Supporting Pastoralism and Agriculture in Recurrent and Protracted Crises

December 2024

SUPPLEMENTARY ANNEX TO THE TECHNICAL REPORT

BEARING THE BURDEN

Climate change-attributable losses and damages in the Sahel and Greater Horn of Africa

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About SPARC

Climate change, armed conflict, environmental fragility and weak governance, and the impact these have on natural resource-based livelihoods, are among the key drivers of both crisis and poverty for communities in some of the world's most vulnerable and conflict-affected countries.

SPARC aims to generate evidence and address knowledge gaps to build the resilience of millions of pastoralists, agro-pastoralists and farmers in these communities in sub-Saharan Africa and the Middle East.

We strive to create impact by using research and evidence to develop knowledge that improves how the FCDO, donors, non-governmental organisations, local and national governments, and civil society can empower these communities in the context of climate change.

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ACRONYMS

DICE	Dynamic Integrated model of Climate and the Economy
EEA	extreme event attribution
FAO	Food and Agriculture Organization of the United Nations
FAR	fraction of attributable risk
FCDO	Foreign, Commonwealth & Development Office
FUND	Climate Framework for Uncertainty, Negotiation and Distribution
GDP	gross domestic product
IAM	integrated assessment model
IPCC	Intergovernmental Panel on Climate Change
OECD	Organisation for Economic Co-operation and Development
PDNA	post-disaster needs assessment
SGHA	Sahel and Greater Horn of Africa
SLOL	statistical loss of life
SPARC	Supporting Pastoralism and Agriculture in Recurrent and Protracted Crises
VSL	value of statistical life

1. INTRODUCTION

This supplementary annex accompanies the technical report *Bearing the burden: Climate change-attributable losses and damages in the Sahel and Greater Horn of Africa* (2024). It is intended to be read apart from that report, to gain a more profound understanding of the data and concepts presented there. This supplement is a detailed review and assessment of climate change-attributable losses and damages in the agriculture and livestock sectors in the Sahel and Greater Horn of Africa (SGHA).

2. DATA AND METHODOLOGY

2.1 Extreme event attribution analysis

This study uses information from extreme event attribution (EEA) studies that compare the probability of an event that occurred to the probability of the same event occurring in a world without anthropogenic climate change. Probabilistic EEA was first conceptualised by Allen (2003) and later implemented by Stott et al. (2004) to estimate the climate change-attributable impact of the 2003 continental European heatwave that cause high mortality across the region.

Studies using EEA may take a 'probability-based' or 'intensity-based' approach to attribution or hybrid approaches (van Oldenbourgh et al., 2021; Otto, 2017; Stott et al., 2016). The method draws on ensembles of climate models, historical observation data and extreme statistics analysis. In a probability-based EEA, only the differences in relative likelihood of event occurrence in a non-climate change versus climate change world are explored. In this approach, the fraction of attributable risk (FAR) is used to describe how much of an event's probability of occurrence is attributable to climate change.[1] In an intensity-based approach, the share of the intensity of an extreme event attributable to climate change is calculated (e.g. how much heavier a rainfall event was due to climate change).[2] Hybrid approaches use extreme event statistics analysis to determine trends in an event type's (e.g. heatwave) intensity and its return period (how probable an event of a particular intensity occurs). Under hybrid approaches, ensembles – multiple climate model runs – are then used to simulate how likely

1 The probabilistic methods can be approached from either a Bayesian or a frequentist perspective, with possible impact of the choice on the outcomes. However, Newman and Noy (2023) do not distinguish between the two perspectives, citing the limited availability of Bayesian attribution studies.

2 Some of the examples include Frame et al. (2020a) and Smiley et al. (2022), who estimated the economic cost of 2017 Hurricane Harvey using probability-based and intensity-based approaches, respectively. Similarly, Imada et al. (2020) use a probability-based approach to show that human-induced warming increased the probability of regional heavy rainfall events in 2017 and 2018 over western Japan.

it is that a climate extreme of a particular intensity would occur in a hypothetical world without climate change, and in the current world with climate change. The combination of the extreme event statistics of historical observation data and from the ensembles of models is then used to produce estimates about the influence of climate change on the intensity and probability of a particular event or group of events (van Oldenbourgh et al., 2017).

Robust EEA requires sufficiently long (ideally since at least the 1950s or earlier) observation records with minimal gaps. 'Confidence in attribution is higher for extreme event types where there are long-term historical records of observations without significant gaps, climate models are able to adequately simulate the extreme event and the event is purely meteorological' (NAS, 2016: 5-6). Events that are purely meteorological are heatwaves, cold snaps or heavy rainfall events. Secondary extreme weather events such as flooding, droughts or wildfires are more difficult to detect a climate change signal in, as these extremes are also dependent on human-built infrastructure and land-use change. For example, non-extreme amounts of rainfall may trigger flooding in urban areas with a large part of their area covered by roads and buildings; the impervious surfaces do not allow the rain to infiltrate the soil, which leads to flooding.

As with Newman and Noy (2023) and Panwar et al. (2023), the FAR value is calculated using the following formula:

$$FAR = 1 - \frac{P_0}{P_1}$$

P_0 = Probability of a climate extreme occuring without climate change
P_1 = Probability of a climate extreme occuring with climate change

Based on the above formula, the FAR value will lie between 0 and 1 in cases where risk of a climate event is increased due to anthropogenic greenhouse gas emissions ($P_1 > P_0$). Thus, an FAR value of 0 means that climate change had no influence on the probability of occurrence of that event, and an FAR value of 1 means that the event would not have been possible without anthropogenic climate change (Jézéquel et al., 2018; Newman and Noy, 2023). Conversely, the FAR value will be negative when the likelihood of an event decreases because of climate change (i.e. $P_1 < P_0$).[3]

Frame et al. (2020b) suggested that FAR values can be used to estimate climate change-attributable economic costs when both types of data are available. Newman and Noy (2023) extended this approach and extrapolated the FARs for individual events to national, regional and global scales and matched those with socioeconomic costs of extreme events to estimate climate change-attributable loss and damage. Given the paucity of attribution studies in low-income countries (including in the SGHA region), Newman and Noy (2023) based the extrapolation of FARs for individual climate extreme event types and regions on explicit assumptions of aggregation and generalisability (discussed in Section 2.2).

It should be noted that there are other methods of estimating the global cost of climate change, typically known as the integrated assessment models (IAMs). These IAMs such as the Dynamic Integrated model of Climate and the Economy (DICE) (Nordhaus, 2017) and the

3 There are very few events in the Panwar et al. (2023) dataset used for this study with a negative value of FAR, except for cold temperature events where almost all extreme events have a negative FAR value.

Climate Framework for Uncertainty, Negotiation and Distribution (FUND) (Anthoff and Tol, 2011) are most widely used and equally criticised. Typically, macroeconomic modelling is embedded in these IAMs to estimate the economic cost of climate change, expressed as a function of global or regional mean temperature (Diaz and Moore, 2017; Newman and Noy, 2023). These models therefore tend to introduce additional ad hoc modification to include cost of extreme climate events in their assessments (Bouwer, 2011; van den Bergh, 2009; Nordhaus, 2017). While the current EEA-based analysis may not be directly comparable to the IAMs, it still produces a new form of evidence that suggests a substantial underestimation of the current economic cost of climate change (Newman and Noy, 2023).[4]

2.2 Data collection and description

As with Newman and Noy (2023) and Panwar et al. (2023), this study uses two major data sources: the attribution studies to extract FAR estimates, and socioeconomic cost data for climate events from the EM-DAT database. Missing observations in the EM-DAT database are also complemented with additional data from post-disaster needs assessment (PDNA) studies. Such studies are also used to generate preliminary estimates of agriculture loss and damage (discussed later in this section).

Newman and Noy (2023) have compiled a global dataset of FARs from attribution studies[5] for specific events, matched with socioeconomic cost data for the same events from the EM-DAT database over the period 2000—2019. This dataset was further updated by Panwar et al. (2023) to include attribution studies conducted until 2022 (until 25 September 2023).

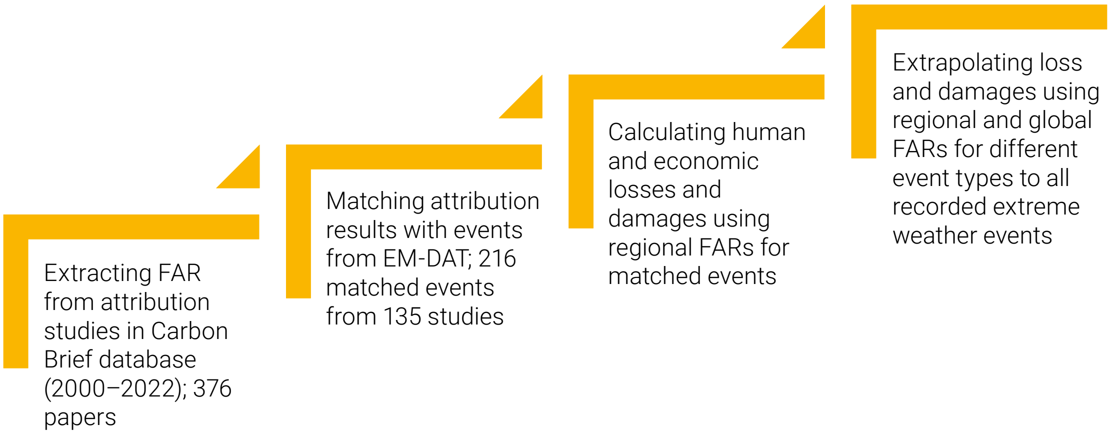
Newman and Noy (2023) applied hierarchical criteria (see Figure A1-1) in selecting the attribution studies and then matching them with human and economic cost estimates from the EM-DAT database using temporal (date, month and year) and geographical (region and country) criteria. In cases where more than one study was available for a specific event, the attribution study with 'better' research quality[6] was used.

4 See Newman and Noy (2023) for a comparison of EEA estimates with DICE and FUND estimates of climate-attributable economic cost of extreme weather events.

5 The FARs in the Newman and Noy (2023) dataset were extracted from the attribution studies conducted globally and listed in the Carbon Brief attribution database (Attribution – CarbonBrief 2024).

6 Newman and Noy (2023) use Scimago Journal Rank (SJR) to determine research 'quality', giving preference to an FAR measurement that comes from a higher-ranked SJR publication. For non-refereed studies such as from the World Weather Attribution network, an average of SJR scores for all studies is used as proxy.

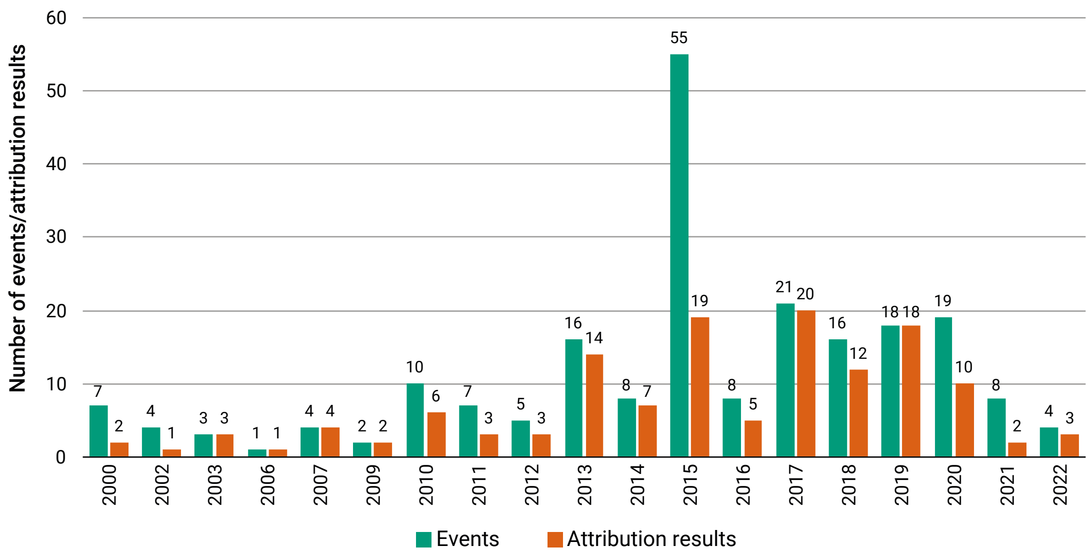
FIGURE A1-1: ANALYTICAL APPROACH USED IN EXTRACTING FRACTION OF ATTRIBUTABLE RISK AND EXTRAPOLATING LOSS AND DAMAGE



Source: Panwar et al. (2023)

The master dataset from Panwar et al. (2023) includes 216 matched climate extreme events that occurred during 2000–2022. Matched events are mapped from 135 attribution studies, as many of the studies (e.g. regional studies) covered multiple events. As in Figure A1-2, a majority (81%) of the matched events are from 2013 onwards owing to the increased frequency of EEA studies in recent years.

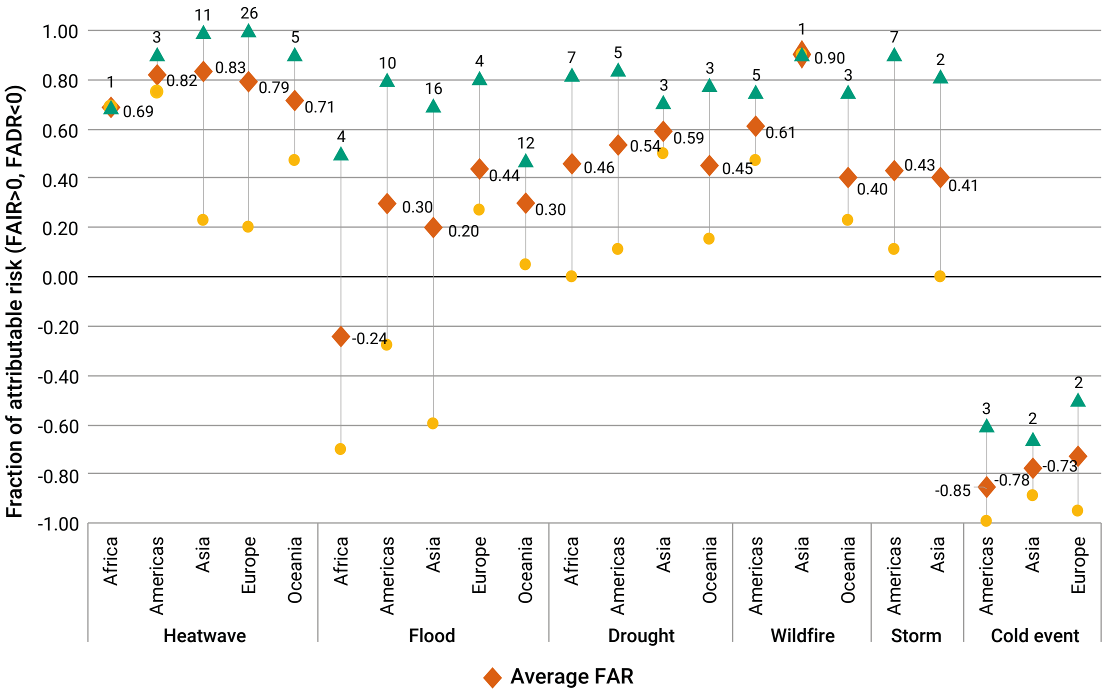
FIGURE A1-2: ANNUAL DISTRIBUTION OF MATCHED ATTRIBUTION RESULTS AND NUMBER OF EVENTS



Source: Panwar et al. (2023) and Newman and Noy (2023)

Flood and heatwave have the largest share of attribution results (34% each), followed by drought (13%), storm (7%), wildfire (7%) and cold wave (5%). As in Figure A1-3, out of the 216 matched events, 183 are associated with increased risk (FAR greater than 0), while 25 events are associated with decreased risk of occurrence (FAR less than 0). For eight events, the risk remains unchanged (FAR = 0).[7]

FIGURE A1-3: DISTRIBUTION OF FRACTION OF ATTRIBUTABLE RISKS (MINIMUM, MAXIMUM AND MEAN) ACROSS MATCHED EVENTS BY EVENT TYPE AND CONTINENTS



Source: Panwar et al. (2023) and Newman and Noy (2023)

Based on the global average of FARs, 50% of the probability of drought occurrence is due to anthropogenic climate change. The average FAR for floods is low, at 23%, because floods have a wider range of positive and negative FAR estimates, which is linked with them being secondary hazards. Floods are heavily mediated by the built environment, and some floods – such as storm surges and coastal flooding – are not triggered by heavy rainfall. Storms have an average FAR estimate of 42%, while average FAR estimates for heatwaves and wildfire are 79% and 57%, respectively. FAR estimates for heatwaves are the most robust globally due to significant length of observation data and clear climate change signals; multi-model climate projections for heatwaves are also the most robust (greater model agreement), though possibly underestimated in the SGHA region due to a cold bias in the models (IPCC, 2021).

Attribution studies are not equally distributed across continents, and Africa has just 12 attribution studies, or 9% of the related results. There are very few or no attribution results for many continent–event type combinations, especially for Africa and including the SGHA region, which has only four attribution results. Attribution results for Africa are available only for heatwaves, flood and drought events, with no identified attribution study for other hazard types. In the absence of region-specific attribution results, global averages are used to approximate climate change probability attribution of a hazard type.

7 Newman and Noy (2023) consider FAR value between 0 and -0.1 as 'unchanged' risk.

2.3 Post-disaster needs assessment analysis to estimate agriculture loss and damage

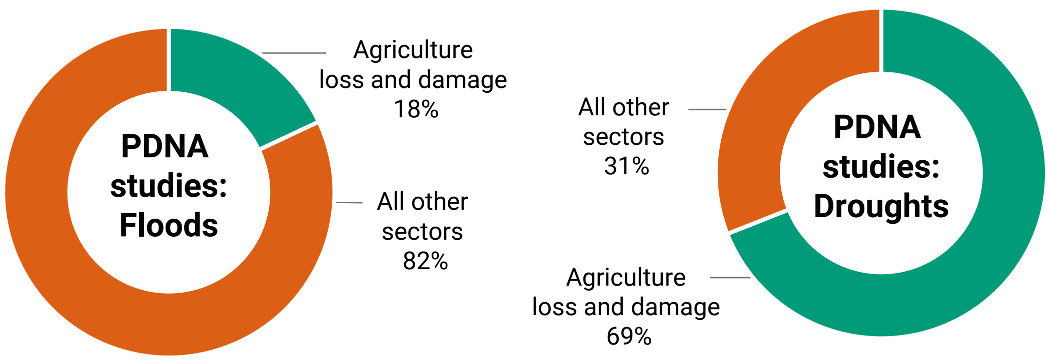
There is no global and/or regional database on agriculture loss and damage due to extreme weather events. This is also true for the countries in the SGHA region, where no consolidated dataset (at national level) on agriculture losses is available. The Food and Agriculture Organization (FAO) provides some estimates of 'potential' crop and livestock production losses due to disasters; however, these estimates are not publicly available other than in the overview presented in its flagship reports published at infrequent intervals (see FAO, 2023).

Disaster impact estimates provided in PDNA studies cover only 'direct' loss and damages and exclude indirect impacts. Nevertheless, in the absence of data on agriculture loss and damage, the present analysis relied on the 'economic damages' records from the EM-DAT database and generated preliminary estimates of agriculture loss and damage. For this, an analysis of the PDNA studies conducted during 2008—2024 in the SGHA region served as a benchmark to calculate the share of the agriculture sector in total economic damages reported in EM-DAT.

Globally, there are 89 PDNA studies/surveys available for 60 countries during 2008—2024, available online on PreventionWeb, ReliefWeb and the Global Facility for Disaster Reduction and Recovery (GFDRR).[8] Out of the 88 PDNA studies, 30 studies are from Africa, including 10 PDNA studies (5 droughts, 4 floods and 1 storm) from the SGHA region.

Agriculture sector loss and damage in relation to total economic loss and damage across all sectors (e.g. human settlements, infrastructure, etc.) is calculated based on the analysis of PDNA studies from the SGHA region (see Figure A1-4). Thus, the average share of agriculture in the total economic loss and damage for floods and droughts is used as a basis for slicing the total economic damage estimates reported in the EM-DAT database (see Figure A1-5). Similarly, the average share of livestock and crop loss and damage in total agriculture loss and damage is calculated. Table A1-1 shows an example of how agriculture loss and damage is calculated.

FIGURE A1-4: AVERAGE SHARE OF AGRICULTURE LOSS AND DAMAGE IN TOTAL ECONOMIC LOSS AND DAMAGE ACROSS ALL SECTORS FROM POST-DISASTER NEEDS ASSESSMENT STUDIES CONDUCTED IN THE SAHEL AND GREATER HORN OF AFRICA REGION

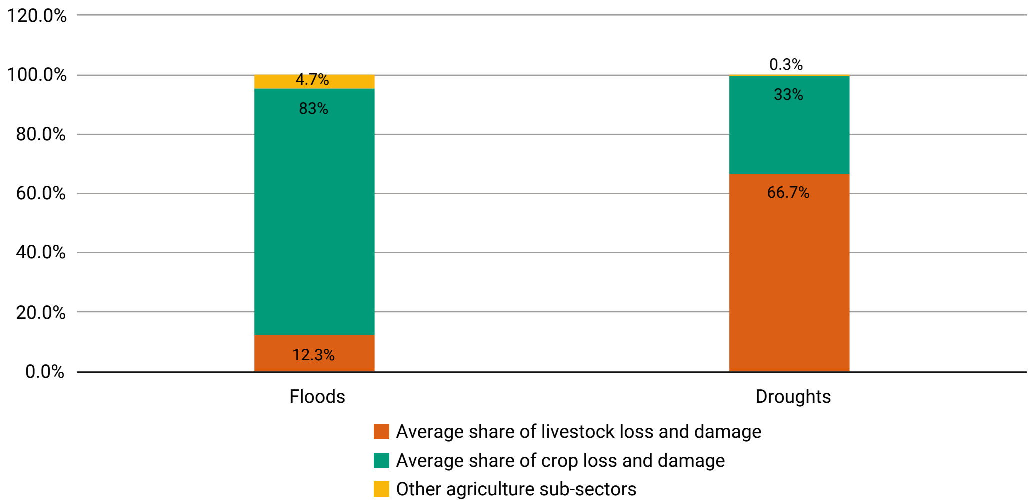


Note: Analysis is based on nine PDNA studies conducted for the SGHA region during 2008–2024.

Source: Authors' figure, using PDNA dataset provided by FAO

8 The data compiled from the 88 PDNA studies was used in the FAO (2023) report and shared by the FAO team for this analysis.

FIGURE A1-5: AVERAGE SHARE OF LIVESTOCK AND CROP LOSS AND DAMAGE IN TOTAL AGRICULTURE LOSS AND DAMAGE, BASED ON POST-DISASTER NEEDS ASSESSMENT STUDIES CONDUCTED IN THE SAHEL AND GREATER HORN OF AFRICA REGION



Note: Analysis is based on nine PDNA studies conducted for the SGHA region during 2008–2024.

Source: Authors' figure, using PDNA dataset provided by FAO

TABLE A1-1: EXAMPLE DEMONSTRATING PROCESS OF CALCULATING AGRICULTURE LOSS AND DAMAGE

(1) Economic damage as reported in EM-DAT for floods/droughts	(2) Estimated agriculture loss and damage based on average share of agriculture in all sectors' losses from the PDNA analysis For floods: (2) = (1) x 18% For droughts: (2) = (1) x 69%	(3) Estimated livestock loss and damage based on average share of livestock loss and damage in all sectors' losses from the PDNA analysis For floods: (3) = (2) x 12.3% For droughts: (3) = (2) x 66.7%	(4) Estimated crop loss and damage based on average share of crop loss and damage in all sectors' losses from the PDNA analysis For floods: (4) = (2) x 83% For droughts: (4) = (2) x 33%

Source: Authors' own

2.4 Calculating loss and damage

As with Newman and Noy (2023) and Panwar et al. (2023), the climate change-attributable loss and damage is quantified by combining the data on FAR estimates for individual event types (and direct economic costs (human, economic and agriculture costs). This can be mathematically expressed as follows:

$$CC\_loss\ \&\ damage_i = FAR_i * socio\_economic\ cost_i$$

Subject to availability of attribution studies, the FARs for loss and damage calculations in the SGHA region are extrapolated using both regional (for droughts) and global average (for floods) methods. Consequently, spatial, temporal and per event (disaster type) loss and damage are estimated for the SGHA region.

Newman and Noy (2023) use value of statistical life (VSL) calculations as the basis to assess the economic cost of human mortality. They use a VSL of $7.0837 million per life lost, which is an average of VSL estimates used by governments in the United States ($11.6 million) and the United Kingdom (£2 million). To maintain equity and enable comparison, this study also uses the same VSL value for all countries in the SGHA region and all other countries regardless of time and place of demise. As a next step, attributable statistical loss of life (SLOL) is calculated by multiplying VSL estimates with total attributable deaths. Thus, the total attributable loss and damage is a sum of attributable SLOL and economic damages. Agriculture loss and damage estimates do not include SLOL, as they are only linked with economic damage estimates reported in the EM-DAT database.

2.4.1 Limitations of data and methodology

Panwar et al. (2023) and Newman and Noy (2023) noted a range of limitations in the data and methods used as part of the EEA analysis. Some of the key ones as highlighted by these studies, and specific limitations related to the SGHA study region, are summarised below.

- **EEA attribution methodology:** EEA draws on ensembles of climate models, historical observation data and extreme statistics analysis. Throughout the SGHA region, historical observation becomes scarce after the 1980s due to instability affecting maintenance of weather stations and national hydromet capacities. This makes it difficult to conduct the statistical analysis necessary to detect a climate change signal in some events. Additionally, the SGHA has complex rainfall dynamics, influenced by the West and East African monsoon systems. The monsoons have high year-to-year and multidecadal variability and are influenced by multiyear to multidecadal processes such as the El Niño Southern Oscillation or the Atlantic Multidecadal Oscillation. Untangling a climate change signal in precipitation extremes (or a lack of excess) is difficult against the high natural variability; attributable signals in temperature extremes are easier to detect.

- **Uneven geographical distribution of attribution studies:** The climate attribution studies are limited in number and unequally distributed across the world. Many attribution studies are conducted in high-income countries (including China), and very few in low-income countries. Only 9% of the 135 attribution studies in this study are from Africa, while over half are from North America and Europe. This mismatch in study distribution has reduced variation in estimates and forced the FAR extrapolation for the SGHA region using regional and global averages. By increasing geographical coverage of attribution studies, especially in Africa, estimates of climate-attributable loss and damage will become more robust.

- **Limited attribution results for some hazard types:** There is an uneven spread of attribution studies for different natural hazard types. Heatwave and flood each have 34% of the total attribution results, out of 135 attribution studies. In contrast, only 7% of results are associated with storms, despite it being one of the costliest event types worldwide. Similarly, only 13% of the attribution studies pertain to droughts. Newman and Noy (2023) note that the main reason for this discrepancy could be the difficulty of attributing storms (and drought) to climate change, compared with, for example, heatwaves, which have direct evapotranspirative effects and are rather straightforward to attribute (see also Noy et al., 2023).[9]

- **Difficulty in matching attribution with socioeconomic data:** Unclear spatial and temporal boundaries of the events being analysed can make it difficult to match FAR estimates with socioeconomic cost data. For example, there were a few attribution results where the 'start' and 'end' date of an event was not clearly defined, making it difficult to confidently match these with EM-DAT data records.

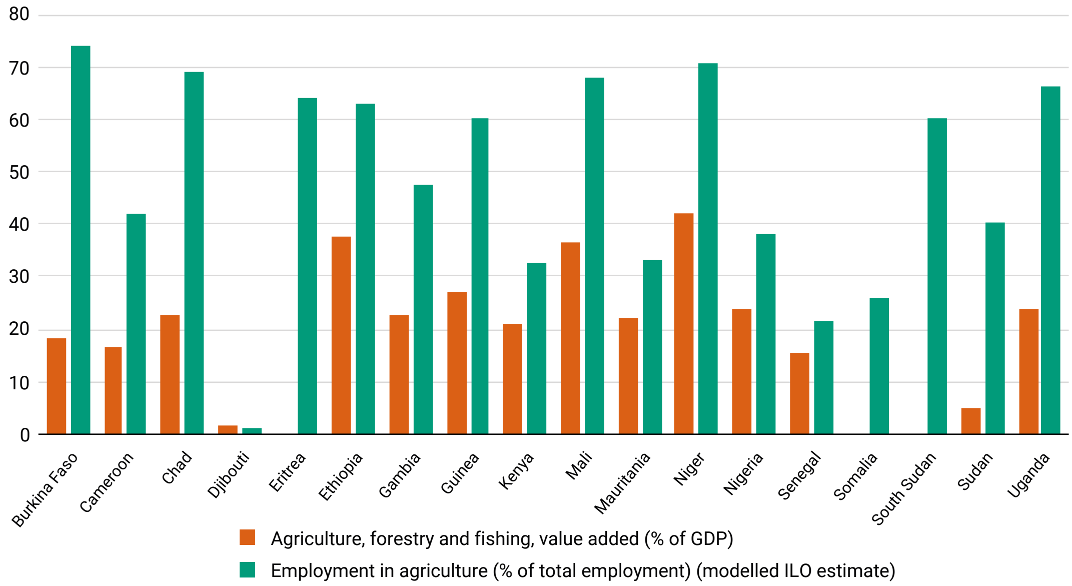
- **Gaps in the socioeconomic data:** The socioeconomic cost data used in this study has several limitations, such as missing observations and validity, geographical coverage and granularity (see Panwar and Sen, 2020). A total of 7,403 events were recorded in the EM-DAT database between 2000 and 2022, out of which 5,812 events had human and/or economic cost data recorded. For the 18 countries of the SGHA region, out of 527 total events (88 droughts, 399 floods, 31 storms, 3 wildfires and 2 heatwaves), 493 had the number of human deaths and/or people affected recorded, while economic cost figures were recorded for only 60 events. Because of its event inclusion criteria, EM-DAT only covers 'intensive' events and leaves out numerous 'extensive' events (low effect but frequently recurring). These may not be noteworthy individually, but cumulatively they can represent a large economic cost. Furthermore, EM-DAT does not include data specifically on damages in sectors such as agriculture.

- **Absence of indirect costs and non-economic loss and damage:** EM-DAT estimates only include direct costs (human fatalities, number of people affected, and economic losses) of disasters, but not their indirect macroeconomic and fiscal consequences or non-economic losses, which are usually difficult to estimate. Therefore, the 'direct' loss and damage estimates calculated for this study are only indicative, and the 'total cost' of climate change-attributable loss and damage (including indirect and non-economic loss and damage) could be several times higher.

9 One of the reasons for lack of attribution for many of droughts – at least the lack of rain aspect – is that the estimates are still within the range of natural variability because they are tied to multiyear or multidecadal teleconnections. Where the climate change signal is emerging in hydrological and agricultural droughts in Africa is due to higher temperatures increasing evaporation. The five consecutive failed rainy seasons in Somalia and other parts of the Horn of Africa were within the realm of natural variability (e.g. a triple-dip La Niña, while rare, is still within natural variability). However, the above-average temperatures worsened water loss and vegetation death as part of the drought.

3. SUPPLEMENTARY FIGURES AND TABLES

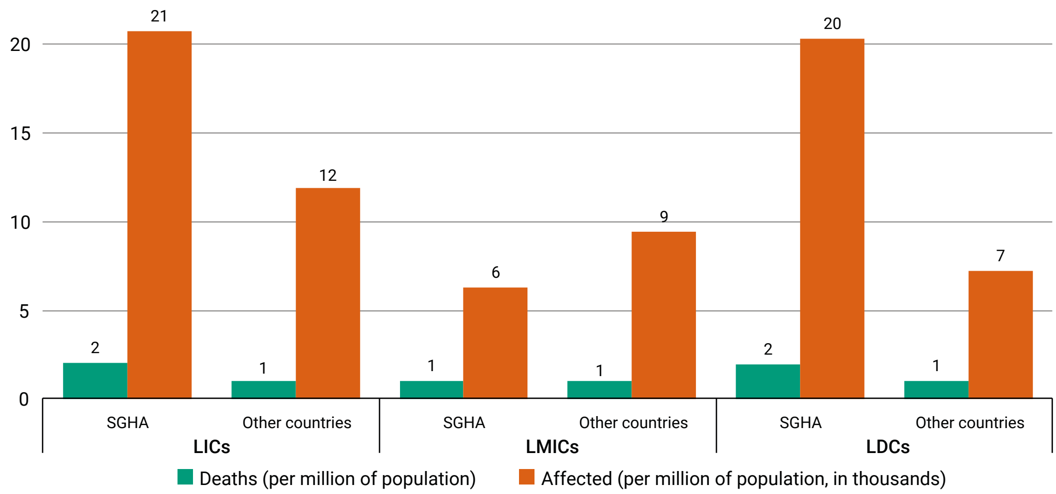
FIGURE A2-1: AGRICULTURE, FORESTRY AND FISHING VALUE ADDED AND EMPLOYMENT, 2022



Note: No data was available for agriculture, forestry and fishing value added in 2022 for Eritrea, South Sudan and Somalia; this figure is based on World Bank national accounts data, Organisation for Economic Co-operation and Development (OECD) National Accounts data files, and the International Labour Organization modelled estimates database.

Source: Authors' figure, using World Bank Group (n.d.)

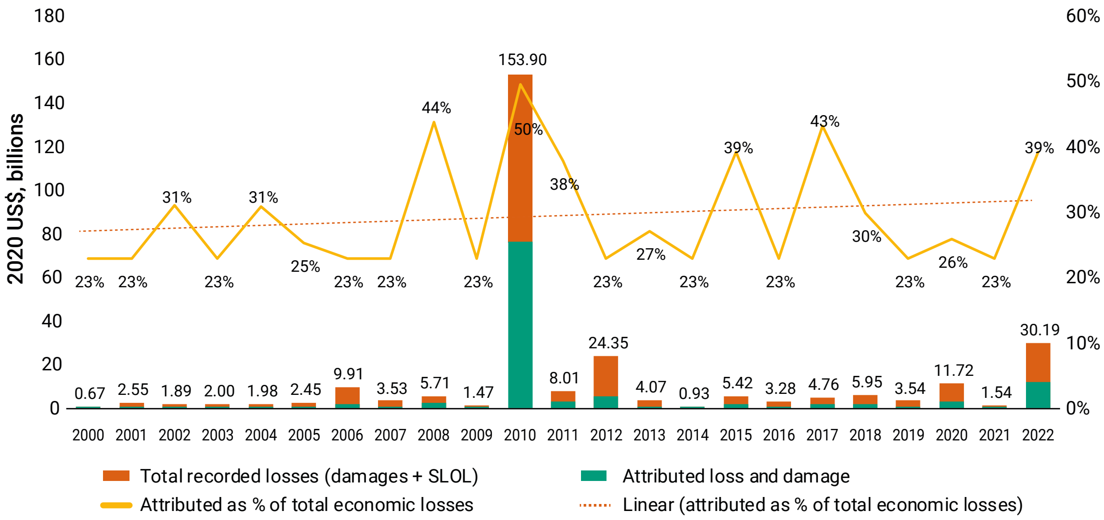
FIGURE A2-2: AVERAGE ANNUAL CLIMATE-ATTRIBUTABLE HUMAN LOSSES IN SAHEL AND GREATER HORN OF AFRICA AND OTHER (NON-SAHEL AND GREATER HORN OF AFRICA) COUNTRIES, 2000–2022



Note: Analysis is based on EM-DAT disaster damage records, using global average FARs. Figures are rounded. LDCs: least-developed countries; LICs: low-income countries; LMICs: lower-middle-income countries.

Source: Authors' own, based on EM-DAT (n.d.)

FIGURE A2-3: ANNUAL DISTRIBUTION OF CLIMATE-ATTRIBUTABLE LOSS AND DAMAGE ($ 2020 BILLIONS)



Note: Analysis is based on EM-DAT disaster damage records, using global average FARs. All figures are in 2020 US$. SLOL: statistical loss of life.

Source: Authors' own, based on EM-DAT (n.d.)

TABLE A2-1: PRELIMINARY ESTIMATES ON TOTAL AND CLIMATE-ATTRIBUTABLE AGRICULTURE LOSS AND DAMAGE DUE TO FLOODS AND DROUGHTS COMBINED 2000–2022 (2020 $ MILLIONS)

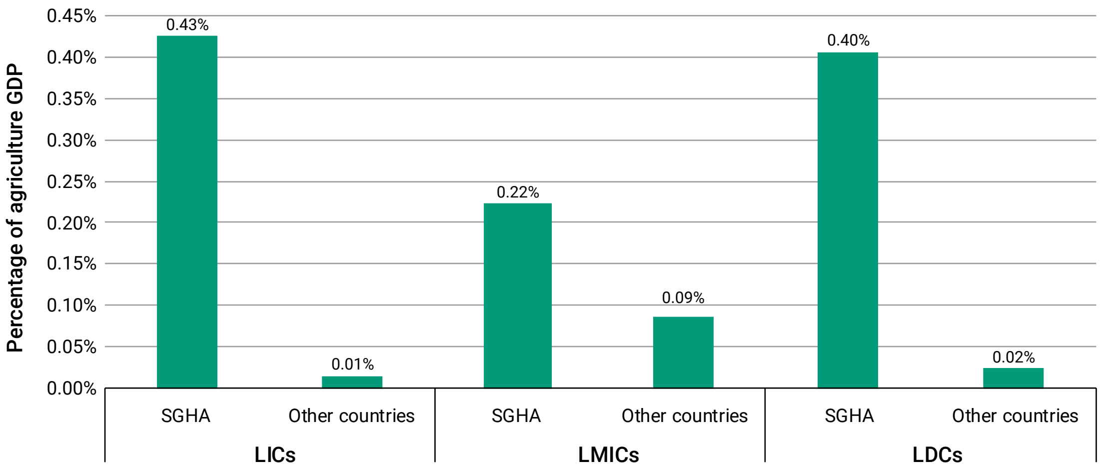
Cumulative (2000–2022)	Livestock		Crops		Agriculture total	
	Total	Attributable	Total	Attributable	Total	Attributable
Burkina Faso	5.68	1.31	38.33	8.82	46.18	10.62
Cameroon	0.41	0.09	2.76	0.63	3.32	0.76
Chad	0.28	0.06	1.90	0.44	2.29	0.53
Djibouti	110.89	55.44	54.86	27.43	166.25	83.12
Ethiopia	2,826.01	1,412.92	1,400.22	699.51	4,239.06	2,118.81
Kenya	6,018.37	3,006.05	3,050.16	1,503.94	9,099.98	4,524.52
Mali	121.77	60.88	60.24	30.12	182.56	91.28
Mauritania	0.05	0.01	0.33	0.08	0.40	0.09
Niger	58.84	13.53	397.07	91.33	478.40	110.03
Nigeria	538.61	123.88	3,634.50	835.94	4,378.92	1,007.15
Senegal	4.74	1.09	31.97	7.35	38.52	8.86
Somalia	3,783.31	1,891.34	1,883.22	938.37	5,684.24	2,838.38
Sudan	113.45	26.09	765.53	176.07	922.32	212.13
Uganda	616.87	308.40	306.09	152.78	925.79	462.58
Grand total	**14,199.26**	**6,901.10**	**11,627.20**	**4,472.82**	**26,168.23**	**11,468.88**

Note: All figures are in 2020 $ millions. Agriculture loss and damage figures are estimated from the total economic damage records of EM-DAT.

Source: Authors' own, based on EM-DAT (n.d.)

The extrapolation of agriculture losses and damages is based on average contribution of the agriculture sector to the total economic loss and damages reported across the PDNA studies conducted between 2008 and 2024 in the SGHA region (see Chapter 2 of this Supplementary Annex for more details). Figures for Eritrea, the Gambia, Guinea and South Sudan could not be calculated due to a lack of data.

FIGURE A2-4: AVERAGE ANNUAL CLIMATE-ATTRIBUTABLE AGRICULTURE LOSS AND DAMAGE IN SAHEL AND GREATER HORN OF AFRICA AND OTHER (NON-SAHEL AND GREATER HORN OF AFRICA) COUNTRIES AS A PERCENTAGE OF TOTAL AGRICULTURE GDP, 2000–2022



Note: Agriculture loss and damage figures are estimated from EM-DAT total economic damage records. LDCs: least-developed countries; LICs: low-income countries; LMICs: lower-middle-income countries

Source: Authors' own, based on EM-DAT (n.d.)

A recent report by the FAO (FAO, 2023) presents estimates of potential production losses due to natural hazard-related disasters globally between 1991 and 2021 (mostly climate-related). The report uses counterfactual yields for livestock and crop sub-sectors and differentiates those from actual yields to calculate disaster-induced yields for 186 items and 197 countries.

The FAO report presents average total production losses (1991–2021) in the agriculture sector (livestock and crops) as a percentage of agriculture GDP by sub-regions in Africa – Western, Middle and Eastern Africa. In the absence of data disaggregated by country in the report, these inputs are used in the present analysis, and average annual agriculture losses (1991–2021) from all hazard events are estimated using the regional estimates and average agriculture gross domestic product (GDP) for the SGHA countries. Using event-wise contribution to agriculture losses from the FAO report, these average estimates are deconstructed to get estimates for droughts and floods. Furthermore, the average contributions of crop and livestock sub-sectors are calculated using event-wise average contribution based on the analysis of PDNA studies. Notable here is that these are only indicative estimates used to present the potential scale of agriculture loss and damages. As such these estimates should not be used as actual estimates from the FAO report.

Based on these assumptions, average annual climate-attributable agriculture loss and damage in the SGHA region could be as high as $2.3 billion between 1991 and 2021, amounting to roughly 4–15% of the agriculture GDP across the region (Table A2-2). A disaggregated analysis based on the country-level data from the the FAO could reveal more insights into the climate-attributable agriculture loss and damage.

TABLE A2-2: 'INDICATIVE' TOTAL AND CLIMATE-ATTRIBUTABLE AGRICULTURE (INCLUDING CROP AND LIVESTOCK) LOSS AND DAMAGE FOR THE SAHEL AND GREATER HORN OF AFRICA REGION (AVERAGED), 1991—2021

Indicative averages (1991—2021)	Livestock ($ millions)		Crops ($ millions)		Total agriculture	
	Total	Attributable	Total	Attributable	Total	Attributable
Burkina Faso	12.64	8.21	15.33	10.85	27.98	19.06
Cameroon	60.93	39.57	73.90	52.31	134.83	91.88
Chad	27.57	17.90	33.43	23.67	61.00	41.57
Djibouti	0.26	0.17	0.32	0.23	0.58	0.40
Eritrea	2.20	1.43	2.67	1.89	4.87	3.32
Ethiopia	313.04	203.30	379.69	268.77	692.73	472.08
Gambia	1.85	1.20	2.24	1.58	4.08	2.78
Guinea	8.66	5.63	10.51	7.44	19.17	13.07
Kenya	196.96	127.92	238.90	169.11	435.86	297.03
Mali	20.22	13.13	24.52	17.36	44.74	30.49
Mauritania	5.95	3.86	7.22	5.11	13.17	8.97
Niger	15.45	10.03	18.74	13.26	34.18	23.29
Nigeria	413.91	268.81	502.04	355.38	915.94	624.19
Senegal	13.54	8.80	16.43	11.63	29.97	20.42
Somalia	33.02	21.44	40.05	28.35	73.07	49.79
South Sudan	5.76	3.74	6.99	4.95	12.75	8.69
Sudan	296.61	192.64	359.77	254.67	656.38	447.31
Uganda	108.23	70.29	131.28	92.93	239.51	163.22

Source: Authors' calculations using FAO (2023)

4. STUDIES ON THE IMPACTS OF DISASTERS ON MACROECONOMIC INDICATORS

Table A3-1 outlines the various and most relevant studies' findings of the empirical analyses examining the nexus between disasters and macroeconomic indicators. This provides insights into both short- to medium- and long-term impacts across different countries and regions integrated into our study area.

TABLE A3-1: STUDIES ON THE IMPACTS OF DISASTERS ON MACROECONOMIC INDICATORS

Study reference	Dependent variable(s)	Event type	Sample (size)	SGHA countries included	Data period	Estimation methodology	Key findings
I. Short- to medium-term Impact (up to 5 years)							
Shabnam (2014)	GDP per capita growth rate	Total number of people killed and people affected by floods	187 countries	Not indicated	1960–2010	OLS (Ordinary Least Square) FE (Fixed Effects)	The total number of people affected by flooding has a negative impact on the growth rate of GDP per capita, while the number of deaths has no substantial effect.
Fomby et al. (2013)	GDP per capita growth, agricultural and non-agricultural per capita value-added growth	Number of affected and losses from drought, flood, earthquake and storm variables	84 countries. 60 developing and 24 developed (OECD) countries	Not indicated	1960–2007	Panel: Vector Auto Regression (VAR) X	Floods have a positive impact, while droughts have negative effects, especially on agricultural growth.
Loayza et al. (2012)	GDP growth, sectoral growth	Number of deaths and people affected by drought, flood, earthquake and storm variables	94 countries. 68 developing and 26 developed (OECD) countries	Not indicated	1961–2005	Generalised Method of Moments (GMM) panel estimator	Hazards impact economic growth variably, with diverse disaster effects across hazard types and sectors, since hazards moderate in intensity may positively affect certain sectors, while severe ones generally do not. The latter particularly impact developing countries more significantly than developed ones across multiple sectors.

Study reference	Dependent variable(s)	Event type	Sample (size)	SGHA countries included	Data period	Estimation methodology	Key findings
Schumacher et al. (2011)	GDP growth per capita	Number of deaths and economic losses related to cyclones, droughts, earthquakes, floods, landslides and volcanoes	181 developing countries	Not indicated	1980–2004	Tobit estimator	The relationship between losses and wealth crucially depends on the intensity of the hazard.
Noy (2009)	GDP growth rate	Number of people killed, number of people affected and amount of direct damage due to natural hazards	109 developing and developed countries	Not indicated	1970–2003	Dynamic GMM	Natural hazards exhibit a statistically observable impact on the macroeconomy when measured by property damage, whereas alternative measures using population indicators show no statistically identifiable evidence of macroeconomic costs.
Toya and Skidmore (2007)	GDP growth	Hazard-induced deaths and damages	151 OECD and developing countries	Not indicated	1960–2003	OLS (FE)	Per capita income is inversely correlated with both deaths and damages/GDP.
Raddatz (2007)	GDP growth	External shocks, including natural hazards	40 lower-income countries	Burkina Faso, Cameroon, Chad, Ethiopia, Guinea, Kenya, Mali, Mauritania, Niger, Nigeria, Senegal, Uganda	1965–1997	Panel: VAR	External shocks such as natural hazards on average account for only a small fraction of the volatility of these countries' real GDP.

Study reference	Dependent variable(s)	Event type	Sample (size)	SGHA countries included	Data period	Estimation methodology	Key findings
Felbermayr et al. (2014)	GDP growth	Number of people killed and affected, and property damaged by natural hazards	108 countries	Not indicated	1979–2010	OLS (FE) and GMM	The GeoMet data reveal a substantial negative and robust average impact effect of disasters on growth.
Kahn (2005)	Real GDP per capita	Number of deaths and people affected by natural hazards	73 countries	Ethiopia, Kenya, Nigeria	1980–2002	OLS and instrumental variables (IV)	Democracies and nations with higher-quality institutions suffer fewer disaster deaths than poor nations.
Cavallo et al. (2022)	Real GDP per capita growth	Natural hazards (geophysical; meteorological; hydrological and climatological)	203 developing and developed countries	Cameroon, Chad, Djibouti, Ethiopia, Gambia, Guinea, Senegal, Somalia	1970–2019	Average treatment effect	Disasters related to natural hazards have a negative impact on economic growth. The impact is larger for poorer countries, concluding that the impact of natural disasters on growth is an economic development issue.
Zhao et al. (2023)	GDP growth	CO_2, temperature, precipitation fluctuation	44 countries in 6 climatic zones in Africa	Burkina Faso, Cameroon, Chad, Gambia, Kenya, Mali, Mauritania, Niger, Nigeria, Senegal, Uganda	2000–2019	Panel VAR and OLS (FE)	Temperature fluctuation affects African countries' economic growth differently across six climate zones. While inverted U-shaped effects are observed in tropical rainforest and tropical dry zones, a U-shaped effect in warm temperate humid regions, a positive impact on coastal regions and no significant impact on inland countries were found.

Study reference	Dependent variable(s)	Event type	Sample (size)	SGHA countries included	Data period	Estimation methodology	Key findings
López et al. (2016)	GDP growth	Number of intense hydrometeorological hazards and carbon accumulation	184 countries	Burkina Faso, Cameroon, Chad, Djibouti, Eritrea, Ethiopia, Gambia, Guinea, Kenya, Mali, Mauritania, Niger, Nigeria, Senegal, Somalia, South Sudan, Sudan	1970–2013	Negative Binomial Models (FE)	Disasters related to intense hydro meteorological hazards had a negative impact on GDP growth.
Abidoye et al. (2015)	GDP growth rate	Temperature variability	34 African countries	Burkina Faso, Cameroon, Chad, Kenya, Niger, Nigeria, Senegal, Sudan, Uganda	1961–2009	Linear hierarchical regression	A negative impact of climate change on economic growth is found. A 1°C increase in temperature reduces GDP growth by 0.67 percentage points.
Hochrainer-Stigler (2015)	GDP growth	Number of people killed and affected, and financial losses from disasters	1,473 large disaster events across countries	-	1970–2006	Multivariate linear regression models, Time Series Regression (ARIMA)	The analysis supports the hypothesis that the impacts of natural hazard-related disasters on economic growth probably depend on the socioeconomic situation prior to the event.

Study reference	Dependent variable(s)	Event type	Sample (size)	SGHA countries included	Data period	Estimation methodology	Key findings
Panwar et al. (2019)	GDP per capita, agricultural value added per capita, non-agricultural value added per capita	Intensity of floods, droughts, storms and earthquakes	102 countries (29 developed and 73 developing)	Burkina Faso, Cameroon, Chad, Ethiopia, Guinea, Kenya, Mali, Mauritania, Nigeria, Senegal, Sudan, Uganda	1981–2015	The system GMM approach	Natural hazards have diverse economic impacts across economic sectors depending on disaster types and their intensity, and the impacts are statistically stronger in developing countries.
II. Long-term impact (up to 10 years and beyond)							
Owusu-Sekyere et al. (2021)	Annual percentage of GDP growth	Exposure to a hazard (drought, cyclone, flood), susceptibility, coping capacity, and adaptive capacity of countries.	5 Southern Africa Development Community (SADC) countries	Not included	2005–2019	Dynamic panel data techniques that control for country- and time-specific characteristics, heteroscedasticity, serial correlation, and cross-sectional dependence (CSD) of the error term	Extreme events have a negative contemporaneous impact on economic growth in the studied countries.
Diop et al. (2024)	GDP	Intensity of natural hazards	25 African countries	Burkina Faso, Cameroon, Djibouti, Eritrea, Kenya, Niger, Nigeria, Senegal, Uganda	1980–2020	Generalised synthetic control method (GSC)	Severe extreme events induce a significant and continuous reduction of GDP many years after the event, depending on the level of capital and the aspects of governance quality.

Study reference	Dependent variable(s)	Event type	Sample (size)	SGHA countries included	Data period	Estimation methodology	Key findings
Adjei-Mantey et al. (2019)	GDP per capita, agriculture growth, industrial growth, service growth	Number of deaths and people affected by natural hazard-related disasters	50 sub-Saharan African countries	Not indicated	1980–2015	OLS panel	A significant negative effect of weather/climate hazards is observed in economic growth, growth in agricultural value added and growth in industrial value added. Results also show that disaster effects appear and persist in the post-year periods.
Iqbal Khan et al. (2022)	GDP per capita	Number of people affected by natural hazard-related disaster event	98 countries	Cameroon, Ethiopia, Gambia, Guinea, Kenya, Mauritania, Nigeria, Sudan, Tanzania, Uganda	1995–2019	GMM	Natural hazards have a negative impact on income. In addition, the economic cost of natural hazards is relatively high in low-income countries and mild in high- and upper-middle-income countries.
Cavallo et al. (2013)	GDP per capita	Large-scale natural hazard-related disaster	196 countries	Not indicated	1970–2008	Cross-country comparative case study with a synthetic control methodology	Disasters related to natural hazards have no significant effect on subsequent economic growth unless they spark a radical political revolution.

Study reference	Dependent variable(s)	Event type	Sample (size)	SGHA countries included	Data period	Estimation methodology	Key findings
Shimada (2021)	GDP per capita and agricultural production	Number of persons affected and deaths related to flood, drought and storm	90 African countries	Not indicated	1961–2011	Panel data with FE, random effects (RE) and pooling	Natural hazards have adverse effects on Africa's economic growth, agriculture and poverty levels, contributing to armed conflicts, with droughts emerging as the primary driver of negative impacts, particularly impacting staple crops such as maize and coffee, while exacerbating urban poverty and conflict.
Skidmore and Toya (2002)	Per capita GDP growth	Total hazard events	89 countries	Cameroon, Kenya, Mali, Niger, Senegal, Uganda	1960–1990	OLS (FE)	Geophysical hazards have no effects, while climatic hazards may have positive effects on economic growth in the long term.
Noy and Nualsri (2007)	Per capita GDP growth	Number of people killed and property damaged by hazards	107 OECD and non-OECD countries	Cameroon, Kenya, Mali, Niger, Senegal, Uganda	1970–2003	GMM	The number of people killed seems to be decreasing long-term GDP growth, while damage has no impact.
Raddatz (2009)	GDP growth	Event dummies using criteria set by the IMF (2003)	112 countries	Not indicated	1975–2006	Panel VAR and Auto-Regressive Distributed Lag (ARDL)	The results indicate that a climate-related disaster reduces real GDP per capita. Among climatic hazards, droughts have the largest average impact, with cumulative losses of 1% of GDP per capita.

Study reference	Dependent variable(s)	Event type	Sample (size)	SGHA countries included	Data period	Estimation methodology	Key findings
Jaramillo (2009)	GDP growth	Number of people killed and affected, and property damaged by hazards	113 countries	Burkina Faso, Cameroon, Chad, Guinea, Kenya, Mali, Niger, Nigeria, Senegal, Uganda	1960–1996	OLS	Natural hazards have negative effects on economic growth, and this impact is permanent for some countries in the long term.
Klomp (2015)	Sovereign default risk as a proxy of debt sustainability	Large-scale natural hazards	40 market emerging countries	Not indicated	1992–2008	GMM for dynamic panel approach	Natural hazards significantly increase the sovereign default premium paid by bondholders.
Berlemann et al. (2016)	GDP growth	Exogenous drought indicator derived from rainfall data	153 countries	Not indicated	1960–2002	OLS (FE)	A significantly negative long-term growth effect of droughts in both highly and less developed countries.
Mukherjee et al. (2018)	GDP per capita	Total number of fatalities, number of affected, injured and homeless people	189 countries/ regions	Not indicated	1970–2010	Random parameter modelling approach (FE)	Flood is the most devastating hazard to affect country/region-level economic growth.

Note on estimation methodology abbreviations: OLS: Ordinary Least Square, FE: Fixed Effects, VAR: Vector Auto Regression, GMM: Generalised Method of Moments

Source: Updated from Panwar (2020)

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