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The Impacts of Disasters on African Agriculture

New Evidence from Micro-Data

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Abstract

Disasters affect millions of people each year and cause economic losses worth many billions of dollars globally. Reporting on disaster impacts in research, policy, and news primarily relies on macro statistics based on disaster inventories. The macro statistics suggest that a relatively small share of disaster damages accrues in Africa. This paper, instead, uses detailed survey micro-data from six African countries to quantify disaster damages in one key sector: crop agriculture. The micro-data reveals much higher damages and more people affected than the macro statistics would indicate. On average, 36 percent of the agricultural plots in the sample suffer crop losses due to adverse climatic events. In the countries and time period analyzed, these losses reduced total crop production by an average of 29 percent. Importantly, many of these losses are underreported or undetected in key disaster inventories and therefore elude macro statistics. In the case of droughts and floods, the economic losses recorded in the micro-data are $5.1 billion higher than in the macro statistics, affecting 145 million to 170 million people, more than four times as many as the macro statistics suggest. The difference stems mostly from smaller and less severe but frequent adverse events that are not recorded in disaster inventories.

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The Impacts of Disasters on African Agriculture: New Evidence from Micro-Data

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Introduction

In 2022, natural disasters led to over $220 billion in economic losses, affecting 185 million people.[1] Losses in 2023 are on track to exceed the previous year's[2] and large-scale disasters, such as record extreme heatwaves, the violent monsoon in India, and a prolonged severe drought in the Horn of Africa have received widespread media and public attention.[3–6] The frequency and intensity of disasters and their impacts has increased over the last decades, a trend that is set to continue, and likely accelerate, due to climate change and global warming.[7–12]

Reporting on disaster impacts relies predominantly on macro statistics. A key data source is the Emergency Events Database (EM-DAT), which is a publicly available global inventory of disaster impacts that is widely used in media,[13] research,[14] and policy reports, including recently the World Bank's 2023 'Atlas of the Sustainable Development Goals' and the Food and Agriculture Organization's (FAO) 2021 report on 'The impact of disasters and crises on agriculture and food security.'[15,16]

Here, we offer a different approach to studying disaster impacts, based on survey micro-data. We quantify the value of crop production losses due to adverse climatic events on more than 120,000 fields across six African countries and study the impacts of these events on African agriculture, rural populations, and the national economies. Agriculture is a key sector, on which many households in the region depend for their livelihoods, especially the poor and rural households.[17] Agriculture dependent households are thought to be particularly at risk of suffering the impacts of climate change and adverse shocks. Climate change and natural disasters are expected to be especially severe in rural areas in this region,[18,19] while smallholder agricultural production remains predominantly rainfed and the adoption of drought or heat resistant seeds or other such climate-smart technologies is limited.[20]

We document that crop losses due to adverse shocks are common and costly both to individual farm households and to the economy at large, and that farmers often suffer multiple shocks in the same season. Taken together, production losses have a substantial aggregate impact. Importantly, these events and their impacts are underreported or undetected in common macro data sources for disaster reporting, such as EM-DAT.

Our analysis of micro-data offers an important complementary perspective to analyses based on aggregate statistics derived from disaster inventories. Aggregate statistics are critical to the study of disaster impacts, providing annual data at a global scale. They are less well-suited to capture the differential impacts of disasters on different population groups, especially poor and vulnerable people.[21–23] This is because they account primarily for damages to assets and losses in agricultural production whose value is greater and better documented among richer households and in richer countries. For instance, according to the most recent estimates of EM-DAT, about 70% of economic losses due to disasters occurred in the Americas, compared to just under 4% in Africa.[24] A recent study using the same data source concluded that disaster impacts do not affect poor people as much as the general population.[25] In contrast, evidence from survey micro-data suggests that poorer households and individuals are more exposed and less resilient to adverse climatic and environmental shocks and suffer disproportionately greater well-being losses than better-off households.[18,22,26] Our analysis suggests that production losses due to adverse climatic events are meaningful not only for the well-being of low-income households individually but, because of how many households are affected, they are significant also for the whole economies of our study countries and on a global scale.

Results

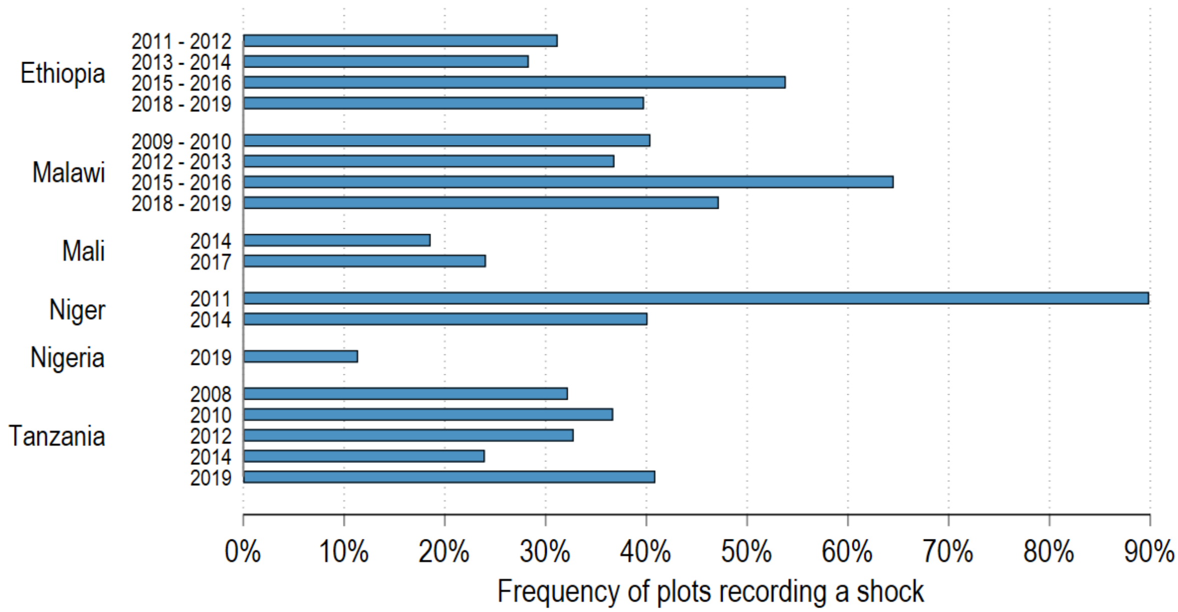
Crop losses are widespread and significant

The data used in this analysis is from the Living Standards Measurement Study-Integrated Survey on Agriculture (LSMS-ISA) in Ethiopia, Malawi, Mali, Niger, Nigeria, and Tanzania. These data were harmonized across countries and cover close to 120,000 fields on around 30,000 farms. The data show that crop losses due to disasters and adverse climatic events are widespread and significant in African smallholder agriculture. Farmers report crop losses on between 11% (Nigeria 2018/19) and 90% of plots (Niger 2011), depending on country and year (Figure 1, Panel A and Table 1). Overall, 36% of plots in our sample report a crop loss. Farmers reported losing, on average, 53% of their harvest on plots affected by crop shocks (Panel B and Table 1). Losses vary across countries and years, ranging from 48% of harvest (Ethiopia 2018/19) to 71% of harvest (Niger 2011). Disaster losses have also become more common over time (Table 3). In the 11 years from 2008 to 2019 that our dataset spans, the estimated likelihood of a plot incurring a disaster loss increased by close to 10 percentage points. This is seemingly driven by a higher prevalence of small shocks as the estimated share of harvest lost on plots with any loss decreased by on average 1.1 percentage points with every year studied.

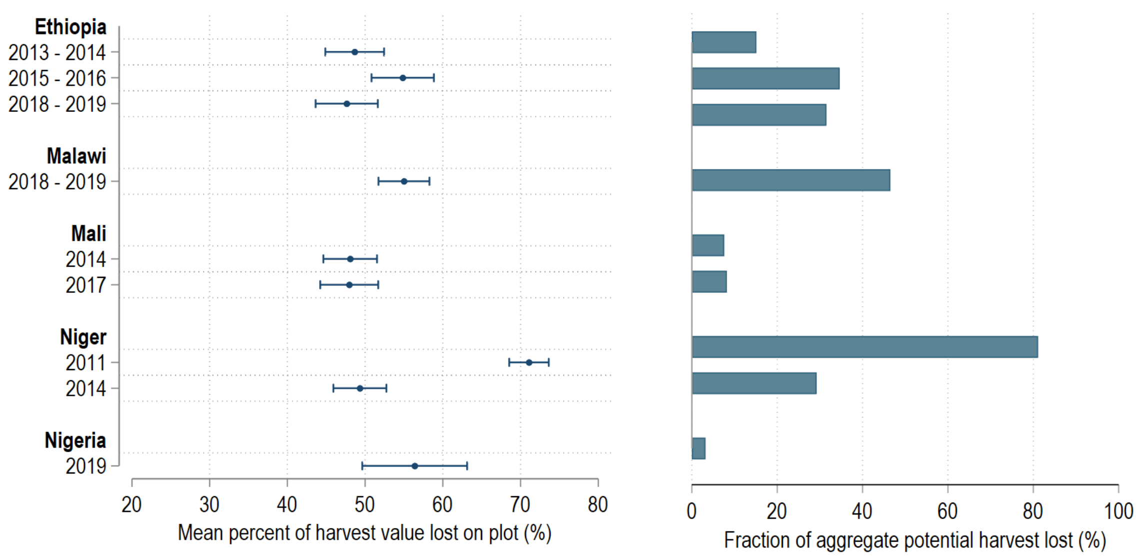
In aggregate, crop losses due to adverse climatic events reduce the total national crop production by between 3% in Nigeria 2018-19 and 81% in Niger in 2011. A total of 29% of potential harvest value is lost across the countries and agricultural seasons observed in our dataset (Figure 1, Panel C and Table 4]).

Figure 1. Panel A displays the prevalence of crop shocks on plots across country-waves. Panel B displays the mean percent of potential harvest value lost on plot, by country-wave, as well as the fraction of aggregate potential harvest lost (valued with current prices), per country-wave

A



B



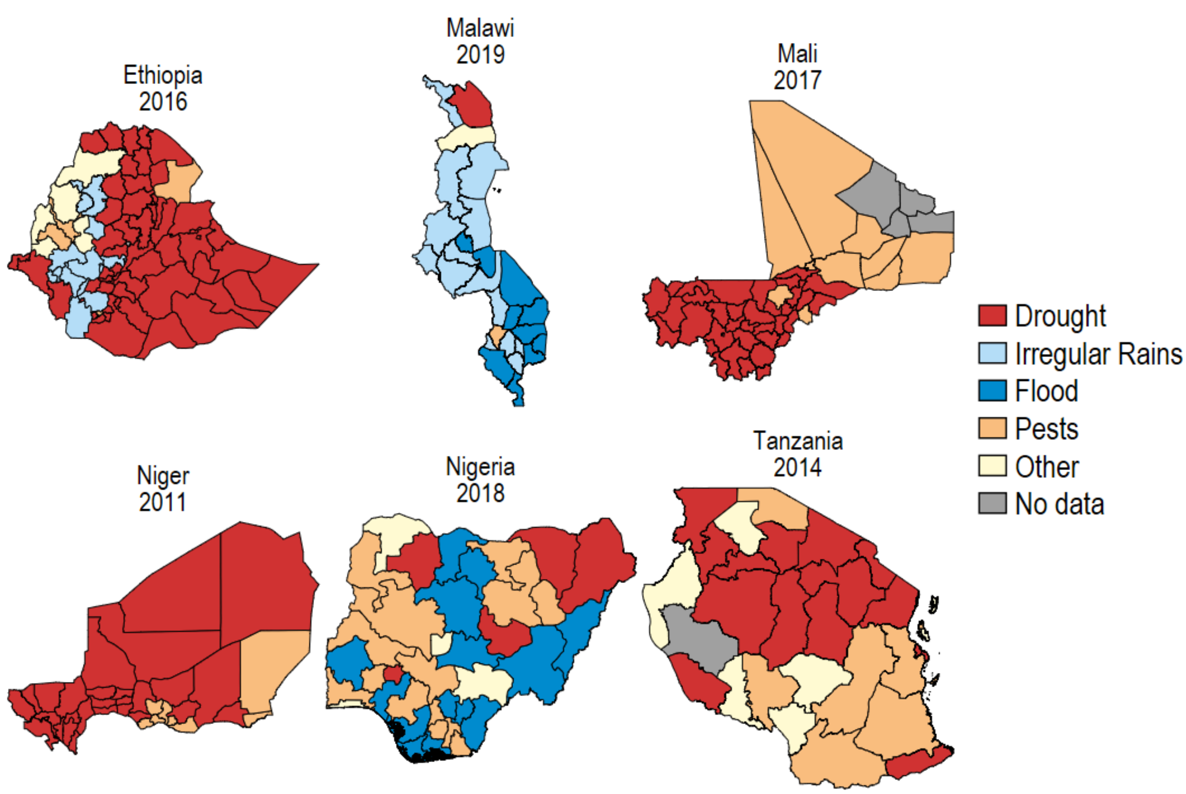
Crop production is impacted by multiple shocks

Farmers face a diversity of adverse climatic shocks. Multiple shocks are recorded to affect agricultural production in each year and across all countries (Table 1). There are also some instances of multiple shocks affecting the same farm in a given agricultural season (Table 5). This ranges from 1.5% of farms (Tanzania 2014) to 21% of farms (Ethiopia 2018-2019).

Overall, drought is the most common shock, with 22% of plots in our sample recording a crop loss due to drought (Table 1). One in ten plots records losses due to irregular rains, meaning erratic rainfall at unusual times in the agricultural season. Pests are also widespread across our sample, affecting 6.3% of all plots. Still, there is substantial variation across countries and years. The severity of the damages caused varies between different events (Table 2). Floods in particular cause more damage than other shocks, reducing crop production per plot on average by 62%. Losses from pests and irregular rains tend to be smaller. However, there is again some variation between different countries and farming environments (Table 6).

Which shocks are the most prevalent varies also within countries. Figure 2 illustrates this for selected countries and years, showing the most reported events by subnational administrative divisions. There is some geographical clustering, but we commonly see different events accounting for most of the impacted plots in different areas of the same country in the same year. This is true even in years with exceptionally severe disasters such as the droughts in Niger in 2011 and Ethiopia in 2015-16 where the vast majority but not all areas of the country recorded drought as the primary loss reason.

Figure 2. Most common disaster events by administrative unit, selected countries and years



Crop losses differ locally and between farmers

Not all farmers and plots are equally affected. Some are less likely to experience a loss even in the face of an adverse climatic event. Here we show that shock exposure and impacts can differ even between neighboring plots in the same area. We limit this analysis to droughts. Given the nature of droughts, all plots in the same small geographic cluster should be faced with the same drought shock – but the impacts of that drought can differ. Indeed, in 41% of the geographical clusters in our sample, some but not all plots report being affected by a drought (Table 12). This finding holds also for plots growing the same crops. In 31% of clusters, some but not all maize plots suffer drought losses (32% for sorghum plots and millet plots). The result extends to plots with the same crops cultivated by the same households (Table 13): for farms that record a drought shock on one of their maize plots, close to two-thirds of other maize plots on the same farm also record drought-related crop losses.

These findings suggest that disaster impacts are highly localized, consistent with the high spatial concentration that meteorological events can have.[28] Further, idiosyncratic factors, such as land characteristics and management practices, and happenstance play a role in determining whether and how much production is affected. We find that plot elevation is negatively associated with the likelihood of experiencing losses and the size of the losses incurred (an effect almost twice as strong for floods compared to other disasters), while smaller plots are less likely to suffer losses but record higher losses when they are affected (Tables 7 and 8). Losses on intercropped plots are 7.5 percentage points lower than on mono-cropped plots, though intercropped plots are more likely to experience a loss in the first place (+3.6 percentage points). Plots farmed in more input and technology intensive ways appear more resilient to crop losses due to adverse events.

Disaster exposure and impact also vary according to who manages the plot. Plots managed by women are more often affected by disaster losses (+2.2 percentage points) than plots managed by men and these losses are also larger on average (+4.4 percentage points; Table 10). These differences are likely because plots managed by women are endowed and farmed differently than plots managed by men, which in turn may follow from differential access to inputs and land between women and men.[27]

Aggregate data sources underestimate impacts of extreme events on crop production

How do disaster impacts as captured in the survey data compare to estimates from other commonly used data sources? Here, we contrast the results from the survey microdata with publicly available estimates of disaster impacts from the Emergency Events Database (EM-DAT). EM-DAT aggregates reports from UN agencies, governments, insurance companies, research institutes and the media into a global inventory of disaster impacts.[29] EM-DAT is the preeminent and only publicly available data source of this kind, used widely in disaster reporting and research.[30] We focus on two disaster types, droughts and floods, and compare two estimates: the number of people affected and the total economic damages caused in the years which the survey micro-data covers. We create aggregate figures from the micro-data using population sampling weights.

On both metrics, and for both drought and flood impacts, the micro-data estimates on average exceed the EM-DAT estimates, that is, for years in which there is information from both sources, the survey micro-data find more people affected and higher damages from droughts and floods (Figure 3 and Tables 14 and

16). Moreover, there are many instances in which the EM-DAT records no disaster impacts at all. This is true especially for droughts, where the microdata suggests that droughts are prevalent to some degree across every country-year combination covered, while EM-DAT records droughts affecting the population in only a third of cases. Estimates of the economic value of disaster impacts are mostly missing in the EM-DAT data for the study countries, even in years when drought and flood events were recorded to affect the population in the study countries (Tables 15 and 17).

Large, salient drought and flood episodes have better coverage in the EM-DAT, such as the severe droughts in Niger in 2011[31,32] and Ethiopia in 2015-16,[33,34] or the droughts and floods Malawi in 2015-16,[35,36] which were widely covered in international media at the time. The events that go unreported in EM-DAT are smaller, on average, in terms of the population affected and the damages caused. However, we show that such smaller, under-covered events have substantial overall impacts. More than a fifth of the population suffered production and income losses in the droughts in Malawi in 2009-2010 and in Mali in 2074, according to our micro-data estimates, while there is no coverage of these events in the EM-DAT for the same years. Overall, we estimate the total number of people affected by droughts or floods in all instances covered by the microdata is between 145 million and 170 million, more than 4 times higher than what is reported in the EM-DAT for the same periods and the same shocks.

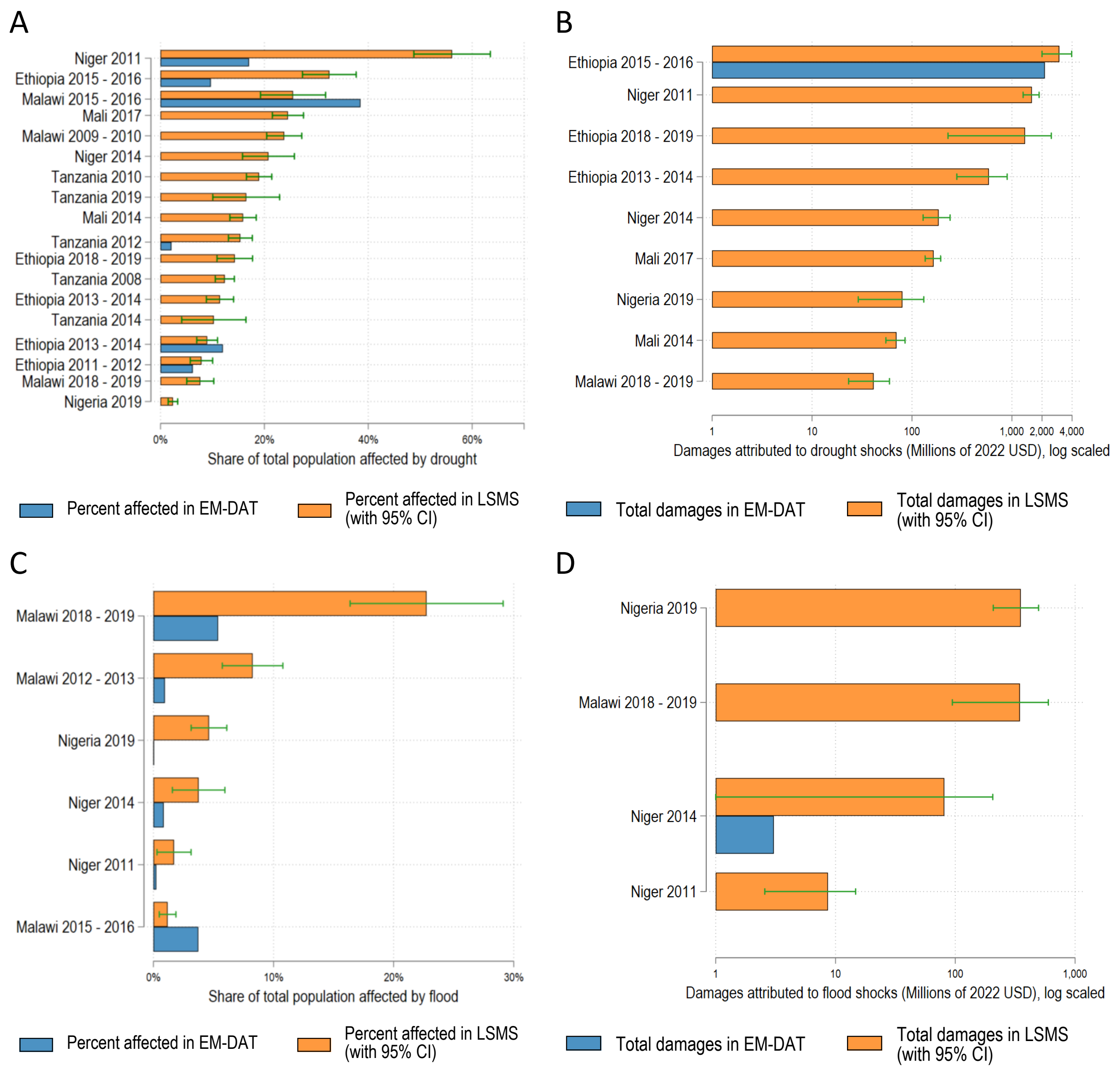
The micro-data analysis suggests that the aggregate value of the disaster impacts on crop production is substantial. For the drought in Ethiopia in 2015-2016, the micro-data crop loss estimates are much larger than the total economic damage reported in the EM-DAT. For the 2014 floods in Niger, the estimated value of crop losses exceeds the total damage reported in the EM-DAT data by almost USD 78 million (in 2022 USD values). In the other years there is no damage estimate in EM-DAT, but our survey micro-data documents even some large disaster impacts, such as in Niger in 2011 and Ethiopia in 2018-2019 with estimated losses of USD 1.6 billion and USD 1.4 billion, respectively. Taken together, we estimate that across the countries and years captured in the microdata, there were USD 5.1 billion in drought and flood damages unaccounted for in the EM-DAT data (Table 18).

What explains these discrepancies? Disaster inventories such as EM-DAT and survey microdata differ in a number of meaningful ways. Most importantly, disaster inventories do not measure shock impacts themselves but instead aggregate data from government sources, humanitarian organizations, the media, and others. They therefore rely on the comprehensiveness and accuracy with which shocks due to natural hazards are covered by one or more of these sources.[30,37] Less salient events as well as those affecting marginalized population groups are less likely to be reported on and less likely to have detailed information on the affected population or economic and welfare impacts.[37–40] This is particularly acute in LMICs where the density of information for disaster repositories to draw on is much lower and a large share of damages is uninsured.[30,37] Shocks in LMICs in general and smaller events (in terms of intensity or the population affected) in particular are more likely to have incomplete or inaccurate information in disaster repositories or are not covered at all.[30,37,41,42] Microdata such as the LSMS-ISA measure shock impacts on smallholder farmers where they occur by asking farmers directly. They therefore do not suffer from the same limitations regarding the recording of smaller, less salient, or more localized shocks and their impacts as disaster repositories.

Smaller shocks or adverse climatic events may not be considered disasters as disasters suggest a minimum level of severity. For an event to be recorded in the inventory, the EM-DAT requires a minimum of 100 people to be affected (injured, homeless, in need of immediate assistance) or an official declaration of emergency or appeal for international assistance – arguably a sensible set of criteria for a disaster inventory. Not all events recorded in the micro-data meet these requirements. Importantly, the events recorded in the micro-data have substantial impacts on the livelihoods of farmers and the economies of the study countries.

At the same time, micro-data has drawbacks and limitations. First, it is rare that microdata in low- and middle-income countries are available annually, with surveys typically implemented every few years. Shock coverage and detail depend on the survey design, which typically differs from country to country. Finally, microdata does not provide the same cross-country coverage as disaster repositories. With these limitations, the microdata naturally also provides an incomplete picture (see discussion in *Appendix A*).

Figure 3. Comparison of shock prevalence and impact between EM-DAT and LSMS-ISA data.



Note: Panel A displays a comparison of the total estimated individuals affected by droughts between EMDAT (in blue) and LSMS-ISA data (in orange), while panel B shows a comparison of the estimated damages (in millions of 2022 dollars), in years where damages could be estimated in the LSMS-ISA surveys. Panel C displays a similar comparison for floods, in years where floods are listed as a potential shock in the LSMS-ISA data, while panel D shows a comparison of estimated damages from floods. Confidence intervals for panels B and D were calculated before log-transformation, and are hence asymmetrically situated around log-scaled point estimates.

Discussion

We explore the crop production impacts of adverse climatic events on 120,000 fields on 30,000 smallholder farms in Sub-Saharan Africa. Smallholder agriculture is of special interest for achieving SDGs 1 and 2 as it remains the primary means of livelihood for many of the world's poor.[43]

Our findings generate new insights and advance our understanding of the disaster risks and losses that smallholder farmers face. Other studies have investigated the vulnerability of smallholder farmers to disasters and environmental shocks.[44–47] These studies have mostly focused on single geographies and stopped short of quantifying the value of disaster related losses in smallholder agriculture. Other studies have relied on macro-data from disaster inventories to assess the impact of disasters on agriculture.[14]

Here we offer a cross-country perspective using harmonized survey micro-data from six African countries. We value crop production losses to assess the economic importance of disaster impacts on rural households and African agriculture and the regional economies more broadly. The analysis shows that disaster related crop production losses among African smallholder farmers are widespread and significantly reduce the production of affected farms. In any given year, between 18% and 94% of crop-farming households suffer such crop losses and on average 53% of plots' harvest potential is lost when they are hit by adverse shocks.

In aggregate, disaster impacts reduce the national crop production by 29% every year on average and by up to 81% in years with large-scale disasters. These results show that crop production losses due to adverse climatic events are significant both for individual farms and for the entire sector and the study countries' economies.

We show that the EM-DAT disaster inventory misses out on a meaningful share of disaster impacts in the agricultural sector in Africa when compared to the micro-data analysis. The micro-data captures many smaller, more localized disaster events, which are less salient and therefore less likely to be reported on and register in the disaster inventory.[37,48] At the same time, disaster impacts are more likely to be missing entirely in lower-income settings.[30] Our analysis shows that less salient and underreported disaster events still have significant economic impacts.

The findings have implications for policies and interventions aimed at disaster risk reduction and resilience building. For such policies to be effective, it is important to recognize the risks from less salient and under-reported adverse events and offer ways to insure households' livelihoods against their impacts. The findings also have implications for research and measurement. Research and analysis using aggregate global data such as EM-DAT are likely missing some disaster impacts in poorer countries and among poorer people. This concerns also tracking progress towards the SDGs, in particular SDG target 1.5, which seeks to reduce the vulnerability of the poor to extreme weather events, and SDG target 13.1, which seeks to strengthen resilience and adaptive capacity to climate-related hazards and natural disasters in all countries.[15] Survey micro-data such as the LSMS-ISA have more limited country and temporal coverage. Inventory and survey data offer complementary perspectives on disaster impacts and combining both sources will likely yield a more complete and nuanced understanding of the issue that will promote more effective policy design. In particular, information on disaster impacts from survey micro-data could be incorporated systematically into disaster inventories. Improving micro-data systems is key to systematically utilizing micro-data for monitoring and reporting of emergency events. More flexible and higher frequency data collection is needed to provide better temporal coverage and account for disaster impacts when they occur. Phone surveys, which have only recently become more widely adopted in low-income settings, may provide this function, for instance as part of mixed-mode survey systems that combine traditional in-person surveys with data collection over the phone.[49] Integration of geospatial data can improve spatial coverage and facilitate better identification of natural hazards and disaster occurrence.[50,51] Sampling protocols of household surveys can be optimized to better capture disaster impacts and greater harmonization of survey methods and measurement instruments in line with best practices can benefit data quality.

Our study faces several limitations. The valuation of losses relies on human reporting which is subject to human error, respondents' incentives, misreporting, and misperceptions. The data allows for a detailed analysis of disaster impacts on crop production, but other aspects of disaster impacts on agriculture are absent. This concerns, for example, damages to agricultural assets, storage losses, or impacts on livestock. Further, the data is representative of the household sector in study countries but misses commercial and larger farms. This implies that we are likely underestimating the full extent of disaster crop losses. As the analysis is focused on agriculture, we do not discuss damages incurred in other sectors.

Methods

A. LSMS-ISA microdata

We use plot-level survey data from the Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) in Ethiopia, Malawi, Mali, Niger, Nigeria, and Tanzania. The LSMS-ISA comprise a series of harmonized, national, multi-topic household panel surveys with a distinct focus on agriculture. We harmonized data on agricultural outputs, inputs, and plot characteristics for close to 30,000 households over the six countries for a total of 18 survey waves collected between 2008 and 2019. The combined dataset contains over 120,000 plot observations. More specifically, the dataset includes data from the Ethiopian Social Survey (waves 1 to 4), Malawi's Integrated Household Panel Survey (waves 1 to 4), Mali's *Enquête Agricole de Conjoncture Intégrée* (waves 1 and 2), Niger's *Enquête National sur les Conditions de Vie des Ménages et Agriculture* (waves 1 and 2), Nigeria's General Household Survey (wave 4) and Tanzania's National Panel Survey (waves 1 to 5). Households are selected to be representative of the population at the national and sub-national level using a two-stage stratified sampling design with census enumeration areas (EAs) as primary sampling units and households as secondary sampling units. Households are then tracked through time, except for Mali which only tracks enumeration areas (EAs). Each survey wave covers an agricultural production cycle or season.

B. EM-DAT aggregate data

We compare survey estimates to country-level data from is the Emergency Event Database (EM-DAT). EM-DAT is the preeminent public database taking stock of shocks on a global scale and widely used for research and to inform policy[52]. Both natural (e.g., geophysical, meteorological) and technological (e.g., industrial accidents) events are recorded, along with information on disaster damages valued in 2022 USD. The EM-DAT compiles information from a broad range of sources including insurance companies, international organizations, press agencies and governmental agencies. Disasters are recorded if they provoke 10 or more deaths, affect 100 or more people (injured/ homeless/ in need of immediate assistance) or are accompanied by an official declaration of emergency or appeal for international assistance.[29]

C. Variable construction

Valuation of crop production

Plot-level crop production was calculated using survey variables which were collected after the harvest in each season and country. Farmers report harvest quantities for each seasonal crop grown on each plot.

The harvest quantity on each plot was then valued using a set of constant crop prices. Specifically, each price corresponds to the median crop sale price calculated in one survey round in each country. Applying constant prices for each crop-country combination eliminates the effect of relative price fluctuations over time. This allows us to isolate the impact of disasters on harvest quantity rather than measuring their impact on quantity *and* prices. An alternative approach was used to calculate and report aggregate losses, such as in Table 4 and Figure 3. In these cases, country and wave specific prices were calculated, by estimating median farmer sale prices for different crop types. This was done to reflect losses as they were perceived by farmers in the year of the shock. Whether current or constant, harvest values are initially calculated in local currency units and then converted and adjusted to 2020 USD using exchange rates and a CPI drawn from a library of the World Bank World Development Indicators. [53] Yields, defined as the value of production per hectare, were obtained by dividing the total harvest value on the plot by GPS-measured plot area. Finally, yields are winsorized at the 1st and 99th percentiles (while allowing full losses to be equal to 0).

Identification of disaster events and loss size

Identification of disaster events is based on farmers reporting crop production losses before harvest for each crop on each of their plots. Specifically, for each crop cultivated on each plot, farmers are asked whether the area harvested was less than the area planted, i.e. if some of their crop has been lost, along with the cause of the loss in harvested area. In Ethiopia, farmers are further asked whether the crops they harvested had any damage on them and what the cause of damage was. We define disaster crop losses as any loss in crop area or any damage on the crops harvested due to climatological (drought, irregular rain, hail, wildfire), hydrological (flood) or biological (insect infestation, disease) reasons. This does not include losses due conflict, unavailability of inputs or other household or socio-economic events. We denote a plot with a disaster loss as any plot for which at least one crop on the plot had a disaster-induced loss.

To calculate the size of disaster losses, we use farmers' reports of the share of the planted area lost due to disasters and, where available, the percent of damage on crops that were harvested. To determine the potential harvest that could have been achieved in the absence of disaster losses, we employ the methodology proposed by the Food and Agriculture Organization (FAO).[54,55] This means determining the realized harvest for each crop on the plot, as described in the preceding section, and scaling it up in proportion to the planted area lost and degree of damage on the crop that is attributed to disasters. The quantity lost equates to the difference between the potential harvest without disaster losses and the realized harvest. To aggregate losses across crops, we value loss quantity of each crop on each plot using a constant set of prices, which we then convert to 2020 US dollars. In order to correct for outliers in the self-reported data, we winsorize these loss values at the 99th percentile.

Equation (1) formalizes the construction of the plot-level loss aggregate.

$$L_{i,s} = \sum_{j=1}^{N} p_j \times \left(Y_{i,j,s}^{p} - Y_{i,j,s}^{r}\right)$$
$$= \sum_{j=1}^{N} p_j \times \left(\left(Y_{i,j,s}^{r} \times \frac{1}{1-l_{i,j,s}} \times \frac{1}{1-d_{i,j,s}} \right) - Y_{i,j,s}^{r} \right)$$
$$= \sum_{j=1}^{N} p_j \times \left(Y_{i,j,s}^{r} \times \left(\frac{1}{(1-l_{i,j,s})(1-d_{i,j,s})} - 1 \right) \right) \tag{1}$$

Where the value of harvest loss on plot *i* in agricultural season *s* is equal to the difference between the potential harvest in the absence of disasters, Y^p and the realized harvest reported by the farmer Y^r. The potential harvest is calculated by scaling up realized harvest in proportion to the share of the planted area lost to disasters, $l_{i,j,s}$, and the percent of damage on the crop, $d_{i,j,s}$. The quantity lost is then valued in terms of the median selling price for crop *j* in the country *p* and aggregated at the plot level across all crops on the plot.

Imputation of full losses

In case the harvest for a crop on a plot is fully lost (i.e., $l_{i,j,s} = 1$ or $d_{i,j,s} = 1$), Equation (1) is not defined. Instead, we estimate the quantity lost in these cases by imputing potential harvest values using a Gaussian normal regression imputation method.[56] To this end, we define a model where potential harvest is the outcome variable, regressed on the set of explanatory variables, along with country and crop fixed effects. The explanatory variables used in the imputation are the following: (i) agricultural input variables, specifically, plot area, non-hired labor days spent working on the plot (e.g., family labor), as well as hired labor value, inorganic fertilizer value and seed value. In similar fashion to the production values described above, a constant set of prices was computed within each country, based on median purchase prices. These input variables are all expressed in per hectare terms, winsorized and logged; (ii) an agricultural asset index was computed using a principal component analysis based on an inventory of household assets; (iii) plot-level dummy variables were included to indicate if a plot is irrigated, pesticides are used, organic fertilizers are applied, the plot is intercropped, and if the plot is owned by the household; (iv) gender of the primary decisionmakers on each plot; (v) household-level variables household size and dummies for livestock ownership, electricity access and urban/rural residence; (vi) finally, a set of geophysical variables consisting of plot elevation, a topographic wetness index, and the distance of the household from the closest population center and closest road.

Our final imputed value is obtained by calculating the mean of 100 imputations.

Table 19 contains an overview of the available data and variables for each country and agricultural season covered.

D. Estimation

i. Disaster crop losses in Sub-Saharan Africa

Our main descriptive analysis of disaster prevalence and intensity is conducted at the plot-level and involves the estimation of means, proportions, and frequencies at the national level as well as pooled across countries. These estimates, as well as any household-level estimates of disaster exposure formed by aggregating across plots belonging to the same farm, are weighted using the probability weights described in a separate section below (*Sampling weights*).

ii. *Disaster type and frequency*

Similarly, our estimates of the prevalence of different shock types is conducted at the plot-level and involves the estimation of frequencies at the national level and pooled across countries using the household sampling weights. Our estimates of the most common shock type within enumeration areas are based on simple, unweighted frequencies.

iii. *Heterogeneity in disaster impacts across farms*

Our multivariate analysis focuses on two main outcome variables: a binary variable indicating any disaster crop loss and a continuous variable denoting the percentage share of the total potential harvest that was lost to disasters. We estimate all models with the binary crop loss indicator as outcome variable via maximum likelihood using logistic regression. Models with the percent share of harvest lost as outcome variable are estimated via ordinary least squares regression. Our independent variables for these multivariate regressions are comprised of plot characteristics (plot size, elevation, a topographical wetness index, an indicator for ownership of the plot, and main crop fixed effects), as well as plot management (hired labor and fertilizer input use, irrigation, intercropping), plot manager (age, gender, and education), and household characteristics (urban/rural residence, an indicator for livestock farming, and electricity access). Models pooling the sample across countries further include country fixed effects. We also conduct multivariate analysis using a binary variable capturing the gender of the plot manager as outcome variable and plot- and plot-management characteristics as independent variables. As before, all multivariate regressions are weighted using the sampling weights.

iv. *Different disaster impacts on neighboring plots*

Our analysis of differences in drought impact within the same enumeration areas first determines whether some but not all plots belonging to the same enumeration area recorded a drought loss and then estimates the simple, unweighted proportion of enumeration areas for which this is the case. Our analysis of within-household differences in shock impacts first limits the sample to households with multiple maize plots and where at least one of the household's maize plots recorded a drought shock. We then calculate the share of remaining maize plots belonging to the same household that also record a drought loss and report a simple, unweighted average of this share across households for each country and year.

v. *Comparison of survey micro data with aggregate sources*

Our estimates of the number of people affected by disasters and aggregate economic losses are totals at the national level and employ the household-level sampling weights.

In order to the compare drought and flood impacts using LSMS-ISA data with those using EM-DAT data, we use two metrics: the share of individuals "affected" by the shock and the estimated total value of damages. Since the LSMS-ISA surveys run every two to three years, we only retain events in the EM-DAT database for which the start or end date is within a year containing LSMS-ISA data. The comparison for flood shocks is possible in fewer countries and years due to limitations in the microdata questionnaire's scope in some cases (Table 18).

In order to compute the total number of individuals impacted by a shock within a specified period in the EM-DAT database, we aggregate the total number of people "affected" by the shock in the macro data. Affected persons are those that are reportedly injured, homeless, or otherwise in need of "immediate assistance."[29] To estimate the total number of individuals affected by a shock in the LSMS-ISA microdata, we construct population weights by multiplying household weights by household size. These weights are then used as expansion factors, which we multiply by a dummy variable equal to one in the household report a shock on any of its cultivated plots. We then add up this product to calculate an expansion estimator.[57,58]

To obtain shares of the total population, the numbers of individuals affected in both EM-DAT and the LSMS-ISA data are divided by total yearly population estimates drawn from a library of the World Bank World Development Indicators.[53]

We then compute the estimated damages from both droughts and floods in the periods and years covered by LSMS-ISA data. We first aggregate the "total damages" estimated in the EM-DAT database, defined as the values of total losses "directly or indirectly related to the disaster", in 2022 USD values. Using LSMS-ISA microdata, we aggregate the estimated value of crop losses for each household. In this case, the value of losses is calculated by multiplying the potential value of total output using *current* prices by the estimated percentage of output lost at the plot level. Contrary to the rest of our analysis, we do not apply a common set of prices to value output and losses, but rather median crop prices faced by farmers at the time of their crop production. The loss values are then converted to 2022 USD values, in order to allow comparison with EM-DAT data. As above, we use population weights as expansion factors, that we multiply with our loss value estimates.[57,58]

Sampling weights

In the survey data, household sampling weights are used to compute estimates that are representative of the national or subnational population. These reflect the inverse probability of selection into the sample, are adjusted to account for non-response and survey design choices, and are post-stratified to ensure that they sum to known household population totals.[59]

Moreover, a further adjustment was made to ensure that the weights in the study sample sum to the total population of households, because only a subset of LSMS-ISA households report cultivating seasonal crops. More formally, we can define a set of households indexed by h (where $h = 1, \dots, N^1$) within a country-wave, where each household is associated with a sample weight W_h. After restricting the dataset to households that cultivate crops, the total number of households in the country-wave drops from N^1 to N^2, and weights are adjusted such that:

$$w_h = \frac{W_h}{p_h} \times \frac{\sum_{h=1}^{N^1} W_h}{\sum_{h=1}^{N^2} W_h}$$

Where p_h denotes the number of plots in household h on which seasonal crops are grown, and w_h is the final adjusted weight.

The resulting weights were used to compute estimates in our analysis. Wherever population means are estimated, the standard errors provided with the estimate takes into account the clustered and stratified sampling design.[57] All regression models with continuous variables as outcomes are estimated using ordinary least squares regression, while regressions with binary outcomes are estimated via maximum likelihood using a logistic regression model.

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Appendix

Table 1: Frequency of plots recording a shock, by country-year

Country	Year	Frequency of plots recording a disaster shock	Frequency of plots recording a drought shock		Frequency of plots recording a flood shock		Frequency of plots recording an irregular rain shock		Frequency of plots recording a pest shock	
			All plots	Disaster plots	All plots	Disaster plots	All plots	Disaster plots	All plots	Disaster plots
Ethiopia	2011 - 2012	31.19 %	16.96 %	55.16 %	missing	missing	11.39 %	37.41 %	4.89 %	16.06 %
	2013 - 2014	28.32 %	11.14 %	40.14 %	missing	missing	9.94 %	36.60 %	7.35 %	30.52 %
	2015 - 2016	53.83 %	41.89 %	78.29 %	missing	missing	17.55 %	34.88 %	3.48 %	7.97 %
	2018 - 2019	39.76 %	19.81 %	50.63 %	missing	missing	14.15 %	37.17 %	6.95 %	21.12 %
Malawi	2009 - 2010	40.40 %	24.34 %	60.26 %	missing	missing	missing	missing	1.05 %	2.61 %
	2012 - 2013	36.82 %	8.18 %	22.22 %	8.64 %	23.47 %	17.80 %	48.33 %	2.85 %	7.75 %
	2015 - 2016	64.54 %	30.77 %	47.68 %	1.06 %	1.56 %	40.61 %	62.92 %	2.21 %	3.42 %
	2018 - 2019	47.18 %	5.60 %	11.86 %	21.65 %	45.81 %	19.77 %	41.91 %	7.97 %	16.76 %
Mali	2014	18.59 %	14.44 %	77.71 %	missing	missing	1.75 %	9.41 %	1.05 %	5.63 %
	2017	24.07 %	22.78 %	94.64 %	missing	missing	0.45 %	1.89 %	3.08 %	1.97 %
Niger	2011	89.88 %	65.81 %	73.22 %	0.64 %	0.71 %	missing	missing	27.69 %	30.81 %
	2014	40.11 %	23.43 %	58.41 %	2.75 %	6.86 %	missing	missing	11.08 %	27.63 %
Nigeria	2019	11.39 %	2.59 %	26.06 %	4.88 %	50.72 %	missing	missing	5.49 %	48.85 %
Tanzania	2008	32.21 %	14.52 %	47.11 %	missing	missing	missing	missing	13.99 %	45.45 %
	2010	36.70 %	21.52 %	60.74 %	missing	missing	missing	missing	10.00 %	28.29 %
	2012	32.78 %	19.91 %	62.79 %	missing	missing	missing	missing	9.86 %	31.05 %
	2014	23.96 %	11.38 %	49.72 %	missing	missing	missing	missing	8.05 %	35.00 %
	2019	40.89 %	25.80 %	65.03 %	missing	missing	missing	missing	12.39 %	31.21 %
All countries	2008 – 2019	36.34 %	22.17 %	61.66 %	6.80 %	14.44 %	10.49 %	31.31 %	6.30 %	16.83 %

Note: some questionnaires (the IHPS, for example) allow respondents to report multiple shock types on a single plot.

Table 2: Mean fraction of potential harvest lost at the plot level, by country-year

Country	Year	Mean fraction of potential harvest lost, all plots	Mean fraction of potential harvest lost, on plots affected by drought	Mean fraction of potential harvest lost, on plots affected by floods	Mean fraction of potential harvest lost, on plots affected by irregular rains	Mean fraction of potential harvest lost, on plots affected by pests
Ethiopia	2013 - 2014	48.66%	53.46 %	missing	49.36 %	45.22 %
	2015 - 2016	54.84%	59.71 %	missing	55.90 %	47.35 %
	2018 - 2019	47.63%	46.91 %	missing	47.65 %	42.36 %
Malawi	2018 - 2019	55.00%	57.17 %	62.65 %	49.79 %	49.26 %
Mali	2014	48.08%	48.37 %	missing	38.11 %	40.73 %
	2017	47.96%	47.50 %	missing	35.75 %	66.73 %
Niger	2011	71.09%	71.79 %	77.53 %	missing	66.96 %
	2014	49.33%	52.90 %	56.79 %	missing	40.97 %
Nigeria	2019	56.38%	36.38 %	61.87 %	missing	30.71 %
All countries	2011 – 2019	53.49%	56.75 %	62.28 %	51.52 %	46.52 %

Note: only point estimates are reported. Plots with no losses are excluded. Sample weights are used to calculate estimates.

Table 3: Linear trend in shock exposure and size

	(1) Any loss Full sample	(2) Percent lost With any loss	(3) Percent lost Full sample
Year	0.00829***	-1.137**	0.0986
	(0.00231)	(0.519)	(0.368)
Constant		2,344**	-178.4
		(1,047)	(741.5)
Observations	121,983	31,746	91,280
Country FE	YES	YES	YES

Note: Marginal effects from logit regression (Column 1) and results from OLS regressions (Columns 2 and 3). Columns 1 and 3 are unconditional, column 2 is conditional on any loss on the plot. The estimates are weighted to be nationally representative. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Total fraction of aggregate potential harvest lost, by country-year

Country	Year	Fraction of total potential harvest lost in shocks
Ethiopia	2013 - 2014	15.14 %
	2015 - 2016	34.63 %
	2018 - 2019	31.52 %
Malawi	2018 - 2019	46.53 %
Mali	2014	7.59 %
	2017	8.22 %
Niger	2011	81.12 %
	2014	29.24 %
Nigeria	2019	3.19 %
Pooled	2011-2019	28.57 %

Note: Sample weights are used to calculate estimates. Current prices are used to value losses and attainable harvest

Table 5: Share of households affected by multiple disaster shocks on their plots

Country	Year	Percent of households that report disaster losses from multiple sources
Ethiopia	2011 – 2012	8.99 %
Ethiopia	2013 - 2014	12.58 %
Ethiopia	2015 - 2016	20.92 %
Ethiopia	2018 - 2019	21.02 %
Malawi	2012 - 2013	4.50 %
Malawi	2015 - 2016	15.03 %
Malawi	2018 - 2019	15.05 %
Tanzania	2008	5.09 %
Tanzania	2010	4.25 %
Tanzania	2012	3.04 %
Tanzania	2014	1.46 %
Tanzania	2019	4.52 %

Note: Sample weights are used to calculate estimates. Only waves which allow the reporting of multiple shock types on each listed crop are retained.

Table 6: Loss size by shock type

Dependent variable: Percent of harvest lost	(1) Ethiopia	(2) Malawi	(3) Mali	(4) Niger	(5) Nigeria
Drought	6.570***	7.767***	2.536	3.183	-4.939
	(1.853)	(2.668)	(3.966)	(2.235)	(4.152)
Pests	5.955***	-4.283	11.48*	-6.561**	-10.28**
	(1.731)	(2.867)	(6.384)	(2.710)	(4.711)
Flood		15.11***		-1.935	9.263*
		(2.995)		(5.656)	(4.984)
Constant	34.08***	47.68***	45.31***	64.71***	31.80***
	(1.145)	(1.944)	(3.875)	(2.292)	(4.936)
Observations	10,478	2,180	7,389	6,537	449
Crop FE	YES	YES	YES	YES	YES
Survey Wave FE	YES	YES	YES	YES	YES

Note: Results from OLS regressions with the share of potential harvest lost as outcome variable. Base category for shock dummies is other shock. The estimates are weighted to be nationally representative. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Heterogeneity in disaster exposure by plot characteristics

Dependent variable: Any disaster loss on plot	(1) Pooled	(2) Ethiopia	(3) Malawi	(4) Mali	(5) Niger	(6) Nigeria	(7) Tanzania
Any hired labor on plot	-0.0151	-0.00717	-0.0513***	-0.000535	-0.0291	-0.00315	-0.0130
	(0.0111)	(0.0242)	(0.0167)	(0.0142)	(0.0205)	(0.0217)	(0.0151)
Any inorganic fertilizer used	-0.0445***	-0.0482**	0.0236	-0.0621***	-0.0527*	-0.0357**	-0.0885***
	(0.0109)	(0.0187)	(0.0161)	(0.0171)	(0.0289)	(0.0154)	(0.0290)
Any organic fertilizer used	0.0285***	0.0666***	0.0382**	-0.00299	-0.00833	-0.0106	-0.0126
	(0.0105)	(0.0195)	(0.0158)	(0.0160)	(0.0255)	(0.0188)	(0.0266)
Plot is irrigated	-0.00339	0.000150	-0.0647	-0.201***	-0.169***	0.00297	0.0370
	(0.0211)	(0.0334)	(0.0592)	(0.0461)	(0.0535)	(0.0305)	(0.0502)
Plot is intercropped	0.0491***	0.0353	0.146***	-0.0335	-0.0271	-0.0221	0.0419**
	(0.0117)	(0.0242)	(0.0181)	(0.0292)	(0.0364)	(0.0164)	(0.0207)
Plot is owned	-0.000302	0.0200	-0.00111	-0.0542**	-0.0529	-0.0296	-0.00966
	(0.0121)	(0.0199)	(0.0215)	(0.0246)	(0.0329)	(0.0184)	(0.0234)
Log plot area (ha)	0.00875***	0.00983*	0.0219***	0.000514	-0.0272***	-0.0122*	0.0339***
	(0.00333)	(0.00504)	(0.00568)	(0.00562)	(0.00835)	(0.00677)	(0.00803)
Plot topographic wetness index	0.00731***	0.00315	0.00503	0.00210	0.00349	0.00134	0.0121***
	(0.00165)	(0.00407)	(0.00345)	(0.00244)	(0.00267)	(0.00161)	(0.00225)
Plot elevation (m)	-9.16e-05***	-8.41e-05***	-0.000371***	-0.000299**	-0.000172	-2.12e-05	-6.58e-05***
	(1.60e-05)	(2.64e-05)	(3.41e-05)	(0.000131)	(0.000186)	(4.61e-05)	(2.37e-05)
Urban household	-0.0211	0.00330	-0.115***	-0.0356	0.0446	-0.0212	0.0273
	(0.0206)	(0.0529)	(0.0410)	(0.0484)	(0.0472)	(0.0249)	(0.0291)
Household engaged in livestock farming	0.00545	0.0210	-0.00556	0.0271	-0.145***	-0.0153	0.0398**
	(0.0101)	(0.0211)	(0.0133)	(0.0203)	(0.0466)	(0.0182)	(0.0173)
Household has access to electricity	0.0711***	0.120***	0.0173	-0.0240	-0.0302	0.00143	0.0195
	(0.0161)	(0.0241)	(0.0283)	(0.0167)	(0.0493)	(0.0197)	(0.0358)
Observations	116,773	39,801	17,900	31,257	9,004	6,623	12,187
Crop FE	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	NO	NO	NO	NO	NO	NO

Note: Average marginal effects from multivariate logit regressions. Base category for crop fixed effects is 'other crop'. The estimates are weighted to be nationally representative. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Heterogeneity in loss size by plot characteristics

Dependent variable: Percent of harvest lost	(1) Pooled	(2) Ethiopia	(3) Malawi	(4) Mali	(5) Niger	(6) Nigeria
Any hired labor on plot	-5.120***	-3.632	-3.179	-0.707	-4.162***	-9.870*
	(1.762)	(2.236)	(3.237)	(1.977)	(1.454)	(5.065)
Any inorganic fertilizer used	-8.073***	-7.744***	-2.133	-15.47***	-4.415**	-17.28***
	(1.512)	(1.885)	(1.885)	(2.563)	(1.955)	(4.320)
Any organic fertilizer used	0.707	3.476*	-3.111**	-4.282**	-6.589***	-8.291**
	(1.315)	(1.842)	(1.522)	(2.106)	(1.183)	(4.103)
Plot is irrigated	3.450	1.126	9.046	-20.15***	4.865	14.80*
	(3.063)	(3.636)	(14.07)	(6.356)	(4.255)	(8.736)
Plot is intercropped	-7.513***	-3.781	-1.550	-6.306*	-6.367***	-36.05***
	(1.754)	(2.329)	(2.454)	(3.550)	(1.773)	(4.865)
Plot is owned	-1.945	-2.300	6.057*	-2.874	-2.586	-3.114
	(1.556)	(2.017)	(3.122)	(3.702)	(1.645)	(4.379)
Log plot area (ha)	-2.565***	-2.782***	-4.610***	-0.255	-0.599	0.394
	(0.410)	(0.497)	(1.109)	(0.686)	(0.427)	(1.383)
Plot topographic wetness index	0.263	0.576*	0.0928	0.993***	0.0383	0.0686
	(0.206)	(0.301)	(0.434)	(0.344)	(0.249)	(0.451)
Plot elevation (m)	-0.00727***	-0.00650***	-0.0250***	-0.0179	-0.00721	0.00584
	(0.00214)	(0.00228)	(0.00404)	(0.0187)	(0.0108)	(0.00892)
Urban household	4.463	12.26***	-3.747	5.014	1.584	-5.863
	(2.772)	(2.829)	(3.387)	(6.587)	(2.659)	(5.539)
Household engaged in livestock farming	-2.395	1.289	0.157	3.039	-9.035***	-2.391
	(1.733)	(2.353)	(1.820)	(3.219)	(2.203)	(4.460)
Household has access to electricity	2.388	1.600	3.479	-1.266	-2.625	5.226
	(1.946)	(2.219)	(4.478)	(2.336)	(2.222)	(4.404)
Constant	64.21***	53.17***	61.56***	55.52***	84.30***	104.4***
	(6.177)	(7.224)	(9.642)	(10.15)	(6.901)	(10.39)
Observations	30,845	14,896	2,059	7,130	6,071	689
Crop FE	YES	YES	YES	YES	YES	YES
Country FE	YES	NO	NO	NO	NO	NO

Note: Results from OLS regressions with the share of potential harvest lost as outcome variable. Base category for crop fixed effects is 'other crop'. The estimates are weighted to be nationally representative. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Heterogeneity in disaster exposure by plot manager characteristics

	Pooled		Ethiopia		Malawi		Mali		Niger		Nigeria		Tanzania	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Dependent variable: Any disaster loss on plot	No control	Control	No control	Control	No control	Control	No control	Control	No control	Control	No control	Control	No control	Control
Female plot manager	0.0222**	0.0267***	0.00350	0.0126	0.0529***	0.0272**	0.0843***	0.0614***	0.0503*	0.0475*	0.0386*	0.00467	0.0138	0.0355*
	(0.00939)	(0.00904)	(0.0171)	(0.0169)	(0.0137)	(0.0123)	(0.0237)	(0.0215)	(0.0293)	(0.0280)	(0.0207)	(0.0165)	(0.0201)	(0.0186)
Age of plot manager (decades)	0.00727***	0.00708***	0.00829*	0.00750*	0.00112	0.00407	0.0124***	0.0124***	-0.0137***	-0.00896*	0.00774	0.00564	0.0119**	0.00878*
	(0.00249)	(0.00237)	(0.00457)	(0.00418)	(0.00446)	(0.00416)	(0.00443)	(0.00429)	(0.00525)	(0.00517)	(0.00542)	(0.00533)	(0.00523)	(0.00481)
Plot manager has primary educ	-0.0140	-0.0138	-0.0176	-0.0258	-0.0467***	-0.00906	-0.0386*	-0.0178	-0.0609	-0.0594	0.0186	-0.00118	-0.0216	-0.00847
	(0.0125)	(0.0124)	(0.0300)	(0.0285)	(0.0145)	(0.0140)	(0.0224)	(0.0216)	(0.0480)	(0.0473)	(0.0155)	(0.0179)	(0.0314)	(0.0336)
Observations	115,041	115,041	39,289	39,289	17,123	17,123	31,019	31,019	8,911	8,911	6,591	6,591	12,107	12,107
Controls	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Crop FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO

Note: Average marginal effects from multivariate logit regressions. Controls include dummy variables for input use (any hired labor, any inorganic fertilizer, any organic fertilizer), plot characteristics (plot area, irrigation, intercropping, plot ownership, elevation, and a topographic wetness index), household characteristics (urban/rural residence, livestock farming, and electricity access) as well as main crop and country fixed effects. The estimates are weighted to be nationally representative. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 10: Heterogeneity in loss size by plot manager characteristics

	Pooled		Ethiopia		Malawi		Mali		Niger		Nigeria	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable: Percent of harvest lost on plot	No controls	Controls	No controls	Controls	No controls	Controls	No controls	Controls	No controls	Controls	No controls	Controls
Female plot manager	4.405***	2.303**	3.345**	1.968	3.952	2.363	5.167	0.988	5.025***	3.789**	10.76**	-0.0518
	(1.158)	(1.136)	(1.448)	(1.385)	(2.383)	(2.128)	(3.452)	(2.895)	(1.742)	(1.754)	(5.463)	(6.238)
Age of plot manager (decades)	0.231	0.285	0.373	0.407	-0.995	0.0282	-0.537	-0.385	-0.382	-0.0241	0.974	-0.303
	(0.320)	(0.315)	(0.384)	(0.377)	(0.871)	(0.797)	(0.663)	(0.544)	(0.481)	(0.474)	(1.837)	(1.328)
Plot manager has primary educ	-0.0273	-1.641	-1.508	-3.215	0.497	1.915	-4.344	-1.184	-5.307*	-3.501	5.493	-1.332
	(1.831)	(1.686)	(2.362)	(2.192)	(2.893)	(2.226)	(2.950)	(2.775)	(2.759)	(2.510)	(4.983)	(5.349)
Constant	49.31***	62.68***	48.94***	51.42***	55.91***	60.52***	49.98***	57.01***	65.99***	83.15***	46.19***	106.0***
	(1.923)	(6.404)	(2.152)	(7.456)	(4.869)	(9.858)	(3.617)	(10.82)	(2.491)	(7.111)	(10.01)	(15.73)
Observations	30,230	30,230	14,680	14,680	1,739	1,739	7,100	7,100	6,027	6,027	684	684
Crop FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO

Note: Results from OLS regressions with the share of potential harvest lost as outcome variable. Controls include dummy variables for input use (any hired labor, any inorganic fertilizer, any organic fertilizer), plot characteristics (plot area, irrigation, intercropping, plot ownership, elevation, and a topographic wetness index), household characteristics (urban/rural residence, livestock farming, and electricity access) as well as main crop and country fixed effects. The estimates are weighted to be nationally representative. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 11: Heterogeneity in plot endowment and management by gender of the plot manager

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: Female plot manager (dummy)	Pooled	Ethiopia	Malawi	Mali	Niger	Nigeria	Tanzania
Any hired labor on plot	0.0342***	0.0336**	0.000582	-0.0254**	0.0644***	0.0473**	0.0560***
	(0.00878)	(0.0145)	(0.0148)	(0.0104)	(0.0148)	(0.0216)	(0.0201)
Any inorganic fertilizer used	-0.00474	0.0159	-0.0149	-0.0206	-0.00489	-0.0373**	-0.00251
	(0.00879)	(0.0125)	(0.0154)	(0.0138)	(0.0349)	(0.0176)	(0.0275)
Any organic fertilizer used	-0.0128	0.0127	0.0234	-0.0381***	-0.0375**	-0.0367*	-0.0167
	(0.00924)	(0.0114)	(0.0186)	(0.00935)	(0.0150)	(0.0211)	(0.0309)
Plot is irrigated	-0.0332	0.0234	-0.0671	-0.0956***	-0.244**	-0.0418	-0.0718
	(0.0246)	(0.0339)	(0.0703)	(0.0274)	(0.100)	(0.0610)	(0.0489)
Plot is intercropped	0.0184**	-0.0168	0.0698***	-0.0224	-0.0544***	0.0287**	0.0430*
	(0.00844)	(0.0149)	(0.0129)	(0.0225)	(0.0206)	(0.0144)	(0.0225)
Plot is owned	0.0268***	0.0907***	0.0897***	-0.00327	-0.0335**	-0.00298	-0.00916
	(0.00988)	(0.0173)	(0.0239)	(0.0189)	(0.0148)	(0.0181)	(0.0195)
Log plot area (ha)	-0.0423***	-0.0245***	-0.0524***	-0.0229***	-0.0461***	-0.0498***	-0.0619***
	(0.00258)	(0.00297)	(0.00706)	(0.00363)	(0.00667)	(0.00567)	(0.00795)
Plot topographic wetness index	0.00105	-0.00154	0.00110	0.00154	-0.00162	-0.000648	0.00310
	(0.00141)	(0.00271)	(0.00386)	(0.00135)	(0.00156)	(0.00176)	(0.00323)
Plot elevation (m)	-2.96e-05**	2.91e-07	-9.40e-05***	-0.000297***	0.000227**	-0.000188*	-5.01e-06
	(1.17e-05)	(1.59e-05)	(3.27e-05)	(5.32e-05)	(0.000110)	(9.64e-05)	(2.13e-05)
Urban household	0.00322	0.0744**	0.0166	-0.0568**	-0.0634*	-0.0347	0.0214
	(0.0153)	(0.0356)	(0.0350)	(0.0274)	(0.0378)	(0.0281)	(0.0268)
Household engaged in livestock farming	-0.0888***	-0.142***	-0.103***	0.00674	-0.00526	-0.00275	-0.0921***
	(0.00932)	(0.0152)	(0.0147)	(0.0124)	(0.0200)	(0.0202)	(0.0195)
Household has access to electricity	-0.00878	-0.0308**	-0.0621*	0.00794	-0.0857**	0.0115	-0.0408
	(0.0115)	(0.0144)	(0.0345)	(0.00813)	(0.0384)	(0.0205)	(0.0333)
Observations	118,311	40,243	17,932	31,138	8,803	7,773	12,307
Crop FE	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	NO	NO	NO	NO	NO	NO

Note: Average marginal effects from multivariate logit regressions. Base category for crop fixed effects is 'other crop'. The estimates are weighted to be nationally representative. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 12: Heterogeneity in drought reports within enumeration areas, by crop type

		Drought			
		All crops	Maize	Sorghum	Millet
Ethiopia	2011-2012	39.4	16.1	18.6	13.3
	2013-2014	43.8	26.3	24.9	12.7
	2015-2016	55.8	34.3	29.0	23.3
	2018-2019	48.6	27.7	26.9	10.5
Malawi	2009-2010	62.6	58.4	76.0	30.0
	2012-2013	25.7	28.0	36.2	30.0
	2015-2016	33.0	36.3	43.2	40.0
	2018-2019	17.5	11.7	20.5	16.7
Mali	2014	29.7	13.9	20.6	14.4
	2017	44.5	28.1	32.2	32.2
Niger	2011	78.6	41.7	68.1	82.4
	2014	66.4	28.6	62.6	63.6
Nigeria	2019	20.7	8.9	7.6	6.4
Tanzania	2008	55.9	51.9	0.0	50.0
	2010	59.3	57.6	58.1	55.6
	2012	46.9	44.4	37.9	26.3
	2014	32.1	29.7	66.7	50.0
	2019	42.1	44.6	87.5	33.3
All countries	All years	41.1	31.1	31.5	32.1

Note: Share of enumeration areas with heterogenous drought reports, pooled and by crop type. Heterogeneous reports are defined as enumeration areas where at least one plot recorded a drought loss and at least one plot did not. Columns 2, 3, and 4 compare only plots that grew the same crop. Enumeration areas with only a single plot with the crop are excluded.

Table 13: Mean frequency of plots with drought shocks within household, conditional on at least one drought shock being recorded

Country	**Survey**	**Mean drought shock frequency of plots with the same crop within household** *Restricted to plots with maize* (1)	**Mean drought shock frequency of plots with the same crop within household** *Restricted to plots with maize* (2)
Ethiopia	2011 – 2012	68.75 %	*n≤10*
Ethiopia	2013 – 2014	62.52 %	70.76 %
Ethiopia	2015 – 2016	82.33 %	91.07%
Ethiopia	2018 – 2019	59.68 %	72.81 %
Malawi	2010	88.08 %	93.52 %
Malawi	2013	65.77 %	100.00 %
Malawi	2016	71.77 %	88.89 %
Malawi	2019	38.89 %	40.00 %
Mali	2014	65.83 %	69.91 %
Mali	2017	62.97 %	62.72 %
Niger	2011	*n≤10*	90.29 %
Niger	2014	*n≤10*	69.01 %
Nigeria	2019	24.40 %	57.14 %
Tanzania	2008 – 2009	43.22 %	*n≤10*
Tanzania	2010 – 2011	52.65 %	67.39 %
Tanzania	2012 – 2013	56.57 %	*n≤10*
Tanzania	2014 – 2015	44.25 %	*n≤10*
Tanzania	2019 – 2020	51.19 %	*n≤10*
All countries		66.56 %	79.55 %

Note: These frequencies are conditional on at least one plot with the same crop (maize in col (1) or sorghum in col(2)) experiencing a drought shock, the household having more than one crop plot with the same specific crop (maize in col (1) or sorghum in col(2)), and a sample size of over 10 observations to calculate shares.

Table 14: Share of the national population affected by droughts according to EM-DAT and LSMS-ISA data

Country	Year	Percent of the population affected by drought using LSMS-ISA data	Percent of the population affected by drought using EM-DAT data
Ethiopia	2011 - 2012	7.88 % [5.73 % ; 10.04 %]	6.20 %
	2013 - 2014	11.45 % [8.83 % ; 14.07 %]	*missing*
	2015 - 2016	32.50 % [27.33 % ; 37.67 %]	9.68 %
	2018 - 2019	14.30 % [10.88 % ; 17.72 %]	*missing*
Malawi	2009 - 2010	23.82 % [20.44 % ; 27.20 %]	*missing*
	2012 - 2013	8.98 % [6.98 % ; 10.98 %]	*missing*
	2015 - 2016	25.51 % [19.25 % ; 31.78 %]	*missing*
	2018 - 2019	7.66 % [5.06 % ; 10.26 %]	*missing*
Mali	2014	15.89 % [13.35 % ; 18.43 %]	*missing*
	2017	24.53 % [21.54 % ; 27.53 %]	*missing*
Niger	2011	56.14 % [48.77 % ; 63.50 %]	17.03 %
	2014	20.78 % [15.78 % ; 25.78 %]	*missing*
Nigeria	2019	2.39 % [1.49 % ; 3.29 %]	*missing*
Tanzania	2008	12.38 % [10.55 % ; 14.21 %]	*missing*
	2010	18.98 % [16.54 % ; 21.42 %]	*missing*
	2012	15.38 % [13.08 % ; 17.68 %]	2.09 %
	2014	10.27 % [4.08 % ; 16.45 %]	*missing*
	2019	16.50 % [10.07 % ; 22.93 %]	*missing*

Note: missing entries correspond to cases where either no event was reported or information on the population affected was missing in the EM-DAT. 95% confidence intervals for estimated totals are calculated with LSMS-ISA microdata

Table 15: Total estimated value of crop production lost (LSMS-ISA) and total aggregate economic losses (EM-DAT) due to droughts

Country	Year	Total aggregate losses due to drought (in 2022 dollars) in LSMS-ISA	Total aggregate losses due to drought (in 2022 dollars) in EM-DAT
Ethiopia	2013 - 2014	589 million [281 ; 896]	*missing*
	2015 - 2016	2,980 million [2000 ; 3960]	2,134 million
	2018 - 2019	1,354 million [229 ; 2479]	*missing*
Malawi	2018 - 2019	41 million [23 ; 60]	*missing*
Mali	2014	70 million [55 ; 85]	*missing*
	2017	165 million [136 ; 194]	*missing*
Niger	2011	1.583 million [1294 ; 1871]	*missing*
	2014	185 million [129 ; 241]	*missing*
Nigeria	2019	80 million [29 ; 131]	*missing*

Note: missing entries correspond to cases where either no event was reported or information on the population affected was missing in the EM-DAT. 95% confidence intervals for estimated totals are calculated with LSMS-ISA microdata

Table 16: Share of the national population affected by floods according to EM-DAT and LSMS-ISA data

Country	Year	Percent of the population affected by floods according to LSMS-ISA data	Percent of the population affected by floods according to EM-DAT data
Malawi	2012 - 2013	8.26 % [5.73 % ; 10.78 %]	0.95 %
	2015 - 2016	1.18 % [0.49 % ; 1.87 %]	3.74 %
	2018 - 2019	22.75 % [16.37 % ; 29.12 %]	5.38 %
Niger	2011	1.72 % [0.30 % ; 3.13 %]	0.24 %
	2014	3.76 % [1.58 % ; 5.95 %]	0.85 %
Nigeria	2019	4.62 % [3.17 % ; 6.08 %]	0.03 %

Note: missing entries correspond to cases where either no event was reported or information on the population affected was missing in the EM-DAT. 95% confidence intervals for estimated totals are calculated with LSMS-ISA microdata

Table 17: Total estimated value of crop production lost (LSMS-ISA) and total aggregate economic losses (EM-DAT) due to floods

Country	Year	Total aggregate flood loss (2022 dollars) in LSMS-ISA	Total aggregate flood loss (2022 dollars) in EM-DAT
Malawi	2018 - 2019	346 million [95 ; 598]	*missing*
Niger	2011	9 million [3.00 ; 15]	*missing*
	2014	81 million [0 ; 205]*	3 million
Nigeria	2019	352 million [208 ; 496]	*missing*

*Note: missing entries correspond to cases where either no event was reported or information on the population affected was missing in the EM-DAT. 95% confidence intervals for estimated totals are calculated with LSMS-ISA microdata *Negative lower bounds were cut at 0.*

Table 18. Estimated combined impacts of drought or flood events captured in LSMS-ISA

Country	Year	Number of individuals affected by droughts and/or floods	Share of total population affected by droughts and/or floods	Value of damages from droughts and/or floods	Number of individuals affected by droughts and/or floods	Share of total population affected by droughts and/or floods	Value of damages from droughts and/or floods
		LSMS-ISA	LSMS-ISA	LSMS-ISA	EM-DAT	EM-DAT	EM-DAT
Ethiopia	2011 - 2012	7.4 million [5.4 ; 9.5]	7.9 % [5.7 % ; 10.0 %]		5.846 million	6.30 %	
	2013 - 2014	11.4 million [8.8 ; 14.0]	11.4 % [8.8 % ; 14.1 %]	589.6 million [280.9 ; 898.2]	52 thousand	0.10 %	3.5 million
	2015 - 2016	34.2 million [28.8 ; 39.6]	32.5 % [27.4 % ; 37.6 %]	2,981.3 million [1,999.0 ; 3,963.7]	10.904 million	10.40 %	2,134.4 million
	2018 - 2019	16.3 million [13.1 ; 19.5]	14.3 % [11.5 % ; 17.1 %]	1,355.7 million [227.9 ; 2,483.4]	200 thousand	0.20 %	
Malawi	2009 - 2010	3.5 million [3.0 ; 4.0]	23.8 % [20.5 % ; 27.1 %]		38 thousand	0.30 %	
	2012 - 2013	2.6 million [2.2 ; 3.1]	16.5 % [13.5 % ; 19.5 %]		2.05 million	13.00 %	
	2015 - 2016	4.6 million [3.5 ; 5.7]	26.4 % [20.1 % ; 32.8 %]		7.341 million	42.40 %	594.6 million
	2018 - 2019	5.4 million [4.1 ; 6.7]	28.5 % [21.5 % ; 35.4 %]	379.9 million [123.0 ; 636.7]	1.001 million	5.40 %	
Mali	2014	2.8 million [2.4 ; 3.2]	15.9 % [13.4 % ; 18.4 %]	70.0 million [54.7 ; 85.3]	No entry		
	2017	4.7 million [4.2 ; 5.3]	24.5 % [21.7 % ; 27.4 %]	164.7 million [135.4 ; 194.0]	No entry		
Niger	2011	9.8 million [8.5 ; 11.1]	56.7 % [49.1 % ; 64.4 %]	1,589.9 million [1,298.4 ; 1,881.3]	3.041 million	17.40 %	
	2014	4.7 million [3.6 ; 5.8]	24.1 % [18.4 % ; 29.8 %]	265.6 million [129.5 ; 401.7]	166 thousand	0.90 %	3.1 million
Nigeria	2019	13.6 million [10.5 ; 16.7]	6.8 % [5.3 % ; 8.4 %]	427.5 million [274.4 ; 580.6]	71 thousand	0.00 %	0.0 million
Tanzania	2008	5.3 million [4.5 ; 6.1]	12.4 % [10.6 % ; 14.2 %]		10 thousand	0.00 %	
	2010	8.6 million [7.5 ; 9.7]	19.0 % [16.5 % ; 21.4 %]		50 thousand	0.10 %	
	2012	7.3 million [6.3 ; 8.4]	15.4 % [13.1 % ; 17.7 %]		1.0 million	2.10 %	

	2014	5.2 million [2.1 ; 8.4]	10.3 % [4.1 % ; 16.5 %]		40 thousand	0.10 %	3.1 million
	2019	9.9 million [6.2 ; 13.6]	16.5 % [10.4 % ; 22.6 %]		5 thousand	0.00 %	
All countries	2008 - 2019	157.0 million [144.6 ; 170.3]		7,824.2 million [6,168.6 ; 9,479.8]	31.814 million		2,738.6 million

Note: both point estimates and 95% confidence intervals are reported

Table 19. Overview of disaster loss information availability in the LSMS-ISA microdata

Country	Year	Ability to quantify partial losses	List of disaster shocks options provided in the dataset
Ethiopia	2011 - 2012	No	Drought; Rains: Fire; Insects; Crop disease; Locusts; Hail
	2013 - 2014	Yes	
	2015 - 2016	Yes	
	2018 - 2019	Yes	
Malawi	2009 - 2010	No	Drought; Irregular rains; Floods (not in wave 1); Fire; Insects; Disease
	2012 - 2013	No	
	2015 - 2016	No	
	2018 - 2019	Yes	
Mali	2014	Yes	Drought; Rains; Fire; Insects; Disease
	2017	Yes	
Niger	2011	Yes	Insects and bird attacks; Plant illness; Drought; Flood
	2014	Yes	
Nigeria	2019	Yes	Drought; Flood; Pest;
Tanzania	2008	No	Drought; Rain; Fire; Insects
	2010	No	
	2012	No	
	2014	No	
	2019	No	

Appendix A: Comparison of data from disaster inventories and microdata

Data from disaster inventories such as EM-DAT and from microdata such as the LSMS-ISA differ in a number of meaningful ways. This includes their coverage of different shock types and sizes, the affected population, and time frame, as well as their detail, accuracy, and comparability across countries. These dimensions determine the respective strengths and weaknesses of each data source and can give rise to differences in estimates of disaster incidence and severity.

Disaster inventories collate reports from a variety of data sources on a per-event basis and are subject to the coverage and detail of information provided in these underlying sources.[37] Typically, this data comes aggregated, most often at the country-level. On the other hand, microdata, in our case, is based on household surveys that interview a sample from the target population and population-level estimates are formed based on this sample.

Shock coverage

Coverage of shocks in disaster inventories varies depending on the underlying source data for each event. While large, salient shocks are likely reported across one or more sources that disaster inventories rely on (such as news reports or data bases from international organizations) and are therefore likely covered in disaster inventories, this is somewhat less likely for small or idiosyncratic shocks.[30,37] Such small shocks may therefore go unrecorded. For similar reasons, some shock types are more likely to be covered in disaster inventories than others.[37,42]

Conversely, microdata is based on reports directly elicited from those affected by the shocks in question. They are therefore more granular and able to cover small and localized shocks. At the same time, shock recording in microdata sources is subject to the design of the survey questionnaire such as the list of shocks covered, and the number of shocks recorded.

Population coverage

Disaster inventories are not limited to a specific population of interest and can, in principle, cover any event affecting any population group so long as this is reported in a source the disaster inventory can draw on. The lack of an explicit focus and reliance on reports from underlying sources, in turn, means that coverage for poor and marginalized population groups is more likely to be incomplete.

Microdata from household surveys focuses on (stratified) samples from a well-defined target population. In the case of the LSMS-ISA surveys, the samples are typically drawn to be nationally representative of the general population at the national and sub-national levels, and of urban and rural areas. This means that even poor and marginalized populations can be explicitly covered. At the same time, coverage is limited to the sample and affected by gaps in coverage wherever the sample is not fully representative of the population affected by a shock.

Temporal coverage

A major strength of disaster inventories is their ability to record shocks at any time they occur so long as they get reported. Over the long run, this means that coverage of shocks improves as shock recording in underlying sources gets more exact and comprehensive.[37] In contrast, temporal coverage in microdata is intermittent: limited to the years in which the survey is implemented and the recall period of the survey.

Detail of available information

The breadth of coverage in disaster inventories across time and space often comes at the cost of limited detail and missing information.[30,37,48] This particularly concerns the economic and welfare impact of shocks which are often difficult to quantify, especially so for uninsured damages.[37,40] Detail and completeness of the available information in disaster repositories is thus related to the size and salience of a shock. Further, the data provided in disaster inventories typically offers little opportunity for disaggregation, be it by affected population groups, geographies, or other key variables. As a consequence, disaster inventories often lack sufficient information to quantify disaster impacts on (asset-) poor but highly vulnerable population groups.[21]

As microdata sources elicit shock reports directly from those affected by them, they offer a high level of detail and completeness of information even for small or idiosyncratic events, for shocks that affect poor or marginalized population groups, and for their impact on uninsured damages and other, less salient domains of disaster impact. Depending on the design of the survey, shock and impact recording is often highly granular and allows for disaggregation and analysis along a broad range of ancillary information collected in the survey.

Accuracy of data

Data recorded in disaster inventories typically relies on reports from one or few sources. Especially where events are small and therefore only reported in a single data source, this exposes disaster inventories to possible inaccuracies in the source from which information is drawn.[37] Even though reports of the number of people affected and the economic impact of any disaster are almost always estimates, disaster inventories rarely provide information that quantifies the uncertainty associated with any individual or collection of estimates.

Estimates from microdata, on the other hand, are based on a large number of data points collected from the population of interest. This also allows to explicitly quantify (part of) the uncertainty inherent in estimates of disaster impact. While the large samples underlying estimates from microdata attenuate the effect of inaccuracies in individual data points, microdata, as any data source, is still subject to possible systematic measurement error.

Comparability of source data

Disaster inventories, and EM-DAT in particular, stand out for their broad coverage of events across geographies and time. To achieve this, disaster inventories need to rely on a wealth of different sources that vary according to their reliability, reporting standards, and definitions. Such idiosyncrasies are seldom explicit in collated records as part of disaster inventories but limit the comparability of data across different events and contexts.[37]

Within the same survey, information collected in microdata is typically harmonized and comparable across events covered. While microdata are subject to differences in survey and questionnaire design across contexts, such differences are usually explicit. Analysts can therefore take these differences into account when making comparisons and there is scope for harmonization across contexts as in the case of the LSMS-ISA suite of surveys.

Geographical differences

Many of the previously discussed sources of inaccuracies in estimates of disaster incidence and severity are more pronounced in low- and middle-income countries (LMICs).[21,30,37,42] This goes in particular for data from disaster inventories that depend on the comprehensiveness of coverage in the underlying data sources they draw on. For example, the density of information on shocks and natural disasters is lower in LMICs meaning that shocks are more likely to go unreported, information is more likely to be incomplete or inaccurate, poor and marginalized population groups are more likely not to be covered, and the impact on them is more likely to be underestimated due to a higher share of uninsured damages and a lower value of affected assets. On the side of microdata, surveys in high-income countries may provide more accurate data due to the availability of more sophisticated measurement approaches and higher levels of education among respondents which may positively affect the accuracy of self-reported information.

Dimension	Disaster Inventories	Microdata
Coverage		
Shock coverage (Threshold and hazard bias)	• Subject to reporting in aggregate data sources and reports • Salient shocks likely covered but data less sensitive to idiosyncratic or small shocks • Coverage varies by shock type	• Based on “grassroots” reports elicited from those affected by shocks • Granular and able to cover small and localized shocks • Shock recording subject to questionnaire design (list of shocks, number of shocks recorded)
Population coverage (Population coverage biases)	• Coverage depending on comprehensiveness of coverage in underlying data sources (e.g. news reports) but not limited to a specific population of interest • under-coverage of poor and marginalized population groups within countries likely	• Limited to (stratified) sample of target population • Potential for gaps in coverage wherever shock impacts not well represented by sample • Poor and marginalized population groups explicitly covered
Temporal coverage (Temporal coverage biases)	• Continuous coverage but subject to improvements in quality of reports in the long run	• Intermittent coverage limited to years in which survey was conducted and/or recall period of survey questions
Detail and accuracy		
Detail of available information (Missing data biases)	• Dependent on information reported in sources, limited detail and frequently missing information in some dimensions	• High level of detail and completeness of data collected, even for small and

	of shock impacts (e.g. economic and welfare impacts) • Detail and completeness of information related to size and salience of shock • No or limited ability to disaggregate information • Incomplete recording of uninsured damages • Lack of information to quantify impact on (asset-)poor but highly vulnerable population groups	idiosyncratic shocks as well as poor or vulnerable population groups • Information collected at highly disaggregated level but can be aggregated • Available information subject to survey design
Accuracy of data (Accounting biases)	• Regularly relying on one or few sources per event and exposed to measurement error therein • Usually based on approximations without ability to quantify uncertainty or accuracy	• Estimation based on (large) sample from population of interest • Explicit quantification of uncertainty in estimates • Subject to systematic (non-classical) measurement error
Comparability of source data	• Broad coverage across geographies and time • Exposed to idiosyncrasies in reporting protocols between different data sources without them typically being explicit	• Increased scope for harmonized data collection across contexts • Idiosyncrasies in data collection between different microdata sources are explicit
Geographical differences		
Geographical differences	• Lower information density in LMICs and lower ability to draw on ancillary data sources for shock recording • Systematic under-coverage of events and marginalized population groups in LMICs • Lower accuracy of data due to lower density of (independent) sources of information • Underestimation of impacts in LMICs due to higher share of uninsured damages and low value of affected goods and assets	• Potentially greater accuracy of microdata in HICs due to use of more sophisticated measurement approaches and higher levels of education among respondents

Appendix B: Estimated impact for floods *or* droughts, and for all shocks, in the LSMS-ISA

Table B1. Estimated impact of all adverse shocks captured in the LSMS-ISA

Country	Year	Estimate number of individuals affected by all shocks	Estimate share of total population affected by all shocks	Estimate damages from all shocks
Ethiopia	2011 - 2012	14 million [12 ; 17]	15.00 % [12.40 % ; 17.60 %]	
	2013 - 2014	34 million [30 ; 39]	34.20 % [29.80 % ; 38.60 %]	34 million [30 ; 39]
	2015 - 2016	52 million [46 ; 57]	49.30 % [43.90 % ; 54.60 %]	52 million [46 ; 57]
	2018 - 2019	31 million [27 ; 36]	27.60 % [23.60 % ; 31.60 %]	31 million [27 ; 36]
Malawi	2009 - 2010	6 million [5 ; 6]	39.00 % [34.20 % ; 43.90 %]	
	2012 - 2013	6 million [5 ; 7]	36.40 % [32.00 % ; 40.80 %]	
	2015 - 2016	9 million [7 ; 11]	52.30 % [41.70 % ; 62.80 %]	
	2018 - 2019	9 million [7 ; 11]	49.30 % [39.00 % ; 59.50 %]	9 million [7 ; 11]
Mali	2014	4 million [3 ; 4]	21.90 % [18.90 % ; 25.00 %]	4 million [3 ; 4]
	2017	5 million [4 ; 6]	26.20 % [23.10 % ; 29.30 %]	5 million [4 ; 6]
Niger	2011	12 million [11 ; 13]	70.80 % [63.70 % ; 77.90 %]	12 million [11 ; 13]
	2014	7 million [6 ; 8]	36.70 % [30.00 % ; 43.40 %]	7 million [6 ; 8]
Nigeria	2019	18 million [15 ; 22]	9.20 % [7.50 % ; 11.00 %]	18 million [15 ; 22]
Tanzania	2008	11 million [10 ; 12]	25.20 % [22.50 % ; 28.00 %]	
	2010	14 million [13 ; 15]	30.80 % [27.80 % ; 33.90 %]	
	2012	11 million [10 ; 13]	23.90 % [21.00 % ; 26.90 %]	
	2014	9 million [5 ; 14]	18.30 % [9.90 % ; 26.60 %]	
	2019	14 million [10 ; 19]	23.70 % [16.20 % ; 31.20 %]	
All countries	2008 - 2019	268 million [251 ; 285]		10,611 million [8,892 ; 12,330]

Note: both point estimates and 95% confidence intervals are reported