones that happen every 25 to 100 years, which have lasting effects and can put hundreds of millions in poverty (100-year return period droughts can push 700 million people into extreme poverty around the globe, and 25-year droughts 175 million).

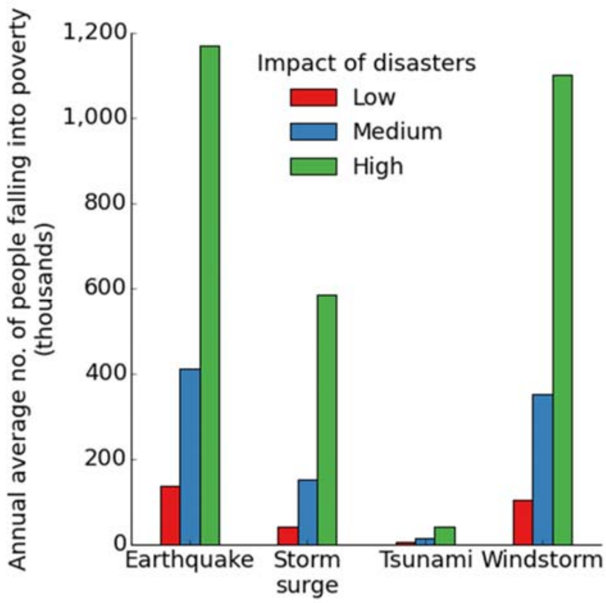

Figure 3 Earthquakes, storm surges, tsunamis and cyclones have a relatively small effect on poverty on average because they happen very rarely.

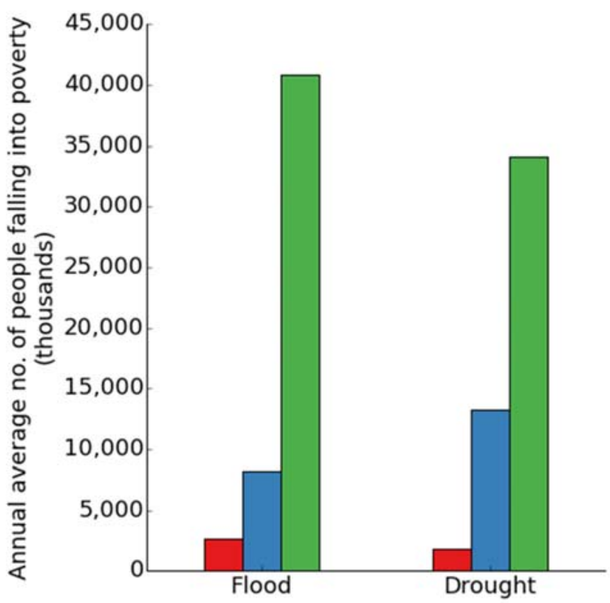

Figure 4 Flood and drought happen more frequently and bring millions of people in extreme poverty every year.

Finally, to assess the average number of people who fall into poverty or stay in poverty because of natural disasters every year, all events are aggregated in an annual average for each type of disaster (Figure 3, Figure 4).

Altogether earthquakes, storm surges, tsunamis and cyclones bring between 300,000 and 2.9 million people into extreme poverty on average per year, while floods and drought together bring between 7 and 75 million people into extreme poverty on average every year.

4. Discussion

Of course, these numbers should be used with caution because they largely underestimate the total impacts of climate change on poverty. First, disaster risk data are not available in all countries, and the impact is calculated only in the countries and for the disasters for which data are available.

Second, these estimates do not include macroeconomic impacts or indirect impacts, and they assume that each disaster happens independently. As such, they disregard some of the elements discussed in Hallegatte et al. (2016, 2017).

And finally, because we rely on household surveys that report only household-level consumption, we cannot explore the intra-household distributional issues, and especially the question of whether children or women are disproportionally affected by natural disasters. Gender inequality has been widely reported— see, for example, Hoddinot et al. (2006) and Rose (1999)—and a disproportionate impact on children is well-identified—see Kousky (2016)—but these important effects cannot be included in this analysis. The estimates proposed here are therefore a lower bound to the impacts of natural disasters on poverty.

5. References

Devarajan, Shantayanan, S. Delfin Go, Maryla Maliszewska, Israel Osorio-Rodarte, and Hans Timmer. 2013. "Stress-Testing Africa's Recent Growth and Poverty Performance." Policy Research Working Paper 6517, Development Prospect Group & Africa Region, Office Of The Chief Economist, The World Bank.

Hallegatte, S., M. Bangalore, L. Bonzanigo, M. Fay, T. Kane, U. Narloch, J. Rozenberg et al. 2016. Shock Waves: Managing the Impacts of Climate Change on Poverty. Climate Change and Development Series. Washington, DC: World Bank.

Hallegatte, S., A. Vogt-Schilb, M. Bangalore, and J. Rozenberg. 2017. Unbreakable: Building the Resilience of the Poor in the Face of Natural Disasters. Climate Change and Development Series. Washington, DC: World Bank.

Hoddinott, J. 2006. "Shocks and Their Consequences across and within Households in Rural Zimbabwe." Journal of Development Studies 42: 301–21.

Hertel, Thomas W., Marshall B. Burke, and David B. Lobell. 2010. "The Poverty Implications of Climate-Induced Crop Yield Changes by 2030." Global Environmental Change, 20th Anniversary Special Issue, 20 (4): 577–85. doi:10.1016/j.gloenvcha.2010.07.001.

Ivanic, Maros, and Will Martin. 2008. "Implications of Higher Global Food Prices for Poverty in Low-Income countries1." Agricultural Economics 39 (November): 405–16. doi:10.1111/j.1574-0862.2008.00347.x.

Ivanic, Maros, Will Martin, and Hassan Zaman. 2012. "Estimating the Short-Run Poverty Impacts of the 2010–11 Surge in Food Prices." World Development 40 (11): 2302–17. doi:10.1016/j.worlddev.2012.03.024.

Kousky, C. 2016. "Impacts of Natural Disasters on Children." Future of Children 26(1): 73–92.

Osorio-Rodarte, Israel, Marcio Cruz, and Maurizio Bussolo. 2015. "GIDD Sectoral Wage Bill Database by Workers´skill Level.".

Rose, E. 1999. "Consumption Smoothing and Excess Female Mortality in Rural India." Review of Economics and statistics 81 (1): 41–49.

Rozenberg, J. and Hallegatte, S., 2015. The impacts of climate change on poverty in 2030 and the potential from rapid, inclusive, and climate-informed development. Policy Research Working Paper 7483. Washington, DC: World Bank.