Policy Research Working Paper 10619

Counting People Exposed to, Vulnerable to, or at High Risk From Climate Shocks

A Methodology

Miki Khanh Doan
Ruth Hill
Stephane Hallegatte
Paul Corral
Ben Brunckhorst
Minh Nguyen
Samuel Freije-Rodriguez
Esther Naikal

WORLD BANK GROUP
Poverty and Equity Global Practice &
Climate Change Group
November 2023

Abstract

Based on global datasets, 4.5 billion people were exposed to extreme weather events (flood, drought, cyclone, or heatwave) in 2019, an increase from 4 billion in 2010. Among exposed people in 2019, 2.3 billion people lived with less than $6.85 per day and about 400 million lived in extreme poverty (on less than $2.15 per day). This paper presents a methodology to estimate the number of people who are *at high risk from extreme weather events,* defined as the people who are exposed to these events and highly vulnerable to them. Vulnerability is proxied by a set of indicators measuring (1) the physical propensity to experience severe losses (proxied by the lack of access to basic infrastructure services, here water and electricity) and (2) the inability to cope with and recover from losses (proxied by low income, not having education, not having access to financial services and not having access to social protection). Estimates from 75 countries for which data on all indicators are available suggest that, in 2019, 42 percent of the total population (and 70 percent of people exposed) are at high risk from extreme weather shocks, if one indicator is enough to be considered as highly vulnerable. If high vulnerability is defined based on being vulnerable on two dimensions or more, then 12 percent of the total population (and 20 percent of people exposed) are at high risk from extreme weather shocks. The trend between 2010 and 2019 can be explored in a subset of countries covering 60 percent of the world population. In these countries, even though the population exposed to extreme weather events has been increasing, the number of people at high risk has declined. The exception is Sub-Saharan Africa where the number of people at high risk has increased between 2010 and 2019.

This paper is a product of the Poverty and Equity Global Practice and the Climate Change Group. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/prwp. The authors may be contacted at rhill@worldbank.org or shallegatte@worldbank.org.

Counting people exposed to, vulnerable to, or at high risk from climate shocks – A methodology

Doan, Miki Khanh ⓡ Ruth Hill ⓡ Stephane Hallegatte ⓡ Paul Corral ⓡ Ben Brunckhorst ⓡ Minh Nguyen ⓡ Samuel Freije-Rodriguez ⓡ Esther Naikal[1]

Keywords: Risk, Exposure, Vulnerability, Resilience, Climate change, Development

JEL: Q54, C81, D69

[1] Author order randomized using the American Economics Association author randomization tool.

1 INTRODUCTION

At any one time some households are experiencing income growth and moving out of poverty, whilst others are experiencing setbacks and falling into poverty (Dang and Dabalen, 2018). Poverty reduction requires a focus on both advancing welfare gains and protecting households from setbacks. Extreme weather events are one type of setback experienced by households and are increasing in frequency with climate change (Hallegatte et al., 2016). Not only do these extreme weather events increase poverty when they occur, they cast a long shadow on welfare, as they can result in lost assets and investments that limit welfare gains for many years to come (Dercon, 2004; Lybbert et al., 2004; Alderman, Hoddinott, and Kinsey, 2006; Aizer and Currie, 2014; Dercon and Porter, 2014; Andrabi, Daniels, and Das, Forthcoming). Extreme weather events can also keep people poor, sometimes because they are so frequent that they make capital accumulation impossible and sometimes because households engage in costly behavior to avoid or respond to them (Elbers, Gunning, and Kinsey, 2007; Carter and Lybbert, 2012; Karlan et al., 2014).

In this paper, we propose a method for estimating the number of people at high risk from extreme weather events, and provide preliminary estimates based on available data. Because everybody is at risk, since every individual is – at least to some extent – vulnerable to extreme weather events, the indicator aim to identify people who are at *high* risk or *highly* vulnerable to these risks.

We use the traditional framework in which risk is the combination of hazard, exposure, and vulnerability. The hazard is the potential occurrence of an extreme event; the exposure is the people affected in that location; and vulnerability is the propensity or predisposition of these people to be adversely affected.[2] The approach taken in the paper is to use data to proxy for vulnerability, rather than using modeling to estimate risk.

The challenge is that measuring risk, vulnerability, or the expected economic and welfare costs of future climate events requires measuring something that has not occurred yet. There are two broad approaches in the literature used to do this. The first one takes a modeling approach and estimates the welfare (or consumption) cost of these events in a probabilistic framework (as in Hallegatte et al. 2017), making it possible to define a population at high risk based on a threshold in welfare losses (e.g., the people with high expected annual welfare loss, or the people with high probability of experiencing large losses).

The other approach identifies and combines proxies for high vulnerability or high probability of experiencing large losses. Proxies are characteristics of households that are observed today and are highly correlated with vulnerability or the likelihood of large losses from extreme weather events. It is this latter approach that is explored in this paper, using a selection of the proxies informed by a large literature, including ex post analyses of past disasters and modeling work.

This methodological work is being undertaken to contribute to discussions on how to measure progress on the World Bank's new vision of "a world free of poverty on a livable planet". While the final choice of indicators, cutoffs and data used will need further work and discussions, the goal of this paper is to present a methodological approach and preliminary estimates, with the objective to contribute to discussions and

[2] Other estimates use different frameworks, sometimes separating the physical vulnerability of assets (as in catastrophe modeling focusing on asset losses) and the socioeconomic ability to cope with and recover from the losses (needed to estimate the full economic impact or the effect on welfare). Here, these two dimensions are merged into a broader vulnerability definition that include physical and socioeconomic aspects.

collect ideas and feedback on these issues. This paper should be considered work in progress and updated versions with more data and analyses will be published over the next months.

In this paper, we start by quantifying the number of people *exposed* to extreme weather events globally today. We find that a 4.5 billion people are exposed to an extreme flood, drought, cyclone, or heatwave. Of those exposed, 2.3 billion are poor at the $6.85 poverty line (the median poverty line of upper middle-income countries) and 390 million are extremely poor at the $2.15 poverty line (the median poverty line of low-income countries).

Then, we identify the exposed households who are particularly *vulnerable* and therefore *at high risk* of experiencing severe economic impacts from these events. There are many determinants of vulnerability but we can broadly group determinants into two aspects: (i) the physical propensity to experience severe income, asset or health loss and (ii) the inability to cope with and recover from the losses through income or transfers (public and private). We use available data to provide some indicative estimates on these two aspects of vulnerability.

Physical propensity to experience severe losses is proxied using data on access to water and electricity. These are chosen to reflect the ability of a household to still access clean water in the face of lack of water availability or flood-contamination of water supplies, and the ability of households to access cooling appliances to cope with heatwaves.[3] However, more work on the right infrastructure indicators to use is needed and different dimensions of physical vulnerability are important for different types of shocks, for instance access to markets and emergency services, or coverage by early warning systems that help anticipate and mitigation impacts of extreme weather.

Inability to cope or recover is measured as not having income to manage the impact of a shock; not having education to switch livelihoods or access information and resources to recover; not having access to public support such as social protection; and not having access to financial services.

In structure the measure is similar to the World Bank's multidimensional poverty measure (World Bank, 2018), although some of the dimensions considered are different and deprivations are counted just for those exposed to extreme weather events. In particular, we present the number of people highly vulnerable according to each separate indicator, and count the number of indicators according to which individuals can be considered highly vulnerable. A household is at high risk if it is exposed and highly vulnerable according to one or more dimensions.

The approach proposed is applicable to most countries. However, the data requirements are still intensive, as is the case with other multidimensional measures of household wellbeing. Each dimension captures an important aspect of vulnerability but reduces country coverage as not all surveys have all required measures. The dimensions chosen for the worked example in this paper were chosen because they had good coverage, but even then, the cost of adding each dimension in terms of coverage is clearly seen. Adding additional relevant dimensions – such as livelihoods or occupation or building quality – would make this challenge even larger and create a trade-off between coverage and comprehensiveness.

[3] Having access to basic infrastructure services is not an absolute protection against natural disasters, in particular if these services are interrupted or disrupted during an extreme event. In some cases, access to these services can even backfire, for instance if piped water become contaminated after a storm. However, people with access to these services can still be considered as less vulnerable than people who do not have access to them.

Although conceptually vulnerability is undeniably multifaceted, as work on this measure continues it will be important to assess whether the cost of each dimension (in terms of data requirements and the burden that places on coverage and updating) is worth the benefit in terms of identifying a different set of people as vulnerable than would be possible with a narrower set of measures. The limited pairwise correlation across the indicators used in this paper suggests that using several dimensions add value (compared with, e.g., using income as a unique proxy for vulnerability). However, further work will be needed to use data from multiple data sources such as by using survey to survey imputation.

Using the approach proposed and data readily available we generate an estimate for 75 countries and 77 percent of the world's population. If high vulnerability is defined based on a single dimension, as many as 42 percent of the population are at high risk from extreme weather shocks. This is 70 percent of the population that is exposed. If high vulnerability is defined based on two dimensions or more, then 12 percent of people (20 percent of those exposed) are at high risk from extreme weather shocks.

This work extends and complements previous work. For instance, Rentschler, Salhab, and Jafino (2022) calculates the number of people exposed to floods and in poverty. This paper builds on it by looking at other extreme weather events and assessing how many people are exposed to any one of these events with a similar severity and return period as used in Rentschler, Salhab, and Jafino (2022). It also extends the work by looking not only at those that are currently poor and exposed, but also those are at high risk from the adverse impacts of those shocks. Additionally, the recent IPCC report finds that approximately 3.3 to 3.6 billion people live in contexts that are highly vulnerable to climate change (IPCC, 2022).

There are also a number of global indicators that address the dimensions of climate risk and vulnerability (e.g., ND GAIN (Notre Dame Global Adaptation Initiative), INFORM (Index for Risk Management, UNDP), Global Climate Risk Index (German Watch)). The method proposed in this paper adds to this global indicator work by taking a measurement approach that is much more focused on household-level vulnerability and risk. Unlike other indices which use data aggregated to the national level for each of their dimensions of climate risk and vulnerability, which makes it challenging to aggregate across dimensions, we use the household as our unit of analysis, considering exposure and vulnerability at the household level. We overlay data on exposure to extreme weather events with household data at the subnational level, thereby providing a more granular and spatial assessment of vulnerable populations globally.

Finally, there are modeling efforts that measure global exposure to multiple climate-related or natural hazards, such as UN-ISDR (2015), Pesaresi et al. (2017), Maes et al. (2022). These estimates often focus on asset losses (i.e., the repair or replacement value of damaged or lost assets). Based on estimates of asset losses from UN-ISDR (2015), Hallegatte et al. (2017) estimated the number of people falling in poverty every year due to storms, floods, droughts, and earthquakes, the socioeconomic resilience (as the ability of households to cope with and recover from disaster losses), and the risk to well-being (as the expected loss of welfare due to natural hazards). As highlighted above, this paper follows a different approach by estimating the number of people with high exposure and using proxies to measure vulnerability rather than metrics based on monetary losses. However, the key drivers of vulnerability are similar, focusing on poverty and income, financial inclusion, coverage of social protection, and ability to respond. In as much as people lack these mechanisms their ability to respond to shocks is diminished and hence are considered vulnerable.

There are important caveats to this study and estimates.

First, these numbers only reflect those exposed to severe weather events, as the thresholds used to estimate these numbers were selected to reflect weather events that cause significant damage. Lower intensity events can still cause substantial impacts on poverty, perhaps cumulatively larger given they occur with higher frequency (Hallegatte et al., 2020). The estimates presented here do not consider events of all intensities nor all types of events, so it is important to note they do not represent the total number of people whose welfare is impacted by weather events.

Second, the people exposed or at high risk from extreme weather events are not the same as those exposed to climate change risks, even though there is a strong overlap, especially over the next decades. The approach based on extreme event proposed here may not capture the impacts of changes in average conditions, for instance when water scarcity makes it impossible to produce certain crops, even during good years, or when labor productivity is reduced by heat even during normal days. Also, this indicator will capture the vulnerability to droughts, even in places where climate change makes drought less likely. Replacing the historical hazard data by climate scenarios is relatively straightforward but would require agreement on the scenarios and models to be used. Our approach is justified by the fact that many climate risks will be experienced first as a change in the frequency and intensity of extreme events (e.g., sea level rise will first be experienced as more frequent coastal floods, even though it will eventually lead to permanent land loss). Capturing the risks linked to changes in average conditions but not extreme event would require a deeper adjustment to the methodology.

Third, the data choices and challenges that this paper sets out also highlights the need to invest in data and methods to increase our ability to identify and count who is vulnerable. Some of the data limitations have already been highlighted, and throughout the paper we highlight additional areas where further data investments are needed. Since reducing the number of people at high risk of climate hazards is important to achieve successful development and poverty reduction, it is important to improve how we monitor and track progress in these dimensions. This paper sets out one framework that can be used to do this, even though there is no unique definition.

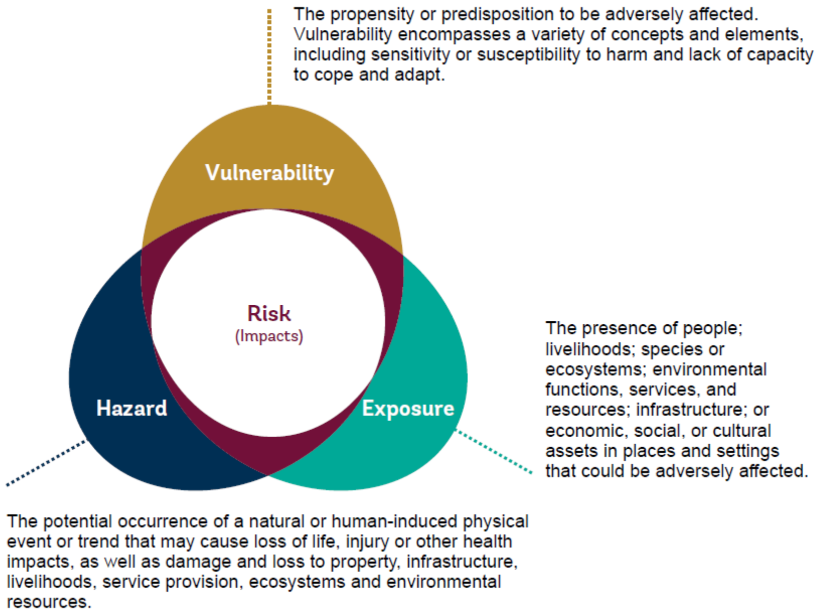
Finally, the appropriate definition of the methodology depends on how it will be used. At one extreme, everybody can be considered at risk from climate hazards, at least to some extent. Another extreme is to identify the people in the world who are at extremely high risk. The selection of the right thresholds and dimensions of exposure and vulnerability will need to depend on the use of the indicator and the objective of its measure. A final measure will require consensus around the core risks and the core dimensions of vulnerability and meaningful cutoffs to use. This paper uses thresholds that can be adjusted, depending on how the metric is to be used. We hope the framework presented promotes a data-based discussion, and a discussion that also encourages the investments needed to address data gaps.

Section 2 of this paper sets out how exposure and vulnerability are being defined, and the approach taken in the paper to measure vulnerability. Section 3 of this paper outlines how exposure, poverty and vulnerability are measured in this analysis and the data used. Section 4 presents result. Section 5 sets out an agenda for work on improving measurement of vulnerability and concludes.

2 Proposed approach to identifying those at risk

There are three components that determine the impact or risk of an extreme weather event on people: hazard, exposure, and vulnerability (Figure 1). Hazard in this case is the potential occurrence of an extreme weather event "the occurrence of a value of a weather or climate variable above (or below) a threshold value near the upper (or lower) ends ('tails') of the range of observed values of the variable" (IPCC, 2012) Exposure refers to what could be affected by the weather event in that location, such as the number and type of buildings, or in this case, the people residing in that location. Vulnerability is the propensity or predisposition of these people to be adversely affected and includes not only physical characteristics of the assets and livelihoods that determines a person's susceptibility to harm, but also the socioeconomic characteristics that determine its capacity to cope and adapt.

Figure 1: The impact of extreme weather events: hazard, exposure and vulnerability



Source: IPCC

Identifying those who are at risk from an extreme weather event requires (i) defining the extreme event and the likelihood with which it will occur, (ii) determining who is exposed, and (iii) identifying those who have high levels of vulnerability and are likely to experience severe adverse consequences. Given everyone is exposed to some risk and vulnerable to some extent, the value of this work comes in setting relevant definitions for extreme events and for levels of vulnerability. In this paper we focus on extreme events and high levels of economic vulnerability, in identifying households that are particularly vulnerable to economic impacts of shocks.

The next section discusses in detail how the first two are measured. We focus on four types of extreme events—floods, cyclones, drought and heatwaves—and consider different levels of intensity for these events and different probabilities that these events are expected to occur. The number of people exposed to these events are considered for different thresholds of shock intensity and probability. Gridded data on hazard probabilities and population are used to generate these estimates.

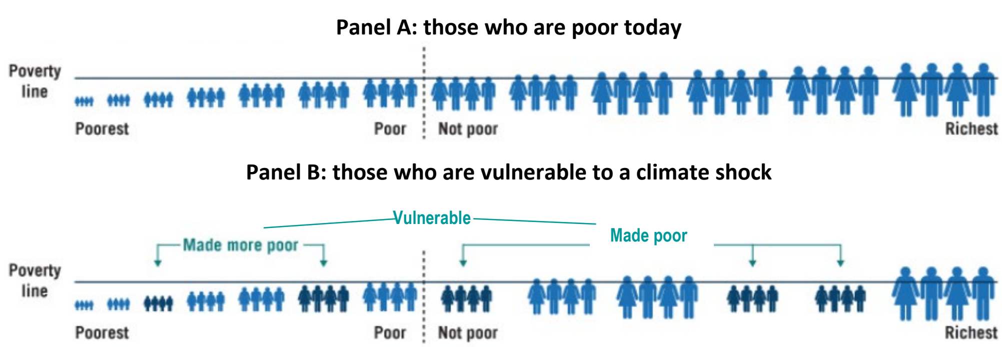
The biggest challenge is in identifying which of these exposed households are highly vulnerable to experiencing adverse consequences of weather events. Figure 2 highlights the empirical challenge. For a given measure of welfare, we have well established measures to identify those who are above or a below a given threshold, and this is something that we can observe at a given point in time using survey data. In the case of monetary poverty, we can consider households whose consumption or income per capita is below a poverty line (panel A). Thus, for households that are exposed we can assess which households are currently extremely poor in that their consumption is less than the international poverty lines of $2.15 a day, and which households are poor in that their consumption is less than $6.85 a day. We present estimates of this using available data.

However, vulnerability needs to identify which households above and below a poverty line today are particularly vulnerable to their welfare worsening with a given event in the future—in this case an extreme weather event (panel B). This is not something that can be directly observed in household survey data since extreme events by definition occur only rarely and may not be included in the recent data. Instead, it needs to be modelled or proxied with existing, observed household characteristics.

The vulnerability of a household to an extreme weather event will depend on the characteristics of the household that determine the event's initial impact and the ability of a household to cope with that event (Ligon and Schechter, 2003; Günther and Harttgen, 2009; Hallegatte et al 2017; Dang and Lanjouw, 2017; Hill and Porter, 2017; Gallardo, 2018). This is reflected in the IPCC definition, vulnerability includes both "the sensitivity or susceptibility to harm" and "the lack of capacity to cope and adapt". So, for example, a household may experience a loss in agricultural income from a weather event. The size of that agricultural income loss will depend on the ability of the household to protect yields from a drought by using irrigation for example, or its ability to move cattle to protect them from loss in a flood. If agricultural income is lost, the size of total income losses will depend on whether the household is able to compensate for losses in agricultural income by earning income from other activities. If total income is lost the degree to which this impacts consumption will depend on its ability to smooth consumption through borrowing and saving or receiving remittances from friends and family. All these aspects of a household's characteristics will determine its vulnerability to weather shocks.

While there will likely be considerable overlap between those that are poor and vulnerable (out of those exposed), it is not complete. In particular many households that are not poor are vulnerable to extreme weather events and can be made poor by these events.

Figure 2: Identifying those who are vulnerable to a climate shock



Measuring vulnerability on a global scale for four different types of weather event requires selecting indicators that proxy which households are those that are vulnerable. There are many indicators that could be used. When households are confronted with climate-related shocks, the degree to which their welfare is affected depends on various factors. Deficiencies in these dimensions increases their vulnerability to climate shocks. We propose that indicators should be selected to capture two aspects of vulnerability: (i) a person's physical propensity to experience severe income, asset or health loss, (ii) the ability of a person to cope with and recover from asset or income loss. In this paper we select indicators to cover both aspects using data that was readily available for multiple countries:

- For physical vulnerability we consider access to improved water and electricity. This is a very small set of infrastructure measures, driven in part by evidence in the literature, but also by what measures were readily available at the subnational level on a global scale. Other measures that could be considered are access to sanitation or irrigation, mobility and access to markets or services, investments in water drainage infrastructure, improved household dwelling structures, resilient farming practices, and access to early warning systems.
- For ability to cope and recover, we consider not having sufficient income to manage the impact of a shock; not having education to switch livelihoods or access information and resources to reduce income losses; not having access to public support; and not having access to financial services.

The selection of these variables is motivated further in a subsequent section, along with a description of the data used to measure them.

Transparency and coverage are important characteristics of a global measure. Transparency may require a certain simplicity, because a measure that becomes too complicated can be hard to interpret, and the drivers of change can be opaque. Coverage requires data being available for as many countries as possible and updated frequently over time. Although adding more dimensions of vulnerability is attractive given the multidimensional nature of vulnerability, this can often run counter to achieving simplicity and coverage. Survey data is the source of the indicators of vulnerability used here and survey data is unavailable for some countries on each indicator. Coverage sometimes declines when an additional indicator is added (World Bank 2018). It is thus important to ascertain that adding a new indicator adds value in that it allows a good number of people to be identified as vulnerable that would not have been identified without its inclusion. In other words, an indicator adds value when its correlation with other indicators is low.

In the absence of a model, an aggregation of indicators into a single index requires deciding how the different indicators are to be weighted[4], whether to take into account the depth of deprivation on a given indicator, and on how many indicators a household has to be deprived to be considered vulnerable (see World Bank 2018 for a full discussion of considerations). We follow the approach of the World Bank's multidimensional poverty measure (World Bank 2018) and present the number of people vulnerable according to each separate indicator and counting the number of indicators that individuals are deprived on. As with the World Bank's multidimensional measure of poverty, the index is thus a simple expression of an approach whereby the number of deprivations for one person are counted (Atkinson 2003).

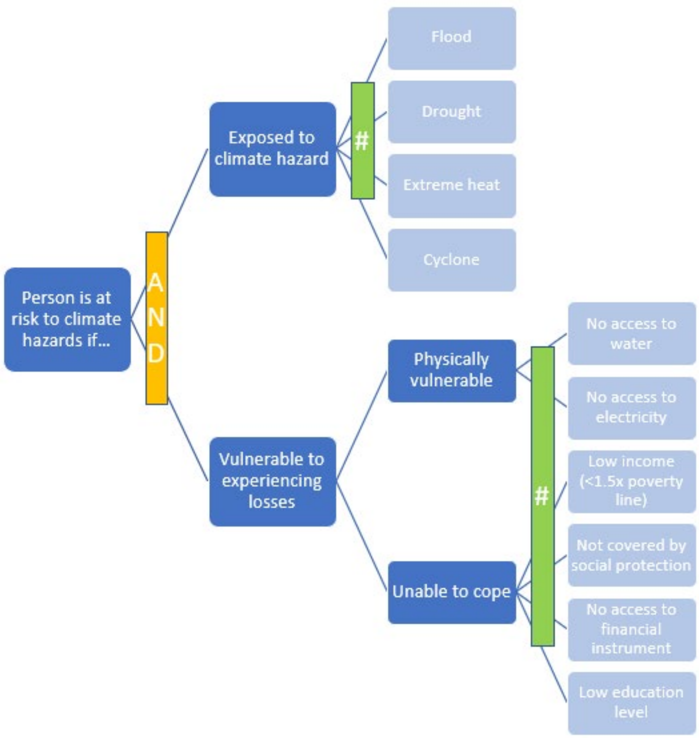
People at risk are people that are exposed and vulnerable. Figure 3 summarizes the measure, highlighting that someone is at risk if they are exposed, and vulnerable. While we propose this core structure of the measure of at risk, this still leaves much to be decided such as the selection of events, probabilities, indicators and number of events and indicators on which someone is exposed or vulnerable. We propose that someone is exposed if they are exposed to any one natural hazard and vulnerable if they are

[4] Applying no weights is also a choice on weighting as it assumes all dimensions are equally important.

vulnerable on two or more of the dimensions considered.[5] Other hazards, dimensions of vulnerability and counts could be considered.

The next two sections provide more detail on how exposure is determined and on how vulnerability is measured. Exposure is measured using gridded hazard and population data, while vulnerability is measured using survey data aggregated to subnational units larger than grids, but smaller than a country. We thus make a large assumption that vulnerability rates are uniform across the unit they represent, and further work is needed to determine the size of the bias in this assumption (see final section).

Figure 3: Measuring those at risk



The dark blue squares highlight the proposed structure and the light blue squares indicate the specific application used in this paper.

3 MEASURING EXPOSURE

We estimate the number of people who live in places that are exposed to four types of extreme weather events: flood, drought, heatwaves, and cyclones. This requires first defining each extreme event by specifying thresholds for their intensity and then defining the probability that such an event will occur (or return period). We identify the population exposed to extreme events defined by several intensity thresholds and return periods by overlaying global gridded hazard and population datasets.

The intensity of each event can be measured using physical units, for example, the maximum inundation depth in meters for floods, or the maximum sustained wind speed in meters per second for cyclones. Characterizing the intensity of events with a single metric is an important simplification since other

[5] It can also be informative to look at the number of events they are exposed to/vulnerable on as a measure of severity of exposure/vulnerability.

features of an event may be important determinants of, for instance, the speed or duration of flooding. This simplification is necessary to define a unique severity threshold per hazard and we use intensity metrics well established in the literature. An intensity threshold helps focus on events that may cause substantial losses or exclude those that are, in general, easy to cope with.

Return periods are a common, but sometimes misunderstood, metric describing the occurrence of hazards. They describe the likelihood that a hazard event occurs at or above a specific intensity: in any given year, there is a 50% probability of experiencing an event as intense or more intense than the 2-year return period event; and a 1% probability of experiencing an event as intense or more intense than the 100-year return period event. It means that it is not impossible to experience two 100-year events in a single year. Table 1 shows the likelihood a person will experience events of different return periods, assuming the hazard distribution does not change over time.

When we count the number of people exposed to the 100-year flood with a threshold at 50 cm, we count the people who have more than a 1% chance of experiencing a 50-cm flood in any given year. This will include people who are much more likely to be flooded (e.g., the people who get flooded every other year in many tropical cities), as well as people who have a 1% chance every year to be affected by much deeper floods (e.g., a 2m deep flood). In sum, we consider locations exposed if events exceed a given intensity with a minimum probability (or maximum return period).

Table 1: Return periods and likelihood of experiencing events

Return period of event	Likelihood of a person experiencing event…			
	in 10 years	in 20 years	in 50 years	in a lifetime
10-year	65%	88%	99%	99%
20-year	40%	64%	92%	99%
100-year	10%	18%	39%	63%

The hazard datasets used for analysis are summarized in Table 2, including the return periods and intensity thresholds initially considered for each type of event. All datasets are publicly accessible. Different thresholds are initially considered, but for much of the analysis the return period and intensity thresholds are set to specific values discussed further below.

Table 2: Hazard data and thresholds defining exposed places

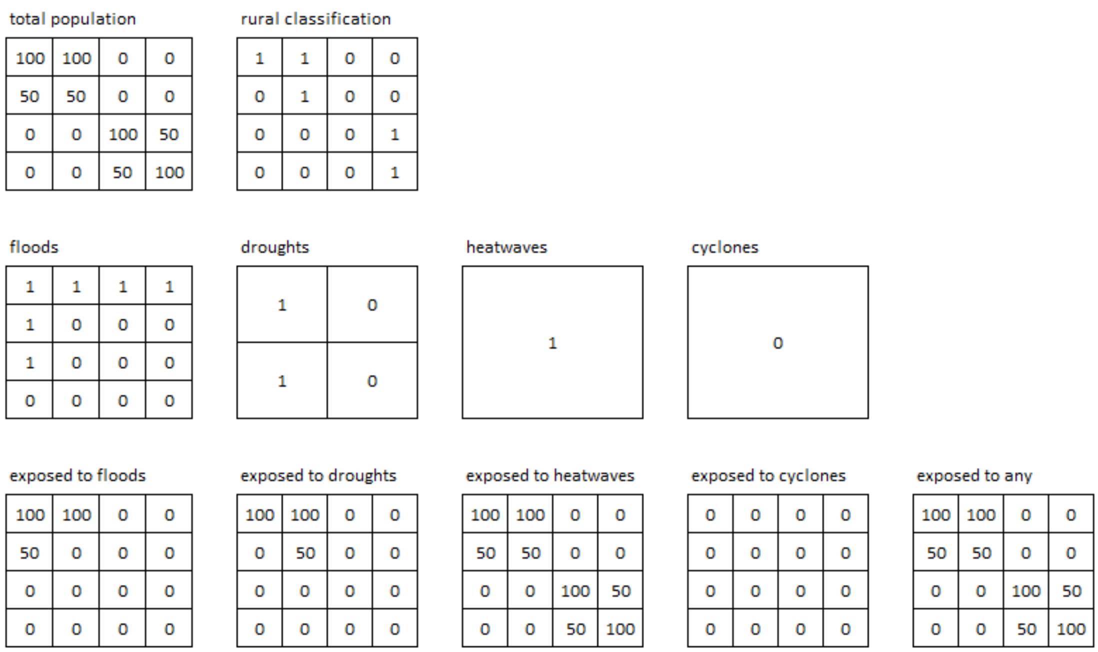
Hazard	Source	Spatial resolution	Type	Return periods (years)	Intensity thresholds defining extreme events
Flood	Rentschler, Salhab, & Jafino (2022)	3” (~90 m)	Modelled	100	An inundation depth of at least 0.15 m, 0.5m, 1.5m
Agricultural drought	FAO (2023), and Schiavina, Melchiorri & Pesaresi (2023)	~30” (1 km)	Historical	5,10,15,20,40*	At least 30 percent, and at least 50 percent of cropland or grassland affected in any season, confined to rural areas
Heatwave	Ridder et al. (2017)	5’ (~10 km)	Modelled	5, 20, 100	A three-day running mean maximum Wet Bulb Globe Temperature (WBGT) of greater than 32°C, 33°C, 34°C, 35°C, and 36°C
Cyclone	Bloemendaal, Haigh, de Moel et al. (2020)	6’ (~11 km)	Modelled	10, 20, 30, 40, 50, 60, 70, 80, 90, 100	A wind speed of at least the Category 1, Category 2, and Category 3 thresholds

Notes: * If the threshold was reached in any year since records began 39 years ago (1984-2022).

We use global gridded population data (GHS-POP – R2023A) from the Global Human Settlement Layer (GHSL) produced by the Joint Research Centre, European Union (Schiavina, Freire, Alessandra, and MacManus, 2023). The dataset provides residential population estimates at 5-year intervals from 1975 to 2030 with a spatial resolution of 3 arcseconds or 30 arcseconds (approximately 90 m and 1km, respectively). The population estimates are disaggregated from census or administrative units to grid cells, informed by the distribution, density, and classification of built-up areas derived from satellite imagery mapped for the GHSL in the same year.[6]

We estimate only the population directly exposed to each shock as indicated by the spatial union of hazard maps and population headcount at the grid cell level. Importantly, our restriction to local exposure means that our estimates do not consider nonlocal impacts of extreme events, such as the impact of hazards on markets and prices due to crop loss or damage to infrastructure.[7] Nor do we account for other important spatial spillovers associated with extreme events, such as migration away from affected areas, or secondary hazards including diseases.

Figure 5: Overlay of population and hazard layers



Notes: The figure shows a simplified representation. The categorical hazard data is first resampled so that grid cells align with the population grid. Differences in the size of grid cells shown reflect qualitative differences in the resolution of hazard data but are not to scale. Arbitrary numbers are chosen to demonstrate how we calculate the number of people exposed to each hazard and any of the four hazards. The first row shows the total population and the rural classification for the same 4x4 grid. The rural classification is used to determine exposure to drought. The second row shows binary hazard maps for floods, droughts, heatwaves, and cyclones. The last row shows the number of people exposed to each hazard and to any hazard.

[6] Schiavina, Melchiorri, Pesareri, Politis et al. (2023) describe the GHSL 2023 data in detail. No single gridded population dataset can satisfy all applications (Leyk et al., 2019; Yin et al., 2021). The populations of GHSL are closer to statistical values than alternatives such as WorldPop because the main data source is statistical data and the spatialization method maintains the population in the administrative region (Chen et al. 2020). This is suitable for our global application and merging with representative survey data.

[7] Estimates suggest that the impact of infrastructure disruptions on businesses and households is much larger than the direct impact on infrastructure (that is the cost of repair and reconstruction).

The method to estimate exposure proceeds as follows. First, we generate categorical hazard maps for several return periods indicating the areas exposed to events exceeding each intensity threshold. Second, since the hazard and population data come from different sources with varying resolutions, we resample the hazard maps to align grid cells with the GHS population grid using nearest-neighbor matching. For flood, we resample the 3-arcsecond flood map to align with the GHS population grid of the same 3-arcsecond resolution.[8] We count the population exposed to different levels of flooding at this high resolution and then aggregate to a 30-arcsecond grid (approximately 1 km) for overlaying with other hazards.[9] Hazard data for drought, heatwaves and cyclones uses a coarser spatial resolution than the flood maps (1 km, 10 km, and 11 km, respectively), also reflecting that these events are less localized. We resample each of these three hazard maps to the 30-arcsecond GHS population grid. Finally, we calculate the number of people exposed at grid level by overlaying the population grid. Figure 5 illustrates the approach to estimating the number of people exposed to each type of extreme event and to any.

In the following subsections we describe the hazard data used in more detail, and how the four hazards are overlaid.

3.1 Flood

We use flood data from Rentschler, Salhab, and Jafino (2022) which indicates the maximum inundation depth for a 100 year return period considering the three most common flood types: (1) Fluvial flooding, occurring when intense precipitation or snow melt causes rivers to overflow; (2) Pluvial flooding, occurring when rainwater builds up beyond the absorptive capacity of soil; and (3) Coastal flooding, caused by storm surges and high tides in coastal areas. Country-level pluvial and fluvial flood data are from the 2019 version of the Fathom Global 2.0 flood hazard dataset (Sampson et al., 2015). These were combined with a separate coastal flood hazard map generated using the LISFLOOD-FP hydrological model (Rentschler et al. 2023). While Rentschler, Salhab, and Jafino (2022) provide gridded exposure headcounts to flood risk by admin area, we ignore the existing population count in their dataset and use only the information on inundation depths for 100-year return period flooding. We merge the data for all 187 countries to create a global dataset at a 3-arcsecond resolution and consider the following inundation depths as thresholds for being exposed to floods: 15cm, 50cm and 150cm.[10] It is important to note that the dataset used does not account for artificial flood protection structures. Although the use of the undefended flood maps may lead to an overestimation of exposure in areas with flood protection systems, there is evidence that many low-income lower-middle income countries do not have any flood protection system against even light flooding (Hallegatte et al., 2017; Rozenberg and Fay, 2019; Rentschler, Salhab, and Jafino, 2022).

[8] The maximum misalignment using nearest neighbor resampling at this resolution is approximately 45 meters.

[9] Smith et al. (2019) use the High-Resolution Settlement Layer (HRSL) population density map (at 1 arcsecond) and observe that current estimates of flood exposure using GHSL may overstate flood risks in rural regions while potentially underestimating these risks in urban areas. Other alternatives such as WorldPop an LandScan also overestimate the number of people exposed to floods. However, the HRSL is only available for the year 2015.

[10] The flood hazard maps are available from https://datacatalog.worldbank.org/search/dataset/0062763/Global-Flood-Exposure--Gridded-exposure-headcounts-by-country. The inundation depth is the maximum from the three types of flooding considered. Inundation depths are assigned one of five categories: no risk, low risk (0 – 15 cm), moderate risk (15– 50 cm), high risk (50 – 150cm), and very high risk (> 150 cm).

3.2 Drought

We use Historic Agricultural Drought Frequency data from FAO, which defines drought events based on the Agricultural Stress Index (ASI) (FAO, 2023). Unlike the other hazards used in this paper, this drought data does not follow a probabilistic modeling approach and thus is less amenable to modelling extreme values. The historical frequency of severe droughts is calculated using the entire 39-year time series, spanning from 1984 to 2022. The ASI is based on remote sensing vegetation (NDVI) and land surface temperature (BT4) data, combined with information on agricultural cropping cycles derived from historical data and a global crop mask. Specifically, the vegetation health index (VHI) is defined as a weighted combination of two anomaly indicators of vegetation and temperature, which are based on the deviations of the actual observation from the historical range of NDVI and BT4. The pixels with a VHI value below 35% over a growing season (up to 2 seasons) are considered as experiencing severe drought. The ASI then captures the percentage of crop or grassland pixels within each administrative unit (based on the Global Administrative Unit Layers by FAO) affected by severe drought.[11] FAO provides data with a spatial resolution of 30 arcseconds (approximately 1 km) depicting the frequency of severe drought in areas where 30 or 50 percent of the cropland or grassland is affected by severe drought (as defined by ASI) for two seasons. We restrict drought exposure to rural areas using the GHSL application of the Degree of Urbanisation methodology (stage I) recommended by the UN Statistical Commission for classification (GHS-SMOD – R2023A), available at a resolution of 1km (Schiavina, Melchiorri, and Pesaresi, 2023). We consider return periods ranging from 5 to 40 years (based only on historical frequency) and map rural areas where more than 30 and 50 percent of cropland or grassland were affected in any growing season.

3.3 Heat

We use global extreme heat hazard data from Ridder et al. (2017) prepared for the World Bank.[12] The hazard is categorized using the simplified Wet Bulb Globe Temperature indicator representing temperature, humidity, and radiative impacts. The WBGT is derived from global daily maximum air temperature and dew point temperatures for a 30-year period (1981-2010) from the ERA-Interim Global archive and topographic data from the Global Multi-resolution Terrain Elevation Data 2010. These 10-km resolutions yearly maxima of 3-day mean maximal WBGTs are then used to construct the probabilistic hazard intensity maps for a given return period. We utilize the 5, 20 and 100-year return period maps and define locations exposed to heatwave if the annual maxima of 3-day mean maximal WBGTs exceeds 32, 33, 34, 35 and 36°C.

3.4 Cyclone

We use a global synthetic tropical cyclone dataset from Bloemendaal, Haigh, de Moel et al. (2020), generated using a synthetic resampling algorithm called STORM (Synthetic Tropical cyclOne geneRation Model). STORM is applied to 38 years of historical cyclone track data from the International Best Track Archive for Climate Stewardship (IBTrACS) to statistically extend the dataset to 10,000 years of cyclone activity. The data has been validated against historical observations and previous studies (Bloemendaal,

---

[11] The drought hazard maps are available from https://www.fao.org/giews/earthobservation/access.jsp. Refer to Van Hoolst et al. (2016) for more information on the method of constructing ASI. More information on the Global Administrative Unit Layers (GAUL) is available at https://data.apps.fao.org/map/catalog/static/api/records/9c35ba10-5649-41c8-bdfc-eb78e9e65654. At GAUL level 2, there are 63376 districts or counties.

[12] The extreme heat hazard maps are available from https://datacatalog.worldbank.org/search/dataset/0040194/Global%20extreme%20heat%20hazard?version=2.

de Moel, Muis et al., 2020).[13] We use the global STORM tropical cyclone wind speed data with a resolution of 6 arcminutes (approximately 11km) for return periods ranging from 10 to 10,000 years. We define exposed locations if the 10-minute average sustained wind speed exceeds a Category-1 threshold of 29 m/s, a Category-2 threshold of 37.6 m/s and a Category 3 threshold of 43.4 m/s.[14] It is important to note that our measure of cyclone intensity leaves out storm surge and heavy precipitation that generally occur in association with a tropical cyclone.

3.5 Setting thresholds to define extreme events and estimating joint exposure

Whilst the number of people and poor people exposed are initially estimated for events defined by several intensity thresholds and return periods, for further analysis we set these to a specific "risk threshold". Choosing comparable risk thresholds across very different types of shocks is challenging, especially given the events have very different types of impact (e.g., sudden loss of assets for tropical cyclones vs. productivity and health impacts for heatwaves). For each event we have selected an intensity threshold that represents serious damage to either assets, income or morbidity and mortality. These thresholds are as shown in Table 3.

Apart from drought, which is based on observed historical frequency, we use a constant return period of 100 years. This means that the flood, heatwave, and cyclone events exceeding chosen thresholds have at least a 1% probability of occurring in any given year. The 100-year event is commonly used in disaster risk management, in part because it represents an event that an individual is more likely than not to experience in her lifetime (Table 1). These thresholds could be adjusted over time to make risks more comparable across hazards.

Table 3: Thresholds used to define exposure to extreme events

Event	Return period (years)	Intensity threshold
Flood	100	An inundation depth of at least 50cm
Agricultural drought	40*	At least 30 percent of cropland or grassland affected in any season, in rural areas
Heatwave	100	A three-day running mean maximum Wet Bulb Globe Temperature (WBGT) of > 33°C
Cyclone	100	A wind speed of at least the Category 2 threshold (37.6 m/s, 10 min sustained)

In Rentschler, Salhab, and Jafino (2022), inundation depths of at least 0.5 meters indicate a high risk that bring disruptions to livelihoods and economic activity, as well as risk to life for select locations and vulnerable groups. In a different work, Huizinga, De Moel, and Szewczyk (2017) show that for a fluvial and marine flood depth of 0.5 meters, the average share of residential assets lost across regions is 0.38 (a range of 0.22-0.49). Cyclone damage functions also indicate direct economic damage in the range of 0.2-0.5 for category 2 windspeeds for most regions (Eberenz, Lüthi, and Bresch, 2021).

Drought results in a loss in income rather than a loss in assets. A moderate (about a 1 in 10 year) drought is predicted to reduce consumption by 15 percent and 9 percent in Uganda and Ethiopia, respectively (World Bank , 2016; Hill and Porter, 2017), and by 10 percent across most agroecological zones in sub-

[13] The global cyclone hazard maps are available from https://doi.org/10.4121/12705164.v4 and as global scale files compiled by Russell (2022) from https://doi.org/10.5281/zenodo.7438144.
[14] Category-classifications are based on the Saffir-Simpson scale (converted from 1-min to 10-min thresholds).

Saharan Africa (Gascoigne et al., forthcoming). For drought we consider a much less frequent and presumably more severe event, so the loss in consumption may be higher.

Although there are productivity losses associated with extreme heat (Kjellstrom et al., 2018, Foster et al., 2021), here we focus on the loss of life and morbidity associated with extreme heat (without considering the potential major effect of higher temperatures and heat on quality of life and average labor productivity). A WBGT threshold of 33 degrees Celsius corresponds with the reference upper limit for healthy, acclimatized humans at rest to keep a normal core temperature, based on international standard ISO 7243 used to assess heat stress on workers (International Organization for Standardization, 2017). Heat-related mortality and hospital visits increase significantly around this level, disproportionately affecting outdoor workers and the elderly for whom WBGT does not have to exceed 33 degrees Celsius to reach a dangerous level (Cheng, Lung, and Hwang, 2019; Tuholske et al., 2021).

To determine the number of people exposed to any one of the four shocks considered we take the maximum number of people exposed in each 1km grid cell to either of the four hazards (Figure 5). This is done to avoid double-counting. Note that we do not assume everyone in a 1km grid is either exposed or not exposed to flooding by overlaying the data in this way since we first calculate the population exposed to flood using the relevant higher resolution flood and population data.

4 MEASURING VULNERABILITY

In this section we motivate the choice of indicators used to identify households that are vulnerable and discuss the data and methods used to measure them.

4.1 CHOICE OF INDICATORS

As highlighted above we consider two key aspects of vulnerability: (i) the physical propensity to experience severe income, asset or health loss and (ii) the inability to cope with and recover from the losses. Multiple dimensions are considered within each of these. We introduce the proposed indicators for measuring each dimension.

Physical propensity to experience severe loss

Access to electricity and a certain standard of drinking water are critical for economic activity and survival and as such are included in the World Bank's multidimensional poverty measure (World Bank 2018). Additionally, when shocks hit, access to these services is an important determinant of the impact of the shock on welfare. For example, with access to improved drinking water, contaminated water from flooding and storms, or lack of water due to drought has less of an impact. Nevertheless, it is essential to acknowledge that the current indicator of access to improved drinking water, often represented by covered wells in low-income countries, may not sufficiently reflect susceptibility to contamination during extreme events such as floods or droughts. Therefore, there is a need for future work to refine this indicator by considering a potentially higher threshold. Metrics such as "improved piped water" can offer a more precise assessment of the infrastructure safeguarding against water-related risks in the event of shocks. With access to electricity, households are more likely to have assets such as fans that can help with heatwaves. A fuller discussion is available in the World Bank's Lifelines report (Hallegatte et al, 2019). Whilst not a final selection of assets and infrastructure that matter for determining the initial loss of the shock, these measures provide a good first estimate to stimulate discussion. Access to markets and services, access to early warning systems, sanitation, and building and infrastructure quality are also playing a key role in determining disasters' impacts, and has been included in other estimates, but is left for future inclusion here.

Inability to cope with losses

The first dimension of inability to cope is not having income to manage the impact of shocks. The aim of this measure is to identify individuals that have incomes that are too low to be able to meet basic needs should a shock to incomes occur. The motivation for this measure comes from work that has set vulnerability lines for identifying those at risk to falling into poverty. Many of the early estimates on measuring vulnerability to poverty utilized panel data that had repeated observations of welfare outcomes on the same individual and considered households to be vulnerable if the probability that their consumption was below a poverty line was high (Hoddinott and Quisumbing, 2010). In an extension of this work, vulnerability lines were defined—the level of consumption or income that an individual would need in order to have a low probability of falling into poverty (López-Calva and Ortiz-Juarez, 2014). López-Calva and Ortiz-Juarez (2014) proposed using a 10% probability of becoming poor to identify those vulnerable to poverty. Using this approach they calculated that the vulnerability threshold for Chile, Mexico, and Peru was about 2.5 times the poverty line. Similar analysis in Indonesia found that the vulnerability threshold is 1.5 times the poverty line (Jellema et al., 2017; World Bank, 2019). This work is informative, but it is important to note that this approach takes into account both idiosyncratic and covariate shocks, whereas here we focus only on one type of covariate shock, extreme weather events.

This approach—of setting a vulnerability line at some multiple of the poverty line—has been used in World Bank regional reports and poverty assessments in East Asia and the Pacific (EAP), Europe and Central Asia (ECA), Latin America and the Caribbean (LAC), Uganda, Tanzania, Viet Nam, Mongolia, Cambodia, Brazil, Türkiye and others. The multiples used range from 1.25 to 2.5 times the poverty line.[15] In the context of the United States, several studies have considered the threshold between 1.25 and 2 times the Federal Poverty Guidelines to identify those who are poor or near poor including Montgomery et al. (1996), Heggeness and Hokayem (2013), Hair et al. (2015), Saczewska-Piotrowska (2016), Dube (2019). The appropriate multiple will depend on the context, but most studies fall within the 1.5-2 range. In this paper we use 1.5 times the poverty line. As the next section indicates for many countries this is estimated using data on consumption rather than income, as this is the aggregate available.

The second dimension of inability to cope is educational attainment. Research has consistently shown that households with higher level of education have better understanding and ability to process risk information such as weather forecasts and early warnings (Mileti and Sorensen, 1990; Hoffmann and Muttarak, 2017). More educated individuals are also likely to assess and respond to risks more effectively, thereby being better prepared to cope with natural disasters and weather shocks (Helgeson, Dietz, and Hochrainer-Stigler, 2013; Muttarak and Pothisiri, 2013; Muttarak and Lutz, 2014). Moreover, there is evidence suggesting that even the completion of primary education can enhance the ability to cope with a shock. In the Ugandan context, households with a head who has attained some primary education experience a 2.8% reduction in the negative effect of rainfall on crop income compared to those without

[15] Recent poverty assessment reports use a range of multiples of the poverty line to define vulnerability to poverty: 1.25 for Cambodia (Karamba et al. 2022), 1.5 for Indonesia and Myanmar (Pape and Ali 2023; World Bank 2022d), 1.7 for Viet Nam (World Bank 2022b), 1.75 for EAP (Ruggeri Laderchi et al., 2017), and Turkiye (World Bank 2018, World Bank 2023), twice for Brazil, ECA, Honduras, Peru, and Uganda (World Bank 2022a; Bussolo et al. 2018; Robayo-Abril et al. 2023; Word Bank 2023a; World Bank 2016), and almost 2.5 for LAC (World Bank 2021a).

any education (Hill and Mejia-Mantilla, 2017). Similarly, in Ethiopia and Bangladesh, children whose mothers have at least completed primary education do not suffer from stunting as a result of droughts, unlike those whose mothers have no formal education or did not complete primary education (Dimitrova, 2021; Le and Nguyen, 2022).

Furthermore, access to a minimum level of education emerges as a crucial factor across various contexts in determining a household's ability to switch livelihood. Being educated increases the ability of households to access information and to be able to make informed decisions about the alternative livelihood strategies to try and smooth their income (Reardon, 1997; Ellis, 1998; Barrett, Reardon, and Webb, 2001; Abdulai and CroleRees, 2001; Wouterse and Taylor, 2008; Amuedo-Dorantes and Pozo, 2011; van der Land and Hummel, 2013; Liu and Yamauchi, 2014; Hummel, 2016). Recent research by Doberman (2023) shows that historical investments into primary education facilitated adaptation to climate change. People who received education during a large-scale primary schooling expansion in India in the mid-to-late 1990s moved away from agriculture in response to climate change.

The third dimension of inability to cope is access to public support. There is considerable evidence that cash transfers help households to manage shocks. Regular cash transfers to households protect household welfare during crises (de Janvry et al., 2006; Pega et al., 2017; Knippenberg and Hoddinott, 2019; Bottan, Hoffmann, and Vera-Cossio, 2021; Abay et al., 2023). Employment guarantee schemes also play a protective role (Gehrke, 2019; Gelb et al., 2021; Afridi, Mahajan, and Sangwan, 2022). Cash transfers provided in response to a disaster have significant short- and long-run welfare benefits (Del Carpio and Macours, 2010; Macours, Schady, and Vakis, 2012; Mansur, Doyle, and Ivaschenko, 2017; Aggarwal et al., 2020; Banerjee et al., 2020; Brooks et al., 2020; Ivaschenko et al., 2020; Menezes-Filho, Komatsu, and Rosa, 2021; Pople et al., 2021; Afridi, Mahajan, and Sangwan, 2022; Londoño-Vélez and Pablo, 2022).

In this exercise, due to data availability constraints, access to public support is measured by looking at whether households have access to social protection. Ideally, we would have data on whether a household would be covered by social protection in a crisis through social insurance or cash transfers. This could reflect information on who is covered by social insurance (even if not currently receiving any payments) or who could feasibly be reached through an adaptive social protection system (i.e. covered by a social registry and able to receive payments when scale-up rules are applied, see Bowen et al. 2020, World Bank 2021b). However, in the absence of this data, there is some evidence in favor of using information on current coverage, as support is more likely to be available in response to a disaster in places where pre-disaster coverage rates are high. The number of beneficiaries in newly announced social assistance programs during COVID was strongly correlated with the size of the existing social protection system before the crisis (World Bank, 2022c) as was the speed of the response (see, for example, Gentilini et al 2022; Beazley, Marzi, and Steller, 2021).

The final dimension of inability to cope is access to financial services. There is a strong body of evidence showing that households borrow after a disaster to meet basic consumption needs, and transfers of money between family and friends in the aftermath of a disaster are also central to household risk management. Transfers between family and friends is also the most commonly reported way of households financing an emergency (Demirguc-Kunt et al. 2015).

Networks have increasingly been used to insure against covariate shocks as mobile money and higher rates of rural to urban migration have increased the geographic reach of any network (Yang and Choi, 2007; Jack, Ray and Suri, 2013; Blumenstock, Eagle, and Fafchamps, 2016; Meghir et al., 2022; Apeti, 2023). In Kenya, mobile money has strengthened risk-sharing to the point that consumption is fully insured against shocks—because of increasing the number of transfers and the diversity of senders (Jack and Suri, 2014). Similar findings were found for floods in Mozambique (Batista and Vicente, 2023) and for violence in Kenya (Morawczynski and Pickens, 2009). In Tanzania, consumption is fully protected from small village-level rainfall shocks for those who have mobile money (Riley, 2018) and households are protected from falling into poverty and reducing investments in human capital (Abiona and Foureaux Koppensteiner, 2022). As is discussed in more detail in the next section, data on the use of mobile money is not as widespread as access to a bank account. We thus use access to a bank account to indicate whether households have access to financial services to smooth consumption in the face of a shock.

There are dimensions of vulnerability that although very important are hard to measure consistently across countries so are difficult to include in a global measure. For example, race, ethnicity and political exclusions matter, all else equal, in determining the impact of a disaster on a household and how well a household is supported and can cope with the losses. However, defining these for a global measure is challenging even though these could be included in a country level analysis.

4.2 DATA USED AND METHOD FOR OVERLAYING

Many of the indicators come from the same data source. We start by describing this data and then discuss the other data sources used.

The Global Monitoring Database and the Global Subnational Atlas of Poverty

Our measure of income is based on the per capita income or consumption measure collected in national household surveys that forms the basis for poverty measurement. These survey-year income (or consumption) estimates are collated and harmonized across countries and over time to maximize comparability as part of the World Bank's Poverty and Inequality Platform (PIP). These estimates also go into the Global Monitoring Database (GMD) which contains not only the income or consumption aggregate but other data on household characteristics such as access to improved water, access to electricity, and education of adult household members, all of which we use here.[16] This income or consumption data is further extrapolated or interpolated to a common reference year, in this case 2019, and the share of the population falling beneath the international poverty lines in this year—or any other line—can be determined.

To overlay with the geographic data on exposure, we use subnational data on income (or consumption) and other measures when possible. We obtain this using the latest edition (October 2023 vintage) of the World Bank's Global Subnational Atlas of Poverty (GSAP) for the reference year 2019 for 1,733 subnational or national areas across 168 economies, accounting for 97 percent of the global population.[17] The subnational areas are typically administrative boundary level 1 areas, corresponding to the highest subnational unit level such as provinces or states, but they can also be a group of regions defined by the specific sampling strategy and representativeness of the household survey. There are 47 economies (24 percent of the global population) for which poverty estimates are only available at the national level due

[16]Refer to World Bank (2023b) for more information on the methodology to calculate poverty rates.
[17] More information about GSAP is available at Nguyen et al. (2023).

to limited data access, outdated survey, or the size of the country unsuitable for further subnational disaggregation.

We use the national and subnational boundaries in GSAP to overlay shapefile boundaries for each region with the gridded exposure data described above. We then take the sum of the population exposed within the defined boundaries to generate an estimate of the number exposed within the administrative unit. For partially covered grid cells, the population is weighted by the fraction of the 1km grid cell covered by the region. The total number exposed is multiplied by the share of people whose per capita income or consumption falls below a given poverty line in that administrative unit to determine the number of people who are both exposed and poor at a given poverty line in that unit. This is then summed by country, region and globally to provide country, regional and global numbers on exposed and poor. Implicitly, we assume a uniform rate of poverty within each GSAP subnational administrative level. The impact of this assumption is ambiguous since poorer households may be disproportionately located in exposed locations within subnational areas in some cases, (rural drought) but not in others (urban flooding). The direction and size of this bias is something that needs to be tested in future work as discussed further in the final section of the paper.

This data is used for the following measures:

- **Income**: this is calculated as the share of households that have income or consumption less than 1.5 times the poverty line of $2.15 (2017 PPP) for each administrative unit in the GSAP. The data is available for the common reference year of 2019 and is available for 168 countries. At this level of income and consumption there is very little difference between income and consumption (when assessed using countries with data on both, see Wollburg et al 2023) and for the rest of this paper we refer to this measure as income regardless of whether the data used to estimate this comes from an income or consumption aggregate.
- **Education** to switch livelihoods or to access information and resources: this is proxied by a variable reflecting whether the household has an adult that has completed primary education. This is a very low level of education that is likely mostly relevant in lower income countries. The GMD is used because this allows us to have information on education and income for the same household which allows us to know whether an individual is deprived on one or both dimensions. Unlike poverty rates which have been extrapolated or interpolated to a common reference year, the estimates for education come from the year of the survey. In order to avoid using data that is too old, when the survey is outside of the range of +/- 5 years from the reference year we would ideally not use the survey. In practice, for 2019, this means we are using the range 2015-present. When we do this, data is only available for 125 of the 168 countries in the GMD and it is not available for either India or China, two very large countries which are important for global coverage. We present results including and excluding data that falls outside of this year range. In future work we will explore mechanisms to update educational attainment using demographic trends, or other surveys that provide information on education within the country and can be used to impute educational attainment in the GMD.
- **Water**: we use whether a household has access to at least limited standard water, as in the SDG indicator. This is available for 139 countries of 168 for all years and 120 countries for the period 2015-present. There are some countries that are missing data on water access but that have achieved universal access to at least a limited standard of water as per the latest data available in World Development Indicators.[18] For these countries we assume no household is vulnerable on the water dimension. This

[18] Here we define universal coverage as above 98 percent of the population having access.

allows us to include China and Mauritius for example. Data on access to water is missing for India. The latest available data in World Development Indicators indicates that access is 93 percent in India. Including India in our measure of vulnerability without this information on who is missing water may underestimates vulnerability in India by up to 7 percent. Again, future work requires developing methods to impute data for this measure, or whatever infrastructure measure is used, when it is missing.

- **Electricity**: whether a household has access to electricity. This is available for 139 countries of 168 for all years and 120 for the period 2015-present. Again, when this is missing but the World Development Indicator data indicates universal coverage, we assume no household is vulnerable on this dimension.

Social Protection

The Atlas for Social Protection (ASPIRE) database provides the coverage of social protection and labor programs at the national level by household income quintile in each country.[19] Specifically, coverage is defined as the ratio between the number of individuals in the quintile who live in a household where at least one member is a direct or indirect beneficiary of any social assistance, social insurance, and labor programs, and the total number of individuals in that quintile.[20] In order to avoid using data that is too old, when the survey is outside of the range of +/- 5 years from the reference year we do not use the survey. For social protection we used 2018 instead of 2019 to maximize coverage because currently estimates of social protection coverage in 2020 and 2021 are not included in ASPIRE as they reflect the COVID-19 response rather than regular social protection coverage. If no data is available within the range 2013-present social protection data is counted as missing. This results in data being available for 92 countries, such that the inclusion of a social protection indicator limits global coverage. Similarly for 2010, data for the closest year to 2010 is used as long as the survey falls within 2005-2015.

The indicator used captures households currently receiving social protection, when conceptually what we would like to capture is whether or not a household is eligible to receive social protection should the need arise. The indicator we are using is very imperfect as someone in a formal job at the top end of the income distribution, not currently receiving social protection would be counted as vulnerable even though they could rely on social insurance instruments should the need arise. In future work, we will explore the possibility of using eligibility criteria to refine this measure. Additionally, we note that ASPIRE's coverage is estimated using the national representative household surveys, which may capture primarily the largest programs in the country. As a result, the extent to which information on specific transfers and programs is captured in these household surveys can vary across countries.

While poverty and education data are available from the same survey source, this is often not the case for social protection data, and assumptions are needed to estimate social protection at the household level. In future work a more detailed approach could be used to impute whether a household is potentially covered by social protection systems, however for the purposes of this analysis we use information on social protection coverage rates by income quintile to assign each household a probability that they receive social protection. The probability for each household is equal to the coverage rate for the income

---

[19] The ASPIRE database is available at https://www.worldbank.org/en/data/datatopics/aspire. As the majority of surveys used in the ASPIRE database are the same surveys in the GMD, we can explore all three dimensions together (poverty, education, and social protection) at the household level in future analysis.

[20] Social assistance includes unconditional and conditional cash transfers, social pensions (non-contributory), food and in-kind transfers, school feeding, public works, fee waivers and subsidies. Social insurance includes insurance schemes against old age, disability, death of the main household provider, maternity leave and sickness cash benefits, and social health insurance. Labor market programs include active labor market programs such as training or job search assistance and passive labor market programs such as unemployment insurance and benefits.

quintile they are in. We thus assume that coverage rates by quintile are the same for subnational areas as they are for national areas. For the analysis we need to assign whether each household receives social protection or not, so households are randomly assigned social protection based on the probability of coverage.[21] This random assignment is implemented in each country to ensure that the survey population-weighted values from the simulated sample match the reported statistics for access to social protection in each quintile. Subnational values for each country are then calculated for this measure. The random assignment process is repeated 100 times to account for the heterogeneity of households in each subgroup. The averages of subnational indicators from the 100 simulations are used as the final estimates for each country. Given information on the education, water and electricity dimension is also present in the same survey used for poverty estimates, this process also informs the overlap between social protection and these non-monetary dimensions at household level.

For some countries the same survey is used for poverty and social protection data and these surveys are used to assess the accuracy of this approach. Appendix A1 includes the details of this comparison, and indicates that overall, the approach works well with a correlation of 80 percent between survey-based and simulated measures. However, lack of access to social protection tends to be over-estimated in the simulated results, potentially over-estimating vulnerability on this dimension. The method used to impute social protection for households in the GMD can indeed be improved beyond what is done here, but as a first estimate, the approach delivers reasonable results.

Access to financial services

Lastly, we also consider whether a household has access to financial services. We use indicators from the Global Financial Inclusion (Global Findex) database, drawn from nationally representative survey data of about 150,000 people in 148 economies for 2011 and 128,000 people in 123 economies for 2021 as part of the Gallup World Poll.[22] However not all questions are available for all countries. For both years of the Global Findex database, the target population is the entire civilian, noninstitutionalized population age 15 and older. The variable we use indicates whether a respondent has either a financial institution account or a mobile money account, given the strong relationship in the literature on access to mobile money and ability to use informal networks to manage the impact of large climate shocks. We use data from the Global Findex 2021 to overlay with the 2019 poverty data, while the equivalent indicator from the Global Findex 2011 is used to overlay with the 2010 poverty estimates.

The statistics are reported for adults living in the richest 60% and poorest 40% of households for each country.[23] The same method is used to overlay these with poverty (and thereby education), as is used with social protection. We do not have any information on the correlation between access to financial services and access to social protection that we can use to inform the overlap between these two dimensions of welfare at the individual level.

Coverage

Table 4 presents an overview of data availability across the globe for all dimensions. Overall, out of the total of 218 economies, our analysis is based on a sample of 168 economies, representing 97 percent of

---

[21] We use a wsample program written by Corral, P (2023) to perform the random assignment to households.

[22] Refer to Demirgüç-Kunt et al. (2022) for more information on the Global Findex Database 2021 and Demirgüç-Kunt and Klapper (2012) for more information on the Global Findex Database 2011.

[23] The Findex database is available at https://www.worldbank.org/en/publication/globalfindex. We currently use the global dataset but in future work the country level data could be used to generate quintile estimates and overlay in the same was as social protection.

the world's population. While the poverty dimension is available for 168 economies, other dimensions have lower levels of coverage, representing between 46 and 84 percent of the world's population (see Table 5) when the +-5 year filter is included. The significant drop in the number of countries when adding dimensions beyond poverty is sometimes due to limited data access. Consequently, assessing these dimensions at the household level for certain countries is not feasible. For instance, China provides highly aggregated welfare data, consisting of only 20-bin urban/rural distributions rather than microdata files, while for other high-income countries, 400-bin data are extracted from the Luxembourg Income Study (LIS). [24] When we drop the +- 5 year filter and use information on full coverage from World Development Indicators the number of countries increases only slightly but the share of the population covered increases for many indicators as data for India and China can be included. More than three quarters of the World's population is included across indicators with the exception of water where data is missing for India. In the tables below we present results including India, acknowledging that this is an underestimate of the number of vulnerable in India as we do not have information on which households are lacking water.

Table 4: Number of countries with survey data and dimensions of vulnerability in 2019

	All	Income	Education	Social protection	Financial inclusion	Water	Electricity
Region							
East Asia and the Pacific	26	21	15	13	9	14	13
Europe and Central Asia	31	30	25	18	26	24	24
Latin America and the Caribbean	31	25	17	18	17	16	15
Middle East and North Africa	14	12	6	5	9	6	6
Other High-Income economies	60	28	19	0	18	19	19
South Asia	8	7	6	6	5	5	6
Sub-Saharan Africa	48	45	37	32	34	36	37
World	218	168	123	91	118	120	119
World (incl. data older than 5 years and adding in data from WDI)	218	168	129	92	118	126	125

Source: Authors' compilation from the GMD, ASPIRE, and Findex databases.
Notes: Income refers to having less than 1.5*$2.15 per household member, education refers to no adult having primary schooling, social protection refers to not receiving any social protection, and financial inclusion refers to not having a bank or mobile money account. Water refers to access to limited standard water, and access to electricity is as written. The coverage year for education, water and electricity is based on the filters of +- 5 years from 2019, and for social protection is based on the filter of +- 5years from 2017.

[24] For China, we used the Household survey CHIP 2013 for dimensions of education and social protection.

Table 5: Share of population with data on the dimensions of vulnerability in 2019 (%)

	Income	Education	Social protection	Financial inclusion	Water	Electricity
Region						
East Asia and the Pacific	98	97	97	97	30	30
Europe and Central Asia	100	89	81	89	88	87
Latin America and the Caribbean	97	90	92	90	90	87
Middle East and North Africa	97	58	58	81	58	58
Other High-Income economies	93	30	0	30	30	30
South Asia	97	96	96	97	22	96
Sub-Saharan Africa	97	82	84	85	82	82
Income group						
High	93	36	5	36	36	34
Upper-middle	100	95	97	98	39	39
Lower-middle	98	93	92	94	51	93
Low	87	62	60	71	62	62
FCV	92	63	70	75	63	63
World	97	46	60	84	46	45
World (incl. data older than 5 years and adding in data from WDI)	97	82	78	84	66	83

Source: Authors' compilation from the GMD, ASPIRE and Findex databases.

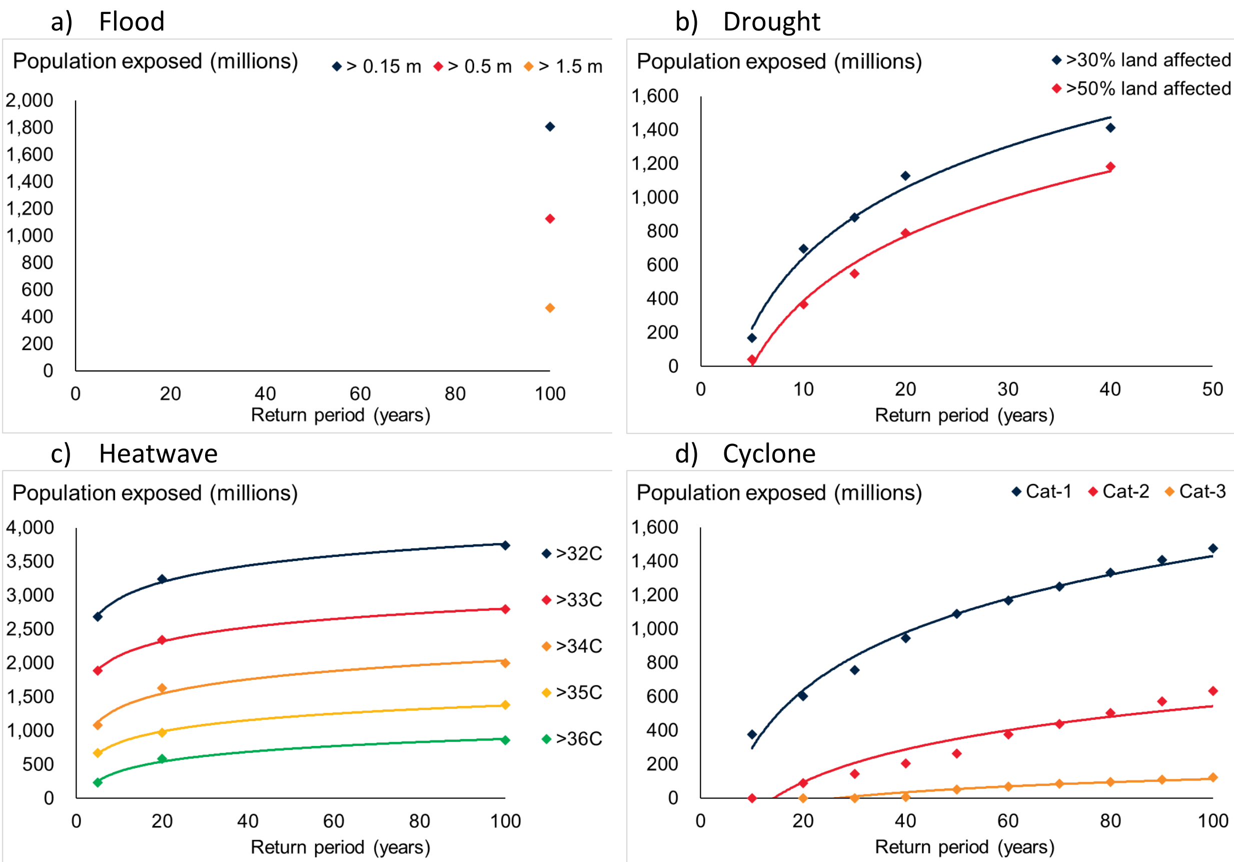
Notes: Income refers to having less than 1.5*$2.15 per household member, education refers to no adult having primary schooling, social protection refers to not receiving any social protection, and financial inclusion refers to not having a bank or mobile money account. Water refers to access to limited standard water, and access to electricity is as written. The coverage year for education, water and electricity is based on the filters of +- 5 years from 2019, and for social protection is based on the filter of +- 5years from 2017.

5 RESULTS

5.1 EXPOSURE TO EXTREME WEATHER EVENTS AND POVERTY

Results are first presented for the number of people exposed to flood, cyclone, drought, and heatwave (Figure 6). Exposure numbers are presented for a range of return periods (from 5 to 100) and using different intensity thresholds to define extreme events: flood inundation of 15cm, 50cm and 150cm; category 1, 2 and 3 winds for cyclones, drought affecting 30 percent and 50 percent of the local area, and heatwaves of 32-36 degrees Celsius. Exposure falls with the event severity and increases with the return period. The number of people exposed to heatwaves is the highest: 3.7 billion people are exposed to the lowest intensity event we consider with a 100-year return period. For floods 1.8 billion are exposed to the lowest intensity event we consider with a 100-year return period, and 1.5 billion for cyclones. 1.4 billion people are exposed to drought with about a 40-year return period. Exposure drops considerably for cyclones when going to the next level of intensity—0.6 billion are exposed to category 2 winds for a return period of 100 years. The drop is less pronounced for other types of events. These graphs show how the choice of severity and probability determine the total exposure (and other subsequent numbers).

Figure 6: Number of people exposed



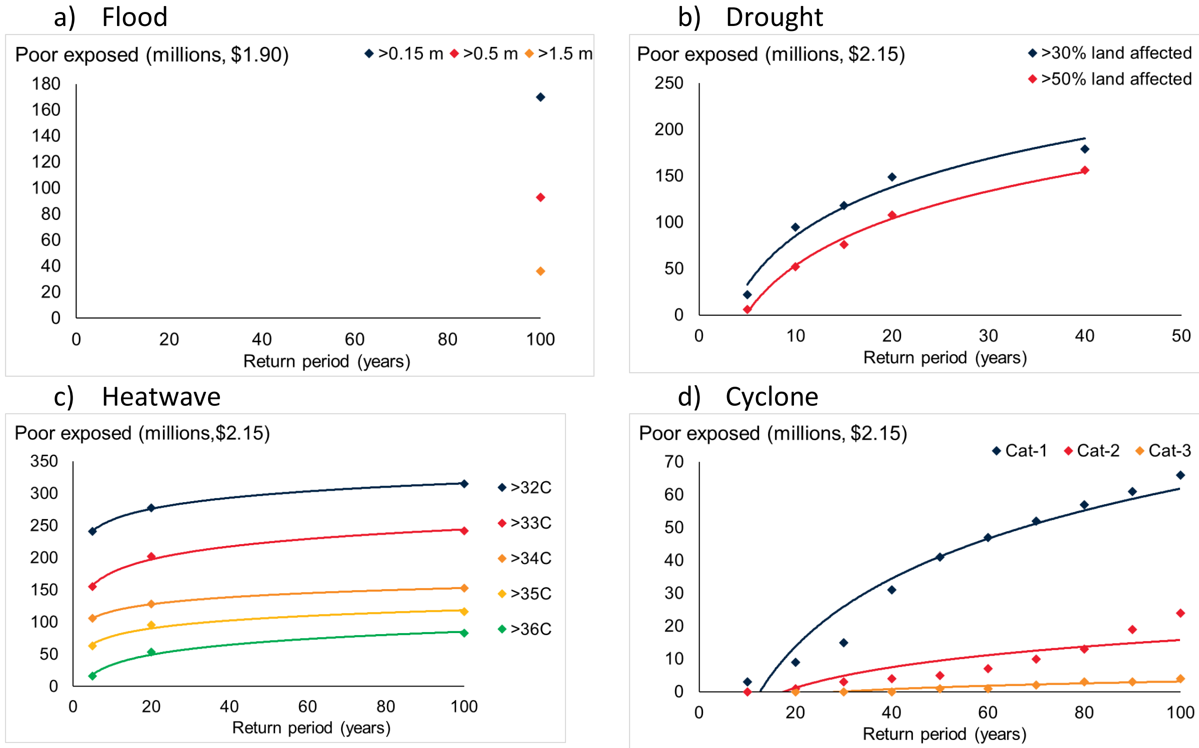
Notes: Estimates use gridded population data for 2020.

The number of people exposed and poor are presented in Figures 7 and 8. Figure 7 shows the numbers of people exposed to the same events and living beneath $2.15 in 2017 PPPs which is about the median poverty line of low-income countries and the international extreme poverty line. Figure 8 presents the numbers of people exposed and living beneath $6.85 in 2017 PPPs, the median poverty line of upper middle-income countries. The same patterns of increasing numbers with lower intensity and lower probability are observed, as would be expected, but interestingly the relative importance of these events for poor people is slightly different compared to the picture for all people presented in Figure 6. Heatwaves remain the shock affecting the most people at both poverty lines, but fewer poor households are exposed to cyclones than floods and droughts, particularly at the extreme poverty line. Additionally, many of the people exposed to heatwaves live between $2.15 and $6.85, so exposure to heatwaves is much higher at the $6.85 line compared to the other events.

Next, we consider exposure and poverty for a given risk threshold. The thresholds and return periods chosen are indicated in Table 3. Table 6 presents the total number of people exposed to each of these events (reflecting a single point on each graph in Figure 6) as well as the number of people that are exposed to at least one of these events.[25] The last two columns of Table 6 show the number of people that are poor out of those exposed, using the two poverty lines of $2.15 and $6.85.

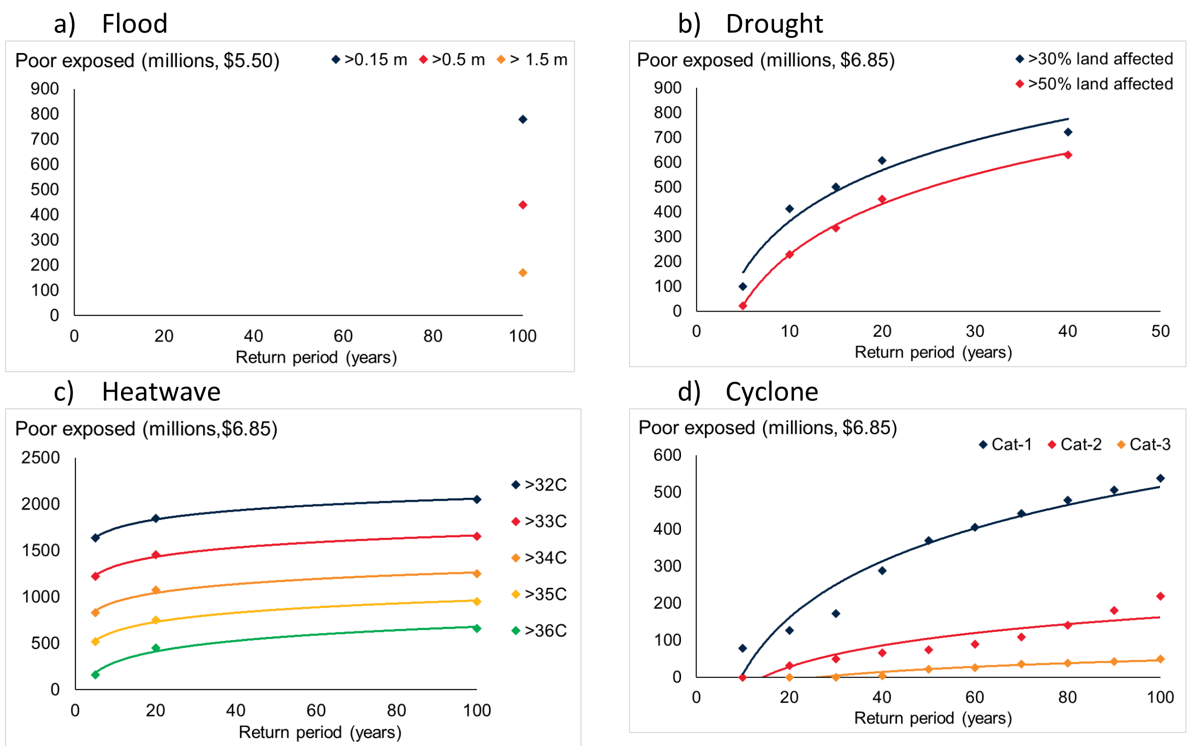
[25] In future work, the number of people susceptible to experiencing multiple events will also be estimated.

Figure 7: Number of people exposed and poor ($2.15)



Notes: Estimates use gridded population data for 2020 and subnational poverty rates for 2019.

Figure 8: Number of people exposed and poor ($6.85)



Notes: Estimates use gridded population data for 2020 and subnational poverty rates for 2019.

We find that 4.5 billion people, more than half the global population, are exposed to one of these four weather events. Of those exposed, 2.3 billion are poor at the $6.85 line, and 390 million are extremely poor (they live on less than $2.15). This means that about a quarter of a million people that are extremely poor are not exposed to the direct impact of extreme weather events. However, these households may be susceptible to experiencing less severe events or the indirect impact of extreme weather events.

Table 6: Number of people exposed and poor to extreme weather events (millions)

	Total population exposed	Share of total population (%)	Population exposed in countries with poverty data	Exposed and poor	
				$2.15	$6.85
Flood	988	13	962	57	424
Drought	1,412	18	1,383	179	723
Heatwave	2,793	36	2,737	242	1,653
Cyclone	634	8	601	24	219
Any shock	4,460	57	4,335	389	2,276

Notes: Poverty estimates are available for 1,733 subnational regions in 168 economies, accounting for 97% of global population. The total number of poor people is 692 million at $2.15 and 3,560 million at $6.85 when overlaying 2019 subnational poverty rates with 2020 gridded population data.

Exposure by region and income classification is presented in Table 7. South Asia (SAR) is the region whose population is most exposed to shocks, with 87 percent exposed (driven by very high rates of exposure to heatwaves). East Asia and the Pacific (EAP) follows. Exposure is lowest in Europe and Central Asia (ECA) and Latin America and the Caribbean (LAC), but even in these regions a third of the population is exposed. Important differences in exposure are present across regions. Drought is the most predominant shock in ECA and in Sub-Saharan Africa (SSA). In SAR and the Middle East and North Africa (MENA), exposure to heatwaves is the highest. Exposure varies less across type of shocks in LAC and EAP.

Table 7: Number of people exposed, by region and income category (millions)

	Total population	Flood	Drought	Heat	Cyclone	Any shock	Any shock (% of population)
Region							
East Asia & Pacific	2,073	407	322	810	247	1,308	63
Europe & Central Asia	494	36	117	18	0	155	31
Latin America & Caribbean	628	56	96	48	35	205	33
Middle East & North Africa	402	47	43	93	0	156	39
Other High Income	1,029	104	159	101	182	452	44
South Asia	1,829	246	332	1,481	132	1,589	87
Sub-Saharan Africa	1,119	66	314	186	5	471	42
Income group							
High	1,155	116	198	101	184	500	43
Upper-middle	2,867	430	449	841	188	1,450	51
Lower-middle	2,939	377	561	1,683	214	2,110	72
Low	614	39	175	112	15	276	45
FCV	757	66	176	255	12	389	51

Notes: Regions use the Poverty and Inequality regional classification, which differs from the regional classification used by the World Bank. Some economies, mostly high-income economies, are excluded from the geographical regions and are included as a separate group referred to as "other high income" (or "industrialized economies" or "rest of the world" in earlier publications). https://datanalytics.worldbank.org/PIP-Methodology/lineupestimates.html#regionsandcountries. See annex for numbers using World Bank geographic regions. Income groups are for FY21 (data for calendar year 2019).

In table 8, poverty and exposure are broken down by region and income category. A large share of the population is exposed and poor in SAR and SSA by both poverty lines. The shocks important to poor households at the $6.85 poverty line are split relatively evenly across type of shock for EAP and LAC and split relatively evenly across flood, drought and heatwave for MENA and LAC. In SAR, heatwaves still dominate as the most important event type for poor people also, and in SSA exposure to drought and heatwaves is high among poor people.

Table 8: Number of people exposed and poor, by region and income group (millions)

	Flood	Drought	Heat	Cyclone	Any shock	Any shock (% of population)
$2.15 poverty line						
Region						
East Asia & Pacific	3	3	2	2	8	0
Europe & Central Asia	1	2	3	0	5	1
Latin America & Caribbean	3	6	1	3	11	2
Middle East & North Africa	2	4	11	0	15	4
Other High Income	1	1	1	1	3	0
South Asia	25	36	155	14	167	9
Sub-Saharan Africa	22	127	69	3	181	16
Income group						
High	1	1	1	1	3	0
Upper-middle	5	9	2	1	15	1
Lower-middle	36	94	199	16	260	9
Low	16	74	40	6	110	18
FCV	16	69	75	3	125	17
$6.85 poverty line						
Region						
East Asia & Pacific	116	95	199	88	372	18
Europe & Central Asia	5	16	11	0	28	6
Latin America & Caribbean	17	32	12	15	66	11
Middle East & North Africa	27	18	46	0	78	19
Other High Income	1	2	2	3	6	1
South Asia	201	271	1,215	109	1,302	71
Sub-Saharan Africa	58	287	170	4	424	38
Income group						
High	2	4	2	3	9	1
Upper-middle	114	118	196	45	365	13
Lower-middle	273	438	1,355	158	1,652	56
Low	35	163	100	13	251	41
FCV	48	153	199	10	312	41

Notes: Regions use the Poverty and Inequality regional classification, which differs from the regional classification used by the World Bank. Some economies, mostly high-income economies, are excluded from the geographical regions and are included as a separate group referred to as "other high income" (or "industrialized economies" or "rest of the world" in earlier publications). https://datanalytics.worldbank.org/PIP-Methodology/lineupestimates.html#regionsandcountries. Income groups are for FY21 (data for calendar year 2019).

5.2 At risk to extreme weather events

For these same events and risk thresholds, we consider the share of households that are exposed and highly vulnerable. Being highly vulnerable is defined as failing to reach the threshold in or lacking access to one or more dimensions (e.g., lacking access to electricity or coverage by social protection or having an insufficient income). The share of the global population for which we have data varies across the dimensions so in addition to presenting the number of people exposed and highly vulnerable we present the share of the global population that is exposed to a shock and highly vulnerable by each dimension

(Table 9). The share of people exposed and highly vulnerable on the water dimension is only 6 percent, compared to much larger populations for education, electricity and access to finance (16-17 percent). Social protection is the dimension on which the most people are vulnerable (31 percent).

Table 9: Number of people exposed and vulnerable in each indicator (millions)

	Water	Electricity	Income	Education	Social protection	Financial inclusion
Flood	38	86	142	92	348	252
Drought	132	246	343	226	470	373
Heat	89	412	632	391	848	781
Cyclone	13	41	65	33	173	109
Any shock	222	593	903	561	1,400	1,157
As a share of population in sample	6%	17%	12%	16%	31%	18%

Notes: Water and electricity refer to whether a household has access to improved water and electricity respectively. Income refers to having less than 1.5*$2.15 per household member, education refers to no adult having primary schooling, social protection refers to not receiving any social protection, and financial inclusion refers to not having a mobile money or bank account. The population coverage for each dimension is different (see coverage tables above for details).

Each indicator that is added increases complexity and reduces coverage, so it is informative to look at the degree to which each indicator is capturing new information not included by other indicators. Table 10 provides some information on this by showing the pairwise correlation in the share of the population counted as vulnerable on each indicator at the subnational unit level. Considering all pairwise correlations, the correlation between income and electricity is the highest. In general, the pairwise correlations between indicators are quite low indicating that new information is being added with each indicator.

Table 10: Correlation between indicators

	Water	Electricity	Income	Education	Social protection	Access to financial services
Water	1					
Electricity	0.60	1				
Income	0.65	0.80	1			
Education	0.53	0.68	0.66	1		
Social protection	0.39	0.48	0.58	0.43	1	
Access to financial services	0.38	0.41	0.56	0.47	0.47	1

Notes: The table shows pairwise correlation coefficients for the share of population counted as vulnerable. Subnational units are weighted equally. The number of observations varies between 1,156 and 1,605 depending on availability of data.

For the 74 countries for which we have data on all six dimensions and India for which we have data on five dimensions, we look at the number of people exposed and highly vulnerable on multiple dimensions. These 75 economies cover 77 percent of the world's population and 90 percent of the world's population excluding "Other High-Income Economies". Results are presented in table 11. More than half of the people in these economies are exposed to at least one of the shocks considered (60 percent). Given the correlation between the different dimensions is quite low, the share of population in our sample counted as highly vulnerable on any of these indicators of ability to cope is quite high, 70 percent of the exposed population is vulnerable and as a result 42 percent of the population is at high risk in that they are highly vulnerable and exposed. This number drops considerably when considering combinations of dimensions. For 2 or more dimensions, only 20 percent of the exposed population is highly vulnerable, and so 12 percent of the population is at high risk. The share of the population at high risk when considering vulnerability on more than 3 dimensions is 5 percent.

Table 11: Number of people highly vulnerable on multiple dimensions (millions)

	Population exposed	Exposed and highly vulnerable on … dimensions					
		1	2	3	4	5	6
Flood	802	565	160	52	19	7	2
Drought	1088	782	198	105	69	39	11
Heat	2516	1756	512	208	82	33	9
Cyclone	397	278	80	21	5	1	0
Any shock	3603	2541	714	292	135	62	17
Share of population (any shock)	60%	42%	12%	5%	2%	1%	0.3%

Note: dimensions of vulnerability considered are water, electricity, income, education, social protection and access to finance.

To assess how the results vary when applying different data coverage rules, in table 12 we present results when not including India (given the lack of data on water access for India) and when applying the +-5 years rule which additionally excludes China and a few other countries. We see that although the exposure data changes quite a bit, the share of households exposed and vulnerable across one or multiple dimensions is relatively constant.

Table 12: Number of people vulnerable on multiple dimensions (millions)

	Share of population covered	Exposed to any shock	Exposed to any shock and vulnerable on … dimensions					
			1	2	3	4	5	6
All countries	77%	60%	42%	12%	5%	2%	1%	0.3%
Excluding India	60%	54%	45%	12%	5%	3%	1%	0.4%
Applying the +-5 year rule	42%	46%	39%	12%	6%	4%	2%	1%

Note: dimensions of vulnerability considered are water, electricity, income, education, social protection and access to finance.

5.3 Trends in exposure, poverty and vulnerability over time

We take a first look at the question of whether exposure and vulnerability to extreme weather events is increasing or decreasing over time. We calculate the number of people exposed in 2010 by assuming that the hazard distribution has not changed appreciably in the last 10 years and calculating the number of people exposed based on the population distribution in 2010. While this is a useful first approximation of the trend, it is an oversimplification as the hazard distribution has likely changed between these two points in time. Global climate change is affecting the distribution of temperatures and other weather variables over time, including drought risk, precipitations, and tropical cyclone frequency and intensity. Over a decade, these changes would however be expected to remain relatively small. Flood risks, in contrast, can vary more rapidly in response to land use change (e.g., deforestation or urbanization), modification to river beds or flows (e.g., dams or dredging), and flood management infrastructure (e.g., dikes). Here, we assume the physical hazard fixed, and explore the evolution of exposure and vulnerability driven by changes in population localization and socioeconomic characteristics.

The results presented in Table 13 indicate that the number of people exposed has increased by an average of 12 percent (ranging from 9 percent increase in the number of people exposed to cyclones to a 14 percent increase in the number of people exposed to drought), which is in line with population growth.

Although the numbers of people exposed have increased over time, the numbers of people exposed and poor have fallen, thanks to the reduction in global poverty. This is true for all extreme weather event types and for both poverty lines. That said, there are some substantial differences in the rate of reduction across shocks and poverty lines. The reduction in exposure and poverty has been slowest for drought. At the $6.85 line, the reduction was negligible and even at the $2.15 line, the reduction was only 23 percent, half the speed of progress for other shocks at this line. Poverty reduction has been relatively slow, and population growth relatively high, in places that are exposed to drought. A second important point is that the reduction in the number of people exposed and poor has been much slower at the $6.85 line (11 percent reduction) than at the $2.15 line (47 percent reduction). While this in part reflects the fact that the number of people in poverty at this line globally has fallen more slowly than the $2.15 line (World Bank 2022c) it also reflects the particularly slow progress in places affected by drought and heatwaves.

Table 13: Exposure and poverty over time (millions)

	2010			2019		
	Exposed	Poor ($2.15)	Poor ($6.85)	Exposed	Poor ($2.15)	Poor ($6.85)
Flood	865	130	524	962	57	424
Drought	1,209	234	738	1,383	179	723
Heatwave	2,434	538	1,863	2,737	242	1,653
Cyclone	549	69	270	601	24	219
Any shock	3,871	733	2,549	4,335	389	2,276

Notes: The sample includes 168 economies accounting for 97 percent of the global population for both years. 3,977 million people were exposed to any event in 2010 when not restricting the sample to countries with poverty data.

Table 14: Number of people exposed and vulnerable in each dimension, over time (millions)

	Income	Education	Social protection	Financial inclusion	Water	Electricity
2010						
Flood	264	137	297	414	37	108
Drought	422	244	387	560	95	216
Heat	1082	485	750	1,350	84	458
Cyclone	139	59	152	195	16	48
Any shock	1,432	699	1,203	1,910	190	632
2019						
Flood	142	138	346	242	32	85
Drought	343	259	456	327	103	240
Heat	632	509	845	758	73	411
Cyclone	65	61	173	109	10	41
Any shock	903	721	1,382	1,091	181	586

Notes: Income refers to having less than 1.5*$2.15 per household member, education refers to no adult having primary schooling, social protection refers to not receiving any social protection, and financial inclusion refers to not having a bank account.

When we look at the dimensions of vulnerability we also see, for the most part, a reduction in vulnerability across dimensions (Table 14). Table 14 reports the number of people vulnerable just for countries for which we have data across two points in time. This is the full set of countries in the case of income, but for other dimensions it results in a handful of countries being dropped in each case. As to be expected given the changes in poverty reported in Table 13, the number of people exposed and highly vulnerable on the income dimension has gone down over time—by 37 percent. The reduction in the number of people exposed and vulnerable on the financial inclusion dimension has also gone down substantially, by 43 percent. There is little change when considering the education dimension. There are modest reductions in the number of people exposed and without access to water or electricity (5 percent and 7 percent, respectively). In the case of social protection, the number of people exposed and vulnerable has increased by 15 percent over time. Further work is needed to understand why this is. Regional numbers are presented in Table A5 in the annex.

Data is available on all indicators in 2010 and 2019 for 45 countries representing 61 percent of the World's population in 2019. Table 15 presents the share of the population exposed and highly vulnerable using data for these 45 countries. The results indicate that by any count, the global number of people at risk is falling, by 9% with one dimension and 24% with two dimensions, even though exposure is increasing by 12%. This corresponds to reductions in the number of people vulnerable in every region covered with the exception of Sub-Saharan Africa where the number of people vulnerable increased between 2010 and 2019.

Table 15: Number of people exposed and at risk, over time (millions)

	2010				2019			
	Population exposed	Population exposed and vulnerable on … dimensions			Population exposed	Population exposed and vulnerable on … dimensions		
		1	2	3		1	2	3
Flood	627	522	182	85	698	486	139	45
Drought	765	636	206	93	868	597	157	74
Heat	2109	1804	626	343	2358	1622	480	187
Cyclone	344	290	108	45	389	271	78	21
Any climate shock	2861	2421	833	423	3193	2207	634	244
By selected regions for any climate shock								
East Asia and Pacific	1165	885	309	97	1253	801	183	24
Europe and Central Asia	77	54	16	2	76	33	6	1
Latin America and Caribbean	70	61	24	7	78	58	18	4
South Asia	1386	1259	465	286	1569	1103	379	161
Sub-Saharan Africa	164	162	20	32	217	211	49	55

Note: dimensions of vulnerability considered are water, electricity, income, education, social protection and access to finance.

6 DISCUSSION

This paper sets out an approach for estimating the number of people highly vulnerable to a specific type of climate risk—the risk of directly experiencing an extreme weather event. The paper has shown how the selection of the extreme weather event and the dimensions, indicators and cutoffs of vulnerability determine the final number identified. The purpose of this working paper is to generate a discussion on the choices made in this assessment, in the context of a broader work program to improve how the World Bank measures the impact of its operations and monitor progress on development and climate.

In estimating numbers for as many countries as possible, the paper also highlights the significant data needs required for quantifying the number at risk. The paper uses simplifying assumptions to overlay different datasets. Even then, defining a measure for a large enough number of countries is challenging.

There is no single definition of exposure and vulnerability. Different definitions will be more appropriate for different uses, or to inform different decisions. Here, we test the methodology with one set of thresholds and return periods to facilitate a first discussion on the approach. A next step will be to add additional relevant dimensions and to perform systematic sensitivity analyses to better understand how absolute values and trends change with different thresholds.

In addition, within the choices we have made there is a need to (i) better characterize extreme heat events; (ii) consider data on other dimensions of vulnerability; and (iii) refine the measure used for social protection vulnerability so that it captures eligibility to be covered, not current receipt of benefits. Data work that is ongoing will also bring more data on education into the analysis; the source data used for heat to be updated; and a probabilistic distribution for drought based on historical data to be used.

Moving forwards, different decisions can be made about how to aggregate across multiple dimensions on both the exposure and vulnerability side. Being exposed to multiple shocks, for example, has not been considered in the current work but is likely to matter for welfare impacts. The dimensions of vulnerability considered have not been tailored to the specific impacts associated with each type of shock, although some dimensions we do not have such as access to air-conditioning could be critical for heatwaves but irrelevant for a cyclone. It will also be important to further analyze how the different dimensions of vulnerability are correlated with each other at household level and spatially with exposure to extreme events. Future work can explore these relationships to better inform what is missed or gained by including each dimension, and the extent to which they could be substitutes in terms of protecting against severe losses or helping household recover from extreme weather events.

For this measure to be a useful monitoring tool it needs to have sufficient global coverage and to be updated regularly over time. This requires developing methods to impute dimensions for countries where data is not available in the same survey—a very rudimentary approach was used in the current paper to do this for social protection and financial inclusion, but this can be extended to other indicators and improved--and developing methods for updating non-monetary measures. For example, education can be updated by using data on enrollment of children becoming adults in the latest survey even if it falls outside the reference period.

One limitation of our method is related to the spatial resolution of our vulnerability data. We calculate the population share deprived in each set of dimensions at subnational level (at best) and assume the exposed population within these regions, estimated at a much higher resolution (90m for flooding), has the same dimensions of vulnerability as those not exposed. This will introduce bias to the extent vulnerability indicators, like poverty and infrastructure, are spatially correlated with exposure within regions. For example, there is evidence that poor people with lower coping capacity are more likely to live in rural areas, which may lead us to underestimate the population at risk from drought. Future work can investigate what difference it makes when more spatially disaggregated vulnerability data is used, for example comparing estimates using subnational versus national poverty rates, or gridded data measuring infrastructure access versus survey-based estimates. For global coverage to be meaningful it will also be important to have spatially disaggregated data for China and updated spatially disaggregated data for India.

Setting out this approach has also highlighted four areas of measurement work that would benefit a global measure of vulnerability. First, generating global spatially disaggregated measures of poverty. This work has used administrative data, but there is room to experiment with how to disaggregate further. Second, further innovations on the method used to overlay dimensions from different data sources. A simple method was used for social protection and financial inclusion data, but further work could be undertaken on this to implement survey to survey methods across a wider range of dimensions of vulnerability. Third, developing a method to impute and line-up estimates of non-monetary vulnerability as is done for the income measure using methods developed for the global poverty measurement work. Finally, we have relied on historical datasets to define the probabilities of extreme events. As such this analysis provides a picture of who is vulnerable today. In order to say something about the future, the impact of a changing climate on the risk faced will need to be taken into account (see Baquie and Foucault, 2023).

References

Abay, K. A., Yonzan, N., Kurdi, S., & Tafere, K. (2023). Revisiting Poverty Trends and the Role of Social Protection Systems in Africa during the COVID-19 Pandemic. *Journal of African Economies*, *32*(Supplement_2), ii44-ii68. https://doi.org/10.1093/jae/ejac041

Abdulai, A., & CroleRees, A. (2001). Determinants of income diversification amongst rural households in Southern Mali. *Food Policy*, *26*(4), 437-452. https://doi.org/10.1016/S0306-9192(01)00013-6

Abiona, O., & Foureaux Koppensteiner, M. (2022). Financial inclusion, shocks, and poverty: Evidence from the expansion of mobile money in Tanzania. *Journal of Human Resources*, 57(2), 435-464.

Afridi, F., Mahajan, K., & Sangwan, N. (2022). Employment Guaranteed? Social Protection During a Pandemic. *Oxford Open Economics*, *1*. https://doi.org/10.1093/ooec/odab003

Aggarwal, S., Jeong, D., Kumar, N., Park, D.S., Robinson, J., & Spearot, A. (2020). Did COVID-19 Market Disruptions Disrupt Food Security? Evidence from Households in Rural Liberia and Malawi. Working Paper 27932, National Bureau of Economic Research, Cambridge, MA.

Aizer, A. and Currie, J. (2014). The intergenerational transmission of inequality: maternal disadvantage and health at birth. *Science* 344(6186), pp. 856-861.

Alderman, H., Hoddinott, J., and Kinsey, B. (2006). Long term consequences of early childhood malnutrition. *Oxford Economic Papers* 58(3), pp. 450-474.

Amuedo-Dorantes, C., & Pozo, S. (2011). Remittances and Income Smoothing. *American Economic Review*, 101 (3): 582-87.

Andrabi, T., Daniels, B., and Das, J. Forthcoming. Human capital accumulation and disasters: Evidence from the Pakistan earthquake of 2005. *Journal of Human Resources*.

Apeti, A. E. (2023). Household welfare in the digital age: Assessing the effect of mobile money on household consumption volatility in developing countries. *World Development*, *161*, 106110. https://doi.org/10.1016/j.worlddev.2022.106110

Banerjee, A., Faye, M., Krueger, A., Niehaus, P., & Suri, T. (2020). Effects of a Universal Basic Income during the Pandemic. Working paper, University of California San Diego.

Baquie, S., & Foucault, G. (2023). Background Note on Bringing Climate Change into Vulnerability Analysis. Washington, D.C.: World Bank.

Barrett, C., Reardon, T., & Webb, P. (2001). Nonfarm income diversification and household livelihood strategies in rural Africa: Concepts, dynamics, and policy implications. *Food Policy*, 26(4), 315-331. https://doi.org/10.1016/S0306-9192(01)00014-8

Batista, C., & Vicente, P. C. (2023). Is mobile money changing rural Africa? Evidence from a field experiment. *Review of Economics and Statistic*s, 1-29.

Beazley, R., Marzi, M., & Steller, R. (2021) Drivers of Timely and Large-Scale Cash Responses to COVID19: what does the data say? Social Protection Approaches to COVID-19 Expert Advice Service (SPACE), DAI Global UK Ltd, United Kingdom

Bloemendaal, N., De Moel, H., Muis, S., Haigh, I. D., & Aerts, J. C. (2020). Estimation of Global Tropical Cyclone Wind Speed Probabilities Using the STORM Dataset. *Scientific data*, 7(1), 377.

Bloemendaal, N., Haigh, I. D., de Moel, H., Muis, S., Haarsma, R. J., & Aerts, J. C. (2020). Generation of a Global Synthetic Tropical Cyclone Hazard Dataset Using STORM. *Scientific data*, *7*(1), 40.

Blumenstock, J E, N Eagle and M Fafchamps (2016), "Airtime transfers and mobile communications: Evidence in the aftermath of natural disasters", Journal of Development Economics, 120, 157-181 Bottan, N., Hoffmann, B., & Vera-Cossio, D. A. (2021). Stepping up during a crisis: The unintended effects of a noncontributory pension program during the Covid-19 pandemic. *Journal of Development Economics*, *150*, 102635. https://doi.org/10.1016/j.jdeveco.2021.102635

Bottan, N., Hoffmann, B., & Vera-Cossio, D. A. (2021). Stepping up during a crisis: The unintended effects of a noncontributory pension program during the Covid-19 pandemic. *Journal of Development Economics*, 150, 102635. https://doi.org/10.1016/j.jdeveco.2021.102635

Bowen, T. V., C. Del Ninno, C. Andrews, S. Coll-Black, U. Gentilini, K. Johnson, Y. Kawasoe, A. Kryeziu, B.P. Maher, A. Williams, 2020. Adaptive Social Protection : Building Resilience to Shocks International Development in Focus Washington, D.C. : World Bank Group. http://documents.worldbank.org/curated/en/579641590038388922/Adaptive-Social-Protection-Building-Resilience-to-Shocks

Brooks, W., Donovan, K., Johnson, T., & Oluoch-Aridi, J. (2020). Cash Transfers as a Response to COVID-19: A Randomized Experiment in Kenya. Discussion Paper 1082, Yale University, New Haven, CT.

Bussolo, M., Davalos, M. E., Peragine, V., & Sundaram, R. (2018). Toward a New Social Contract: Taking on Distributional Tensions in Europe and Central Asia. Europe and Central Asia Studies. Washington, D.C.: The World Bank.

Carter, M. R., & Lybbert, T. J. (2012). Consumption versus Asset Smoothing: Testing the Implications of Poverty Trap Theory in Burkina Faso. *Journal of Development Economics*, *99*(2), 255-264. https://doi.org/10.1016/j.jdeveco.2012.02.003

Chen, R., Yan, H., Liu, F., Du, W., & Yang, Y. (2020). Multiple global population datasets: Differences and spatial distribution characteristics. *ISPRS International Journal of Geo-Information*, 9(11), 637. https://doi.org/10.3390/ijgi9110637

Cheng, Y. T., Lung, S. C. C., & Hwang, J. S. (2019). New approach to identifying proper thresholds for a heat warning system using health risk increments. *Environmental Research*, 170, 282-292. https://doi.org/10.1016/j.envres.2018.12.059

Coles, S. (2001). An Introduction to Statistical Modelling of Extreme Values, Springer, pp 208.

Corral, P. (2023). wsample (Version v1.0.0-beta) [Computer software]. https://github.com/pcorralrodas/wsample

Dang, H.A.H. and Dabalen, A.L. 2018. Is Poverty in Africa Mostly Chronic or Transient? Evidence from Synthetic Panel Data. *Journal of Development Studies* 55 (7): 1527–47.

Dang, H.A.H., and Lanjouw, P.F. 2017. Welfare Dynamics Measurement: Two Definitions of a Vulnerability Line and Their Empirical Application. *Review of Income and Wealth* 63 (4): 633–60. https://doi.org/10.1111/roiw.12237

De Janvry, A., Finan, F., Sadoulet, E., & Vakis, R. (2006). Can conditional cash transfer programs serve as safety nets in keeping children at school and from working when exposed to shocks? *Journal of Development Economics*, *79*(2), 349-373. https://doi.org/10.1016/j.jdeveco.2006.01.013

Del Carpio, X.V., & Macours, K. (2010). Leveling the Intra-Household Playing Field: Compensation and Specialization in Child Labor Allocation. In Child Labor and the Transition between School and Work. United Kingdom: Emerald Group Publishing Limited.

Demirgüç-Kunt, A., & Klapper, L. (2012). Measuring Financial Inclusion: The Global Findex Database. World Bank Policy Research Working Paper 6025.

Demirgüç-Kunt, A., Klapper, L., Singer, D., & Ansar, S. (2022). The Global Findex Database 2021: Financial Inclusion, Digital Payments, and Resilience in the Age of COVID-19. Washington, D.C.: The World Bank.

Demirguc-Kunt, A., Klapper, L., Singer, D., & Van Oudheusden, P. (2015). The Global Findex Database 2014: Measuring Financial Inclusion around the World. Policy Research Working Paper No. 7255. Washington, D.C.: The World Bank.

Dercon, S. and Porter, C. 2014. Live aid revisited: long-term impacts of the 1984 Ethiopian famine on children. *Journal of the European Economic Association* 12 (4): 1542-4766

Dercon, Stefan. 2004. "Growth and Shocks: Evidence from Rural Ethiopia." Journal of Development Economics 74 (2): 309–29. https://doi.org/10.1016/j.jdeveco.2004.01.001.

Dimitrova, A. (2021). Seasonal droughts and the risk of childhood undernutrition in Ethiopia. *World Development*, *141*, 105417. https://doi.org/10.1016/j.worlddev.2021.105417

Dobermann, T. (2023). How building up the human capital of the world's poor can help lessen the climate crisis. *LSE Business Review*.

Dube, A. (2019). Minimum Wages and the Distribution of Family Incomes*. American Economic Journal: Applied Economics*, 11(4), 268-304.

Eberenz, S., Lüthi, S., & Bresch, D. N. (2021). Regional Tropical Cyclone Impact Functions for Globally Consistent Risk Assessments. *Natural Hazards and Earth System Sciences*, 21(1), 393-415.

Elbers, C., Gunning, J.W., and Kinsey, B. (2007). Growth and Risk: Methodology and Micro Evidence. *The World Bank Economic Review* 21 (1): 1–20.

Ellis, F. (1998). Household strategies and rural livelihood diversification. *The Journal of Development Studies*, 35:1, 1-38.

Erman, A., E. Motte, R. Goyal, A. Asare, S. Takamatsu, X. Chen, S. Malgioglio, A. Skinner, N. Yoshida, and S. Hallegatte. 2020. The road to recovery the role of poverty in the exposure, vulnerability and resilience to floods in Accra. *Economics of Disasters and Climate Change* 4: 171-193.

FAO. (2023). Agricultural Stress Index System (ASIS): Historic Agricultural Drought Frequency (Global - 1 Km). http://www.fao.org/giews/earthobservation/

Foster, J., Smallcombe, J. W., Hodder, S., Jay, O., Flouris, A. D., Nybo, L., & Havenith, G. (2021). An advanced empirical model for quantifying the impact of heat and climate change on human physical work capacity. *International Journal of Biometeorology*, 65, 1215-1229. https://doi.org/10.1007/s00484-021-02105-0

Gallardo, M. (2018). Identifying vulnerability to poverty: A Critical Survey. *Journal of Economic Surveys*, 32(4), 1074-1105. https://doi.org/10.1111/joes.12216

Gascoigne, J., Baquie, S., Vinha, K., Skoufias, E., Calcutt, E., Kshirsagar, V., Meenan, C., & Hill, R. Forthcoming. The Welfare Cost of Drought in Sub-Saharan Africa. Washington, D.C.: The World Bank.

Gehrke, E. (2019). An Employment Guarantee as Risk Insurance? Assessing the Effects of the NREGS on Agricultural Production Decisions. The World Bank Economic Review, World Bank Group, vol. 33(2), pages 413-435.

Gelb, A., Giri, A., Mukherjee, A., Rautela, R., Thapliyal, M., & Webster, B. (2022). Beyond India's Lockdown: PMGKY Benefits During the COVID-19 Crisis and the State of Digital Payments. CGD Policy Paper 257. Washington, DC: Center for Global Development. https://www.cgdev.org/publication/beyond-indias-lockdown-pmgky-benefits-during-covid-19-crisis-and-state-digital-payments

Gentilini et al. 2022. Social Protection and Jobs Responses to COVID-19: A Real-Time Review of Country Measures. World Bank.

Günther, I., & Harttgen, K. (2009). Estimating Households Vulnerability to Idiosyncratic and Covariate Shocks: A Novel Method Applied in Madagascar. *World Development*, *37*(7), 1222-1234. https://doi.org/10.1016/j.worlddev.2008.11.006

Hair, N. L., Hanson, J. L., Wolfe, B. L., & Pollak, S. D. (2015). Association of Child Poverty, Brain Development, and Academic Achievement. *JAMA pediatrics*, 169(9), 822–829. https://doi.org/10.1001/jamapediatrics.2015.1475

Hallegatte, S., Bangalore, M., Bonzanigo, L., Fay, M., Kane, T., Narloch, U., Rozenberg, J., Treguer, D., & Vogt-Schilb, A. (2016). Shock Waves: Managing the Impacts of Climate Change on Poverty. Washington, DC: World Bank.

Hallegatte, S., Vogt-Schilb, A., Bangalore, M., & Rozenberg, J. (2017). Unbreakable: Building the Resilience of the Poor in the Face of Natural Disasters. Climate Change and Development. Washington, DC: World Bank. http://hdl.handle.net/10986/25335

Hallegatte, S., J. Rentschler, and J. Rozenberg. 2019. Lifelines: The resilient infrastructure opportunity. Washington, DC: World Bank.

Hallegatte, S., A. Vogt-Schilb, J. Rozenberg, M. Bangalore, and C. Beaudet. 2020. From poverty to disaster and back: A review of the literature. *Economics of Disasters and Climate Change* 4: 223-247.

Heggeness, M. L., & Hokayem, C. (2013). Life on the Edge: Living Near Poverty in the United States, 1966-2011. SEHSD Working Paper. Washington, DC: U.S. Census Bureau.

Helgeson, J. F., Dietz, S., & Hochrainer-Stigler, S. (2013). Vulnerability to Weather Disasters: The Choice of Coping Strategies in Rural Uganda. *Ecology and Society*, 18(2). https://www.jstor.org/stable/26269323

Hill, R. V., & Porter, C. (2017). Vulnerability to Drought and Food Price Shocks: Evidence from Ethiopia. *World Development*, *96*, 65-77. https://doi.org/10.1016/j.worlddev.2017.02.025

Hoddinott, J., & Quisumbing, A. (2010). Methods for Microeconometric Risk and Vulnerability Assessment. In: Fuentes-Nieva, R., Seck, P.A. (eds) Risk, Shocks, and Human Development. Palgrave Macmillan, London. https://doi.org/10.1057/9780230274129_4

Hoffmann, R., & Muttarak, R. (2017). Learn from the Past, Prepare for the Future: Impacts of Education and Experience on Disaster Preparedness in the Philippines and Thailand. *World Development*, *96*, 32-51. https://doi.org/10.1016/j.worlddev.2017.02.016

Huizinga, J., Moel, H.D., & Wojciech, S. (2017). Global Flood Depth-Damage Functions: Methodology and the Database with Guidelines. JRC Publications Repository. April 12, 2017. https://doi.org/10.2760/16510

Hummel, D. (2016). Climate Change, Land Degradation and Migration in Mali and Senegal – Some Policy Implications. *Migration and Development*, 5:2, 211-233. https://doi.org/10.1080/21632324.2015.1022972

International Organization for Standardization. (2017). *Ergonomics of the thermal environment—Assessment of heat stress using the WBGT (wet bulb globe temperature) index (ISO Standard No. 7243:2017)*. https://www.iso.org/standard/67188.html

IPCC. 2012. Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change [Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 582 pp.

IPCC. 2022. Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)]. Cambridge University Press. Cambridge University Press, Cambridge, UK and New York, NY, USA, 3056 pp., doi:10.1017/9781009325844.

Ivaschenko, O., Doyle, J., Kim, J., Sibley, J., & Majoka, Z. (2020). Does 'Manna from Heaven' Help? The Role of Cash Transfers in Disaster Recovery—Lessons from Fiji after Tropical Cyclone Winston. *Disasters* 44 (3): 455–76.

Jack, W., & Suri, T. (2014). Risk Sharing and Transactions Costs: Evidence from Kenya's Mobile Money Revolution. *American Economic Review*, 104 (1): 183-223.

Jack, W., Ray, A., & Suri, T. (2013). Transaction Networks: Evidence from Mobile Money in Kenya." *American Economic Review*, 103 (3): 356-61.

Jellema, J., Wai-Poi, M., & Afka, R. (2017). The Distributional Impact of Fiscal Policy in Indonesia. Washington, DC: World Bank.

Hill, R., & Mejia-Mantilla, C. (2017). With a little help: shocks, agricultural income, and welfare in Uganda. Washington, DC: World Bank.

Karamba, W., Tong, K., & Salcher, I. (2022). Cambodia Poverty Assessment: Toward a More Inclusive and Resilient Cambodia. Washington, DC: World Bank.

Karlan, D., Osei, E., Osei-Akoto, I., & Udry. C. (2014). Agricultural Decisions after Relaxing Credit and Risk Constraints. *The Quarterly Journal of Economics* 129 (2): 597–652. https://doi.org/10.1093/qje/qju002

Kjellstrom, T., Freyberg, C., Lemke, B., Otto, M., & Briggs, D. (2018). Estimating population heat exposure and impacts on working people in conjunction with climate change. *International Journal of Biometeorology*, 62(3), 291-306. https://doi.org/10.1007/s00484-017-1407-0

Knippenberg, E., & Hoddinott, J. F. (2017). Shocks, Social Protection, and Resilience: Evidence from Ethiopia. ESSP working papers 109, International Food Policy Research Institute (IFPRI).

Le, K., & Nguyen, M. (2022). Droughts and child health in Bangladesh. *PLOS ONE*, *17*(3), e0265617. https://doi.org/10.1371/journal.pone.0265617

Leyk, S., Gaughan, A. E., Adamo, S. B., de Sherbinin, A., Balk, D., Freire, S., ... & Pesaresi, M. (2019). The spatial allocation of population: a review of large-scale gridded population data products and their fitness for use. *Earth System Science Data*, 11(3), 1385-1409. https://doi.org/10.5194/essd-11-1385-2019

Ligon, E., and Schechter, L. (2003). Measuring Vulnerability. *The Economic Journal* 113 (486): C95–102. https://doi.org/10.1111/1468-0297.00117

Liu, Y., & Yamauchi, F. (2014). Population density, migration, and the returns to human capital and land: Insights from Indonesia. *Food Policy*, *48*, 182-193. https://doi.org/10.1016/j.foodpol.2014.05.003

Londoño-Velez, J., & Querubin, P. (2022). The Impact of Emergency Cash Assistance in a Pandemic: Experimental Evidence from Colombia. *The Review of Economics and Statistics*, MIT Press, vol. 104(1), pages 157-165, March.

López-Calva, L.F., & Ortiz-Juarez, E. (2014) A vulnerability approach to the definition of the middle class. *Journal of Economic Inequality,* 12, 23–47 (2014). https://doi.org/10.1007/s10888-012-9240-5

Lybbert, T. J., Barrett, C.B., Desta, S., & Coppock, D.L. (2004). Stochastic Wealth Dynamics and Risk Management among a Poor Population. *The Economic Journal* 114 (498): 750–77. https://doi.org/10.1111/j.1468-0297.2004.00242.x.

Macours, K., Schady, N., &Vakis, R. (2012). Cash Transfers, Behavioral Changes, and Cognitive Development in Early Childhood: Evidence from a Randomized Experiment. *American Economic Journal: Applied Economics*, 4 (2): 247-73.

Maes, M., et al. (2022), "Monitoring exposure to climate-related hazards: Indicator methodology and key results", OECD Environment Working Papers, No. 201, OECD Publishing, Paris, https://doi.org/10.1787/da074cb6-en.

Mansur, A., Doyle, J., & Ivaschenko, O. (2017). Social Protection and Humanitarian Assistance Nexus for Disaster Response: Lessons Learnt from Fiji's Tropical Cyclone Winston. Social Protection and Labor Discussion Paper 1701. Washington, DC: World Bank.

Meghir, C., Mobarak, A. M., Mommaerts, C., & Morten, M. (2022). Migration and Informal Insurance: Evidence from a Randomized Controlled Trial and a Structural Model. *The Review of Economic Studies*, *89*(1), 452-480. https://doi.org/10.1093/restud/rdab021

Menezes-Filho, N., Komatsu, B.K., & Rosa, J.P. (2021). Reducing Poverty and Inequality during the Coronavirus Outbreak: The Emergency Aid Transfers in Brazil. Policy Paper 54, Institute of Education and Research (Insper), Brazil.

Mileti, D. S., & Sorensen, J. H. (1990). Communication of Emergency Public Warnings: a Social Science Perspective and State of-the-Art Assessment. Federal Emergency Management Agency (No. Report ORNL-6609). Oak Ridge, TN.

Montgomery, L. E., Kiely, J. L., & Pappas, G. (1996). The Effects of Poverty, Race, and Family Structure on US Chil'ren's Health: Data from the NHIS, 1978 through 1980 and 1989 through 1991. *American Journal of Public Health*, 86(10), 1401–1405. https://doi.org/10.2105/ajph.86.10.1401

Morawczynski, O., & Pickens, M. (2009). Poor People Using Mobile Financial Services : Observations on Customer Usage and Impact from M-PESA. World Bank Publications - Reports 9492. Washington, DC: World Bank.

Muttarak, R., & Lutz, W. (2014). Is Education a Key to Reducing Vulnerability to Natural Disasters and hence Unavoidable Climate Change? *Ecology and Society*, *19*(1). https://www.jstor.org/stable/26269470

Muttarak, R., & Pothisiri, W. (2013). The role of education on disaster preparedness: case study of 2012 Indian Ocean earthquakes on Thailand's Andaman Coast*.* *Ecology and Society* 18(4): 51. http://dx.doi.org/10.5751/ES-06101-180451

Nguyen, M.C., Yang, J., Dang, H.A., Gonzalez, S., & Gerardo, C. (2023). On the Construction of the World Bank's Subnational Poverty and Inequality Databases: Documentation (English). Global Poverty Monitoring Technical Note no. 31. Washington, D.C.: The World Bank.

Pape, U. J., & Ali, R. (2023) Indonesia Poverty Assessment - Pathways towards Economic Security (English). Washington, D.C.: The World Bank.

Pega, F., Liu, S. Y., Walter, S., Pabayo, R., Saith, R., & Lhachimi, S. K., (2017). Unconditional cash transfers for reducing poverty and vulnerabilities: Effect on use of health services and health outcomes in low- and middle-income countries. *The Cochrane Database of Systematic Reviews*, *2017*(11). https://doi.org/10.1002/14651858.CD011135.pub2

Pesaresi, M., et al. (2017). Atlas of the Human Planet 2017: Global Exposure to Natural Hazards, EUR 28556 EN, doi: 10.2760/19837.

Pople, A., Hill, R., Dercon, S., & Brunckhorst, B. (2021). Anticipatory Cash Transfers in Climate Disaster Response. Working Paper 6, Centre for Disaster Protection, London.

Reardon, T. (1997). Using evidence of household income diversification to inform study of the rural nonfarm labor market in Africa. *World Development*, *25*(5), 735-747. https://doi.org/10.1016/S0305-750X(96)00137-4

Rentschler, J., Avner, P., Marconcini, M., Su, R., Strano, E., Vousdoukas, M., & Hallegatte, S. (2023). Global evidence of rapid urban growth in flood zones since 1985. *Nature*, 622(7981), 87-92. https://doi.org/10.1038/s41586-023-06468-9

Rentschler, J., Salhab, M., & Jafino, B. A. (2022). Flood Exposure and Poverty in 188 Countries. *Nature Communications*, 13(1), 3527.

Rentschler, J; de Vries Robbé, S., Braese, J., Nguyen, D. H., van Ledden, M., & Pozueta Mayo, B. (2020). Resilient Shores: Vietnam's Coastal Development Between Opportunity and Disaster Risk. World Bank, Washington, DC. http://hdl.handle.net/10986/34639

Ridder, K. D., Lauwaet, D., Hooyberghs, H., & Lefebre, F. (2017). Development of a Hazard Screening Protocol for Extreme Heat. VITO NV. https://datacatalog.worldbank.org/search/dataset/0040194/Global%20extreme%20heat%20hazard?version=2

Riley, E. (2018). Mobile money and risk sharing against village shocks. *Journal of Development Economics*, *135*, 43-58. https://doi.org/10.1016/j.jdeveco.2018.06.015
Robayo-Abril, M., Rude, B., Cadena, K., & Espino, I. (2023). Honduras Poverty Assessment: Toward a Path of Poverty Reduction and Inclusive Growth. Washington, D.C.: The World Bank.
Rozenberg, J., & Fay, M. (2019). Beyond the Gap: How Countries Can Afford the Infrastructure They Need while Protecting the Planet. Sustainable Infrastructure. Washington, D.C.: The World Bank.
Ruggeri Laderchi,C., Spatafora,N.L., Sudhir, S. & Zaidi, S.(2017). Riding the wave : an East Asian miracle for the 21st century (English). World Bank East Asia and Pacific Regional Report Washington, D.C.: World Bank Group.
Russell, T. (2022). STORM Tropical Cyclone Wind Speed Return Periods as Global GeoTIFFs (1.0.0) [Data set]. Zenodo. https://doi.org/10.5281/zenodo.7438145
Saczewska-Piotrowska, A. (2016). Near poverty definition, factors, prediction. *Econometrics: Advances in Applied Data Analytic,* 4(54): 82-94.
Sampson, C., Smith, A. M., Bates, P. D., Neal, J. C., Alfieri, L., & Freer, J. E. (2015). A High-resolution Global Flood Hazard Model. *Water resources research*, *51*(9), 7358-7381.
Schiavina, M., Freire, S., Alessandra C., & MacManus, K. (2023). GHS-POP R20–3A - GHS Population Grid Multitemporal (1975-2030). European Commission, Joint Research Centre (JRC) [Dataset] https://doi.org/10.2905/2FF68
2-5B5B-4A22-8F40-C41DA8332CFE
Schiavina, M., Melchiorri, M., & Pesaresi, M. (2023). GHS-SMOD R20–3A - GHS Settlement Layers, Application of the Degree of Urbanisation Methodology (stage I) to GHS-POP R2023A and GHS-BUILT-S R2023A, multitemporal (1975-2030). European Commission, Joint Research Centre (JRC) [Dataset] https://doi.org/10.2905/A0DF7A6F-49DE-46EA-9BDE-563437A6E2BA
Schiavina, M., Melchiorri, M., Pesaresi, M., Politis, P., Carneiro Freire, S.M., Maffenini, L., Florio, P., Ehrlich, D., Goch, K., Carioli, A., Uhl, J., Tommasi, P. & Kemper, T. (2023). GHSL Data Package 2023. Publications Office of the European Union, Luxembourg. https://dx.doi.org/10.2760/098587
Smith, A., Bates, P. D., Wing, O., Sampson, C., Quinn, N., & Neal, J. (2019). New estimates of flood exposure in developing countries using high-resolution population data. *Nature Communications*, *10*(1), 1-7. https://doi.org/10.1038/s41467-019-09282-y
Tuholske, C., Caylor, K., Funk, C., Verdin, A., Sweeney, S., Grace, K., Peterson, P., & Evans, T. (2021). Global urban population exposure to extreme heat. *Proceedings of the National Academy of Sciences*, 118(41), e2024792118. https://doi.org/10.1073/pnas.2024792118
Van der Land, V. & Hummel, D. (2013). Vulnerability and the role of education in environmentally induced migration in Mali and Senegal. *Ecology and Society* 18(4): 14. https://doi. org/10.5751/ES-05830-180414
Van Hoolst, R., Eerens, H., Haesen, D., Royer, A., Bydekerke, L., Rojas, O., L. Yanyun, L., & Racionzer., P. (2016). Fao's AVHRR-Based Agricultural Stress Index System (ASIS) for Global Drought Monitoring. *International Journal of Remote Sensing* 37 (2): 418–439. https://doi.org/10.1080/01431161.2015.1126378
Wollburg, Philip Randolph; Hallegatte, Stephane; Mahler, Daniel Gerszon. The Climate Implications of Ending Global Poverty (English). Policy Research working paper ; no. WPS 10318 Washington, D.C. : World Bank Group.
World Bank (2016). The Uganda Poverty Assessment Report 2016: Farms, Cities, and Good Fortune – Assessing Poverty Reduction in Uganda from 2006 to 2014. Washington, D.C.: The World Bank.
World Bank (2018). Poverty and Shared Prosperity 2018: Piecing Together the Poverty Puzzle. Washington, D.C.: The World Bank.
World Bank (2019). Aspiring Indonesia: Expanding the Middle Class. Washington, D.C.: The World Bank.
World Bank (2021a). The Gradual Rise and Rapid Decline of the Middle Class in Latin America and the Caribbean. Washington, D.C.: The World Bank.

World Bank (2021b). Stress Testing Social Protection. Washington, D.C.: The World Bank.
World Bank (2022a). Brazil Poverty and Equity Assessment: Looking Ahead of Two Crises. Washington, D.C.: The World Bank.
World Bank (2022b). From the Last Mile to the Next Mile – 2022 Vietnam Poverty & Equity Assessment. Washington, D.C.: The World Bank.
World Bank. (2022c). Poverty and Shared Prosperity 2022: Correcting Course. Washington, D.C.: The World Bank.
World Bank (2022d). Progress, Setbacks, and Uncertainty: Effects of COVID-19 and Coup on Poverty in Myanmar. Myanmar Poverty Synthesis Note. Washington, D.C.: The World Bank.
World Bank (2023a). Rising Strong: Peru Poverty and Equity Assessment. Washington, D.C.: The World Bank.
World Bank (2023b). Poverty and Inequality Platform Methodology Handbook. Edition 2023-09. Available at https://datanalytics.worldbank.org/PIP-Methodology/
Wouterse, F., & Taylor, J. E. (2008). Migration and Income Diversification: Evidence from Burkina Faso. *World Development*, *36*(4), 625-640. https://doi.org/10.1016/j.worlddev.2007.03.009
Yang, D., & Choi, H. (2007). Are Remittances Insurance? Evidence from Rainfall Shocks in the Philippines. *The World Bank Economic Review*, 21(2), 219–248. http://www.jstor.org/stable/40282243
Yin, X., Li, P., Feng, Z., Yang, Y., You, Z., & Xiao, C. (2021). Which gridded population data product is better? Evidences from mainland southeast Asia (MSEA). *ISPRS International Journal of Geo-Information*, 10(10), 681. https://doi.org/10.3390/ijgi10100681

APPENDIX A1 – CHECKING THE ASSUMPTION OF JOINT DISTRIBUTION

As we mention above, the main data source for poverty and education comes from the same surveys in the GMD, and the social protection data comes from the ASPIRE, which is also based on household surveys collected in various years. For a small set of 42 countries, we can identify the same household surveys used for the ASPIRE indicator and for poverty and education indicators. For these 42 countries, we construct the joint distribution of poverty and social protection at the household level and aggregate this joint estimate to the subnational level. The subnational joint estimates are compared with the above estimates resulting from the random assignment at the household level due to lack of having indicators in the same survey data.

Figure A1.1 shows the scatter plot at the subnational level of no access to social protection from survey estimates and ones from simulation. On average, the graph shows the correlation of 80%. Simple average from both sources is similar for 557 subnational areas in 42 countries: with 60% from the simulation and 56.4% from the surveys.

Figure A1.2 shows the scatter plot of joint distribution of poverty and no access to social protection. On average, both survey and simulated estimates show similar numbers, with 25% from the simulation and 21.3% from the surveys.

Figure A1.1: Scatter plot of lack of access to social protection (survey estimate vs. simulation)

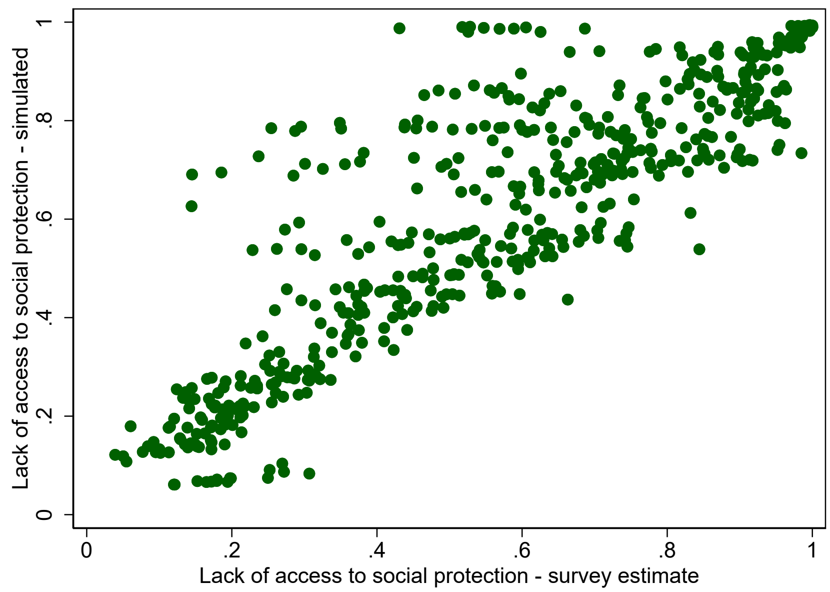
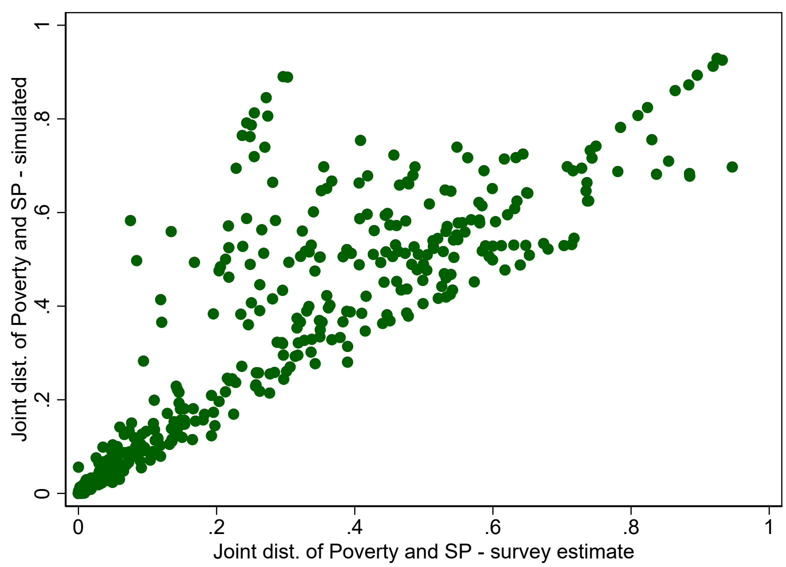


Figure A1.2: Scatter plot of joint distribution of both poor and no access to social protection (survey estimate vs. simulation)



APPENDIX A2–- DATA SOURCE

	2010				2019			
	Survey year	Survey name	Findex year	ASPIRE year	Survey year	Survey name	Findex year	ASPIRE year
Albania	2012	LSMS	2011	2012	2019	HBS	2021	2018
Algeria	2011	ENCNVM	2011		2011	ENCNVM	2021	
Angola	2008	IBEP-MICS	2011		2018	IDREA		2018
Argentina	2010	EPHC-S2	2011	2010	2019	EPHC-S2	2021	2019
Armenia	2010	ILCS	2011	2010	2019	ILCS	2021	2019
Australia	2010	SIH-HES-LIS	2011		2018	SIH-LIS	2021	
Austria	2011	EU-SILC	2011		2019	EU-SILC	2021	
Azerbaijan	2005	HBS	2011	2015	2005	HBS	2022	2015
Bangladesh	2010	HIES	2011	2010	2016	HIES	2021	2016
Belarus	2010	HHS	2011	2010	2019	HHS		2019
Belgium	2011	EU-SILC	2011		2019	EU-SILC	2021	
Belize	1999	LFS		2009	1999	LFS		
Benin	2011	EMICOV	2011		2018	EHCVM	2021	2018
Bhutan	2012	BLSS		2012	2017	BLSS		2017
Bolivia	2011	EH	2011	2011	2019	EH	2021	2019
Bosnia and Herzegovina	2011	HBS	2011	2007	2011	HBS	2021	2015
Botswana	2009	CWIS	2011	2009	2015	BMTHS	2022	2015
Brazil	2011	PNAD	2011	2011	2019	PNADC-E1	2021	2019
Bulgaria	2011	EU-SILC	2011	2007	2019	EU-SILC	2021	
Burkina Faso	2009	ECVM	2011	2014	2018	EHCVM	2021	2018
Burundi	2013	ECVMB	2011		2013	ECVMB		
Cabo Verde	2007	QUIBB		2007	2015	IDRF		
Cameroon	2007	ECAM-III	2011	2007	2014	ECAM-IV	2021	2014
Canada	2010	SLID-LIS	2011		2018	CIS-LIS	2021	
Central African Republic	2008	ECASEB	2011		2008	ECASEB		
Chad	2011	ECOSIT-III	2011	2011	2018	EHCVM	2022	
Chile	2011	CASEN	2011	2011	2019	CASEN	2021	2017
China	2013	CHIP	2011	2013	2013	CHIP	2021	2013
Colombia	2010	GEIH	2011	2010	2019	GEIH	2021	2019
Comoros	2013	EESIC	2011		2013	EESIC	2022	
Congo, Dem. Rep.	2012	E123	2011	2012	2012	E123	2022	2012
Congo, Rep.	2011	ECOM	2011	2005	2011	ECOM	2021	
Costa Rica	2010	ENAHO	2011	2010	2019	ENAHO	2021	2019
Croatia	2011	EU-SILC	2011	2010	2019	EU-SILC	2021	2014
Cyprus	2011	EU-SILC	2011		2019	EU-SILC	2021	
Czechia	2011	EU-SILC	2011		2019	EU-SILC	2021	
Côte d’Ivoire	2008	ENV		2008	2018	EHCVM	2021	2018
Denmark	2011	EU-SILC	2011		2019	EU-SILC	2021	

Djibouti	2012	EDAM	2011	2012	2017	EDAM		2012
Dominican Republic	2010	ENFT	2011	2010	2019	ECNFT-Q03	2021	2019
Ecuador	2010	ENEMDU	2011	2010	2019	ENEMDU	2021	2019
Egypt, Arab Rep.	2010	HIECS	2011	2008	2017	HIECS	2021	2017
El Salvador	2010	EHPM	2011	2010	2019	EHPM	2021	2019
Estonia	2011	EU-SILC	2011		2019	EU-SILC	2021	
Eswatini	2009	HIES	2011	2009	2016	HIES	2022	2016
Ethiopia	2010	HICES		2010	2015	HICES	2022	2018
Fiji	2008	HIES		2008	2019	HIES		2013
Finland	2011	EU-SILC	2011		2019	EU-SILC	2021	
France	2011	EU-SILC	2011		2018	EU-SILC	2021	
Gabon	2017	EGEP	2011	2005	2017	EGEP	2021	2017
Gambia, The	2010	IHS		2010	2020	IHS	2022	2015
Georgia	2010	HIS	2011	2011	2019	HIS	2021	2019
Germany	2010	GSOEP-LIS	2011		2019	GSOEP-LIS	2021	
Ghana	2012	GLSS-VI	2011	2012	2016	GLSS-VII	2021	2016
Greece	2011	EU-SILC	2011		2019	EU-SILC	2021	
Guatemala	2014	ENCOVI	2011	2011	2014	ENCOVI	2022	2014
Guinea	2012	ELEP	2011	2012	2018	EHCVM	2021	2012
Guinea-Bissau	2010	ILAP-II			2018	EHCVM		
Guyana	1998	GLSMS			1998	GLSMS		
Haiti	2012	ECVMAS	2011	2012	2012	ECVMAS		2012
Honduras	2010	EPHPM	2011	2010	2019	EPHPM	2021	2017
Hungary	2011	EU-SILC	2011	2007	2019	EU-SILC	2021	
Iceland	2011	EU-SILC			2016	EU-SILC	2021	
India	2011	NSS-SCH1	2011	2011	2011	NSS-SCH1	2021	
Indonesia	2010	SUSENAS	2011	2011	2019	SUSENAS	2021	2019
Iran, Islamic Rep.	2009	HEIS	2011		2019	HEIS	2021	2018
Iraq	2012	IHSES	2011	2012	2012	IHSES	2021	2012
Ireland	2011	EU-SILC	2011		2018	EU-SILC	2021	
Israel	2010	HES-LIS	2011		2018	HES-LIS	2021	
Italy	2011	EU-SILC	2011		2018	EU-SILC	2021	
Jamaica	2004	SLC	2011	2010	2004	SLC	2021	2017
Japan	2010	JHPS-LIS	2011		2013	JHPS-LIS	2021	
Jordan	2010	HEIS	2011	2010	2010	HEIS	2021	
Kazakhstan	2010	HBS	2011	2010	2018	HBS	2021	2017
Kenya	2015	IHBS	2011	2015	2015	IHBS	2021	2015
Kiribati	2019	HIES		2006	2019	HIES		2019
Korea, Rep.	2010	HIES-FHES-LIS	2011		2016	HIES-FHES-LIS	2021	
Kosovo	2010	HBS	2011	2011	2017	HBS	2021	2017
Kyrgyz Republic	2010	KIHS	2011	2011	2019	KIHS	2021	2019
Lao PDR	2012	LECS	2011	2007	2018	LECS	2021	2018
Latvia	2011	EU-SILC	2011	2009	2019	EU-SILC	2021	

Lebanon	2011	HBS	2011		2011	HBS	2021	
Lesotho	2017	CMSHBS	2011	2010	2017	CMSHBS	2022	2017
Liberia	2007	CWIQ	2011	2007	2016	HIES	2021	2016
Lithuania	2011	EU-SILC	2011	2008	2019	EU-SILC	2021	
Luxembourg	2011	EU-SILC	2011		2019	EU-SILC		
Madagascar	2010	EPM	2011	2010	2012	ENSOMD	2022	
Malawi	2010	IHS-III	2011	2010	2019	IHS-V	2021	2019
Malaysia	2012	HIS	2011	2012	2019	HIS	2021	2016
Maldives	2009	HIES		2009	2019	HIES		2019
Mali	2009	ELIM	2011	2009	2018	EHCVM	2021	2018
Malta	2011	EU-SILC	2011		2019	EU-SILC	2021	
Marshall Islands	2019	HIES			2019	HIES		2019
Mauritania	2008	EPCV	2011	2008	2014	EPCV	2022	2014
Mauritius	2012	HBS	2011	2012	2017	HBS	2021	2017
Mexico	2010	ENIGH	2011	2010	2019	ENIGHNS	2022	2018
Micronesia, Fed. Sts.	2013	HIES			2013	HIES		
Moldova	2010	HBS	2011	2010	2019	HBS	2021	2018
Mongolia	2010	HSES	2011	2010	2018	HSES	2021	2018
Montenegro	2013	SILC-C	2011	2011	2019	SILC-C		2014
Morocco	2013	ENCDM		2009	2013	ENCDM	2021	
Mozambique	2008	IOF		2008	2014	IOF	2021	2014
Myanmar	2015	MPLCS		2009	2017	MLCS	2021	2017
Namibia	2009	NHIES		2009	2015	NHIES	2021	2015
Nauru	2012	HIES			2012	HIES		
Nepal	2010	LSS-III	2011	2010	2010	LSS-III	2021	
Netherlands	2011	EU-SILC	2011		2019	EU-SILC	2021	
Nicaragua	2009	EMNV	2011	2009	2014	EMNV	2021	2014
Niger	2011	ECVMA	2011	2011	2018	EHCVM	2022	2018
Nigeria	2009	LSS	2011	2010	2018	LSS	2021	2018
North Macedonia	2008	HBS	2011		2020	SILC-C	2021	
Norway	2011	EU-SILC			2019	EU-SILC	2021	
Pakistan	2010	HIES	2011	2009	2018	HIES	2021	2018
Panama	2010	EH	2011	2010	2019	EH	2021	2019
Papua New Guinea	2009	HIES		2009	2009	HIES		
Paraguay	2010	EPH	2011	2010	2019	EPH	2021	2019
Peru	2010	ENAHO	2011	2010	2019	ENAHO	2021	2019
Philippines	2009	FIES	2011	2013	2018	FIES	2021	2018
Poland	2011	EU-SILC	2011	2010	2018	EU-SILC	2021	2017
Portugal	2011	EU-SILC	2011		2018	EU-SILC	2021	
Romania	2011	EU-SILC	2011	2011	2019	EU-SILC	2021	2016
Russian Federation	2010	HBS	2011	2007	2019	HBS	2021	2017
Rwanda	2010	EICV-III	2011	2010	2016	EICV-V		
Samoa	2008	HIES		2008	2013	HIES		

Senegal	2011	ESPS-II	2011	2011	2018	EHCVM	2021	2018
Serbia	2013	HBS	2011	2010	2019	HBS	2021	2018
Seychelles	2013	HBS			2018	HBS		
Sierra Leone	2011	SLIHS	2011	2011	2018	SLIHS	2021	2018
Slovak Republic	2011	EU-SILC	2011	2009	2019	EU-SILC	2021	
Slovenia	2011	EU-SILC	2011		2019	EU-SILC	2021	
Solomon Islands	2012	HIES		2005	2012	HIES		
Somalia	2017	SHFS-W2			2017	SHFS-W2		
South Africa	2010	IES	2011	2010	2014	LCS	2021	2019
South Sudan	2009	NBHS		2009	2016	HFS-W3	2021	
Spain	2011	EU-SILC	2011		2019	EU-SILC	2021	
Sri Lanka	2009	HIES	2011	2009	2019	HIES	2021	2019
St. Lucia	2016	SLC-HBS			2016	SLC-HBS		
Sudan	2009	NBHS	2011	2009	2014	NBHS		
Suriname	1999	EHS			1999	EHS		
Sweden	2011	EU-SILC	2011		2019	EU-SILC	2021	
Switzerland	2011	EU-SILC			2018	EU-SILC	2021	
Syrian Arab Republic	2003	HIES	2011		2003	HIES		
São Tomé and Príncipe	2010	IOF		2017	2017	IOF		2017
Taiwan, China	2010	FIDES-LIS	2011		2016	FIDES-LIS	2021	
Tajikistan	2009	TLSS	2011	2011	2015	HSITAFIEN	2021	
Tanzania	2011	HBS	2011	2010	2018	HBS	2021	2014
Thailand	2012	SES	2011	2011	2019	SES	2021	2019
Timor-Leste	2007	TLSLS		2011	2014	TLSLS		
Togo	2011	QUIBB	2011	2011	2018	EHCVM	2021	2018
Tonga	2009	HIES		2009	2015	HIES		
Trinidad and Tobago	1992	PHC	2011		1992	PHC		
Tunisia	2010	NSHBCSL		2010	2015	NSHBCSL	2021	
Turkmenistan	1998	LSMS	2011		1998	LSMS		
Tuvalu	2010	HIES			2010	HIES		
Türkiye	2010	HICES	2011	2010	2019	HICES	2021	2019
Uganda	2012	UNHS	2011	2009	2019	UNHS	2021	2016
Ukraine	2010	HLCS	2011	2011	2019	HLCS	2021	2018
United Arab Emirates	2014	HIES	2011		2019	HIES	2021	
United Kingdom	2010	FRS-LIS	2011		2016	EU-SILC	2021	
United States	2010	CPS-ASEC-LIS	2011		2019	CPS-ASEC-LIS	2021	
Uruguay	2010	ECH	2011	2010	2019	ECH	2021	2019
Uzbekistan	2003	HBS	2011		2003	HBS	2021	2018
Vanuatu	2010	HIES			2019	NSDP		2019
Venezuela, RB	2006	EHM	2011	2006	2006	EHM	2021	
Viet Nam	2010	VHLSS	2011	2010	2018	VHLSS	2022	2014
West Bank and Gaza	2010	PECS	2011	2009	2016	PECS	2021	2016
Yemen, Rep.	2014	HBS	2011	2005	2014	HBS	2022	

Zambia	2010	LCMS-VI	2011	2010	2015	LCMS-VII	2021	2015
Zimbabwe	2017	PICES	2011	2011	2019	PICES	2021	2019

Note: CONS: the welfare type is consumption/expenditure, and INC indicates the welfare type is income. Joint distribution indicates there are joint distribution of household survey data with social protection (ASPIRE) and financial inclusion (Findex).

APPENDIX A3–COUNTRY AND REGIONAL RESULTS

	Pop . exposed to any shock (million)	Share of pop. exposed to any shock (%)	Poor people exposed (million)		Population exposed and vulnerable on the following dimensions						Pop . exposed and vulnerable on any one dimension (million)
			$2.15	$6.85	Income	Education	SP	Finance	Water	Electricity	
Albania	1	42	0	0	0	0	1	1	0	0	1
Algeria	10	24	0	3	0	-	-	-	-	-	0
Angola	6	18	3	5	4	2	5	-	2	4	6
Argentina	14	30	0	2	0	0	7	4	0	-	9
Armenia	1	33	0	1	0	0	0	0	0	-	1
Australia	5	21	0	0	0	-	-	-	-	-	0
Austria	4	46	0	0	0	-	-	0	0	-	0
Azerbaijan	3	27	0	0	0	0	1	1	0	-	2
Bangladesh	167	100	18	139	47	36	99	78	4	37	151
Belarus	2	25	0	0	0	-	1	-	0	-	1
Belgium	3	25	0	0	0	0	-	0	0	-	0
Belize	0	98	0	0	0	-	-	-	-	-	0
Benin	5	40	1	5	3	3	4	3	1	3	5
Bhutan	0	24	0	0	0	0	0	-	0	0	0
Bolivia	3	26	0	1	0	0	1	1	0	0	2
Bosnia and Herzegovina	2	59	0	0	0	0	1	0	0	0	1
Botswana	1	36	0	1	0	0	0	0	0	0	1
Brazil	52	25	4	16	6	9	26	8	1	0	36
Bulgaria	3	45	0	0	0	0	-	1	0	-	1
Burkina Faso	19	87	6	16	10	11	8	12	4	9	18
Burundi	2	17	1	2	2	1	-	-	0	2	2
Cabo Verde	0	30	0	0	0	0	-	-	0	0	0
Cameroon	10	38	3	8	5	3	10	5	3	0	10
Canada	7	18	0	0	0	-	-	-	-	-	0
Central African Republic	2	29	1	1	1	1	-	-	1	1	2
Chad	13	77	4	11	7	9	-	10	4	11	13
Chile	4	19	0	0	0	0	0	0	0	0	1
China	1006	71	1	238	15	168	457	114	0	0	613
Colombia	13	26	1	5	2	1	9	5	0	0	11
Comoros	0	7	0	0	0	0	-	0	0	0	0
Congo, Dem. Rep.	14	15	10	14	12	3	12	10	8	12	14
Congo, Rep.	1	17	1	1	1	0	-	1	0	0	1
Costa Rica	1	23	0	0	0	0	0	0	0	0	1
Croatia	2	53	0	0	0	0	1	0	0	-	1
Cyprus	1	87	0	0	0	0	-	0	0	-	0
Czechia	5	46	0	0	0	0	-	0	0	-	0
Côte d’Ivoire	10	36	1	8	4	5	7	5	2	2	9
Denmark	2	36	0	0	0	0	-	0	0	-	0

Djibouti	1	83	0	1	0	0	1	-	0	0	1
Dominican Republic	11	100	0	2	0	1	5	5	1	0	9
Ecuador	8	44	0	2	1	0	5	3	0	0	6
Egypt, Arab Rep.	46	44	1	33	6	5	3	33	0	0	37
El Salvador	2	27	0	1	0	1	0	1	0	0	1
Estonia	0	20	0	0	0	0	-	0	0	-	0
Eswatini	1	60	0	1	0	0	0	0	0	0	1
Ethiopia	44	37	8	38	19	30	34	23	19	28	43
Fiji	1	100	0	0	0	0	1	-	0	0	1
Finland	1	10	0	0	0	0	-	0	0	-	0
France	26	40	0	0	0	0	-	0	0	-	1
Gabon	0	21	0	0	0	0	0	0	0	0	0
Gambia, The	1	31	0	1	0	0	1	1	0	0	1
Georgia	2	45	0	1	0	0	1	0	0	-	1
Germany	24	29	0	0	0	-	-	-	-	-	0
Ghana	12	36	4	10	6	2	5	4	4	3	11
Greece	4	36	0	0	0	0	-	0	0	-	0
Guatemala	5	29	0	2	1	1	2	3	0	1	4
Guinea	6	42	1	5	2	4	5	4	1	4	6
Guinea-Bissau	1	27	0	0	0	0	-	-	0	0	0
Guyana	0	35	0	0	0	-	-	-	-	-	0
Haiti	11	100	3	9	5	3	9	-	4	7	10
Honduras	5	49	1	2	1	0	3	3	0	0	4
Hungary	4	43	0	0	0	0	-	1	0	-	1
Iceland	0	7	0	0	0	-	-	0	0	-	0
India	1195	86	140	978	405	217	72	269	-	258	752
Indonesia	55	21	2	34	10	2	30	26	5	1	46
Iran, Islamic Rep.	26	30	0	9	2	1	2	3	1	0	7
Iraq	34	80	0	7	0	4	5	28	3	0	30
Ireland	1	26	0	0	0	0	-	0	0	-	0
Israel	1	11	0	0	0	-	-	-	-	-	0
Italy	17	29	0	0	0	0	-	0	0	-	1
Jamaica	3	100	0	1	0	-	-	-	-	-	0
Japan	109	89	1	2	1	-	-	-	-	-	1
Jordan	1	13	0	0	0	0	-	1	0	-	1
Kazakhstan	5	27	0	1	0	0	3	1	0	-	3
Kenya	14	27	5	13	8	4	10	3	5	11	14
Kiribati	0	0	0	0	0	0	-	-	-	-	0
Korea, Rep.	31	62	0	0	0	-	-	-	-	-	0
Kosovo	0	30	0	0	0	0	0	0	0	0	0
Kyrgyz Republic	2	32	0	1	0	0	1	1	0	0	2
Lao PDR	4	50	0	3	1	0	4	2	0	0	4
Latvia	1	28	0	0	0	0	-	0	0	-	0
Lebanon	1	26	0	0	0	0	-	1	0	0	1
Lesotho	1	55	0	1	1	0	0	0	0	1	1

Liberia	2	42	1	2	1	1	2	1	1	2	2
Lithuania	1	43	0	0	0	0	-	0	0	-	0
Luxembourg	0	17	0	0	0	0	-	-	0	-	0
Madagascar	16	59	13	16	15	9	-	12	11	2	16
Malawi	8	42	6	8	7	4	5	5	1	7	8
Malaysia	8	23	0	0	0	0	2	1	0	0	3
Maldives	0	0	0	0	0	0	-	-	-	-	0
Mali	18	86	3	15	7	12	10	10	4	4	18
Malta	0	7	0	0	0	0	-	0	0	-	0
Marshall Islands	0	3	0	0	0	0	0	-	0	0	0
Mauritania	4	89	0	2	1	2	2	3	1	2	4
Mauritius	1	100	0	0	0	0	1	0	0	0	1
Mexico	48	38	1	15	3	2	30	24	2	0	41
Micronesia, Fed. Sts.	0	11	0	0	0	0	-	-	-	0	0
Moldova	1	53	0	0	0	0	1	0	0	0	1
Mongolia	0	14	0	0	0	0	0	0	0	0	0
Montenegro	0	31	0	0	0	-	0	-	-	-	0
Morocco	10	27	0	4	0	1	-	6	1	0	7
Mozambique	13	42	10	13	11	7	12	7	6	2	13
Myanmar	43	81	0	25	3	11	37	22	9	21	42
Namibia	2	61	0	1	1	0	1	0	0	1	1
Nauru	0	0	0	0	0	0	-	-	-	-	0
Nepal	20	67	1	13	3	6	-	9	3	6	15
Netherlands	8	46	0	0	0	0	-	0	0	-	0
Nicaragua	2	35	0	1	0	0	1	2	0	0	2
Niger	22	92	11	21	17	18	15	20	8	18	22
Nigeria	103	51	43	98	70	25	80	59	35	52	102
North Macedonia	1	38	0	0	0	0	-	0	-	-	0
Norway	1	17	0	0	0	0	-	0	0	-	0
Pakistan	203	93	9	169	55	41	159	160	10	17	197
Panama	1	25	0	0	0	0	0	1	-	-	1
Papua New Guinea	2	17	0	1	1	0	-	-	1	1	1
Paraguay	5	71	0	1	0	0	1	2	0	0	3
Peru	9	26	0	4	1	1	2	4	1	1	6
Philippines	88	83	3	53	13	2	51	42	4	5	73
Poland	13	35	0	0	0	0	5	1	0	-	6
Portugal	3	25	0	0	0	0	-	0	0	-	0
Romania	10	51	0	1	0	0	2	3	2	-	6
Russian Federation	32	22	0	2	0	0	7	3	3	2	12
Rwanda	2	15	1	2	1	1	-	-	1	1	2
Samoa	0	100	0	0	0	0	-	-	0	0	0
Senegal	9	53	1	7	3	5	5	4	1	3	8
Serbia	3	41	0	0	0	0	1	0	0	0	1
Seychelles	0	6	0	0	0	0	-	-	0	-	0
Sierra Leone	4	48	1	4	3	1	3	3	2	3	4

Slovak Republic	3	50	0	0	0	0	-	0	0	-	0
Slovenia	1	51	0	0	0	-	-	0	0	-	0
Solomon Islands	0	32	0	0	0	0	-	-	0	0	0
South Africa	11	19	3	8	5	0	1	2	2	0	7
South Sudan	4	36	3	4	3	-	-	-	-	-	3
Spain	12	26	0	0	0	0	-	0	0	-	1
Sri Lanka	4	20	0	2	0	0	3	0	1	0	3
St. Lucia	0	100	0	0	0	-	-	-	-	-	0
Sudan	32	73	7	29	16	12	-	-	13	13	24
Suriname	0	28	0	0	0	-	-	-	-	-	0
Sweden	1	14	0	0	0	0	-	0	0	-	0
Switzerland	3	33	0	0	0	0	-	0	0	-	0
Syrian Arab Republic	12	58	8	11	10	-	-	-	-	-	10
São Tomé and Príncipe	0	24	0	0	0	0	0	-	0	0	0
Taiwan, China	24	100	0	0	0	-	-	-	-	-	0
Tajikistan	5	50	0	3	1	0	-	3	2	0	4
Tanzania	26	44	13	25	19	4	23	13	9	13	26
Thailand	46	64	0	6	0	6	11	2	0	0	18
Timor-Leste	0	24	0	0	0	0	-	-	0	0	0
Togo	3	39	1	3	2	1	3	2	1	2	3
Tonga	0	100	0	0	0	0	-	-	0	0	0
Trinidad and Tobago	1	84	0	0	0	-	-	-	-	-	0
Tunisia	4	33	0	1	0	1	-	3	0	0	3
Turkmenistan	4	58	0	1	0	-	-	-	-	-	0
Tuvalu	0	0	0	0	0	0	-	-	-	-	0
Türkiye	23	28	0	3	0	1	12	6	0	-	15
Uganda	14	32	6	13	9	5	14	5	4	6	14
Ukraine	11	27	0	1	0	0	3	2	-	-	5
United Arab Emirates	9	100	0	0	0	-	-	-	-	-	0
United Kingdom	11	17	0	0	0	4	-	0	0	-	4
United States	145	43	2	3	2	-	-	-	-	-	2
Uruguay	1	17	0	0	0	0	0	0	0	0	0
Uzbekistan	13	40	4	12	8	-	-	-	-	-	8
Vanuatu	0	100	0	0	0	0	0	-	0	0	0
Venezuela, RB	7	26	0	2	1	-	-	-	-	-	1
Viet Nam	56	58	0	10	1	6	37	25	2	0	47
West Bank and Gaza	0	9	0	0	0	0	0	0	0	-	0
Yemen, Rep.	9	29	6	9	7	2	-	8	1	3	9
Zambia	5	28	4	5	4	2	5	3	2	4	5
Zimbabwe	9	57	4	8	6	-	-	-	-	-	6

Note: "-" indicates that the data is not available.

Table A4: Number of people exposed, by region (millions)

	Total population	Flood	Drought	Heatwave	Cyclone	Any shock	Any shock (% of population)
East Asia & Pacific	2,294	445	332	834	401	1,477	64
Europe & Central Asia	914	81	202	18	0	277	30
Latin America & Caribbean	628	56	96	48	35	205	33
Middle East & North Africa	420	47	44	102	0	165	39
North America	371	20	64	68	28	152	41
South Asia	1,829	246	332	1,481	132	1,589	87
Sub-Saharan Africa	1,119	66	314	186	5	471	42

Notes: Geographic regions use the World Bank's regional classification including high-income economies: https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups.

Table A5: Number of people exposed and vulnerable in each dimension, over time by region (millions)

	2010					
	Income	Education	Social protection	Financial inclusion	Water	Electricity
Region						
East Asia and the Pacific	311	182	501	492	36	30
Europe and Central Asia	13	24	42	63	11	0
Latin America and the Caribbean	29	25	79	104	10	12
Middle East and North Africa	11	14	22	71	5	3
Other High-Income economies	3	1		9	1	
South Asia	828	289	324	961	26	344
Sub-Saharan Africa	236	164	236	210	101	242
FCV	178	126	219	156	96	188
	2019					
	Income	Education	Social protection	Financial inclusion	Water	Electricity
Region						
East Asia and the Pacific	45	198	629	212	22	29
Europe and Central Asia	10	1	39	26	9	2
Latin America and the Caribbean	22	20	101	68	7	10
Middle East and North Africa	26	15	10	74	6	4
Other High-Income economies	4	1		1	0	
South Asia	510	300	333	516	18	318
Sub-Saharan Africa	286	185	270	194	119	223
FCV	215	154	235	166	108	188

Notes: Income refers to having less than 1.5*$2.15 per household member, education refers to no adult having primary schooling, social protection refers to not receiving any social protection, and financial inclusion refers to not having a bank account. Water and electricity refer to access to improved water and electricity.