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Shock Waves: Managing the Impacts of Climate Change on Poverty

Background Paper

Disaster Risk, Climate Change, and Poverty

Assessing the Global Exposure of Poor People to Floods and Droughts

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Abstract

People living in poverty are particularly vulnerable to shocks, including those caused by natural disasters such as floods and droughts. Previous studies in local contexts have shown that poor people are also often overrepresented in hazard-prone areas. However, systematic evidence across countries demonstrating this finding is lacking. This paper analyzes at the country level whether poor people are disproportionally exposed to floods and droughts, and how this exposure may change in a future climate. To this end, household survey data with spatial identifiers from 52 countries are combined with present-day and future flood and drought hazard maps. The paper defines and calculates a "poverty exposure bias" and finds support that poor people are often overexposed to droughts and urban floods. For floods, no such signal is found for rural households, suggesting that different mechanisms—such as land scarcity—are more important drivers in urban areas. The poverty exposure bias does not change significantly under future climate scenarios, although the absolute number of people potentially exposed to floods or droughts can increase or decrease significantly, depending on the scenario and the region. The study finds some evidence of regional patterns: in particular, many countries in Africa exhibit a positive poverty exposure bias for floods and droughts. For these hot spots, implementing risk-sensitive land-use and development policies that protect poor people should be a priority.

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Produced by the Research Support Team

Disaster Risk, Climate Change, and Poverty: Assessing the Global Exposure of Poor People to Floods and Droughts

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JEL

Q54, I32, Q50, I30

1. Introduction

Globally, an estimated 700 million people live below the USD $1.90/day poverty line, with many more balancing just above it[1] (World Bank, 2015a). This substantial part of the world population is particularly vulnerable to external shocks, including those caused by natural disasters such as floods and droughts. Such disasters can reduce household income and destroy houses and productive capital. For example, after the 2004 floods in Bangladesh, Brouwer et al. (2007) found that poor households who were affected by the flood lost more than twice as much of their total income as affected non-poor households. This illustrates the consistent finding that poor people are more vulnerable to disaster events (Carter et al., 2007; Rabbani et al., 2013; Patankar and Patwardhan, Forthcoming). In addition to losing more, poor households have a relatively lower capacity to deal with shocks compared to non-poor households due to lower access to savings, borrowing, or social protection (Kundzewicz and Kaczmarek, 2000; Masozera et al., 2007; Highfield et al., 2014).

Natural disasters have consistently been shown to be a key factor responsible for pushing vulnerable households into poverty, and also for keeping households poor (Sen, 2003; Krishna, 2006). Just as importantly, the exposure to natural hazards may reduce incentives to invest and save, since the possibility of losing a home due to a flood or livestock due to a drought makes these investments less attractive (Cole et al., 2013; Elbers et al., 2007). This vulnerability of poor people to natural disaster risk is particularly worrying in the context of climate change, which may increase the frequency, intensity, and spatial distribution of heavy precipitation, floods, and droughts (IPCC, 2012b). Beyond its aggregated impacts, future climate change may represent a significant obstacle to the sustained eradication of poverty (Hallegatte et al., 2016).

Several previous studies have attempted to draw statistical relationships between national-level economic indicators and reported disaster losses on a global scale to find out if poor countries are more affected by natural hazards (Ferreira et al., 2011; Jongman et al., 2015; Kahn, 2005; Peduzzi et al., 2009; Shepherd et al., 2013; Toya and Skidmore, 2007). Although these studies reveal a statistical relationship between vulnerability and average income, they do not investigate the spatial or social distribution of the losses within a country. Recent advances in the global spatial modelling of flood risk (Arnell and Lloyd-Hughes, 2013; Ceola et al, 2014; Hirabayashi et al., 2013; Pappenberger et al., 2012; Ward et al., 2013, 2014, 2015; Winsemius et al., 2013, 2015) and drought risk (Prudhomme et al., 2014; Schewe et al., 2014) have led to improved estimates of the global population exposed to natural hazards under the current and future climate, but these have not been translated into results specific for different incomes within a country.

To our knowledge, the relationship between poverty and exposure to floods and droughts has only been studied on a case-study basis for a few countries. A literature review of 13 of such studies, conducted as part of this paper, shows that poor people are often disproportionately overrepresented in hazard-prone areas. As shown in Figure 1, only one of the 13 studies reviewed finds that non-poor people are more exposed than poor people. Although these cases highlight that a relationship may

[1] http://www.worldbank.org/en/topic/poverty/overview

exist between poverty and exposure, evidence on the global representativeness of these case-study results and general figures on the exposure of poor people is still lacking.

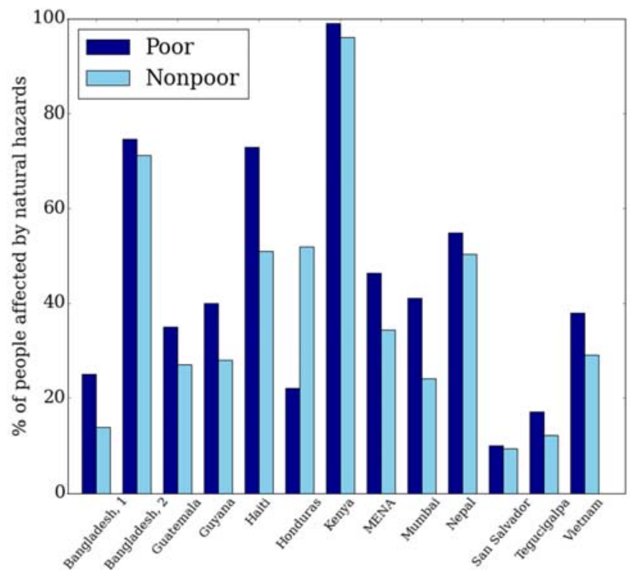


Figure 1. When a disaster hits, poor people are more likely to be affected.

Source: Based on (Akter and Mallick, 2013) for Bangladesh (1) and (del Ninno et al., 2001) for Bangladesh (2); (Tesliuc and Lindert, 2003) for Guatemala; (Pelling, 1997) for Guyana; (Fuchs, 2014) for Haiti; (Carter et al., 2007) for Honduras; (Baker et al., 2005); (Opondo, 2013) for Kenya; (Wodon et al., 2014) for MENA; (Baker et al., 2005; Hallegatte et al., 2010) for Mumbai; (Gentle et al., 2014) for Nepal; (Fay, 2005) for San Salvador and Tegucigalpa, and (Nguyen, 2011) for Vietnam.

Note: Based on thirteen case studies of past disasters, examining the exposure of poor and non-poor people through household surveys. Each study has a different definition of "poor" and "nonpoor" people. Exposure differs based on the type of hazard and context in which it occurs.

In this paper, we present an analysis on the global exposure of poor and non-poor people to river floods and droughts under current climatic conditions as well as a range of future climate scenarios. We combine global river flood and hydrological drought hazard models with detailed household wealth and income data sets for 52 countries, to analyze poverty-specific exposure to current and future hazard levels. In this paper, poverty is defined using the distribution of wealth amongst households within a given country. We explore whether there is a significant exposure bias for poor people to river floods and droughts and whether their exposure increases in the future. We furthermore provide a more detailed assessment at the sub-national level in Morocco and Malawi to demonstrate possible within-country variability of the bias and implications for our results. As data limitations create certain constraints on the analysis, this study should be treated as a first-cut exploration.

2. Review

In this section, we review the complex relationship between poverty and exposure to natural hazards. The causal relationship between poverty and exposure may go in both directions. First, poor people may be more inclined to settle in flood- and drought-prone areas. Second, households affected by

floods and droughts have a higher risk of falling into poverty or being trapped in poverty. Both aspects are discussed in more detail below.

Localization choices across regions and cities are in the first place driven by socioeconomic considerations (housing prices, proximity to jobs, amenities), much more than by natural hazards (Hallegatte, 2012). In particular, households may be willing to accept high levels of risk to get access to opportunities. In a case study in Mumbai for instance, households in flood areas report that they are well aware of the flood risks, but accept them due to the opportunities offered by the area (access to jobs, schools, and health care facilities in particular (Patankar, 2015)). Compounding this incentive for people to reside in flood zones and close to opportunities is the reality that transport is often unreliable, unsafe, or expensive (Dudwick et al., 2011; Gentilini, 2015). In some rural areas, proximity to water offers cheaper transport opportunities and regular floods may increase agricultural productivity (Loayza et al., 2012). People may also settle in risky areas to benefit from opportunities with industries driven by exports in coastal areas (Fleisher and Chen, 1997). These opportunities attract all people – rich and poor – to places that are exposed to natural hazards.

However, at the city or neighborhood level, where the opportunity factors are broadly similar, but risk of floods may be different from neighborhood to neighborhood, poor people might be more exposed due to the effect of lower housing prices in flood zones (Bin and Landry, 2013; Husby et al., 2014). A review of empirical studies for mostly developed countries finds that the range of prices between flood-exposed and non-flood-exposed houses varies widely; a meta-analysis of 37 studies mostly in rich countries finds a spread of −7 percent to +1 percent (Beltran et al., 2015). Poorer people having less financial resources to spend on housing and in general a lower willingness and ability to pay for safety, are more likely to live in at-risk areas. This factor is more likely to exist for floods than for droughts, due to the small-scale variability in flood hazard (for example with floods, impacts can be very different in areas 100 meters apart). Also, it is likely that frequent floods are better included in land and housing prices than flood risks linked to exceptional events (Hallstrom and Smith, 2005).

Alternatively, causality may also go from flood and drought exposure to poverty. Evidence shows that floods affect household livelihood and prospects and increase local poverty levels through the loss of income and assets (see for instance Rodriguez-Oreggia et al., 2013 for an analysis in Mexico). The risk associated with exposure to droughts has been found to increase poverty ex-post (Dercon, 2004; Carter et al., 2007). Further, the impact of disaster risk on poverty occurs through both the visible ex-post channel (the losses when a disaster occurs), as well as the less obvious but as important ex-ante channel: households exposed to weather risk have been shown to reduce investment in productive assets and to select low-risk, low-return activities (Cole et al., 2013; Elbers et al., 2007). This link from natural hazard exposure to poverty may create a feedback loop, in which poor households have no choice but to settle in at-risk zones and as a result face increased challenges to escaping poverty.

This review illustrates the complexity of interactions between natural hazards and poverty. Diversity in this relationship amongst countries is to be expected and therefore evidence from a limited amount of case studies or from cross-country analyses (e.g., Kim, 2012) is not enough to conclude an unequivocal relationship between the existence of poverty and flood and drought hazard. This study therefore aims for a geographically wider analysis of the relationship between natural hazards and poverty than performed before.

3. Data and methods

To examine relationships between poverty and exposure to floods and droughts, we use household surveys from the Demographic and Health Surveys (DHS), which are implemented by ICF International and hosted by the United States Agency for International Development (USAID). Household survey data are available for more than 90 countries, but only 52 countries contain georeferenced data and information on households' wealth. We combine these data for 52 countries with global data sets of flood and hydrological drought hazard derived from global hydrological models. In brief, we first analyze the wealth of households in all areas, and then the wealth of households in areas prone to river floods and/or droughts, to examine differences in wealth between flood/drought prone regions and non-flood/drought prone regions. In the following subsections we describe the data and methods used in detail, namely: (1) the flood and drought indicator maps and how they are derived; (2) the wealth data sets and how these are used in this study; and (3) the methods used to analyze the relationships between poverty and exposure to floods or droughts. The overall workflow is shown in Figure 2, for the example of Colombia.

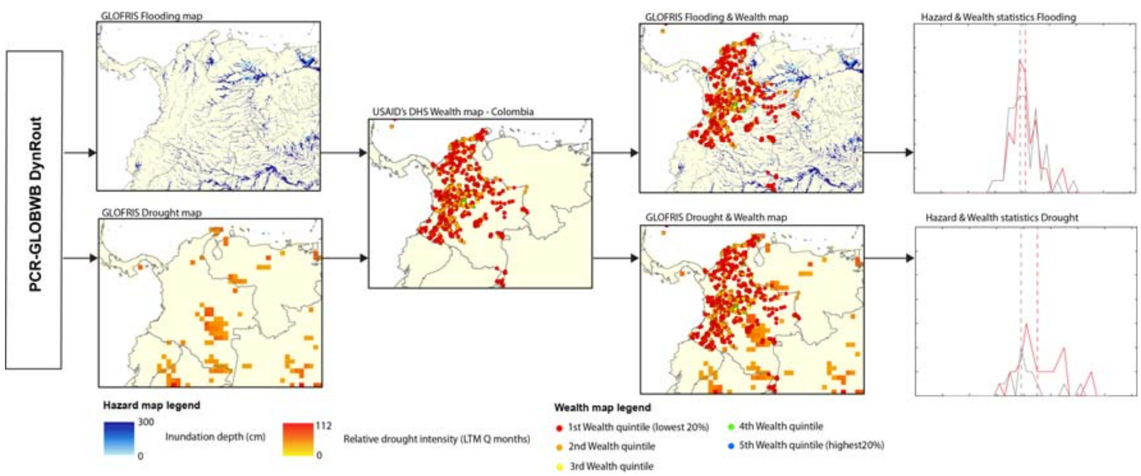


Figure 2. Flow-chart visualizing the modelling and analysis procedure for Colombia. Hazard maps given show the distribution of flood and drought events as simulated using the global hydrological model PCR-GLOBWB DynRout under the EU-WATCH (1960-1999) scenario, with a return period of 100 years.

3.1. Deriving the flood and drought indicators

We use two global model simulation outputs to derive maps showing indicators of flood and drought for a range of different return periods (i.e. the average recurrence interval of a river flood or drought event of a given magnitude, expressed in a certain indicator, further described below). For simplicity, we focus on results from the 10 and 100-year return periods. The flood and drought indicators, the procedure to map these to return periods, and assessments of climate change impacts (due to changes in precipitation patterns) are described in more detail in Appendix A.

3.1.1. Flood hazard

The indicator used to represent flooding is the depth of inundation per grid-cell at 30" (arc seconds) x 30" (approx. 1km x 1km at the equator) resolution. To define whether flood hazard occurs, we use a threshold, in this study set at 0 meter (i.e. any flooding occurring is hazardous). The method uses the

GLOFRIS model cascade inundation downscaling technique, which is described in detail in Winsemius et al. (2013) and applied at global scale in Ward et al. (2013) and Jongman et al. (2015). This method uses the global hydrological model PCR-GLOBWB-DynRout (Van Beek and Bierkens, 2009; Van Beek et al., 2011) to simulate a set of maps showing inundation extent and depth for each grid cell and for all return periods. Three limitations are important to acknowledge at this point. First, we assume that there are no flood protection standards in place. Even though data on protection standards are available for a number of high-income countries (Jongman et al., 2014), a global database of flood protection standards does not exist. However, as protection standards are related to a country's wealth, it is likely that protection standards across the developing countries investigated are relatively low. Second, coastal floods and storm surges are not considered in the analysis (as the model is for river floods only), even though they can have large consequences (Hallegatte et al., 2013). And third, smaller rivers, and pluvial and flash flooding are not represented in the global inundation modelling at its current scale.

3.1.2. Drought hazard

While defining flood conditions may be straightforward (e.g. inundation depth per grid cell per return period), there are many possible definitions of a drought. According to IPCC (2012a) meteorological droughts refer to deficits of precipitation; hydrological droughts refer to negative anomalies in water availability from surface water or groundwater, regardless of human demand; and socio-economic droughts include demand to calculate a water deficit. Each of these drought phenomena can also be defined over different timescales, which are relevant for different issues (e.g. damages to buildings vs. agricultural losses). Here, we applied a variable monthly threshold method (namely the 80% exceedance probability of discharge, Q_{80}) to estimate the yearly maximum cumulative discharge deficit (with respect to the Q_{80} threshold) per grid cell at 0.5° resolution as a measure of hydrological drought (Lehner and Döll, 2001; Wada et al., 2013; Wanders and Wada, 2014), using outputs from the PCR-GLOBWB model Van Beek et al., 2011). A cumulative discharge deficit is the accumulated amount of discharge under the Q_{80} threshold over a continuous period of time.

The resulting maps express the relative intensity of drought conditions to long term mean stream flow conditions and can be interpreted as the amount of time a long-term mean discharge would be needed to overcome the maximum accumulated deficit volume occurring with a certain return period. We assumed that hazardous conditions will occur when this value exceeds 3 months, moreover, we tested the robustness of our results using a 1-month and 6-month threshold. The indicator does not include information on groundwater availability or upstream water use. Furthermore, this indicator does not account for the spatial variability in water needs. The resulting drought values should therefore be interpreted as conservative (underestimating drought hazard), although for an assessment of the actual water scarcity conditions one should include local water needs, upstream water uses, water transfers, and natural or man-made water storages (Wada et al., 2013).

3.1.3. Future flood and drought hazard

Further, the models are used to estimate future climate change impacts on flood and drought hazard, for different time periods (1960-1999, 2010-2049, 2030-2069, and 2060-2099), using meteorological outputs from GCMs, forced by two representative concentration pathways (RCPs, Van Vuuren et al., 2011), which represent scenarios of future concentrations of greenhouse gases (RCP 2.6 and 8.5), and five global climate models (GCMs). Since the GCMs used contain bias due to unrepresented intra-

annual and inter-annual variability (Johnson et al., 2011), we use the difference in annual exposed people between GCM forced model runs in the future and the past to establish changes in the exposure.

3.2. Poverty data sets

A comprehensive spatial database to examine the distribution of poverty within and across countries is not yet available at the required spatial resolution.[2] However, household surveys do contain some spatial information to approximate the location of a household, which we employ in this analysis. Our main analysis is undertaken using spatial wealth data sets from USAID's DHS surveys, and is supplemented by small-area estimates of poverty developed by the World Bank and partner countries.[3]

Fifty-two country-wide DHS surveys contain household-level data on wealth, as well as geo-referenced data providing the coordinate location of the survey cluster (see Appendix B). While the sampling frame differs in each survey, there are typically 500-1,000 survey clusters for each survey, with each cluster containing approximately 25 households. The specific indicator that we use in this study is the DHS "wealth index", an indicator that was used previously to represent poverty (e.g. Barros et al., 2012; Fox, 2012; Ward and Kaczan, 2014). The wealth index is country-specific and assigns an overall score to a household based on weighted scores of the assets they own.[4]

All households in each country are classified in five quintiles (with quintile 1 having the lowest wealth, and quintile 5 the highest). We furthermore classified urban and rural households into quintiles, which enabled us to investigate the exposure across urban and rural populations separately. Importantly, as the wealth index used by DHS is generated relative to other households in the same country, it is comparable only within a country, and not between countries. Wealth index scores can therefore not be directly compared internationally.

To guarantee anonymity of the interviewed households, the geographical locations of the clusters have been randomly allocated by DHS within a radius of maximum 2 km from the real location for urban areas, and 5 km for rural areas. Since floods (opposed to droughts) have a high spatial variability, this uncertainty may affect the flood exposure estimates in particular. To investigate the propagation of the uncertainty of the geographical locations into our flood exposure estimates, we perform 100 random displacements of all geographical locations with a radius of 2 km for urban and 5 km for rural areas, and compute the exposure for each of the 100 displacements. This uncertainty analysis provides an idea of the robustness of results with respect to the random displacement of household locations, but also to errors in the flood maps, for instance linked to topography.

One issue with DHS surveys – and almost all other household surveys – is that they have not been designed to be representative at small spatial scales. Our randomization technique does not explore this error. As a result, they cannot be used to analyze exposure at the very small scale, e.g. in one

[2] Although recent initiatives try and estimate global poverty at high-resolution gridded scales, see for example WorldPop (2015).

[3] https://openknowledge.worldbank.org/handle/10986/6800

[4] For more information, see the DHS wealth index page: http://dhsprogram.com/topics/wealth-index/

particular city or village. Therefore, in this paper we only use aggregate results at the country, country-urban and country-rural level.

We complement our global analysis with two country-level case studies (Morocco and Malawi) for which small-scale poverty maps are available (poverty data representative at the local level). In these case studies we only focus on floods. We focus on the within-country geographical distribution of poverty. Country-level poverty maps, which represent the percentage of the population living below the USD $1.25/day line (this is in consumption terms, using 2005 purchasing power parity (PPP) exchange rates) are developed using the methodology presented in Elbers et al. (2003), combining household surveys with census data.

3.3. Analyzing the relationships between poverty and floods/droughts

To investigate the global exposure of poor people to floods and droughts, we define a 'poverty exposure bias' (PEB) that measures the fraction of poor people exposed, compared to the fraction of all people exposed per country. When estimating the number of people exposed (and not exposed), we multiply the exposed households with their household size and we use household weights to ensure the representativeness of our results. We compute the PEB using:

$$I_p = \frac{\overline{f_p}}{\overline{f}} - 1 \quad (1)$$

Where I_p is the PEB, f_p and f are the fraction of people exposed to floods/droughts in the poorest household quintile within a country and in the entire population, respectively. If I_p is lower than zero, this means that poor people are less exposed to floods/droughts than average. If I_p is above zero, poor people are more exposed than average. The mean values (denoted by the over bar within Eq. 1) of all estimated values for f_p and f, based on the geographical randomization process (see Section 3.2), are used in Eq. 1 in the case of floods. In the case of droughts, only a single value is computed because the drought indicator used has a much larger scale (0.5°) than the uncertainty in household location, and therefore this single value is used instead. Since the wealth index is comparable only within and not between countries, the PEB we calculate in this paper is an estimate of whether poor people are more or less exposed compared to the entire population *within* a specific country. Aggregation of all wealth index data for all countries and computation of a single global PEB is not possible with the data currently available.

3.4. Geographical uncertainty and sample size robustness

From the 100 results with random replacements, we assess the uncertainty of the results due to uncertainty in geographical location as described in Section 3.2. From the 100 varied results, we also establish the standard deviation of f_p. If, for a given country, the standard deviation of f_p is relatively large with respect to the mean, we treat the country's results as uncertain.

A further uncertainty assessment is performed for both floods and droughts to test the significance of the results, which ensures that the results for countries having a very low number of exposed households can be labelled insignificant. We test how robust a positive (or negative) PEB is, given the size of exposed people by bootstrapping with 5,000 samples. Bootstrapping is a significance test to

examine whether the samples in the distribution are dense enough to make a robust estimation of the PEB. For a given country, 5,000 bootstrap populations of the size of the original population are generated, by randomly drawing samples with replacement. In this way, 5,000 values for the PEB for each country are drawn. This process is performed for the nation-wide populations, as well as the urban and rural subdivisions. In case the expected value is positive ($I_p > 0$), we use the 5,000 samples to test for a 95% confidence for H($I_p > 0$). When the expected value is negative, we test for a 95% confidence for H($I_p < 0$).

4. Results and discussion

4.1. Aggregated results

Figure 3 shows the poverty-exposure bias in the 52 countries, in the form of histograms, for the 10-year (in grey) and 100-year (in red) return period event. Results for all countries are provided in Table 1. It shows results for floods nation-wide (column A); flood exposed urban households (column B); droughts nation-wide (column C); and drought exposed rural households (column D). Figure 3 shows that on the national scale, poor are not consistently over or underexposed: for floods and droughts, the median poverty-exposure bias is close to zero, and there are countries with large positive and negative biases. This result supports the review in Section 2**Error! Reference source not found.**: the idea that the relationship between poverty and disaster exposure is impacted by multiple channels and is therefore complex.

For floods, Figure 3 shows that about half of the countries in the analysis have an I_p >0, indicating that in those countries the share of poor people (quintile 1) exposed to flooding, is higher than the share of all households exposed to flooding (note that at this point, no significance test is displayed in the histograms). The other half of the countries exhibits negative exposure biases, consistent with the expectation of a large diversity across countries: results vary from a minimum of –0.78 in Rwanda to a maximum of 1.82 (i.e. the poorest quintile is 182% more exposed than average) in Angola. For both numbers the sign of the estimate is significant ($p < 0.05$).

For droughts, the country-scale results also have a median PEB around 0. The number of countries included in the histogram (15) is much smaller because for many countries, the threshold for being exposed to a drought (set at 3 months) is not reached for any of the households. For floods, 50 out of 52 countries show households that are flooded and are therefore included in the histogram.

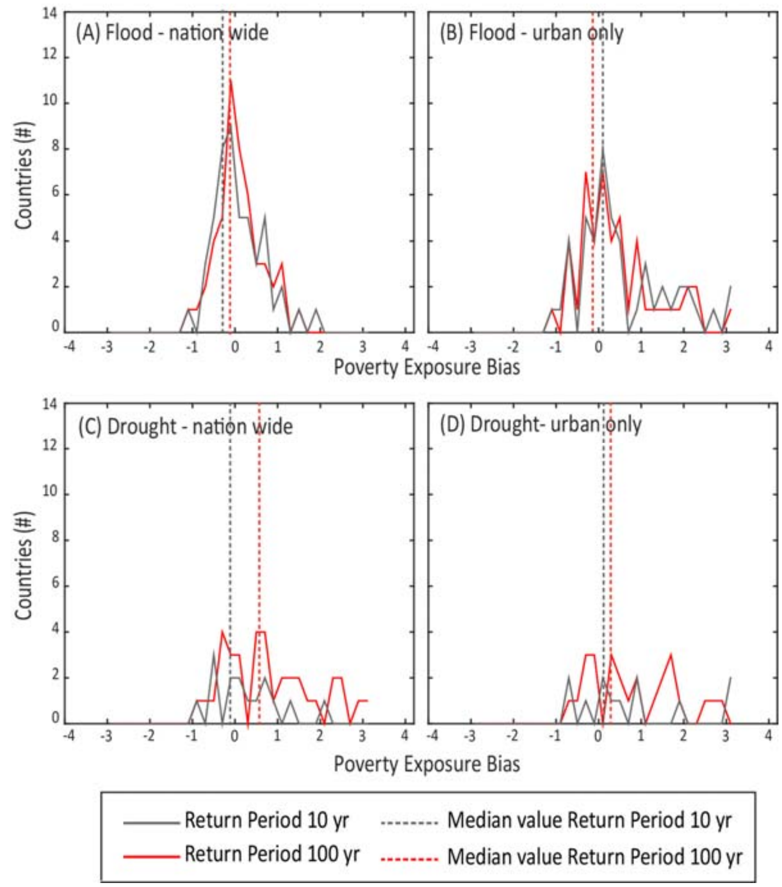


Figure 3. Histograms of the country-scale PEB computed across all 52 countries for a 10-year and 100-year return period for a) floods; b) floods only using urban households; c) droughts; and d) droughts using only urban households.

Furthermore, we find that the difference between the flood PEB for a 10-year and 100-year return period event is small. These results go against the hypothesis that frequent floods would reduce land and housing prices more than exceptional ones and therefore attract more poverty. For droughts, the over-exposure of poor people appears larger for rare events (RP 100) than for more frequent events (RP 10).

We also investigated whether the PEB values are related to GDP, to the number of total people exposed, and to number of poor people exposed. No clear relationships were found, although a larger spread in the values for I_p was found with a small number of (poor) households exposed. This is to be expected since the share of exposed people is smaller in these cases, and a larger share reduces the variance. In the remaining results, we show how this affects significance of our results.

4.2. Geographic distribution of the PEB under present-day climate

4.2.1. Floods

Figure 4 shows the PEB for floods with a return period of 10 years. The results for a higher return period of 100 years (Supp Figure 2) exhibit very similar patterns. In these maps, we include a significance test of the exposure bias being higher than zero (in case of positive exposure bias) or lower

than zero (in case of negative exposure bias) by means of bootstrapping, as explained in Section 3.4.[5] For floods at the national-level, under present-day climate conditions, 35 out of the 52 countries show a significant result. Of these 35, about half (17) exhibit an over-exposure of poor people to (riverine) floods. Another relevant question is whether there are more people (in absolute terms) living in countries with a positive exposure bias. Using country-level population data from the World Bank's World Development Indicators (World Bank, 2015b), we find that 60% of the analyzed population live in countries with a positive and significant exposure bias.

Moreover, regional patterns become visible. In particular, the countries in Southern Africa and the Horn of Africa (except for Ethiopia, Rwanda, Zimbabwe and Mozambique) and the Arab Republic of Egypt have a strong over-exposure of poor people to floods, although not all countries show significant results (Tanzania and Democratic Republic of Congo). In Western Africa, the results show a mixed pattern, although in countries with larger rivers and delta areas (notably Benin, Nigeria and Cameroon), there appears to be a tendency towards poor people being disproportionally exposed to floods. Turning to Asia, Indonesia also gives a moderate but significant signal that poor people are more exposed to floods than average; the same can be seen for South America in Colombia and Guyana.

As discussed earlier, there are also a number of countries where poor people are found to be less exposed to floods than average. These include some of the Asian countries of our sample (Cambodia, Nepal and Philippines, although the PEB for the last is insignificant), some West African countries and most of the countries investigated in Central and South America.

These regional patterns suggest that the variability of the PEB across countries is not a random mechanism nor an artefact of the analysis, but may be a consequence of regional development patterns. It supports the idea that there are different mechanisms at play for regions at different development stages or with different characteristics (e.g., urbanization rates). The balance between these mechanisms may vary, resulting in different PEB values between regions.

It must be noted that the results may be uncertain because the hydrological and inundation model performance may regionally be poorer. In particular in semi-arid regions with large inland wetland areas, such as the Niger River in West Africa, much of the discharge may evaporate within these wetlands. The hydrological model used in this study (as with most global hydrological models) does not accurately represent this river discharge loss, which may cause downstream overestimation of flood depth (see e.g. Neal et al., 2012; Ward et al., 2013).

[5] The additional uncertainty due to uncertain geographic position of the households was found to be insignificant and is therefore not displayed here.

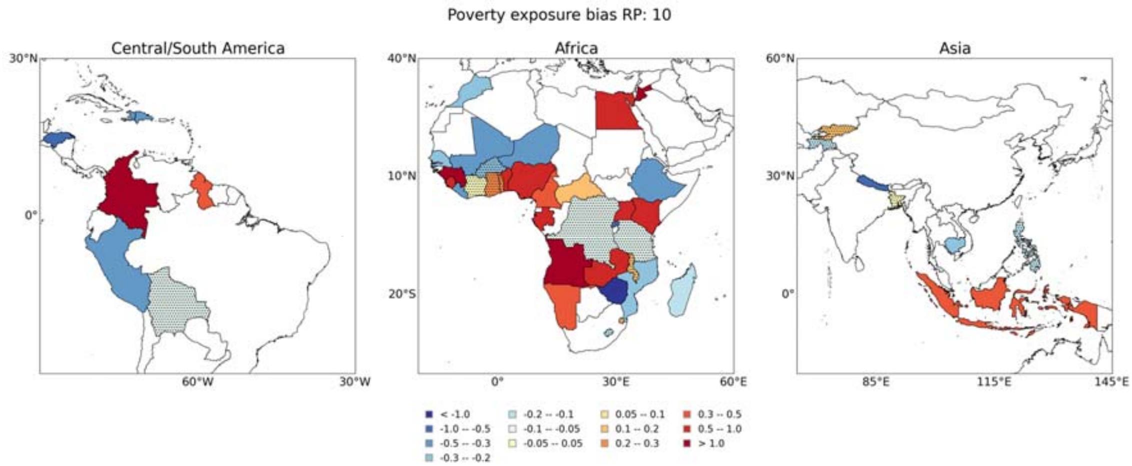


Figure 4. PEB for 10-year return period floods. White areas are not part of the 52 country sample. Areas are dotted when there is a lower than 95% confidence that the sign of the exposure bias is as estimated.

The same analysis was performed using a quintile subdivision over only rural and urban households respectively (that is, examining the PEB only within urban areas and only within rural areas). The results for rural households only show a slight shift to more exposed poor people than the nation-wide numbers, in particular across Southern Africa and South America (shown in Supp Figure 3).

The results for the urban households demonstrate a clear difference: in most countries poor urban households are clearly more exposed to floods than the average urban population (Figure 5). Of the 31 countries with significant results, 22 exhibit a positive exposure bias (and 73% in population terms). This suggests the national poverty-exposure bias may be largely driven by the wealth differences and hazard exposure differences between rural and urban households. There is no such strong signal for rural households, suggesting that different mechanisms may be at play in rural and urban settings. This might be because land scarcity is more acute in urban areas (than in rural areas), creating a stronger incentive for poor people to settle in risky areas due to lower prices.

There are some exceptions to the stronger poverty bias in urban areas: some countries in Western Africa (e.g. Liberia, Ghana) exhibit an opposite signal in urban areas. There, poor urban people seem to be less exposed than the average urban person. Closer inspection of the location of the DHS survey samples show that the urban areas in these countries, where most urban household samples have been taken, are typically concentrated in cities along the coast (e.g. Abidjan, Accra, Lome, Cotonou), where it is likely that coastal flood hazard dominates over river flood hazard. As our flood indicator is for river floods only, a follow-up analysis including coastal floods would be required to test whether coastal flooding may be the main driver for the poverty exposure relationship in these areas.

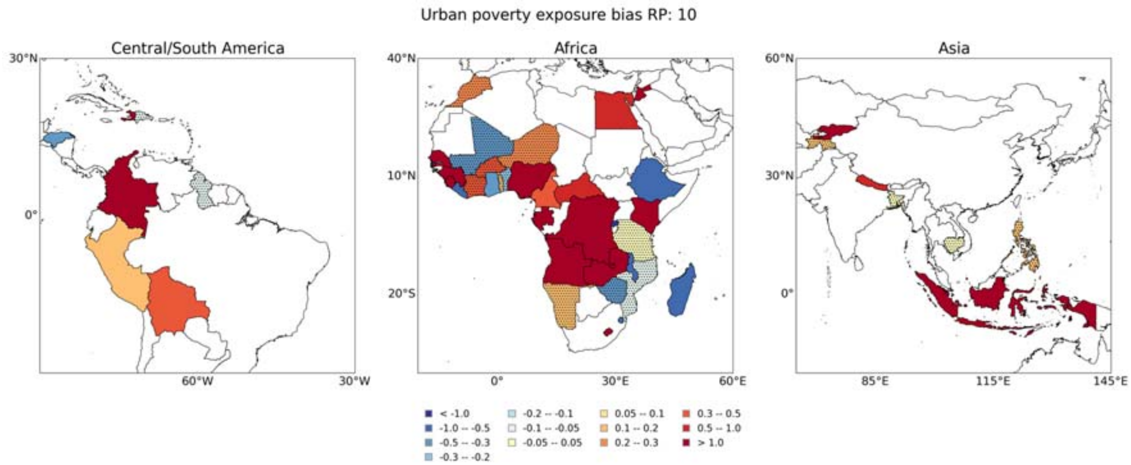


Figure 5. Same as Figure 4 but for urban households only. Note that the quintile subdivision used is based on urban households only.

4.2.2. Droughts

Figure 6 shows the country level PEB for droughts with a return period of 100 years.[6] Of 30 countries with significant results, 24 exhibit an over-exposure of poor people (this is 85% in population terms). In all countries studied in Asia and in many countries in Southern and Western Africa, we find a clear signal that poor households are more exposed to droughts than average: Côte d'Ivoire, Ghana, Togo, and Nigeria show a signal of higher exposure to droughts of poor households compared to average. Other countries to the north and west show the opposite result, i.e. more exposure to droughts for non-poor households. In Southern America poor people appear under-exposed in Bolivia and Peru, but over-exposed in Colombia, Guyana and Honduras.

Many Sub-Saharan African countries show a positive PEB for droughts, as for floods. In many parts of Africa, many poor people are subsistence farmers, and therefore very much dependent on reliable rainy seasons, which makes them also more vulnerable to drought.

[6] Again the results for other return periods are very similar, although the very low return period results yielded no exposed households in many countries.

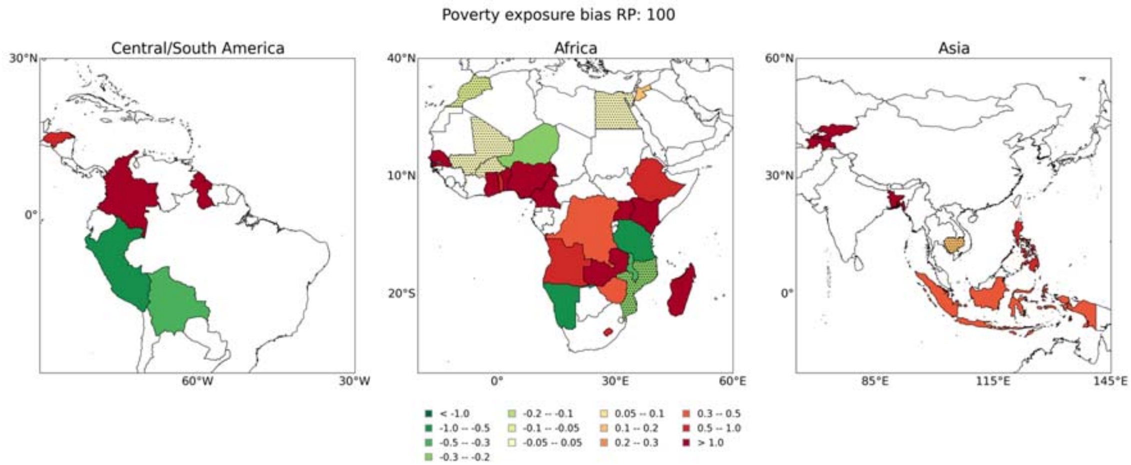
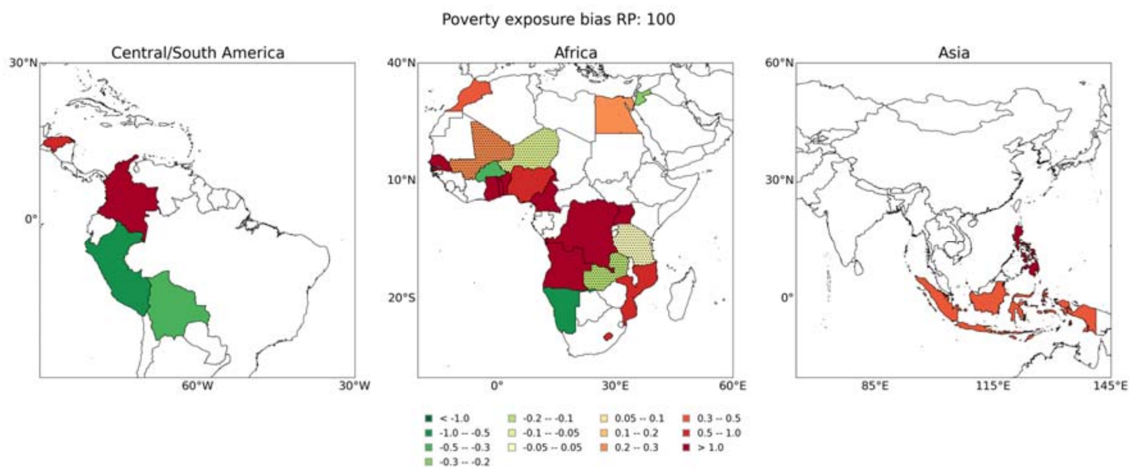


Figure 6. PEB for 100 year return period droughts. White areas are not part of the 52 country sample.

The same analysis was performed for only rural and urban households. The results (see



Supp Figure 4 and Supp Figure 5) generally show similar patterns to the analyses at the country-level. In particular, West African countries on the coast and the South(-East) Asian countries show consistent results for the national, urban and rural analysis, all showing positive PEB. The strong difference between the results for urban and rural for floods seems to be non-existent for drought. This may be due to the different scales of flood and drought hazards. Our flood indicator (and flood processes in general) have a higher spatial resolution (and variability) than drought.

Table 1 Poverty exposure bias and increase in exposure for floods and droughts. For countries where none of the households within the DHS survey were exposed, not available (NA) is stated. Significant results are in bold.

	Poverty exposure bias				Increase in exposure of all households	
	Floods		Droughts		Floods	Droughts
Country	Nation-wide	urban	Nation-wide	urban	Nation-wide	
ALBANIA	-0.10	**0.56**	NA	NA	**9.11**	0.00
ANGOLA	**1.82**	**2.37**	**0.67**	**1.74**	**0.35**	0.00
BANGLADESH	0.02	0.00	**1.61**	NA	**39.55**	0.00
BENIN	**0.84**	-0.24	**1.57**	**2.61**	**3.42**	-17.08
BOLIVIA	-0.08	**0.39**	**-0.32**	**-0.40**	**-10.67**	938.85
BURKINA FASO	-0.30	0.32	-0.01	**-0.30**	56.00	-1.18
BURUNDI	NA	NA	NA	NA	**19.07**	0.00
CAMBODIA	**-0.25**	0.02	0.15	NA	**18.83**	0.00
CAMEROON	**0.38**	**0.45**	**2.21**	**2.51**	**2.17**	-9.45
CENTRAL AFRICAN REPUBLIC	**0.18**	**0.81**	NA	NA	**-8.02**	**-38.67**
COLOMBIA	**1.19**	**1.90**	**2.46**	**2.80**	**9.65**	0.00
COMOROS	NA	NA	NA	NA	0.00	0.00
COTE D'IVOIRE	-0.02	0.36	NA	NA	**-0.96**	0.00
CONGO, DEM. REP.	-0.09	**1.83**	**0.42**	**1.76**	**3.00**	0.00
DOMINICAN REPUBLIC	**-0.40**	-0.09	NA	NA	-27.87	0.00
EGYPT, ARAB REP.	**0.58**	**0.55**	0.03	**0.22**	**42.92**	**-4.30**
ETHIOPIA	**-0.33**	**-0.85**	**0.67**	NA	**12.41**	-47.23
GABON	**0.72**	**1.25**	NA	NA	**-3.05**	0.00
GHANA	0.23	**-0.39**	**1.15**	**1.80**	**-10.28**	51.57
GUINEA	**1.12**	**2.05**	NA	NA	**10.11**	0.00
GUYANA	**0.42**	-0.05	**2.60**	NA	**-23.23**	0.00
HAITI	**-0.48**	**3.52**	NA	NA	**-28.02**	0.00
HONDURAS	**-0.66**	**-0.31**	**0.51**	**0.76**	**-11.80**	**7.34**
INDONESIA	**0.33**	**1.03**	**0.49**	**0.33**	**9.89**	-38.39
JORDAN	**1.55**	**2.08**	**0.15**	**-0.25**	-51.70	**278.59**
KENYA	**0.64**	**1.56**	**2.92**	NA	**12.88**	-21.93
KYRGYZSTAN	0.17	**1.15**	**1.45**	NA	**13.21**	0.00
LESOTHO	-0.11	**1.55**	**0.70**	**0.82**	**0.94**	0.00
LIBERIA	**-0.43**	**-0.69**	NA	NA	**7.71**	0.00
MADAGASCAR	**-0.16**	**-0.60**	**2.28**	NA	**6.51**	0.00
MALAWI	0.10	**-0.68**	**-0.40**	NA	**-1.47**	0.00
MALI	**-0.39**	-0.36	-0.03	0.22	**37.42**	55.27
MOLDOVA, REPUBLIC OF	**-0.52**	-0.03	NA	NA	**-31.39**	0.00
MOROCCO	**-0.24**	0.25	-0.08	**0.44**	-70.26	1122.62
MOZAMBIQUE	**-0.27**	-0.08	-0.28	**0.86**	**3.57**	0.00
NAMIBIA	**0.35**	0.19	**-0.99**	**-0.60**	**-12.30**	**41.21**
NEPAL	**-0.61**	**0.59**	NA	NA	**14.84**	0.00
NIGER	**-0.39**	0.29	**-0.22**	-0.07	90.28	271.40
NIGERIA	**0.52**	**1.06**	**1.28**	**0.50**	**17.37**	355.44
PERU	**-0.49**	**0.17**	**-0.72**	**-0.62**	**20.97**	**2.39**
PHILIPPINES	-0.12	0.18	**0.84**	**1.20**	**10.45**	0.00
RWANDA	**-0.78**	**-1.00**	NA	NA	**13.04**	0.00
SENEGAL	**-0.25**	**1.78**	**1.99**	**1.81**	-5.42	0.00
SIERRA LEONE	**0.69**	**2.63**	NA	NA	**13.38**	0.00
SWAZILAND	0.13	**-0.66**	NA	NA	**-7.92**	0.00
TAJIKISTAN	-0.16	0.11	**1.05**	NA	**-8.91**	0.00
TANZANIA, UNITED REP.	-0.10	0.01	**-0.58**	-0.01	**1.03**	0.00
TIMOR-LESTE	NA	NA	NA	NA	**-12.34**	0.00
TOGO	0.21	0.13	**0.72**	**1.47**	**2.01**	356.18
UGANDA	**0.65**	NA	**3.09**	**1.52**	**31.70**	-11.22
ZAMBIA	**0.68**	**3.40**	**1.25**	-0.13	**3.31**	0.00
ZIMBABWE	**-1.00**	-0.31	**0.49**	NA	**-1.92**	0.00

4.3. The impact of climate change

Climate change is likely to increase the number of people exposed to floods and droughts. To estimate the range of increase in population exposure, we overlay the drought and flood hazard maps used for this paper with present-day and projected population density data sets,[7] for a high-emissions pathway consistent with a 4°C increase in global temperatures. This pathway is known as Representative Concentration Pathway (RCP) 8.5, where global annual GHG emissions (measured in CO2-equivalents) continue to rise throughout the 21st century. We run the analysis for five Global Circulation Models (GCMs).[8] Across the five models, under a high-emissions scenario (RCP 8.5), for droughts, we find the number of people exposed could increase by 9–17 percent in 2030 and 50–90 percent in 2080. For floods, the number of people exposed to river floods could increase by 4–15 percent in 2030 and 12–29 percent in 2080.

To assess how poverty exposure may change in the future as a result of climate change, we calculate the same PEB for a low-emissions pathway consistent with a 2°C increase (RCP 2.6, where global annual GHG emissions peak between 2010-2020, and decline substantially thereafter) and RCP 8.5 and for five GCMs. Besides this, we have used the two scenarios to estimate from the household surveys, how much exposure change is to be expected in the future due to climate change. To ensure that we only see the impact of climate on exposure, we do not include compounding effects such as migration and population growth.

The PEB does not change significantly under the two different future climate scenarios and is therefore not displayed. Of course, hazard does not drive exposure and exposure bias alone. The PEB will change in the future due to other driving mechanisms not assessed in this paper, such as migration, changes in the spatial distribution of poverty, or the general increase in income within countries. Countries with rapid urbanization – such as many in Africa – may exhibit major changes in their flood exposure patterns in the coming decades, independently of climate change and other changes in hazards.

Regions where climate change causes an increase in the annual expected number of people exposed to floods and droughts, and where poor people are generally already more exposed than average (i.e. $I_p > 0$) should be treated as highly climate-sensitive regions for poor people. To locate these, Figure 7 shows the percentage change per country in the annual expected number of people exposed to floods between 1980 and 2050, based on the household data and RCP 8.5, and Figure 8 shows the same for droughts (Table 1 also reproduces results for all countries). RCP 2.6 shows similar changes in exposure although it takes longer before these changes are reached. In some countries, the number of flood-exposed people under climate change rises rapidly; this is the case in the Horn of Africa, parts of West Africa, Egypt, Bangladesh, Colombia, and Bolivia. For droughts, the different GCMs employed show more disagreement in drought extremes, causing less significant results. However, if we use the GCM ensemble average we can again see that in particular West African countries show an increase in the number of exposed people.

[7] For present day, Landscan is used. For 2030 and 2080, data from the Shared Socio-economic Pathways (SSP4 and SSP5) is used. For more information on the SSPs, see O'Niell et al. 2014.

[8] A factor delta approach was used to bias correct for the GCM uncertainty. That is, we examined the factor increase between historical GCM runs and future ones (2030,2080) and superimposed this factor increase on top of the EUWATCH results.

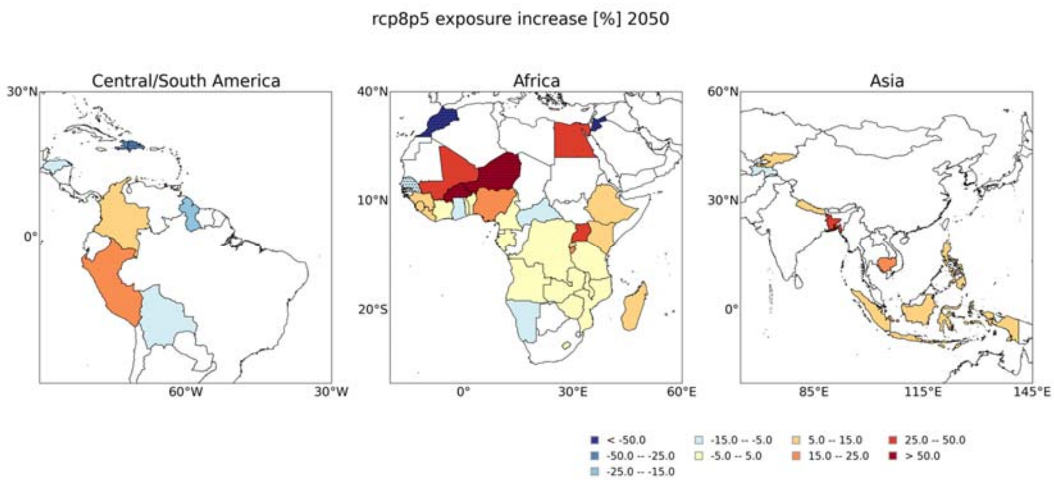


Figure 7. Percentage change in nation-wide average annual number of flood-exposed people in our sample of 52 countries following RCP 8.5 from 1980 until 2050. The GCM ensemble average is shown. Countries where the GCM ensemble standard deviation is higher than 50% of the GCM mean are dotted.

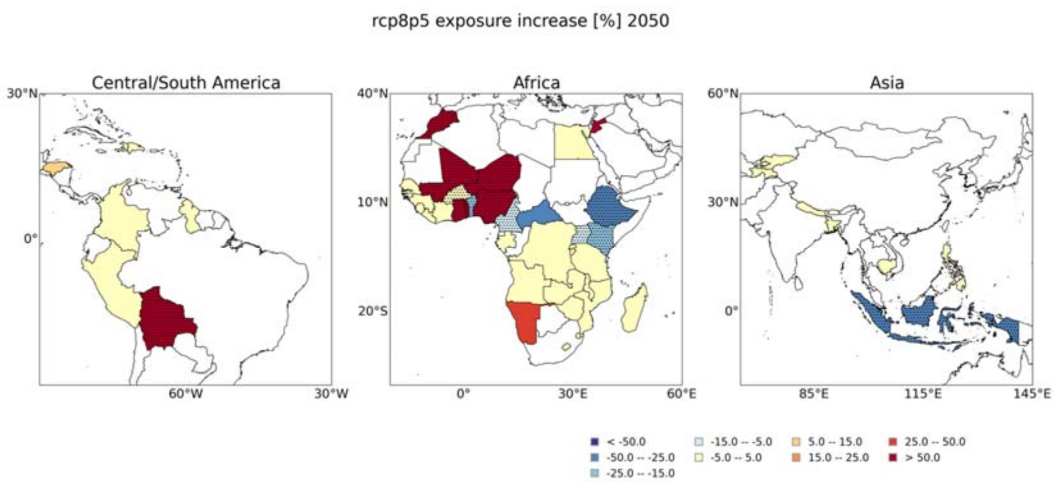


Figure 8. Same as Figure 7, but for droughts.

Finally, we show countries where a combination of disproportionally exposed poor and exposure increase is observed. This is shown for floods in Figure 9 and droughts in Figure 10. We highlight countries with a PEB larger than 10% (i.e. poor people are disproportionally exposed) and an increase in the amount of total exposed people larger than 10%. Clearly, in African countries above the equator, climate change-induced flooding will likely hit poor people the hardest. Under RCP 8.5, in 2050, the marked countries include Egypt, Guinea, Kenya, Nigeria, Sierra Leone, Uganda and Bangladesh. For droughts, only Nigeria and Ghana are facing this situation.[9]

[9] Although the low CO_2 concentration scenario (RCP2.6) shows similar patterns (not shown here), the increase in floods/droughts for 2050 is lower and also the number and share of people exposed does not rise as fast as in the high concentration scenario (RCP 8.5)

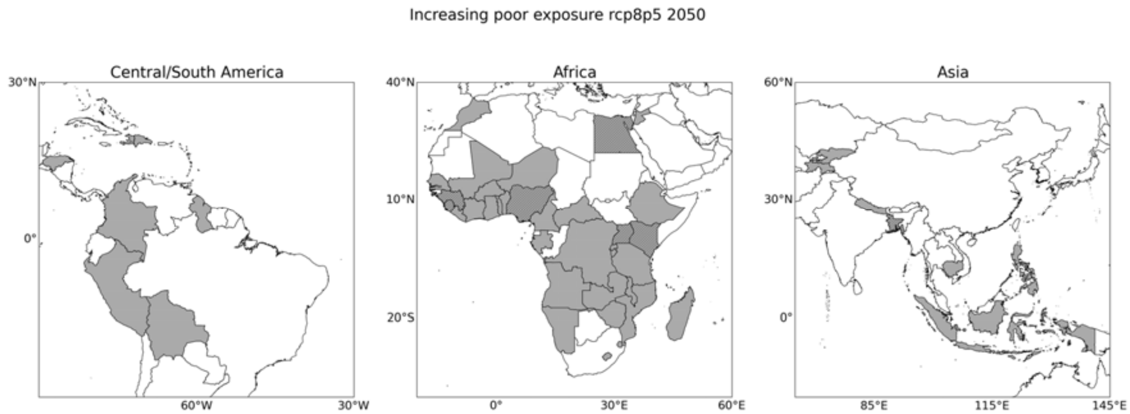


Figure 9 Countries where poor people may become increasingly exposed to flooding in a changing climate with RCP 8.5. The grey coloured countries are the ones included in our analysis. The hatched countries have an exposure bias of at least 10% as well as an increase in average annual number of people exposed to flooding of at least 10% in 2050.

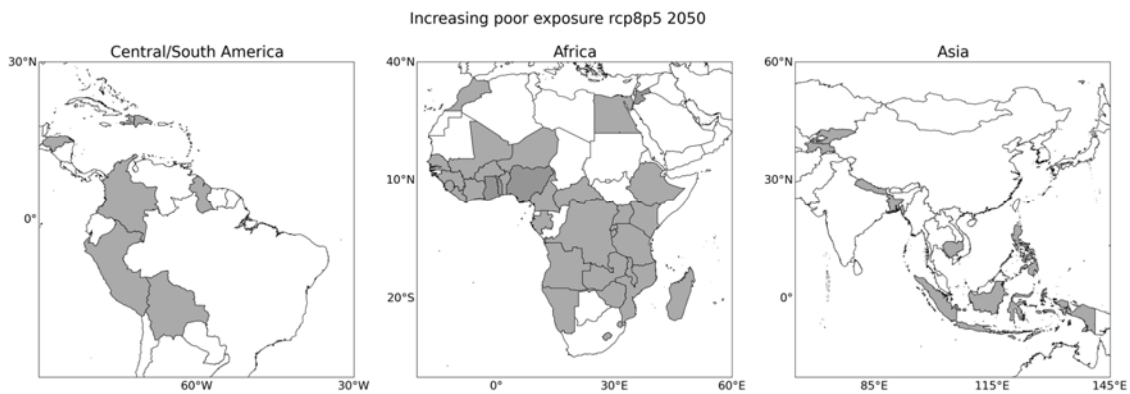


Figure 10 Same as Figure 9 but for droughts. Significant results for exposure increase were only found in a few countries, resulting in a very small number of countries showing a significant increase in poor people exposed.

4.4. Local scale poverty exposure analysis for floods

The national-scale analysis shows that some countries exhibit an over-exposure of poor people to floods and droughts, some show no difference, and others exhibit an over-exposure of non-poor people. This gives rise to the question whether there is a similar variability in the exposure bias within regions of the countries. While the DHS data do not allow for analyses of the patterns within countries (as they are not representative at small scales), in this section we examine the exposure to floods using detailed poverty maps in two countries: Malawi (Traditional Authority or TA-level, from World Bank and Malawi Statistics Office, 2013) and Morocco (commune-level, from Morocco High Commission for Planning, 2013).

These poverty maps provide spatially explicit estimates of poverty, using income as a metric. In both Malawi and Morocco, poverty is defined as the percentage of people within a commune/district who earn less than $1.25 per day in 2005 purchasing power parity (PPP) terms. This measure of poverty is distinctly different from the DHS wealth index. While the wealth index is a measure of assets and structural poverty (and is typically more long-lasting), the measure of poverty we use here is one of

income or consumption (which is typically more variable). On the hazard side, we use the same data source for floods, selecting the 10-year return period flood.

We compare exposure to floods and poverty levels across 1689 communes (for Morocco) and across 370 TAs (for Malawi) for the whole country. This analysis yields similar results to the DHS analysis: for Morocco, we find a negative bias of -0.10 (-0.29 using DHS) and for Malawi a positive bias of 0.08 (0.18 using DHS).

However, there is clear evidence of overexposure of the poor in specific areas of the country, even though there is no bias at the national scale. Figure 11 shows an overlay of commune and district level poverty maps with modelled flood extents in parts of Morocco and Malawi. Specifically, North West Morocco, north of Kenitra, exhibits a high correlation of poverty and exposure; in Malawi, this is the case in the South, at the Shire Basin, close to the confluence with the Zambezi. As an example, in January 2015 the same area experienced a flood event which hit the poorest areas hardest.

(a) Morocco **(b) Malawi**

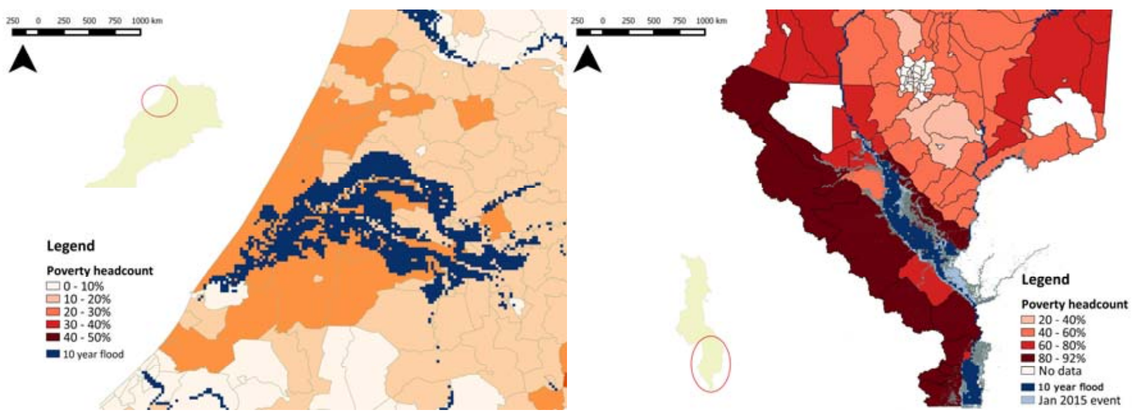


Figure 11 Overlay of poverty headcount maps at subnational level with a map showing 1 in 10 year flooding. Morocco is shown in left panel A. Source: Morocco High Commission for Planning (2013). Malawi is shown in right panel B. The 10 year flood refers to a 10-year return period flood. Sources: World Bank and Malawi Statistics Office (2013), UNOSAT (2015), German Space Agency (2015).

However, as described above, these national-level trends may hide significant heterogeneity within regions. Considering only the northwest of Morocco (left panel of Figure 11), we now find a slightly positive exposure bias of 0.07 as opposed to the -0.24 that we found at national level). For the south of Malawi (right panel of Figure 11), we find a significantly large exposure bias of 0.52 as opposed to. 0.10 (not significant) at national level. These findings support the hypothesis that we can find different biases occurring at different scales. Further, the identification of sub-national areas with a positive exposure bias may provide a rationale for targeting investments in these areas, concerning both protection ex-ante and disaster support ex-post.

These results suggest high variability of the PEB within countries. Differences exist between rural and urban areas, and across lower administrative units such as provinces and cities. While national level studies, such as our analysis with DHS surveys, are useful for starting the discussion on poverty impacts of natural hazards, local decision-makers may require the local level PEB to design their own poverty and risk management strategies. Ideally, such local analyses could make use of higher-resolution flood

or drought maps and local household surveys designed to be representative at the local scale. For example, in Mumbai, local-scale flood data and household surveys revealed that an over-exposure of poor people to floods can be observed (Hallegatte et al., 2016), but varies at very small scale, from one street to the next (Patankar and Patwardhan, 2014).

5. Limitations and recommendations for further research

Consistent with expectations, there is high variability across countries and poor people are not over-exposed to natural hazards everywhere. But the analysis is limited by data availability as the DHS samples are too small to look at regions and within-country variability. The limited number of households per country has implications for the results for droughts in particular: in many countries, there is no overlap between zones with extreme drought conditions (e.g. a minimum of 3 months drought, at 100 year return period yielded only 15 countries with significant results) and households, meaning that no estimate of the PEB for droughts could be made in these cases. A larger number of observations per country would therefore make the results of our analysis more robust. Furthermore, it would allow a more local scale analysis, as performed for Morocco and Malawi, for all countries.

A related limitation is the spatial scale of the analysis. DHS samples are rarely representative within sub-national regions, which limits our ability to examine the poverty exposure bias within specific regions of a country. Furthermore, even the sub-national poverty maps are at the commune or traditional authority level, while higher-resolution data (e.g. poverty maps within a city) would be able to better capture dynamics at the local level, where lower land prices may push poorer people into more risky areas.

Furthermore, ideally, we would compare our results across countries and not just within them. However, the wealth index calculated by DHS is country-specific, meaning that the same value for the wealth index across two different countries may imply a different level of wealth. While some authors have recently suggested the DHS wealth index may be compared across countries (Rutstein and Staveteig, 2013), country-to-country comparability remains difficult. This is one reason why we use relative thresholds (e.g. quintiles) rather than absolute thresholds. Another reason for which we use relative numbers is that if a standard poverty line is used, in some countries an overwhelming majority of the population would be classified as poor (e.g., 70-80% in Malawi with a 1.25USD/day poverty line).

The flood hazard maps used in this study only show whether each grid-cell is flooded (yes or no) for each return period. In reality, the impacts of flooding on people and their assets and productivity are dependent on several other factors. Exposure is only one component of risk: protection (e.g., with dikes or water reservoirs), vulnerability of assets and livelihoods (e.g., quality of housing, savings at financial institutions, and diversification of income), and ability to cope and recover (e.g., access to social protection and credit) are also critical to determine the impact of natural hazards on well-being.

Households living in high-quality elevated houses may not suffer much from a shallow flood (e.g., 10 cm depth), while informal housing may already be damaged. The inundation depth has been shown to be the main determinant of damages to assets (e.g. Penning-Rowsell and Chatterton, 1977; Penning-Rowsell et al., 1994; Wind et al., 1999; Merz et al., 2010; Meyer et al., 2013). In future studies the relationship between the actual depth occurring and wealth could also be examined. Numerous

studies have also shown flood duration to play an important role in flood impacts (Parker et al., 1987; FEMA, 2005; Dang et al., 2010), especially for indirect losses (Lekuthai and Vongvisessomjai, 2001) flood-related health issues (Dang et al., 2010); and flood level rise rate is especially important in terms of mortality (Jonkman et al., 2009). More research is required to examine how these could impact on poverty. Future research may also expand to other hazards, as has been done for extreme temperatures (Park et al., 2015).

Similarly, households that are highly vulnerable to droughts (e.g. with assets strongly relying on available water) may already experience problems during a one-month drought condition, although others may only be exposed if the drought lasts three months or more. To assess the robustness of the drought indicator applied, we test our results using a one-month and six-month threshold. Obviously, more people are exposed with a one-month threshold than with a six-month threshold. For the aggregated PEB results (Supp. Figure 6), we can only find a significant number of exposed households in six countries using a six-month drought threshold with a return period of 10 years; this increases to up to 50 countries, when considering one-month droughts as threshold with a 100 year return period. Notably, median PEB values are above zero for the 100 year return-period drought, and decreases toward and below zero for lower return periods (10 years) droughts and higher drought thresholds.

This suggests that the small sample sizes make it very hard to find a robust exposure bias pattern in many countries. Nonetheless, we found consistent results on the sign of the PEB for sub-Saharan Africa (Nigeria, Cameroon, Democratic Republic of Congo, Togo, and Benin (not significant for a one-month threshold)), Southeast Asia (Philippines, Indonesia (not significant for a six-month threshold)) and Colombia (when comparing the one-, three- and six-month threshold results under the 100-year return period). Other countries showed mixed results over the different threshold values and therefore results over these countries should be treated with a lower confidence.

6. Conclusions

In this paper, we investigated at the country level whether poor and non-poor people are disproportionally exposed to current floods and droughts and how this exposure changes in a changing climate. To this end, we combine global drought and flood hazard and household survey data in 52 countries. The general conclusion is that across countries, poor people are over-exposed to droughts and urban floods. But the situation differs strongly across countries, within countries and based on the type of hazard – for instance, for floods at the national level, we find little evidence of an over-exposure or under-exposure of poor people.

Geographically, the countries where the strongest positive poverty exposure bias (PEB) is found, are concentrated in Africa for both perils. For floods, the countries in Sub-Saharan Africa as well as the horn of Africa and Egypt experience the highest positive PEB. For droughts, poor people are more exposed in almost all countries in Africa, and also South-East Asia shows this signal.

We find that in urban areas, poor people are disproportionally exposed to floods compared to the average, while such a signal is not found for rural households. This is particularly noticeable in Africa, with the exception of several western African countries. In some countries, the absence of a positive PEB at national level may be due to the fact that the gap in wealth between cities and rural areas is

large, combined with the fact that flood hazard is often high in cities. The urban-rural gaps in income and flood risk may thus hide the fact that poor people are more exposed. This hypothesis is further supported by subnational analyses in two countries (Morocco and Malawi), where several regions are identified where poor people are clearly over-exposed, when compared with the rest of the population in the country.

A particular concern is the fact that some of the countries where poor people are overexposed will also experience more frequent flooding or droughts in the future due to climate change. Poverty-vulnerability hotspots appear when combining countries with an overexposure of the poor and an increase in hazards expected from climate change. This signal is found in Burkina Faso, Burundi, Egypt, Ethiopia, Guinea, Kenya, Nigeria, Sierra Leone and Uganda for floods. For drought, Nigeria and Ghana were found to be in this situation although results for Ghana were found to be less robust.

Exposure, the topic of this paper, is only one component of risk. Almost everywhere, the other components of risk – from protection to vulnerability to the ability to cope and recover – are also biased against poor people (Hallegatte et al., 2016), which means that even in places without a poverty bias, poor people may still be at risk. Protection levels and quality are lower in poor countries, and lower in poor neighborhoods and regions. Poor people live in low quality houses that suffer more damage in case of floods, and they have most if not all of their assets in material form, making them more vulnerable to floods. Finally, poor people have limited access to recovery support, such as social protection and credit.

All of these factors combined with the results in this paper advocate for disaster risk management as a pro-poor policy. In countries where we find that poor people are disproportionally exposed to floods and droughts, it is particularly important to integrate risk management policies within poverty reduction strategies, to understand the underlying drivers of the exposure bias, and to correct it through better land-use regulation and other supporting policies. Critically, such policies should support the access of poor people to opportunities, and not stifle them. Where hazards will become more frequent or more intense, implementing risk-sensitive land-use policies that protect poor people, such as flood zoning, should be a priority.

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Author contributions
H.C.W. and P.J.W. computed the flood hazard maps for all projections. T.I.E.V. and P.J.W. established the drought hazard layers for all projections. M.B. prepared shapefiles from the DHS survey data, for use in this study. H.C.W., B.J., P.J.W. and T.I.E.V. established the computational framework to compute the poverty exposure bias. M.B. and S.H. performed background study on poverty and

natural hazards. S.H. initiated the study. All authors have contributed to the conceptualisation of the study and the writing of the manuscript.

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Appendix A. Flood and drought modelling

A.1. Hydrological modelling

The basis of both the flood and drought indicators is the simulation of daily river discharge and runoff using a global hydrological model. For this project, we used simulations carried out using the global hydrological model PCR-GLOBWB (Van Beek and Bierkens, 2009; Van Beek et al., 2011). This model simulates daily discharge and runoff at a horizontal resolution of 0.5° x 0.5°.

The model was forced using daily meteorological fields of precipitation, temperature, and radiation for four different time-periods, namely: (a) 1960-1999, which represents the baseline climate; (b) 2010-2049 (representing 2030); (c) 2030-2069 (representing 2050); and (d) 2060-2099 (representing 2080). The meteorological data for the baseline climate are taken from the WATCH Forcing data (Weedon et al., 2011). The future meteorological data are provided by the ISI-MIP project, and consist of bias-corrected data (Hempel et al., 2013) for an ensemble of five Global Climate Models (GCMs) from the CMIP5 project (Taylor et al., 2012). The GCMs used are GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, and NorESM1-M. For this study, we used climate projections based on 2 representative concentration pathways (RCPs), namely RCP2.6 and RCP8.5. The resolution of the input meteorological data sets for the current and future climate conditions is 0.5° x 0.5°.

For the simulations of floods and droughts, naturalized flow regimes were used, because the operation of reservoirs during flood and drought conditions is highly variable across the globe and requires detailed in-situ information about the flood and drought operation rules of each reservoir. The operations during floods and droughts may vary depending on many factors, for example: the (multi-purpose) use of the reservoir; the history of storage (e.g. after consecutive dry years, reservoir operators often maintain higher storage levels); and the (non-)availability of forecast information or information on release strategies of upstream reservoirs. Therefore, reservoirs were included as if they are natural lakes.

A.2. Simulation of flood indicator

In this study, the indicator used to represent flooding is inundation depth greater than a given threshold (for example, inundation depths >0 m, >0.1 m, etc.). Here we selected a 0 m threshold, therefore including any flooded area regardless of the inundation depth. We used flood inundation maps at a horizontal resolution of 30” x 30” (ca. 1km x 1km at the equator). The simulation of the maps for the current and future time-periods is described in Winsemius et al. (2015). The method uses the GLOFRIS model cascade inundation downscaling technique, which is described in detail in Ward et al. (2013). Here, we provide a brief summary.

Daily gridded flood volumes are simulated at a horizontal resolution of 0.5° x 0.5°, using the DynRout extension to the PCR-GLOBWB model. From these daily flood volumes, annual time-series of gridded maximum flood volumes are extracted for the hydrological years 1960-1999. A Gumbel distribution is

then fit through this time-series (excluding years with zero flood volume), and the resulting parameters of the Gumbel distribution are used to estimate flood volumes for different return periods, conditional on the probability of exceedance of zero flood volume. This results in a set of maps showing the flood volume of each 0.5° x 0.5° grid-cell for all return periods. These are then used as input in the GLOFRIS downscaling module, described in Winsemius et al. (2013), to derive maps showing inundation extent and depth at the high resolution of 30" x 30" (see for an example, Figure 2, top-left graph). Within the simulations, the assumption is made that flood protection is absent. The granularity of the maps (horizontal resolution of 30” x 30”) is good for representing wide floodplain areas (>1km in width), but may be too low to accurately represent all flood processes in riverine regions with steep topography. Here flood plains are usually quite narrow (i.e. < 1 km).

It should be noted that the inundation maps represent only riverine flooding, assuming the absence of flood protection measures. Moreover, they do not include coastal flooding, flooding from smaller streams, or flash floods.

A.3. Simulation of drought indicator

Hydrological drought conditions, or below-normal water availability, were identified using the widely applied variable threshold level method (Fleig et al., 2006; Hisdal and Tallaksen, 2003). In this study we defined the monthly Q_{80}, the mean monthly streamflow that is exceeded 80% of the time, as a measure for hydrological drought (Andreadis et al., 2005; Corzo Perez et al., 2011; Hisdal et al., 2001; Van Loon and Van Lanen, 2012; Sheffield and Wood, 2007; Tallaksen et al., 2009; Wada et al., 2013). Using monthly mean discharge values for the baseline scenario (EU-WATCH 1960-1999), simulated with PCR-GLOBWB (Van Beek et al., 2011), we calculated for each cell its monthly $Q_{80.}$ Following earlier studies (Lehner and Döll, 2001; Wada et al., 2013; Wanders and Wada, 2014), we determined the drought intensity for all combinations of GCM, RCP and time-period as the deficit volume below the Q_{80} threshold level as specified under the baseline scenarios (Supp Figure 1). Subsequently, monthly drought intensities per grid-cell were accumulated using the method developed by Lehner and Döll (2001) and Wanders and Wada (2014), whereby the accumulated volumes are set to zero each time the discharge is higher than the Q_{80} threshold level.

Using these values, we selected the maximum accumulated deficit volume for each hydrological year and a Gumbel distribution was fit through these time-series of maximum yearly standardized values (excluding the years with no deficits) (Engeland et al., 2005; WMO, 2008). The parameters of the Gumbel distribution were used to estimate maximum yearly accumulated deficit volumes of each 0.5° x 0.5° grid-cell for different return periods, conditional on the probability of exceedance of zero discharge deficits. To enable comparison between rivers of different size, we standardized the maximum accumulated deficit volumes found per return period by dividing them by their long-term mean monthly discharge values.

$$V_{MAD_{i,y}} = \max[\sum(0, \tau_{i,m} - Q_{i,m})]_y \quad (1)$$

$$S_{MAD_{i,RP}} = \frac{V_{MAD_{i,RP}}}{Q_{LTM,i}} \quad (2)$$

where V_{MAD} is the maximum accumulated deficit volume [m^3], i is the grid-cell considered, y and RP are the year or return period considered respectively, τ is the Q_{80} threshold [$m^3 s^{-1}$], Q is the simulated monthly discharge [$m^3 s^{-1}$] in month m, Q_{LTM} is the long-term mean simulated monthly discharge, and S_{MAD} is the standardized maximum accumulated deficit volume [s].

The resulting maps express the relative intensity of drought conditions to long-term mean stream flow conditions and can be interpreted as the amount of time a long-term mean discharge would be needed to overcome the maximum accumulated deficit volume under a certain return period. In this study, we used the value of 3 months (of long term mean discharge) as the indicator to represent droughts (for an example, see Figure 2 bottom-left panel). The resolution of the maps represents drought conditions well for areas where droughts generally may be assumed to occur at a large scale (>50 km^2). In regions where drought conditions could be very localized, for example due to highly variable topography and high variability in water availability within a grid-cell, the results may be less representative.

A.4. Changes in risk under climate change

We assessed how climate change affects the poverty exposure bias, as well as the number of exposed people by computing the poverty exposure bias as well as the annual average number of exposed people in 2030, 2050 and 2080 using the hazard maps representative for these periods and for 5 different GCMs.

We also computed the poverty exposure bias and annual exposed people using the hazard maps for the reference period (1960-1999) but established based upon the GCMs rather than the EU-WATCH reanalysis data set. Since the GCMs used contain bias due to unrepresented intra-annual and interannual variability (Johnson et al., 2011), we used the model-model difference in annual exposed people to establish changes in the exposure rather than the absolute outcomes.

Appendix B. Spatial wealth data sets and DHS surveys

DHS surveys cover a wide range of developing countries, and contain geographic points at the cluster level. There are 52 surveys in the DHS program that contain both GPS information at the cluster level and poverty indicators; these are the countries for which we overlay the flood and drought data.[10]

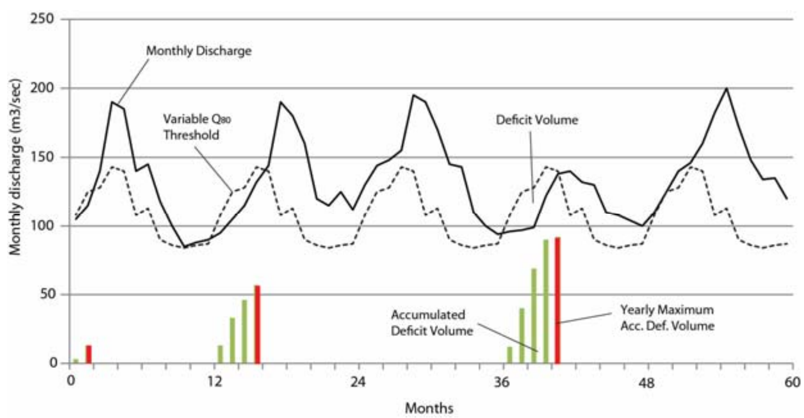
For each household, the DHS provides the wealth index factor score (typically from -200,000 for the poorest households to +200,000 for the richest, with the median at 0). Based on this factor score, quintiles have been calculated taking into account household weights. We employ this quintile classification for our analysis at the national-level. In addition, we recalculate quintiles at the urban-specific and rural-specific levels. This is done for two reasons. First, the structure and distribution of people is very different in rural and urban areas, and thus the dynamics of flood and drought exposure will be different. Second, people in urban areas are typically richer. Thus, we recalculate to compare poor people in each area with non-poor people in the same area. In other words, the new quintiles are relative, i.e. quintile 1 represents the poorest in urban (rural) poor and quintile 5 the urban (rural)

[10] In a few countries, GPS data of clusters are missing, and thus the clusters in the household have been left out of the analysis. However, this is unlikely to impact the results significantly, as they represent <0.01% of all households.

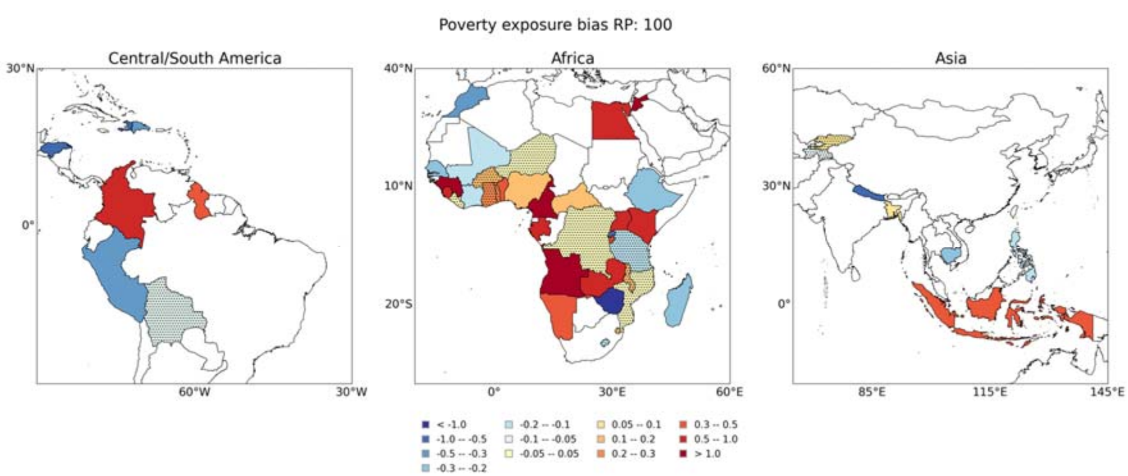
rich. By splitting the sample by urban/rural, we are able to test exposure to floods and droughts at the national, urban, and rural level.

One issue with DHS surveys – and almost all other household surveys – is that they have not been designed to be representative at small spatial scales. At best, they are representative at the spatial scale of a large province or area. Furthermore the process used to select the surveyed households is not always reported explicitly, and often has to account for cost- considerations that can bias the sample. We are well aware of this limit, and it implies that results should be interpreted with caution. The fact that we are working on a large sample of 52 countries compensates for the limit of the analysis at the country level.

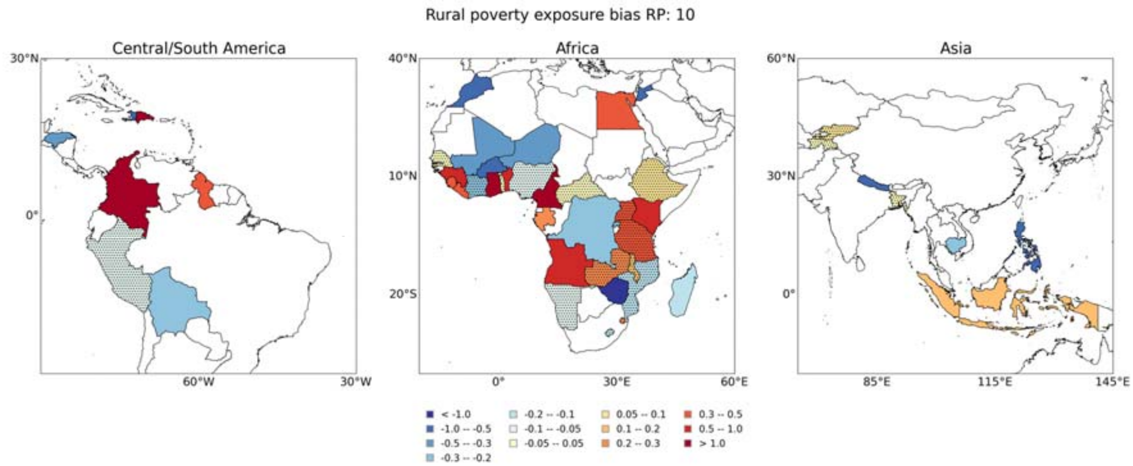
Supplementary Figures and Tables



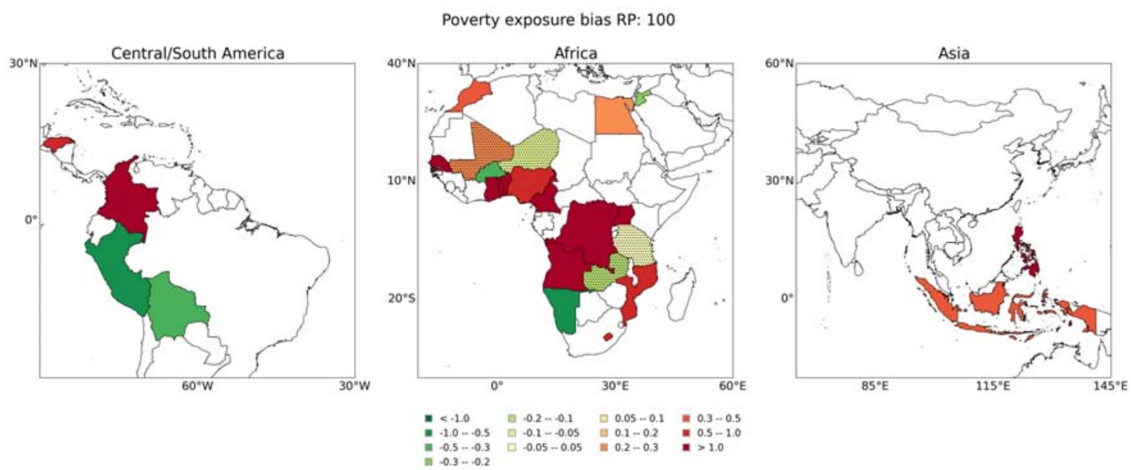
Supp Figure 1. Definition of drought events and accumulated deficit volumes using a variable Q_{80} threshold level, i.e. varying heights of the threshold level throughout the year based on monthly Q_{80} values (after: Lehner and Doll, 2001).



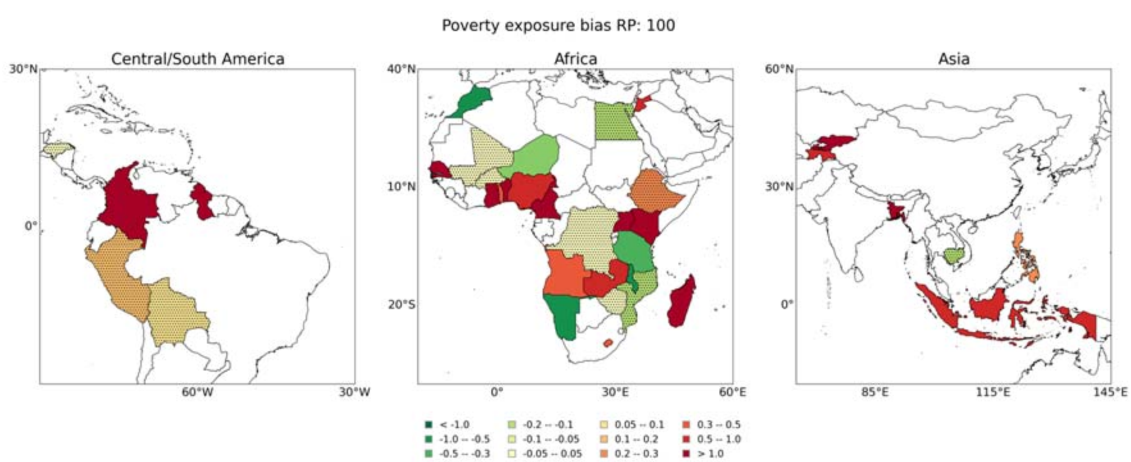
Supp Figure 2. Poverty exposure bias for 100-year return period floods. White areas are not part of the 52 country sample. Areas are dotted when there is a lower than 95% confidence that the sign of the exposure bias is as estimated.



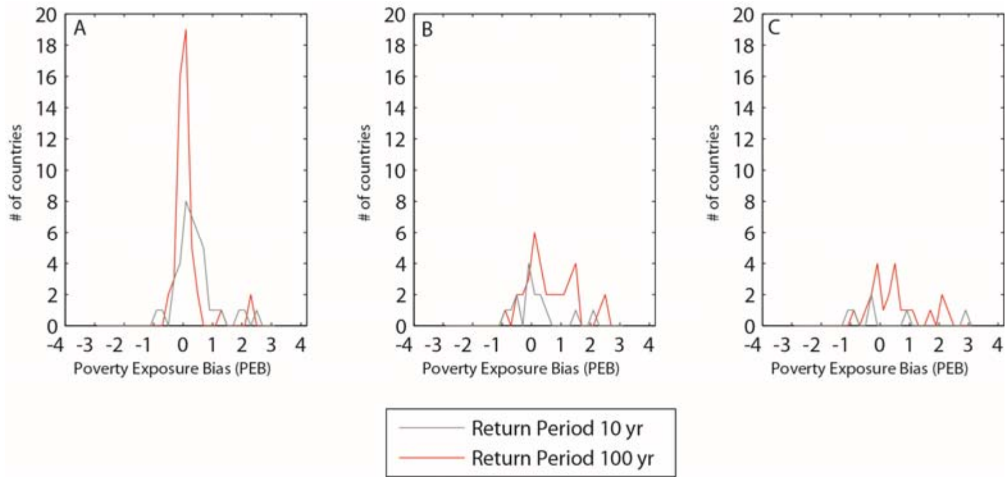
Supp Figure 3. Same as Figure 4 but for rural households only. Note that the quintile subdivision used is based on rural households only.



Supp Figure 4. Same as figure 8 but for urban households only. Note that the quintile subdivision used is based on urban households only.



Supp Figure 5. Same as figure 8 but for rural households only. Note that the quintile subdivision used is based on rural households only.



Supp Figure 6. Histograms of the country-scale poverty exposure biases computed across all 52 countries for a 10-year and 100-year return period for droughts selected by a a) 1-month threshold; b) 3-month threshold; and c) 6-month threshold.