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## Article (Accepted version)
## (Refereed)

This version available at: http://eprints.lse.ac.uk/87536/

Available in LSE Research Online: April 2018

http://eprints.lse.ac.uk

# 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. This paper analyses household survey data

and hydrological riverine flood and drought data for 52 countries to find out whether poor

people are disproportionally exposed to floods and droughts, and how this exposure may

change in a future climate. We find that poor people are often disproportionally exposed to

droughts and floods, particularly in urban areas. This pattern 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

region. In particular many countries in Africa show a disproportionally high exposure of poor

people to floods and droughts. For these hotspots, implementing risk-sensitive land-use and

development policies that protect poor people should be a priority.

## Keywords

Poverty, floods, droughts, global scale, exposure, climate change

**1. Introduction**

Globally, about 700 million people live below the USD $1.90/day poverty line, with many more balancing just above it (World Bank, 2015). This substantial part of the world population is particularly vulnerable to external shocks, including those caused by natural disasters, like floods and droughts. Such disasters can reduce household income and destroy houses and productive capital. For example, after the 2004 floods in Bangladesh, poor households affected by the flood lost more than twice as much of their total income as non-poor households (Brouwer et al., 2007). This illustrates the consistent finding that poor people are more vulnerable to disaster events (Carter et al., 2007). By vulnerability, we refer to the fact that poor people are more susceptible to flooding, e.g. by the fact that they lose a larger fraction of their wealth when they are affected by a natural hazard or have a higher probability of suffering mortality (see e.g. Jongman et al., 2015), and have more difficulty to cope with them. They have a lower capacity to deal with shocks than non-poor households, due to lower access to savings, borrowing, or social protection (Highfield et al., 2014; Kundzewicz and Kaczmarek, 2000; Masozera et al., 2007). By exposure we mean the location of people in flood-prone areas.

Natural disasters are a key factor for pushing vulnerable households into poverty and keeping households poor (Krishna, 2006; Sen, 2003). Just as importantly, 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 change the frequency, intensity, and spatial distribution of floods and droughts (IPCC, 2012). Therefore,

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future climate change may represent a significant obstacle to eradicating poverty

(Hallegatte et al., 2016).

Several previous studies have investigated 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; Shepherd et al., 2013; Toya and Skidmore, 2007). Whilst these studies have found statistical relationships between experienced flood impacts and average income, they have not investigated the spatial or socioeconomic distribution of the losses within countries. Recent advances in the global spatial modelling of floods (Hirabayashi et al., 2013; Pappenberger et al., 2012; Ward et al., 2013; Winsemius et al., 2013, 2015b) and droughts (Prudhomme et al., 2014; Schewe et al., 2014) have led to improved estimates of the global population exposed to natural hazards, but these assessments have not addressed different income groups.

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 in this paper, shows that poor people are often disproportionately overrepresented in hazard-prone areas. As shown in Supp. Figure 2, only one of the 13 studies finds that non-poor people are more exposed than poor people. Although these cases highlight a possible relationship between poverty and exposure, evidence on the global representativeness of these case-study results and general figures on the exposure of poor people is lacking.

In this paper, we analyse global exposure of poor and non-poor people to river floods and droughts under current and future climates. To do this, we combine hazard maps from

79    global river flood and hydrological drought models with detailed household wealth and

80    income datasets for 52 countries. At this stage, we have not yet included coastal flooding,

81    which would result in additional flood impacts. Poverty is defined here using the distribution

82    of wealth amongst households within a given country. We explore whether there is a

83    significant exposure bias for either poor or non-poor people to river floods and droughts

84    and whether their exposure increases in the future. As data limitations create certain

85    constraints on the analysis, this study should be treated as a first-cut exploration.

86    **2. Review**

87    In this section, we review the complex relationship between poverty and exposure to

88    natural hazards. The relationship between poverty and exposure may go in both directions.

89    First, poor people may be more likely to settle in flood- and drought-prone areas. Second,

90    households affected by floods and droughts have a higher risk of falling into poverty or

91    being trapped in poverty. Both aspects are discussed below.

92    Localization choices across regions and cities are in the first place driven by

93    socioeconomic considerations (housing prices, proximity to jobs, amenities), much more

94    than by natural hazards (Hallegatte, 2012). Households may be willing to accept high levels

95    of risk to get access to opportunities. For example, in Mumbai households in flood areas

96    report that they are aware of the flood risks, but accept them due to the opportunities

97    offered by the area such as access to jobs, schools, and health care facilities (Patankar,

98    2016). Compounding this incentive for people to reside in flood zones and close to

99    opportunities is the reality that transport is often unreliable, unsafe, or expensive  (Dudwick

100   et al., 2011; Gentilini, 2015). In some rural areas, proximity to water offers cheaper

101   transport opportunities and regular floods may increase agricultural productivity (Loayza et

4

102   al., 2012). People may also settle in risky areas to benefit from opportunities with industries

103   driven by exports in coastal areas (Fleisher and Chen, 1997). These opportunities attract all

104   people – rich and poor – to places that are exposed to natural hazards.

105       However, at the city or neighbourhood level, where the opportunity factors are

106   broadly similar, but risk of floods may be different from neighbourhood to neighbourhood,

107   poor people might be more exposed due to lower housing prices in flood zones (Bin and

108   Landry, 2013). A meta-analysis of 37 empirical studies, mostly in developed countries, found

109   that prices between flood-exposed and non-flood-exposed houses varies widely, ranging

110   between −7 percent to +1 percent  (Beltran et al., 2015). Poorer people, with fewer financial

111   resources to spend on housing and a lower willingness and ability to pay for safety, are

112   more likely to live in at-risk areas. This factor is more likely to exist for floods than for

113   droughts, due to the small-scale variability in flood hazard. For example with floods, impacts

114   can be very different in areas 100 meters apart.

115       Alternatively, causality may go from flood and drought exposure to poverty.

116   Evidence shows that floods affect household livelihood and prospects, and increase local

117   poverty levels, through the loss of income and assets (e.g. Rodriguez-Oreggia et al., 2013 for

118   an analysis in Mexico). Exposure to droughts has been found to increase poverty ex-post

119   (Carter et al., 2007; Dercon, 2004). Further, the impact of disaster risk on poverty occurs

120   through both the visible ex-post channel (the losses when a disaster occurs), as well as the

121   less obvious ex-ante channel: households exposed to weather risk have been shown to

122   reduce investment in productive assets and to select low-risk, low-return activities (Cole et

123   al., 2013; Elbers et al., 2007). This link from natural hazard exposure to poverty may create a

124     feedback loop, in which poor households have no choice but to settle in at-risk zones and

125     therefore face increased challenges to escaping poverty.


126     **3. Data and methods**

127     We examine relationships between poverty and exposure to river floods and hydrological

128     droughts by combining flood and drought hazard maps from a global hydrological model

129     with household level poverty data for 52 countries. River floods are identified from larger

130     rivers (in the order of 10 000 km$^2$ upstream area and above) only, and hydrological droughts

131     are defined as climatological anomalies in river flows. The household data are taken from

132     household surveys from the Demographic and Health Surveys (DHS), which are carried out

133     by ICF International and hosted by the United States Agency for International Development

134     (USAID).

135     In brief, per country we first analyse the wealth of households in all areas, and then the

136     wealth of households in areas prone to river floods and/or hydrological droughts, and

137     examine the difference between them. We do this by checking for each individual

138     household, whether its geographical position is within a flood/drought prone area or not.

139     Using a precise geographical location is important in particular for floods, as floods can be a

140     very local phenomenon. In the following subsections we describe the data and methods

141     used. More detailed information about data and methods is provided in a background paper

142     (Winsemius et al., 2015a). The overall workflow is shown in Figure 1, for the example of

143     Colombia.

144     **3.1. Deriving the flood and drought indicators**

145  We use a global hydrological model, PCRGLOB-WB (Winsemius et al., 2013) run with the EU-

146  WATCH Forcing Data (Weedon et al., 2011) to derive maps showing indicators of flood and

147  drought hazard. PCRGLOB-WB in brief estimates globally, at 0.5x0.5 degree resolution

148  (about 50x50 km at the equator) on a daily basis over a given run time, how much rainfall

149  runs off to rivers, and how this runoff accumulates in the river network and travels

150  downstream. We use the WATCH Forcing Data, providing 0.5 degree gridded meteorological

151  data needed to drive the model (precipitation, temperature and potential evaporation) to

152  run this model over a 40-year period (1960-1999). From the resulting discharge and water

153  depth time series at 0.5 degree resolution, we derive the hazard indicators for floods and

154  droughts for several return periods (i.e. one divided by the average exceedance probability

155  per year of a flood or drought event of a given magnitude, further described below). An

156  event with associated return period should be interpreted as follows: an event with a very

157  high return period (i.e. an event happening very infrequently) is more severe than an event

158  with a low return period (i.e. a more frequently occurring event). Below we provide a brief

159  description of the model cascade and derivation of flood and drought maps. We provide a

160  more elaborate description in Appendix A. For simplicity, we focus on results for 10 and 100-

161  year return periods.

162  **3.1.1. Flood hazard**

163  Flood hazard is represented by flood inundation depth maps at 30" (arc seconds) x 30"

164  resolution (approx. 1km x 1km at the equator) from the GLOFRIS model cascade, which uses

165  PCRGLOB-WB for its hydrological boundary conditions. In short, the water depths,

166  associated with a given return period (see Section 3.1) at 0.5 degree resolution are

167  downscaled to a much finer resolution using a much more granular elevation dataset. To

168    define whether there is a flood hazard, we applied a threshold set at 0 meter (i.e. any

169    flooding occurring is hazardous). GLOFRIS is described in detail in Winsemius et al. (2013)

170    and applied at the global scale in several studies (Jongman et al., 2015; Ward et al., 2013;

171    Winsemius et al., 2015b). The method does not consider flood protection, as this is

172    relatively low in developing countries. It also does not include coastal floods and flash

173    floods. More details on the derivation of flood hazard maps from the runs with PCRGLOB-

174    WB are provided in Appendix A.2.

175    ### 3.1.2.  Drought hazard

176    We applied a variable monthly threshold method (namely the 80% exceedance probability

177    of discharge, $Q_{80}$) to estimate the yearly maximum cumulative discharge deficit, i.e. the

178    accumulated amount of discharge under the $Q_{80}$ threshold over a continuous period of time,

179    per grid cell at 0.5° resolution as a measure of hydrological drought (Lehner and Döll, 2001;

180    Wada et al., 2013; Wanders and Wada, 2014), using outputs from PCR-GLOBWB. Supp

181    Figure 3 shows the definition of droughts in a graphical form.

182    The resulting maps express the intensity of droughts relative to long term mean

183    discharge and can be interpreted as the amount of time a long-term mean discharge would

184    be needed to overcome the maximum accumulated deficit volume occurring with a certain

185    return period. We assumed that hazardous conditions occur when this value exceeds 3

186    months, and tested the robustness of our results using 1-month and 6-month thresholds.

187    The indicator does not include information on groundwater availability or upstream water

188    use. The resulting drought values should therefore be interpreted as conservative

189    (underestimating drought hazard). Naturally, much more sophisticated drought indicators

190    may be derived by accounting for season, rain-fed or irrigation based agriculture, locally

191    specific demands, but these would all require much more local information and cannot

192    easily be used at the global level.

### 3.1.3.  Future flood and drought hazard

194    The model was also used to estimate future climate change impacts on flood and drought

195    hazard, for different time periods (1960-1999, 2010-2049, 2030-2069, and 2060-2099),

196    using meteorological outputs from five Global Climate Models (GCMs), forced by two

197    representative concentration pathways (RCPs, Van Vuuren et al., 2011), which represent

198    scenarios of future concentrations of greenhouse gases (RCP 2.6 and 8.5, consistent with a

199    2°C and 4°C increase respectively). By "forced," we mean that the GCM outputs are

200    generated by running the GCMs with the concentration of greenhouse gases in the

201    atmosphere prescribed in the RCP scenarios. We have used RCP 2.6 and 8.5 so that we show

202    two very contrasted developments in climate change. Note that climate change does not

203    make floods and drought risks become more severe everywhere. In some regions, floods

204    become less severe and frequent due to reduction in rainfall (shown e.g. by Hirabayashi et

205    al., 2013; Winsemius et al., 2015b); in others increase in precipitation reduces drought

206    severity. Since the GCMs used contain bias due to unrepresented intra-annual and inter-

207    annual variability, we use the difference in annual exposed people between GCM-forced

208    model runs in the future and the past to establish changes in exposure.

### 3.2. Poverty data sets

210    A comprehensive spatial database to examine the distribution of poverty within and across

211    countries is not yet available at the required spatial resolution.[1] However, household

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

212　surveys contain some spatial information to approximate the location of a household, which

213　we employ in this analysis. Our main analysis is undertaken using the "wealth index" (e.g.

214　Barros et al., 2012; Fox, 2012; Ward and Kaczan, 2014) from the USAID's DHS surveys. This

215　index is available across 52 countries that contain geo-referenced household-level data.

216　These countries represent about 23% of the world's population. There are typically 500-

217　1,000 survey clusters for each survey, with each cluster containing approximately 25

218　households.

219　　All households in each country are classified in five quintiles (with quintile 1 having

220　the lowest wealth, and quintile 5 the highest). We furthermore classified urban and rural

221　households into quintiles, which enabled us to investigate the exposure across urban and

222　rural populations separately.

223

224　**3.3. Analysing the relationships between poverty and floods/droughts**

225　To investigate the global exposure of poor people to floods and droughts, we define a

226　'poverty exposure bias' (PEB) that measures the fraction of poor people exposed, compared

227　to the fraction of all people exposed per country. When estimating the number of people

228　exposed, we multiply the exposed households with their household size and use household

229　weights to ensure the representativeness of our results at the national level. The household

230　weight is a measure for the representativeness of the household related to all other

231　households. We compute the PEB using:

232
$$I_p = \frac{f_p}{f} - 1 , \qquad\qquad (1)$$

233    where $I_p$ is the PEB, $f_p$ and $f$ are the fraction of people exposed to floods/droughts in the

234    country (estimated by individually overlaying household location with our flood/drought

235    maps, see Section 3). in the poorest household quintile within a country and in the entire

236    population, respectively. If $I_p$ is lower than zero, poor people are less exposed to

237    floods/droughts than average. If $I_p$ is above zero, poor people are more exposed than

238    average. Since the wealth index is comparable only within and not between countries, the

239    PEB quantifies whether poor people are more or less exposed compared to the entire

240    population *within* a specific country. Aggregation of all wealth index data for all countries

241    and computation of a single global PEB is not possible with the data currently available. We

242    tested our method for robustness regarding uncertainty in the geographical location and

243    sample size using the methods described in Supplementary A.4, and robustness estimates

244    are used in the description of our results.

245    **4.   Results and discussion**

246    All results are summarized in Table 1. Below we describe and analyse the distribution of the

247    results for floods and droughts.

248    **4.1. Geographic distribution of the PEB under present-day climate**

249    **4.1.1.   Floods**

250    Figure 2 shows the PEB for floods with a return period of 10 years. The results for a higher

251    return period of 100 years exhibit very similar patterns (not shown here). For floods at the

252    national-level, under present-day climate conditions 34 out of the 52 countries show a

253    significant result when testing the exposure bias by means of bootstrapping. Of these 34,

254    about half (17) exhibit a disproportionally high exposure of poor people to floods. This result

255    supports the general notion that the relationship between poverty and disaster exposure is

256         impacted by multiple channels and is therefore complex. For instance, where non-poor are

257         more affected by floods, this could mean that the regions investigated offer amenities to

258         richer households, or that the areas are equipped with flood protection to facilitate

259         households. Using country-level population data (World Bank, 2015), we find that these 17

260         countries include 60% of the analysed population.

261         Moreover, regional patterns become visible. In particular, countries in Southern

262         Africa, the Horn of Africa (except Ethiopia, Rwanda, Zimbabwe and Mozambique), and Egypt

263         have a disproportionally high exposure of poor people to floods, although not all countries

264         show significant results (Tanzania and Democratic Republic of Congo). In Western Africa, the

265         results are mixed, although in countries with larger rivers and delta areas (notably Benin,

266         Nigeria and Cameroon) there appears to be a tendency towards poor people being

267         disproportionally exposed to floods. In Asia, poor people are disproportionally exposed (by a

268         moderate but significant amount) in Indonesia; the same can be seen for Central and South

269         America in Colombia and Guyana.

270         There are also several countries where poor people are less exposed to floods than

271         average. These include some of the Asian countries of our sample (Cambodia, Nepal and

272         Philippines, although the PEB for the last is insignificant), some West African countries, and

273         most of the countries investigated in Central and South America.

274

275         The same analysis was performed using a quintile subdivision over only rural and

276         urban households (that is, examining the PEB only within urban areas and only within rural

277         areas). The results for urban households demonstrate a clear difference: in most countries

278 poor urban households are clearly more exposed to floods than the average urban

279 population (Figure 3). Of the 30 countries with significant results, 22 exhibit a positive

280 exposure bias (73% in population terms). This suggests that the national poverty exposure

281 bias may be largely driven by the wealth differences and hazard exposure differences

282 between rural and urban households. There is no such strong signal for rural households,

283 suggesting that different mechanisms may be at play in rural and urban settings. For

284 instance, land scarcity may be more acute in urban areas (than in rural areas), creating a

285 stronger incentive for poor people to settle in risky areas due to lower prices. We have also

286 tested how spatially variable the overrepresentation of poor people can be, by performing

287 an additional assessment on much more local scale in appendix B for Morocco and Malawi.

288 This suggests that very local differences in exposure may be experienced as well.

### 4.1.2. Droughts

290 Figure 4 shows country level PEB for droughts with a return period of 100 years. Again, the

291 results for other return periods are similar, although the very low return period results

292 yielded no exposed households in many countries. Of 30 countries with significant results,

293 24 exhibit a disproportionally high exposure of poor people (85% in population terms). In all

294 countries studied in Asia and in many countries in Southern and Western Africa, we find a

295 clear signal that poor households are more exposed to droughts than average. For instance,

296 Ghana, Togo, Benin, Nigeria and Cameroon in a row all show a signal of higher exposure to

297 droughts of poor households compared to average. Other countries to the north and west

298 show the opposite result, i.e. more exposure to droughts for non-poor households. In

299 Central and South America, poor people appear less exposed in Bolivia and Peru, but more

300 exposed in Colombia, Guyana and Honduras.

301     Many Sub-Saharan African countries show a positive PEB for droughts, as well as

302     floods. In many parts of Africa, many poor people are subsistence farmers, and therefore

303     very dependent on reliable rainy seasons, which makes them more vulnerable to drought. A

304     similar analysis for rural and urban households does not reveal significant differences with

305     the country-scale analysis (see Supp Figures 4 and 5). This may be due to the different scales

306     of flood and drought hazards. Our flood indicator (and flood processes in general) has a

307     higher spatial resolution (and variability) than drought.

308

309     **4.2. The impact of climate change**

310     Climate change is likely to increase the number of people exposed to floods and droughts.

311     To estimate the range of increase in population exposure, we overlay future projected flood

312     and drought hazard maps with present-day population density data[2]. We use a high-

313     emissions pathway consistent with a 4°C increase in global temperatures, the

314     Representative Concentration Pathway (RCP) 8.5. We run the analysis for five GCMs[3]. Across

315     the GCMs, for droughts we find that the number of people exposed could increase by 9–17

316     per cent in 2030 and 50–90 per cent in 2080. For floods, the number of people exposed to

317     floods could increase by 4–15 per cent in 2030 and 12–29 per cent in 2080.

318     To assess how poverty exposure may change in the future due to climate change, we

319     calculate PEB for a low-emissions pathway RCP 2.6 (consistent with a 2°C increase) and high-

320     emissions pathway RCP 8.5 (consistent with a 4 °C increase) and for five GCMs. To ensure

---

[2] For present day population, Landscan is used (http://web.ornl.gov/sci/landscan/)
[3] 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.

321 that we only see the impact of climate on exposure, we do not include compounding effects

322 such as migration and population growth.

323 The PEB does not change significantly under the two different future climate

324 scenarios and is therefore not displayed. Of course, hazard does not drive exposure and

325 exposure bias alone. The expectation is that PEB will change in the future due to other

326 driving mechanisms not assessed in this paper, such as migration, changes in the spatial

327 distribution of poverty, or the general increase in income within countries. Countries with

328 rapid urbanization may exhibit major changes in flood exposure patterns in the coming

329 decades, independently of climate change and other changes in hazards.

330 Regions where climate change causes an increase in the annual expected number of

331 people exposed to floods and droughts, and where poor people are already more exposed

332 than average (i.e. $I_p > 0$) should be treated as highly climate-sensitive regions for poor

333 people. To locate these, Figure 5 shows the percentage change per country in the annual

334 expected number of people exposed to floods between 1980 and 2050, based on the

335 household data and RCP 8.5, and Figure 6 shows the same for droughts (Table 1 also

336 reproduces results for all countries). RCP 2.6 shows similar changes in exposure, although it

337 takes longer before these changes are reached. In some countries, the number of flood-

338 exposed people under climate change rises rapidly; this is the case in the Horn of Africa,

339 parts of West Africa, Egypt, Bangladesh, Colombia, and Bolivia. For droughts, the different

340 GCMs show more disagreement in drought extremes, causing less significant results.

341 However, if we use the GCM ensemble mean we see that in particular West African

342 countries show an increase in the number of exposed people.

15

343      Finally, we have determined countries where a combination of disproportionally

344 exposed poor and exposure increase is observed. We have determined these as countries

345 with a PEB larger than 10% (i.e. poor people are disproportionally exposed) and an increase

346 in the amount of total exposed people larger than 10%. Under RCP 8.5, in 2050, the marked

347 countries include Egypt, Guinea, Kenya, Nigeria, Sierra Leone, Uganda and Bangladesh. For

348 droughts, only Nigeria, Ghana and Togo are facing this situation.[4] These are predominantly

349 African countries, above the equator. Here, climate change-induced flooding will likely hit

350 poor people the hardest, although less than half of the countries have both an overexposure

351 of poor people to floods and an expected increase in flood risks due to climate change.

352 **5. Limitations and recommendations for further research**

353 We found a high variability in results between countries; poor people are not over-exposed

354 to natural hazards everywhere. However, the analysis is limited by data availability, as the

355 DHS samples are too small to look at regions and within-country variability. The limited

356 number of households per country has implications for the results for droughts in particular:

357 in many countries, there is no overlap between zones with extreme drought conditions (e.g.

358 a minimum of 3 months drought, at 100 year return period yielded only 15 countries with

359 significant results) and households, meaning that no estimate of the PEB for droughts could

360 be made in these cases. A larger number of observations per country would therefore make

361 the results of our analysis more robust.

362 A related limitation is the spatial scale of the analysis. DHS samples are rarely representative

363 within sub-national regions, which limits our ability to examine the poverty exposure bias

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[4] 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)

364     within specific regions of a country. Higher-resolution data (e.g. poverty maps within a city)

365     would be able to better capture dynamics at the local level, where lower land prices may

366     push poorer people into more risky areas. Furthermore, the DHS data are clustered with

367     between 500-1000 clusters per-country. This modest number of clusters means that some

368     areas that are flood or drought prone may not be covered by the DHS data, limiting our

369     ability to test robustness.

370     Ideally, we would compare our results across countries and not just within them. However,

371     the wealth index calculated by DHS is country-specific, meaning that the same value for the

372     wealth index across two different countries may imply a different level of wealth. While

373     some authors have recently suggested the DHS wealth index may be compared across

374     countries (Rutstein and Staveteig, 2013), country-to-country comparability remains difficult.

375     This is one reason why we use relative thresholds (e.g. quintiles) rather than absolute ones.

376     Another reason for the use of relative numbers is that, in case of an absolute poverty

377     threshold in some countries an overwhelming majority of the population would be classified

378     as poor, hampering the envisaged analysis.

379       In this study, we have not investigated factors that influence the vulnerability of

380     households to flooding such as the building quality, or other determinants of flood impacts

381     such as flood duration, (Dang et al., 2010; Parker et al., 1987), and its impact on indirect

382     losses such as loss in output and revenue and economic disruption (Lekuthai and

383     Vongvisessomjai, 2001) and flood-related health issues; and flood level rise rate which is

384     especially important in terms of mortality (Jonkman et al., 2009). More research is required

385     to examine how these could impact on poverty (for a review, see Hallegatte et al., 2017).

386    Similarly, households that are highly vulnerable to droughts (e.g. with assets strongly

387    relying on water) may already experience problems during a one-month drought condition,

388    although others may only experience problems if the drought lasts three months or more.

389    To assess the robustness of the drought indicator applied, we also tested our results using a

390    one-month and six-month threshold (shown in Winsemius et al., 2015a). More people are

391    exposed with a one-month threshold than with a six-month threshold. For the aggregated

392    PEB results, we could only find a significant number of exposed households in six countries

393    using a six-month drought threshold with a return period of 10 years. This increases to up to

394    50 countries, when considering one-month droughts as threshold with a 100 year return

395    period. Notably, median PEB values are above zero for the 100 year return-period drought,

396    and decrease toward and below zero for lower return period (10 years) droughts and higher

397    drought thresholds.

398    This suggests that the small sample sizes make it difficult to find a robust exposure bias

399    pattern in many countries. Nonetheless, we found consistent results on the sign of the PEB

400    for sub-Saharan Africa (Nigeria, Cameroon, Democratic Republic of Congo, Togo, and Benin

401    (not significant for a one-month threshold)), Southeast Asia (Philippines, Indonesia (not

402    significant for a six-month threshold)) and Colombia (when comparing the one, three and

403    six-month threshold results under the 100-year return period). Other countries showed

404    mixed results over the different threshold values and therefore results over these countries

405    should be treated with lower confidence.

406    **6.  Conclusions (626)**

407    The general conclusion of this study is that in a large number of the countries investigated,

408    poor people are disproportionally exposed to droughts and urban floods. But the situation

409     differs strongly between countries, within countries, and based on the type of hazard.

410     However, there are geographical patterns: the countries where the strongest bias in

411     exposure of poor is found are concentrated in Africa for both perils. 13 out of 23 countries

412     in Africa with significant results show a positive PEB, most of which are found in the region

413     under 10°N latitude. For droughts, we found significant results in only 30 out of 52

414     countries, due to the low amount of sample observations for our estimate of poverty

415     exposure bias. Nonetheless, from these 30 countries, 24 (representing 85% of the

416     population within the countries with significant results) show a positive poverty exposure

417     bias to droughts.

418     We find that in urban areas, poor people are disproportionally exposed to floods

419     compared to average, while such a signal is not found for rural households. This is

420     particularly noticeable in Africa, with the exception of several western African countries. In

421     some countries, the absence of disproportionate exposure of poor at national level may be

422     due to the large gap in wealth between cities and rural areas, combined with the fact that

423     flood hazard is often high in cities. The urban-rural gaps in income and flood risk may thus

424     hide the fact that poor people are more exposed.

425     A particular concern is the fact that some of the countries where poor people are

426     overexposed will also experience more frequent flooding or droughts in the future due to

427     climate change. We see this in Burkina Faso, Burundi, Egypt, Ethiopia, Guinea, Kenya,

428     Nigeria, Sierra Leone and Uganda for floods. For drought, Nigeria and Ghana were found to

429     be in this situation although results for Ghana were found to be less robust.

430     Exposure, the topic of this paper, is only one component of risk. Almost everywhere,

431     the other risk components – from protection to vulnerability to the ability to cope and

432    recover – are also biased against poor people (Hallegatte et al., 2016), which means that

433    even in places without a poverty bias, poor people may still experience higher risk.

434    Protection levels and quality are lower in poor countries and lower in poor neighbourhoods

435    and regions. Poor people live in low quality houses that suffer more damage in case of

436    floods, and they have most if not all of their assets in material form, making them more

437    vulnerable to floods. Finally, poor people have limited access to recovery support, such as

438    social protection and credit.

439    A recent report (Hallegatte et al., 2017) assessing the well-being impacts from

440    natural disasters suggests that when including all these dimensions – exposure,

441    vulnerability, and the ability-to-adapt, the impact of extreme weather on poverty is more

442    devastating than previously understood, responsible for annual consumption losses of $520

443    billion and pushing 26 million people into poverty every year. The results from this paper on

444    the distribution of the poverty exposure bias across countries were used as an input to the

445    report's analysis, and are one example of an application of this paper's findings.

446    Disaster risk management and poverty reduction go hand in hand. In countries where

447    poor people are disproportionally exposed to floods and droughts, it is particularly

448    important to integrate risk management policies within poverty reduction strategies, to

449    understand the underlying drivers of the exposure bias, and to correct it through better

450    land-use regulation and other supporting policies. Critically, such policies should support the

451    access of poor people to opportunities, and not stifle them. Where hazards will become

452    more frequent or more intense, implementing risk-sensitive land-use policies that protect

453    poor people, such as flood zoning and land entitlement, should be a priority.

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Figure 1. 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 under the EU-WATCH (1960-1999) scenario, with a return

period of 100 years.

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Poverty exposure bias RP: 10
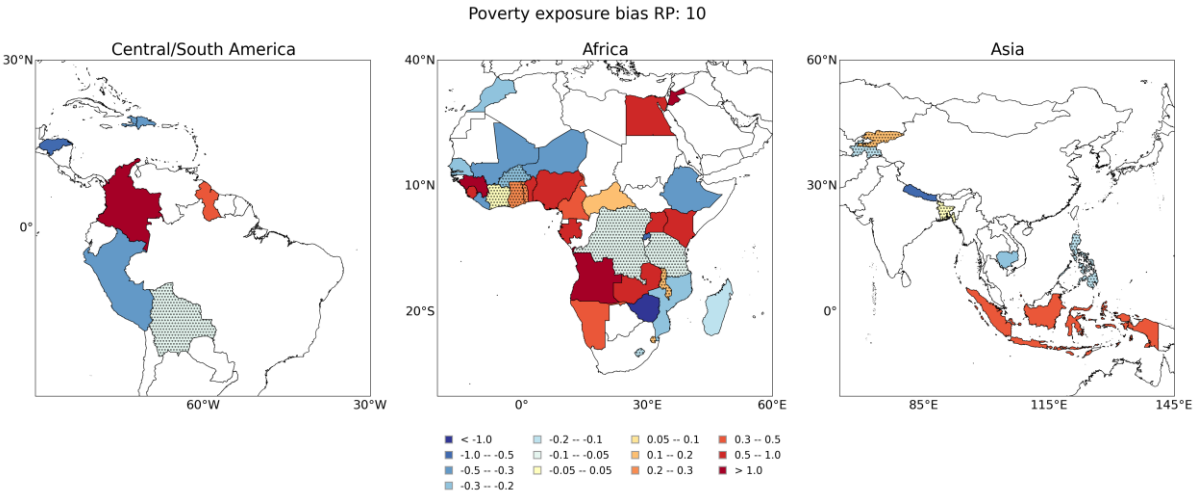
636

637 Figure 2. PEB for 10-year return period floods. White areas are not part of the 52 country

638 sample. Areas are dotted when there is a lower than 95% confidence that the sign of the

639 exposure bias is as estimated.

640

641



Urban poverty exposure bias RP: 10
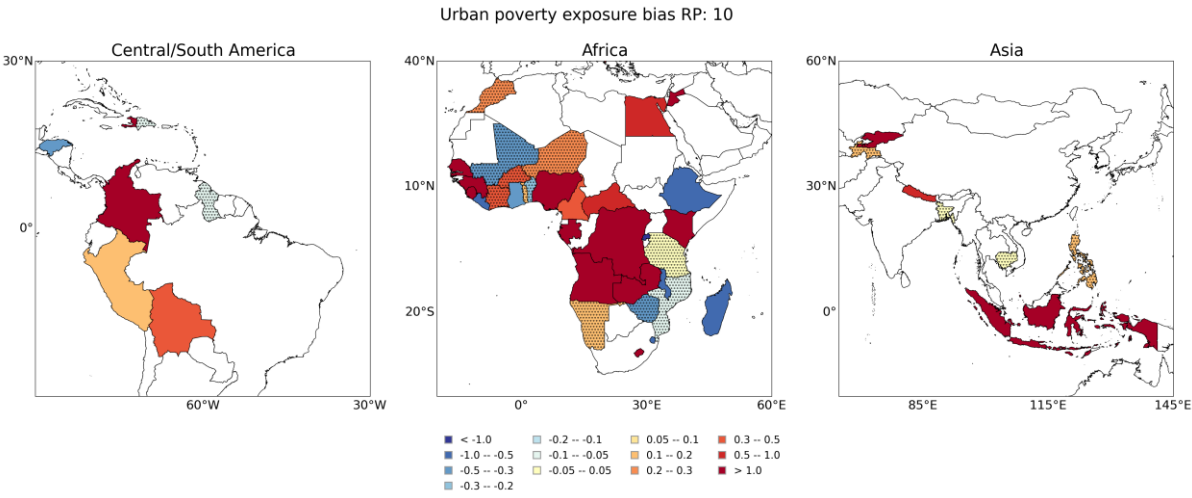
Figure 3. Same as Figure 2 but for urban households only. Note that the quintile subdivision used is based on urban households only.

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Poverty exposure bias RP: 100
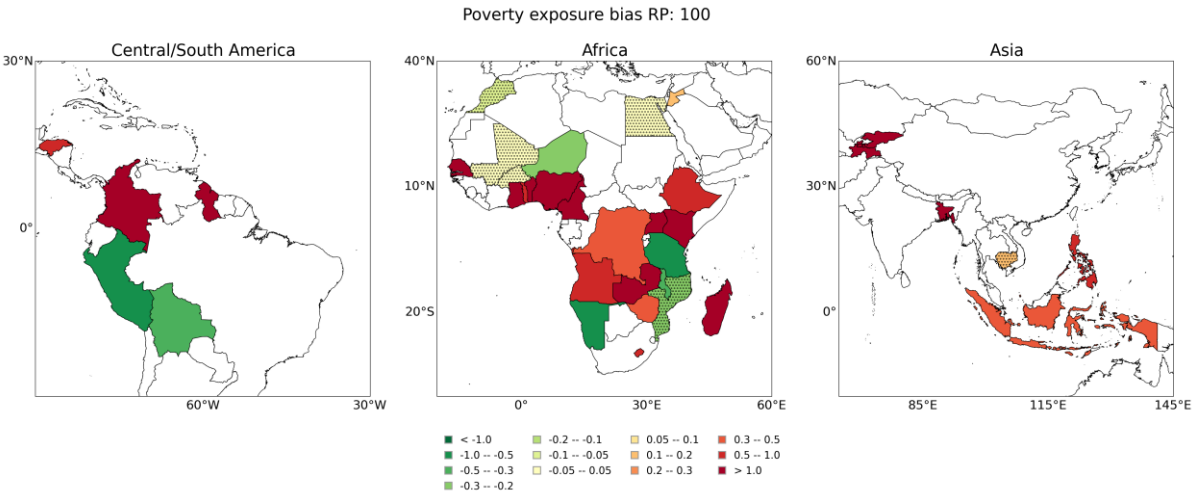
647

648 Figure 4. PEB for 100 year return period droughts. White areas are not part of the 52

649 country sample or have no exposure to droughts at all.

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rcp8p5 exposure increase [%] 2050

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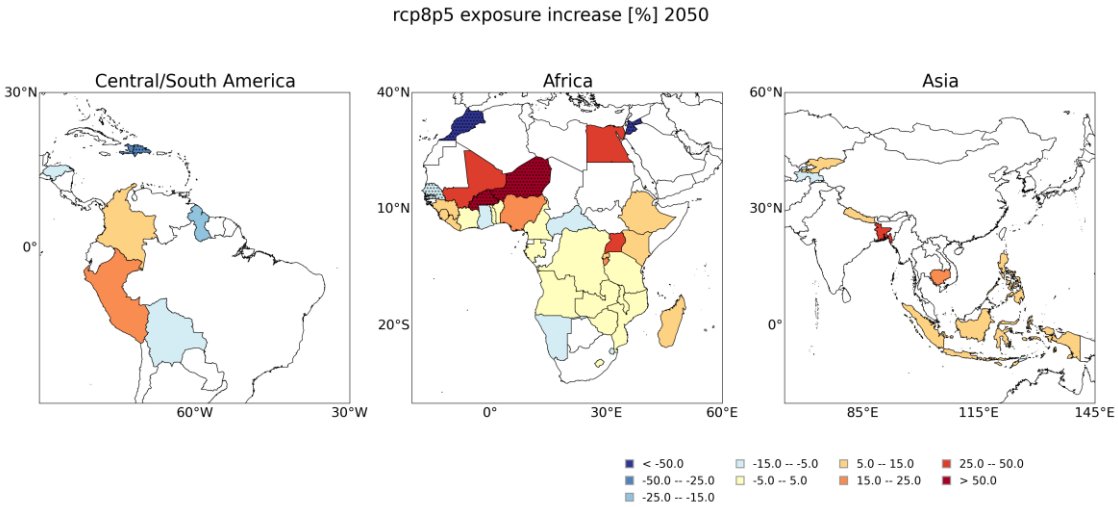
Figure 5. Percentage change in nation-wide average annual number of flood-exposed people
in our sample of 52 countries following RCP 8.5 from 1980 until 2050. The GCM ensemble
average is shown. Countries where the GCM ensemble standard deviation is higher than
50% of the GCM mean are dotted.

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658



rcp8p5 exposure increase [%] 2050

Figure 6. Same as Figure 5, but for droughts.

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661

662 Table 1 Poverty exposure bias and increase in exposure for floods and droughts. For

663 countries where none of the households within the DHS survey were exposed, not available

664 (NA) is stated. Significant results are in bold.

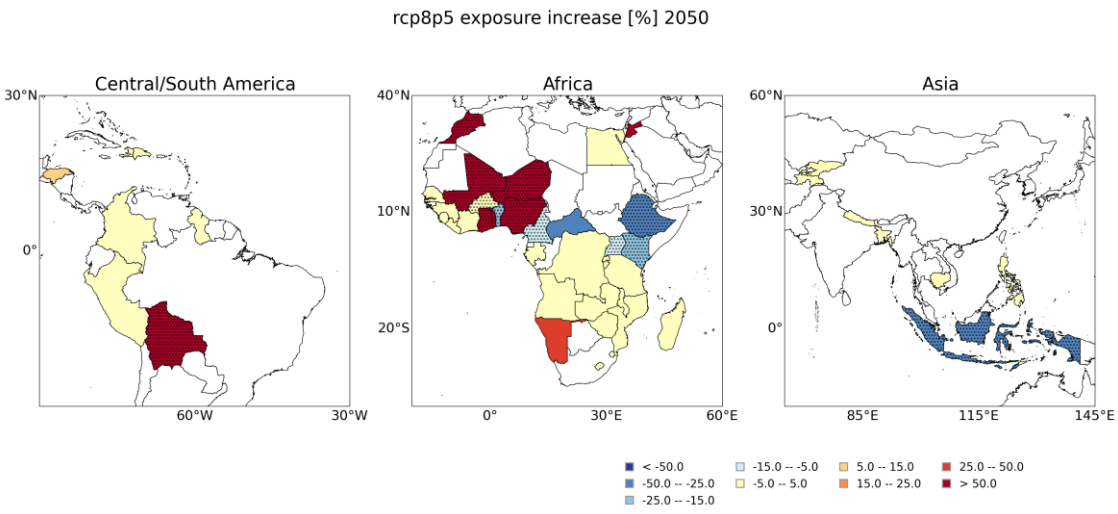| Country | Poverty exposure bias | | | | Increase in exposure of all households | |
| | Floods | | Droughts | | Floods | Droughts |
| | Nation-wide | urban | Nation-wide | urban | Nation-wide | |
|---|---|---|---|---|---|---|
| ALBANIA | -0.10 | **0.56** | NA | NA | **9.11** | 0.00 |
| ANGOLA | **1.82** | **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 | 0.00 | 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 | 0.00 | 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 |

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