Annex

Annex 1: Literature filtering

Defining inclusion and exclusion criteria

For the first round of search, all articles relating to the topic were displayed, but the result proved to be more focused on migrations in North America and Asia besides the unrelated animal migration studies. Therefore, studies with only the following criteria were included:

- Studies focus on migration and displacement caused by environmental change-induced shocks or adverse climate conditions or extreme weather events or sudden or slow-onset extreme climate events.
- Publication year between 1990 and 2021
- Study area - Sub-Saharan Africa
- Language of study - English

The results from the Scopus search engine in Figure 1 show that the number of studies on the topic of environmental changes and migration has greatly increased in the last decade. We also used additional data from the international disaster center based on the same criteria indicated above. We consulted various reports related to the literature selected as an additional source of information. The studies selected through this search process were then examined and some of them were excluded based on their abstract's content, as described in Figure 4. In the last couple of decades, scientific research published on the topic of environmental change/climate change-induced migrations in Africa has mainly originated from the United States, United Kingdom, Austria, Germany, Canada, France, China, Switzerland, Italy, and Spain (Figure S2).

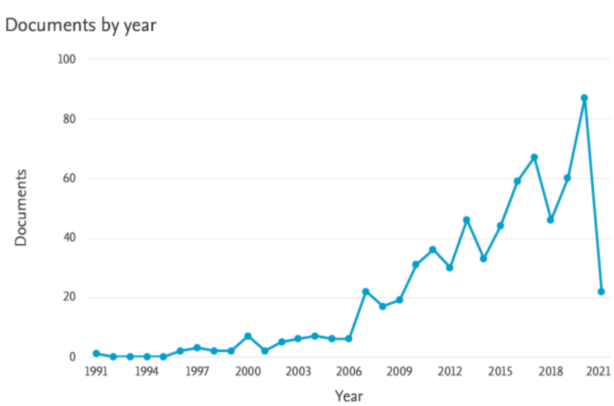


Figure S1: Search results by year of publication.

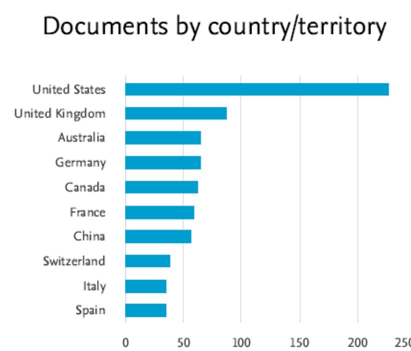


Figure S2: Studies published on the topic of environmental migration by country

Literature search

The meta-analysis began with a search using Scopus, Science Direct, JSTOR, Springer, Wiley Online Library, Taylor & Francis, and google scholar search engines. Despite the broad use of these search engines by the water science, governance, and management sectors, the search in most of the above engines did not yield excellent results, like Scopus. The first search was performed on Scopus with the terms "climate change" OR "environmental changes" OR "extreme events" AND "migration" searched together in the abstract and title. The selected studies were in the English language and published between 1945 and 2021. This search produced 9822 results. Much of the search results were about wildlife migration. Therefore, the search was further refined by *Keywords and date of publication*. The limiting keys were TITLE-ABS (climate AND change OR environmental AND changes OR extreme AND events AND migration) AND (EXCLUDE (PUBYEAR , 1989) OR EXCLUDE (PUBYEAR , 1988) OR EXCLUDE (PUBYEAR , 1987) OR EXCLUDE (PUBYEAR , 1986) OR EXCLUDE (PUBYEAR , 1984) OR EXCLUDE (PUBYEAR , 1983) OR EXCLUDE (PUBYEAR , 1982) OR EXCLUDE (PUBYEAR , 1943)) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (EXACTKEYWORD ,"Climate Change") OR LIMIT-TO (EXACTKEYWORD , "Climate Variation") OR LIMIT-TO (EXACTKEYWORD , "Climate Effect") OR LIMIT-TO (EXACTKEYWORD ,"Population Migration") OR LIMIT-TO (EXACTKEYWORD , "Drought") OR LIMIT-TO (EXACTKEYWORD , "Environmental Change") OR LIMITTO (EXACTKEYWORD , "Extreme Event") OR LIMIT-TO (EXACTKEYWORD , "Floods") OR LIMIT-TO (EXACTKEYWORD , "Flooding") OR LIMITTO (EXACTKEYWORD , "Population Dynamics") OR LIMIT-TO (EXACTKEYWORD , "Sea Level Change") OR LIMIT-TO (EXACTKEYWORD , "Extreme Weather Events") OR LIMIT-TO (EXACTKEYWORD , "Rain") OR LIMIT-TO (EXACTKEYWORD , "Rainfall") OR LIMIT-TO (EXACTKEYWORD , "Environmental Impact") OR LIMIT-TO (EXACTKEYWORD , "Agriculture") OR LIMIT-TO (EXACTKEYWORD , "Global Change") OR LIMIT-TO (EXACTKEYWORD , "Environmental Factor") OR LIMIT-TO (EXACTKEYWORD , "Temperature Effect") OR LIMIT-TO (EXACTKEYWORD , "Erosion") OR LIMIT-TO (EXACTKEYWORD , "Flood") OR LIMITTO (EXACTKEYWORD , "Human Settlement") OR LIMIT-TO (EXACTKEYWORD , "Population Statistics")). The refined search on Scopus produced 668 studies. Figures 2 and 3 elaborate on the additional search requirements used on Scopus to refine the results. Figure 2 shows that migration studies as a driver of sudden and slow-onset environmental changes come from the subject area of Earth and Planetary Sciences (20.5%), Agricultural and Biological Sciences (21.6%), and others (46.2%). From a further search on Scopus, 82% of the studies were articles followed by reviews (8.1%), conference papers (4.9%), and book chapters (4.5%). Even if our study selection focused on SSA, the research originated from the United States, the United Kingdom, Australia, Germany, Canada, France, China, Switzerland, Italy, and Spain in descending order Figure 5.

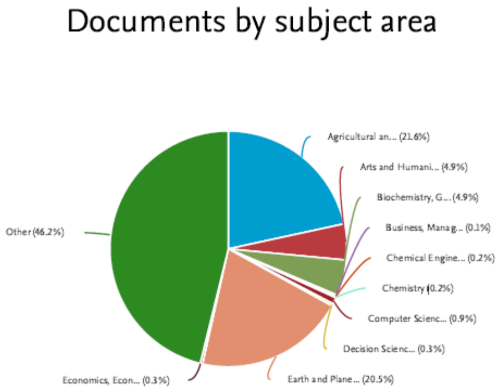


Figure S3: Search results refined by subject area

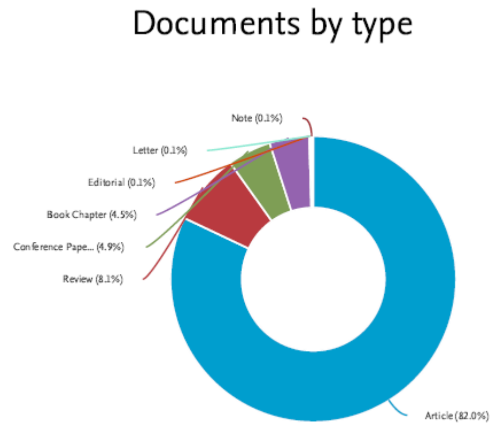


Figure S4: Search results refined by types of documents.

Screening of articles

We then skimmed through the article's abstract to perform a first-round screening. This process excluded 687 articles out of the 875 (668+207) selected from various search engines, leaving us with 188 articles (figure S3). The author downloaded the screened documents for further screening.

Selection of eligible literature and data extraction

Out of the 188 studies identified through search engine selection followed by prescreening, 94 papers were then excluded after further reading. The eligible studies were then examined to extract the following primary data and metadata: region/country, date of the event, type of extreme event or environmental change drivers, and the number of people displaced/migrating as a result of the event. Additional secondary information was also coded, including additional effects (e.g., losses, consequences of environmental changes & exacerbating factors), type of relocation, type of migration, the profession of internally displaced people (IDPs) and migrants, land ownership status of IDPs and migrants, hydrological data analysis or modeling techniques used, source of data, and destination countries/regions were also extracted. Unfortunately, only few selected studies provided information on all these data entries.

During this stage of data harvesting by reading the 94 papers resulting from identification and first screening (Fig 4), we also looked at the reference lists and extracted 75 more studies and tracked down the original citations, leading to a total of 94+75=169 papers. Further reading of all these publications, led to the removal of duplicated studies and of other articles with exclusion criteria (articles which lack the above-mentioned primary data) leaving us with 79 papers, documenting 87 case studies that were included in this metanalysis, see figure S3.

Annex 2: Summary of migration data from literature and international dataset

Table S5: Summary of migration data from literature and EM-DAT

Country	Flood	Storm	Cyclone	Heavy rain	Drought	Landslides	Heat shock	Others
Angola	127230	0	0	0	0	0	0	0
Burundi	58805	18500	0	25000	0	3680	0	0
Benin	436179	0	0	0	0	0	0	1286
Burkina Faso	98176	0	0	0	7873	0	0	0
Botswana	34000	0	0	0	0	0	0	0
Central African Republic	88919	11605	0	102000	0	0	0	0
CÃ´te d'Ivoire	612	0	0	0	0	10000	0	0
Cameroon	48959	0	0	0	0	100	0	0
Democratic Republic of the Congo	74940	5386	20000	233000	0	1778	0	0
Republic of Congo	69500	0	0	163000	0	168	0	0
Comoros	0	300	79000			0		
Djibouti	33500	0	0	0	0	0	0	0
Eritrea	0	15659	0	0	0	0	0	0
Ethiopia	569610	0	0	0	732139	184	0	1004
Gabon	0	800	0	0	0	0	0	0
Ghana	243000	0	0	0	0	0	0	1238
Guinea	4000	0	0	0	0	0	0	0
Gambia	5400	0	0	0	0	0	0	0
Guinea-Bissau	1750	0	3700	0	0	0	0	0
Kenya	7200	0	0	0	1052	20100	0	1063
Liberia	340	5500	0	0	0	0	0	0
Lesotho	0	3620	0	0	0	0	0	0
Madagascar	28482	0	1438807	0	0	0	0	0
Mali	76372	0	0	0	9715	0	0	0
Mozambique	423419	6250	1126740	250000	9715	2500	0	0
Mauritania	58697	160	0	0	69000	0	0	0
Mauritius	0	0	12500	0	0	0	0	0

Malawi	318259	350	86526	0	0	0	0	0
Mayotte	0	0	450	0	0	0	0	0
Namibia	0	0	0	50000	0	0	0	0
Niger	932651	0	0	0	40000	0	0	400230
Nigeria	1256320	1000	0	0	0	1800	745	375
Reunion	0	0	3400	0	0	0	0	0
Rwanda	8055	6000	0	0	0	9920	0	1700000
Sudan	272000	0	0	0	0	0	0	0
Senegal	33992	31000	0	0	0	0	0	0
Somalia	506200	0	0	472000	360000	0	0	400000
South Sudan	294000	0	0	0	0	0	0	0
Swaziland	0	260	500	0	0	0	0	0
Seychelles	110	0	0	0	0	0	0	0
Chad	129088	0	0	0	0	0	0	0
Togo	89874	0	0	0	0	0	0	0
Tanzania	99952	0	2500	0	968	150	4845	84000
Uganda	310575	10100	0	130000	0	4368	994	268
South Africa	30885	16200	0	0	0	0	0	0
Zambia	31000	0	0	60000	140	150	0	0
Zimbabwe	66750	475	67168	0	3000000	0	0	0

Annex 3: Qualitative comparative analysis method and output

This step-by-step QCA analysis describes the steps followed by the fsCQA software to analyses the data on Annex 3, above.

	Primary drivers								Secondary drivers										
Country	Flood	Storm	Cyclone	Heavy rain	Drought	Landslides	Heat shock	Dry spell	Famine	Frstfire	Locust	Indscrty	Dgrdtndtfdst	Rvrlvlrsbnkbrst	Lndinfrtl	Fdinscrty	Wtrscrty	Agrint	Migrants
Angola	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	127230
Benin	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	436179
Botswana	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	34000
Burkina Faso	1	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	105544
Burundi	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	105985
Côte d'Ivoire	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	10612
Cameroon	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	49059
Central African Republic	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	202524
Chad	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	129088
Comoros	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	79300
Democratic Republic of the	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	335104
Djibouti	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	33500
Eritrea	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	15659
Ethiopia	1	0	0	1	1	1	0	1	1	1	1	1	1	0	0	0	0	0	1302833
Gabon	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	800
Gambia	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5400
Ghana	1	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	0	0	243000
Guinea	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4000
Guinea-Bissau	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5450
Kenya	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	1	0	28352
Lesotho	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3620
Liberia	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5840
Madagascar	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1467289
Malawi	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	405135
Mali	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	76372
Mauritania	1	1	0	1	1	0	0	0	0	0	0	0	1	0	0	0	1	0	127857
Mauritius	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12500
Mayotte	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	450
Mozambique	1	1	1	1	1	1	0	0	0	0	0	0	1	1	0	0	0	0	1818624
Namibia	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50000
Niger	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	932651
Nigeria	1	1	0	0	0	1	1	0	0	0	0	1	1	1	0	0	0	0	1259865
Republic of Congo	1	0	0	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	232668
Reunion	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3400
Rwanda	1	1	0	0	0	1	0	0	0	0	0	1	1	0	1	0	1	1	1723975
Senegal	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	64992
Seychelles	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	110
Somalia	1	0	0	1	1	0	0	1	0	0	1	0	0	0	1	1	1	0	1738200
South Africa	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	47085
South Sudan	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	294000
Sudan	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	272000
Swaziland	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	760
The United Republic of Tanzania	1	0	1	0	1	1	1	0	0	0	0	1	1	0	1	0	1	0	191970
Togo	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	89874
Uganda	1	1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	456037
Zambia	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	91290
Zimbabwe	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3132393

Figure S6: sample Crisp set datasheet

I. Constructing a 'truth table'

The first step to synthesizing the raw data is to calibrate them. This step transforms the raw numerical data to set membership scores, based on a certain threshold and makes sure that all the variables conform to external standards (Duşa, 2021). After opening the datasheet on fsQCA software, we will go to "compute" under the "variables" tab as shown in figure 7. Then by clicking "calibrate", we will put our threshold values as per the distribution of the outcome variables. The author specified the values of the interval-scale variable that correspond to the three qualitative breakpoints that structure a crisp set: the threshold for full membership (fuzzy score = 0.95), the threshold for full non-membership (fuzzy score = 0.05), and the cross-over point (fuzzy score = 0.5). The benchmark bounds are circled in red on figure 7 as (3,000,000,370,000, 100), translating into full membership, non-full membership, and cross-over points, respectively. Based on the log odds of full membership, these three benchmarks are used to calibrate the original/conventional values into fuzzy membership scores.

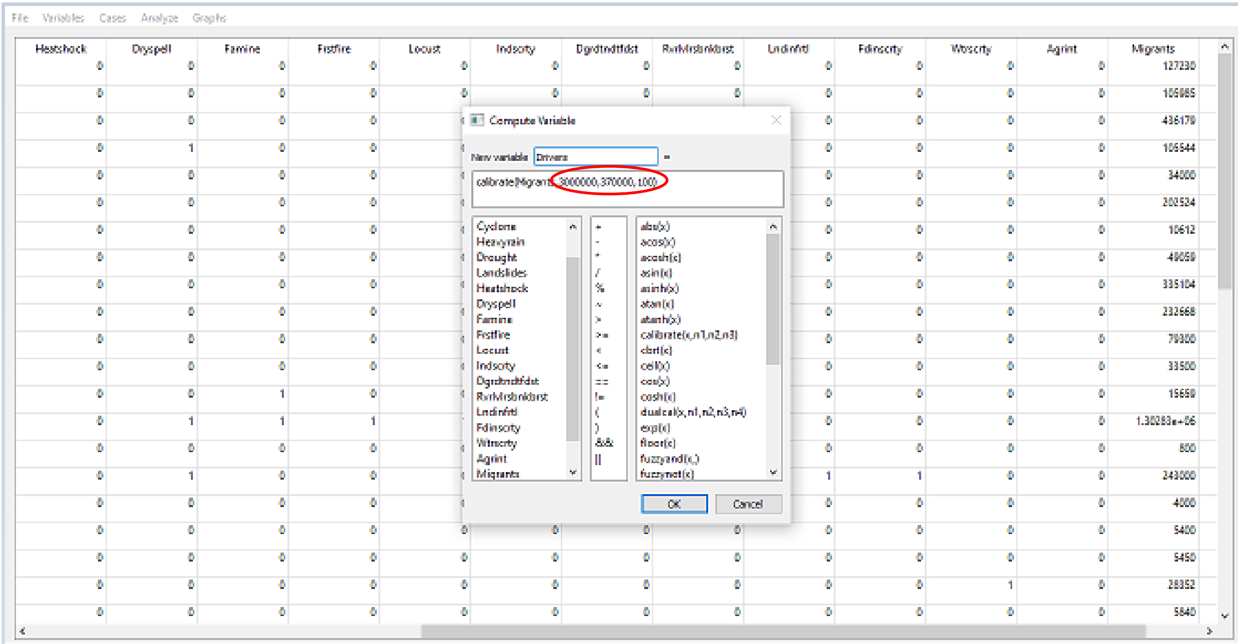


Figure S7: Calibrating variables

Figure 8 below shows the result of calibration of the above data. As shown in the above step the calibrated column named “prmry” is created and it displays the proportion of cases in each truth table row that display the outcome (i.e.) the positions of cases relative to each other calibrated to a value between 0 and 1. We will use the result obtained in figure 8 to construct the truth table.

Figure S8: Results of calibrated data

The casual conditions for this analysis are mainly divided into two as direct drivers (Flood, Storm Cyclone, Heavy rain, Drought, Landslides, Heat shock & Dry spell) and indirect drivers (Famine, Poverty, Forest fire, Locust invasion, Dryland expansion, Ecological degradation, River water level rise, arable/ grazing land degradation, Food insecurity, Water scarcity, Riverbank bursting, Land scarcity, Agricultural intensification, Farmland infertility, Rainfall season shortening, Soil erosion, Desertification & Deforestation). The fsQCA software can only analyze 8-10 causal conditions (drivers) at a time, thus, the casual conditions were divided into smaller combination sets based on the findings of the literature reviews. The review revealed that migrations caused by environmental changes under direct and indirect drivers are further divided into the adverse climate conditions of extreme events, slow on-set events, mixed events, accumulated environmental changes, all extreme events, and all slow on-set events (Fig 5 & 6). Therefore, the truth table construction and further analysis will be based on these small sets. The truth table has 2^k rows, where k represents the 9 causal conditions added below. The first analysis uses the 9 all extreme events / casual conditions shown below in figure 9. The “Prmry” column will be used as an outcome since it is made from the proportion of the original outcome variables.

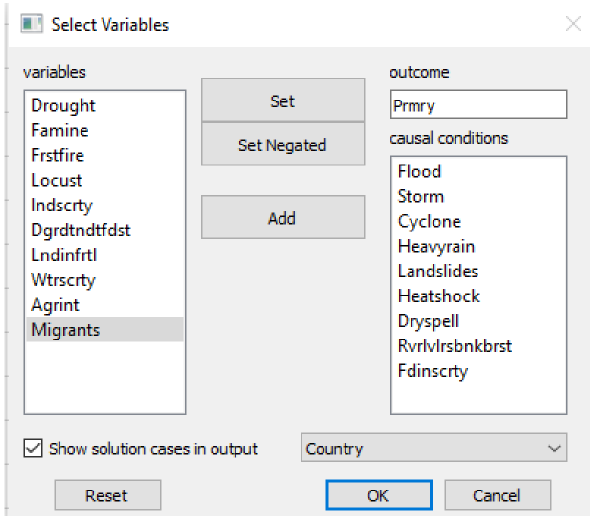
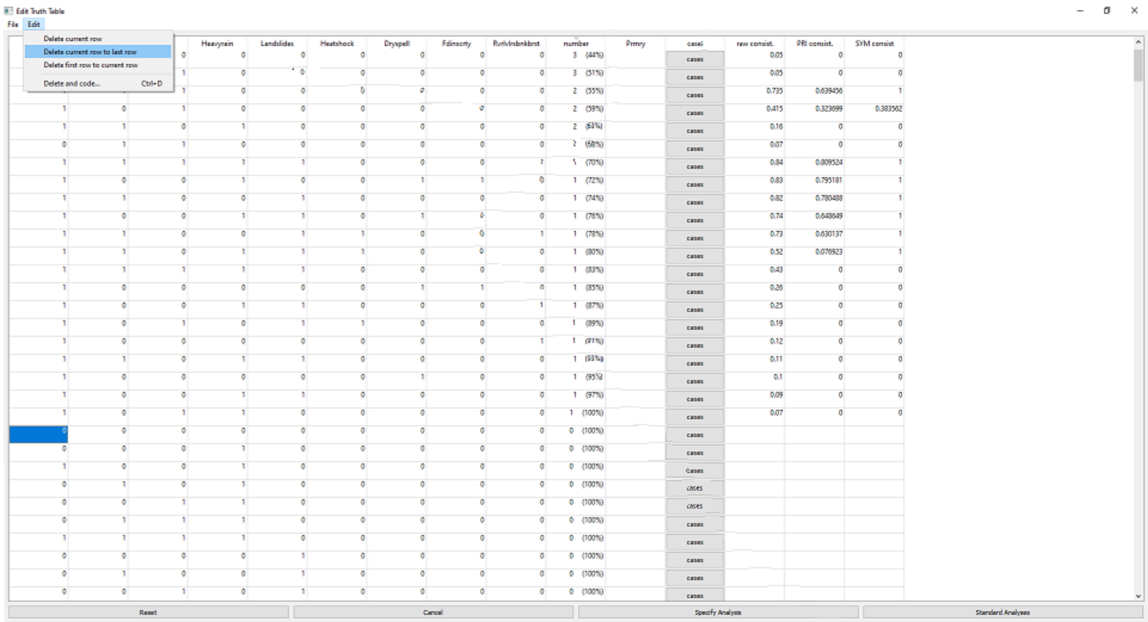


Figure S9: Variable selection for constructing a truth table

Based on these inputs, the software will show all possible combinations of the causal conditions see figure 10. The truth table is generated from the “Truth Table Algorithm” tab under “Analyze” by using the Quine-McCluskey algorithm. The Truth table is one of the most important applications in the analysis that will help us assess the distribution of cases across different logically possible combinations of causal conditions and the consistency of the evidence for each causal combination with the argument that the cases with this combination of conditions constitute a subset of the cases with the outcome.



			Heavyrain	Landslides	Heatshock	Dryspell	Fdinsecrty	Rvrlvlsbnkbrst	number	Prmry	cases	raw consist.	PRI consist.	SYM consist
		0	0	0	0	0	0	0	3 (44%)		cases	0.05	0	0
		1	0	0	0	0	0	0	3 (51%)		cases	0.05	0	0
		1	0	0	0	0	0	0	2 (55%)		cases	0.735	0.639456	1
1	0	1	0	0	0	0	0	0	2 (59%)		cases	0.415	0.323699	0.383562
1	1	0	1	0	0	0	0	0	2 (63%)		cases	0.16	0	0
0	1	1	0	0	0	0	0	0	2 (68%)		cases	0.07	0	0
1	1	1	1	1	0	0	0	1	1 (70%)		cases	0.84	0.809524	1
1	0	0	1	0	0	1	1	0	1 (72%)		cases	0.83	0.795181	1
1	1	0	0	1	0	0	0	0	1 (74%)		cases	0.82	0.780488	1
1	0	0	1	1	0	1	0	0	1 (76%)		cases	0.74	0.648649	1
1	1	0	0	1	1	0	0	1	1 (78%)		cases	0.73	0.630137	1
1	1	0	1	1	1	0	0	0	1 (80%)		cases	0.52	0.076923	1
1	1	1	1	1	0	0	0	0	1 (83%)		cases	0.43	0	0
1	0	0	0	0	0	1	1	0	1 (85%)		cases	0.26	0	0
1	0	0	1	1	0	0	0	1	1 (87%)		cases	0.25	0	0
1	0	1	0	1	1	0	0	0	1 (89%)		cases	0.19	0	0
1	0	0	0	0	0	0	0	1	1 (91%)		cases	0.12	0	0
1	1	0	1	1	0	0	0	0	1 (93%)		cases	0.11	0	0
1	0	0	0	0	0	1	0	0	1 (95%)		cases	0.1	0	0
1	0	0	1	1	0	0	0	0	1 (97%)		cases	0.09	0	0
1	0	1	1	0	0	0	0	0	1 (100%)		cases	0.07	0	0
0	0	0	0	0	0	0	0	0	0 (100%)		cases			
0	0	0	1	0	0	0	0	0	0 (100%)		cases			
1	0	0	1	0	0	0	0	0	0 (100%)		cases			
0	1	0	1	0	0	0	0	0	0 (100%)		cases			
0	0	1	1	0	0	0	0	0	0 (100%)		cases			
0	1	1	1	0	0	0	0	0	0 (100%)		cases			
1	1	1	1	0	0	0	0	0	0 (100%)		cases			
0	0	0	0	1	0	0	0	0	0 (100%)		cases			
0	1	0	0	1	0	0	0	0	0 (100%)		cases			
0	0	1	0	1	0	0	0	0	0 (100%)		cases			

Figure S10: Truth table for extreme events (frequency threshold)

According to the Boolean algebra, if they satisfy any of the additive terms or present, then the outcome is true (Ragin, 2017) (i.e.) If there are 1s representing full membership/existence of one or more drivers then there is migration, see figure 10. The truth table column names are described as:

number – the total number of cases with the specified combination of conditions
raw consist - the ratio of cases in each row that show the outcome (i.e.) the positions of cases relative to each other.
PRI consist – the same as raw consist in crisp set analysis while it is a measure of consistency for fuzzy sets.
SYM consist: an alternative measure of consistency for fuzzy sets based on a symmetrical version of PRI consistency (Ragin, 2017).

The next step is to develop a rule to classify combinations as relevant or irrelevant based on the frequency threshold selection. Using the "number" column, we can sort out the frequency of cases in increasing or decreasing order. The outcomes with 1 or more cases represent relevancy or the existence of migration while 0 represents irrelevancy, therefore we remove the rows with 0 outcomes by going to the "Edit" tab then "Delete current row to last row" as shown in figure 10.

II. Resolving contradictory configurations

QCA attracts many researchers because of its comparative and configurational powers (Czaika, 2021; Rihoux, 2009). After removing cases that cannot meet the frequency threshold, the configuration of the case is distinguished by determining if all values are the subset of the outcome using the measure of the "raw consist" column. The consistency scores are sorted in descending order to evaluate their distribution. Cut-off points are then identified by observing the gaps between the consistency values.

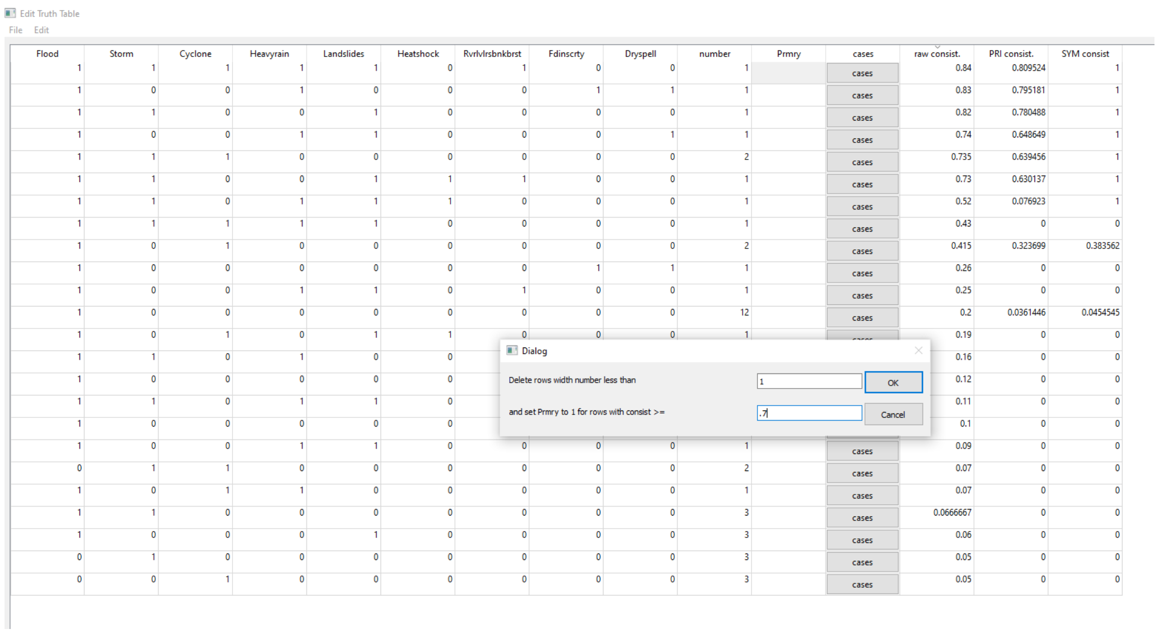
Edit Truth Table

File Edit

Flood	Storm	Cyclone	Heavyrain	Drought	Landslides	Heatshock	Dryspell	number	Prmry	cases	raw consist.	PRI consist.	SYM consist
1	1	1	0	1	0	0	0	1		cases	0.96	0.958333	1
1	1	1	1	1	1	0	0	1		cases	0.84	0.809524	1
1	0	0	1	1	0	0	1	1		cases	0.83	0.795181	1
1	1	0	0	0	1	0	0	1		cases	0.82	0.780488	1
1	0	0	1	1	1	0	1	1		cases	0.74	0.648649	1
1	1	0	0	0	1	1	0	1		cases	0.73	0.630137	1
1	1	0	1	0	1	1	0	1		cases	0.52	0.076923	1
1	1	1	0	0	0	0	0	1		cases	0.51	0.0392157	1
1	1	1	1	0	1	0	0	1		cases	0.43	0	0
1	0	1	0	0	0	0	0	2		cases	0.415	0.323699	0.383562
1	0	0	0	0	0	0	1	1		cases	0.26	0	0
1	0	0	1	0	1	0	0	1		cases	0.25	0	0
1	0	0	0	0	0	0	0	12		cases	0.203333	0.0362903	0.0459183
1	1	0	1	0	0	0	0	1		cases	0.2	0	0
1	0	1	0	1	1	1	0	1		cases	0.19	0	0
1	1	0	1	1	0	0	0	1		cases	0.12	0	0
1	1	0	1	0	1	0	0	1		cases	0.11	0	0
1	0	0	0	1	0	0	1	1		cases	0.1	0	0
1	0	0	1	1	1	0	0	1		cases	0.09	0	0
1	0	0	0	1	0	0	0	1		cases	0.08	0	0
1	0	1	1	0	0	0	0	1		cases	0.07	0	0
0	1	1	0	0	0	0	0	2		cases	0.07	0	0
1	1	0	0	0	0	0	0	3		cases	0.0666667	0	0
1	0	0	0	1	1	0	0	1		cases	0.06	0	0
1	0	0	0	0	1	0	0	2		cases	0.06	0	0
0	1	0	0	0	0	0	0	3		cases	0.05	0	0
0	0	1	0	0	0	0	0	3		cases	0.05	0	0

Figure S11: Cutoff point determination

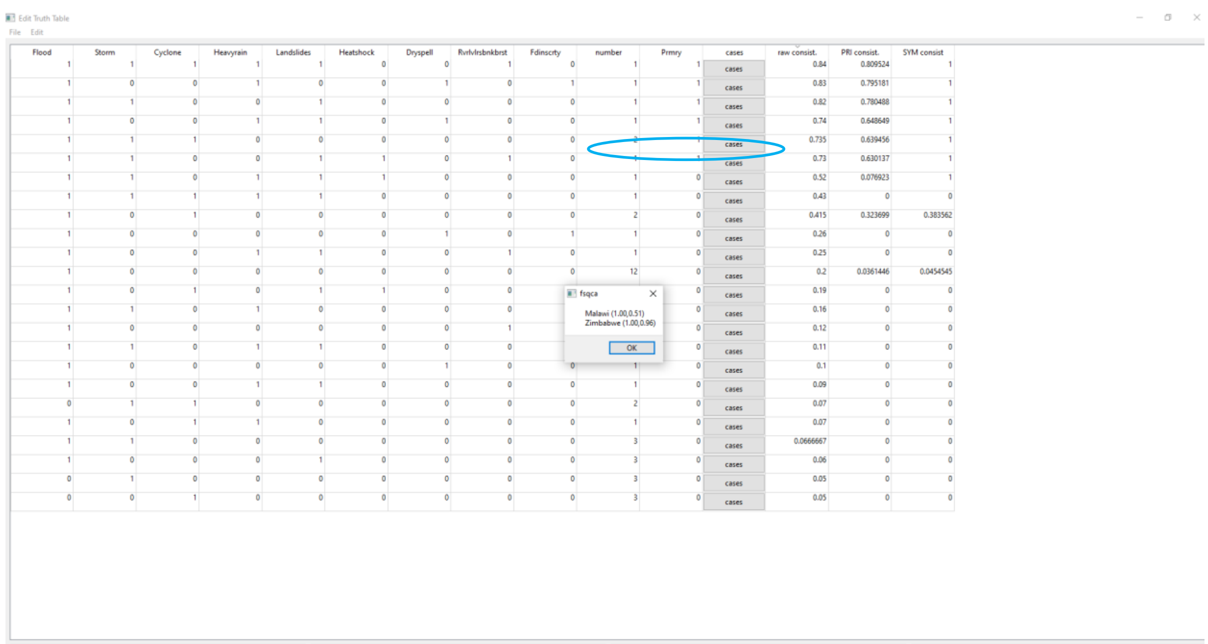
For extreme events we have two major gaps between 0.73 & 0.52 and 0.415 & 0.26, the cut-off point is at 0.7 and 0.4. Consistency values less than 0.75 normally indicate substantial inconsistency (Ragin, 2017). On the other hand, the higher the consistency means, the lower the coverage of cases, while the lower the consistency means, the higher the coverage (Ragin, 2017). Consistency estimates the extent to which the given solution is a subset of the outcome while coverage determines how much of the outcome is explained by the solution (Ragin, 1984, 2017). The relaxation of the cut-off points solely depends on the specific circumstances we want to explain (Groth, 2020; Ide, 2020; Ragin, 1984, 2017). The principal aim of this research is to analyze the coverage of our outcomes in explaining the various drivers of migration and the countries affected by it, therefore the author focused on showing the results of higher coverage and lower consistency. For the first case of all extreme events alone, the author considered 3 thresholds to assess the consequences of lowering and raising cutoff points in practice, see the underlined points in figure 11. These three cut-off points (0.7, 0.4 & 0.06) show which necessary configurations can explain best the outcomes to be considered or not. In order to evaluate the outcomes for each cut-off point, click “Edit” then “Delete and code” on the empty row under the “Prmry” column. This command will bring the function that will automate our outcome, on the dialogue box below the first row represents the default number of cases as 1. The author also uses 1 as it represents the frequency of the combination of the specific conditions and 0.7 is the first cutoff point used. The automated result of this command is shown in figure 13 under the “Prmry” column.



Flood	Storm	Cyclone	Heavyrain	Landslides	Heatshock	Rvrlvlrsbnkbrst	Fdinscrty	Dryspell	number	Prmry	cases	raw consist.	PRI consist.	SYM consist
1	1	1	1	1	0	1	0	0	1		cases	0.84	0.809524	1
1	0	0	1	0	0	0	1	1	1		cases	0.83	0.795181	1
1	1	0	0	1	0	0	0	0	1		cases	0.82	0.780488	1
1	0	0	1	1	0	0	0	1	1		cases	0.74	0.648649	1
1	1	1	0	0	0	0	0	0	2		cases	0.735	0.639456	1
1	1	0	0	1	1	1	0	0	1		cases	0.73	0.630137	1
1	1	0	1	1	1	0	0	0	1		cases	0.52	0.076923	1
1	1	1	1	1	0	0	0	0	1		cases	0.43	0	0
1	0	1	0	0	0	0	0	0	2		cases	0.415	0.323699	0.383562
1	0	0	0	0	0	0	1	1	1		cases	0.26	0	0
1	0	0	1	1	0	1	0	0	1		cases	0.25	0	0
1	0	0	0	0	0	0	0	0	12		cases	0.2	0.0361446	0.0454545
1	0	1	0	1	1	0	0	0	1			0.19	0	0
1	1	0	1	0	0							0.16	0	0
1	0	0	0	0	0							0.12	0	0
1	1	0	1	1	0							0.11	0	0
1	0	0	0	0	0							0.1	0	0
1	0	0	1	1	0	0	0	0	1		cases	0.09	0	0
0	1	1	0	0	0	0	0	0	2		cases	0.07	0	0
1	0	1	1	0	0	0	0	0	1		cases	0.07	0	0
1	1	0	0	0	0	0	0	0	3		cases	0.0666667	0	0
1	0	0	0	1	0	0	0	0	3		cases	0.06	0	0
0	1	0	0	0	0	0	0	0	3		cases	0.05	0	0
0	0	1	0	0	0	0	0	0	3		cases	0.05	0	0

Figure S12: Editing consistency threshold

In the above cut-off point, there are 6 configurations with consistency greater than 0.70 which can be included in the analysis, and 18 configurations that must be eliminated. Each configuration represents the combination of extreme event drivers that caused migration in the countries mentioned in the "cases" column. For instance, see the dialogue box below in figure 14, the two cases described in this configuration are Malawi and Zimbabwe. If this cut-off point is used, that means we will eliminate 18 cases/countries that had migration as a result of the specified configurations. Therefore, the cutoff point of 0.7 is disqualified.



Flood	Storm	Cyclone	Heavyrain	Landslides	Heatshock	Dryspell	Rvrlvlrsbnkbrst	Fdinscrty	number	Prmry	cases	raw consist.	PRI consist.	SYM consist
1	1	1	1	1	0	0	1	0	1	1	cases	0.84	0.809524	1
1	0	0	1	0	0	1	0	1	1	1	cases	0.83	0.795181	1
1	1	0	0	1	0	0	0	0	1	1	cases	0.82	0.780488	1
1	0	0	1	1	0	1	0	0	1	1	cases	0.74	0.648649	1
1	1	1	0	0	0	0	0	0	2	1	cases	0.735	0.639456	1
1	1	0	0	1	1	0	1	0	1	1	cases	0.73	0.630137	1
1	1	0	1	1	1	0	0	0	1	0	cases	0.52	0.076923	1
1	1	1	1	1	0	0	0	0	1	0	cases	0.43	0	0
1	0	1	0	0	0	0	0	0	2	0	cases	0.415	0.323699	0.383562
1	0	0	0	0	0	1	0	1	1	0	cases	0.26	0	0
1	0	0	1	1	0	0	1	0	1	0	cases	0.25	0	0
1	0	0	0	0	0	0	0	0	12	0	cases	0.2	0.0361446	0.0454545
1	0	1	0	1	1	0	0			0	cases	0.19	0	0
1	1	0	1	0	0	0	0			0	cases	0.16	0	0
1	0	0	0	0	0	0	1			0	cases	0.12	0	0
1	1	0	1	1	0	0	0			0	cases	0.11	0	0
1	0	0	0	0	0	1	0	0	1	0	cases	0.1	0	0
1	0	0	1	1	0	0	0	0	1	0	cases	0.09	0	0
0	1	1	0	0	0	0	0	0	2	0	cases	0.07	0	0
1	0	1	1	0	0	0	0	0	1	0	cases	0.07	0	0
1	1	0	0	0	0	0	0	0	3	0	cases	0.0666667	0	0
1	0	0	0	1	0	0	0	0	3	0	cases	0.06	0	0
0	1	0	0	0	0	0	0	0	3	0	cases	0.05	0	0
0	0	1	0	0	0	0	0	0	3	0	cases	0.05	0	0

Figure S13: Inclusion and exclusion of configurations with observation or not respectively (consistency thresholds)

Following the same steps used for cut-off point 0.7, the cases were evaluated for cut-off point 0.4 as well. The result of this evaluation yielded 9 configurations to be included and 15 to be eliminated (See annex 2). This evaluation also goes against our principal goal of analyzing all countries with environmental migration in SSA. The third cut-off point selected by the author because of the main reason for having the lowest consistency and highest coverage point is 0.06. Using this point yields 22 configurations for inclusion and 2 configurations for elimination. One might ask, why not take 0.05 since it has the lowest consistency than 0.06? The fsQCA software doesn't allow including all configurations for evaluation thus, at least one has to be excluded. The cut-off point of 0.06 meets our goal the best. This implies that the respective condition needs to be present in at least 6% of the migration cases.

Analysis and Boolean minimization

There are 2 ways of performing analysis, Specify (single analysis) and Standard analyses (complex, parsimonious, and intermediate). The author selected Standard analysis as it is the only method that derives an intermediate solution. The intermediate solution carries out counterfactual analyses based on the user-provided causal conditions. Once the truth table is fully constructed, "specify analysis" panel will be set to get the most complex solution. The window below appears when clicking the "Specify Analyses" tab, all positive cases will be set to "true" and the others as "false".

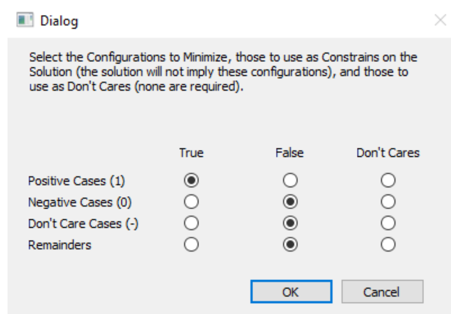


Figure S14: Specify Analysis

In using Specify Analysis, De Morgan's Law gives the complete negation of a given logical equation (Ragin, 2017). When "remainder" combinations are present in the truth table and they are used as "don't cares," then the results of the application of De Morgan Law will yield the most parsimonious solution.

Standard Analyses: Complex solution

The result of the Standard analyses that avoid counterfactual cases or remainders (see IV) is a Complex solution (Ragin, 1984, 2017). It links the outcome with only the presence of the casual conditions, not their absence. One of the main benefits of the QCA method is the possibility of obtaining the same outcome by assessing very complex, different combinations of casual conditions.
The complex solution shown below in figure 14 is produced using the Quine-McClusky algorithm. The solution took into account cases with a minimum frequency as low as (at least) occurring once in the outcome analysis (Frequency cutoff: 1). As explained above, the consistency cutoff point is 0.06.

```
compute: Prmry = calibrate(Migrants,3000000,370000,100)

*********************
*TRUTH TABLE ANALYSIS*
*********************

File:  G:/
Model: Prmry = f(Flood, Storm, Cyclone, Heavyrain, Landslides, Rvrlvlrsbnkbrst, Dryspell, Heatshock, Fdinscrty)
Algorithm: Quine-McCluskey

--- COMPLEX SOLUTION ---
frequency cutoff: 1
consistency cutoff: 0.06
                                                                                  raw        unique
                                                                                coverage    coverage   consistency
                                                                               ----------  ----------  ----------
Flood*Storm*~Cyclone*~Rvrlvlrsbnkbrst*~Dryspell*~Heatshock*~Fdinscrty           0.121441    0.0268006   0.207143
Flood*~Storm*~Cyclone*~Heavyrain*~Landslides*~Dryspell*~Heatshock*~Fdinscrty    0.211055    0.0100503   0.193846
Flood*~Storm*Cyclone*~Landslides*~Rvrlvlrsbnkbrst*~Dryspell*~Heatshock*~Fdinscrty  0.0753769   0.0753769   0.3
Storm*Cyclone*~Heavyrain*~Landslides*~Rvrlvlrsbnkbrst*~Dryspell*~Heatshock*~Fdinscrty  0.134841    0.134841    0.4025
Flood*~Storm*~Cyclone*Heavyrain*Landslides*~Dryspell*~Heatshock*~Fdinscrty      0.0284757   0.020938    0.17
Flood*~Storm*~Cyclone*Heavyrain*Landslides*~Rvrlvlrsbnkbrst*~Heatshock*~Fdinscrty  0.0695142   0.0619766   0.415
Flood*~Storm*~Cyclone*~Landslides*~Rvrlvlrsbnkbrst*Dryspell*~Heatshock*Fdinscrty   0.0912898   0.0695142   0.545
Flood*Storm*~Cyclone*Heavyrain*Landslides*~Rvrlvlrsbnkbrst*~Dryspell*~Fdinscrty    0.0527638   0.0435511   0.315
Flood*Storm*Cyclone*Heavyrain*Landslides*~Dryspell*~Heatshock*~Fdinscrty        0.106365    0.106365    0.635
Flood*~Storm*Cyclone*~Heavyrain*Landslides*~Rvrlvlrsbnkbrst*~Dryspell*Heatshock*~Fdinscrty  0.0159129   0.015913    0.19
Flood*Storm*~Cyclone*~Heavyrain*Landslides*Rvrlvlrsbnkbrst*~Dryspell*Heatshock*~Fdinscrty   0.061139    0.061139    0.73
Flood*~Cyclone*~Heavyrain*~Rvrlvlrsbnkbrst*~Dryspell*~Heatshock*~Fdinscrty      0.301508    0           0.189474
Flood*~Cyclone*Landslides*~Rvrlvlrsbnkbrst*~Dryspell*~Heatshock*~Fdinscrty      0.100503    0           0.2
Flood*~Storm*~Cyclone*~Heavyrain*~Landslides*~Rvrlvlrsbnkbrst*~Heatshock*~Fdinscrty  0.20938     0           0.192308
Flood*~Storm*~Cyclone*~Heavyrain*~Landslides*~Rvrlvlrsbnkbrst*Dryspell*~Heatshock   0.0301508   0           0.18
solution coverage: 0.974874
solution consistency: 0.283902

Cases with greater than 0.5 membership in term
Flood*Storm*~Cyclone*~Rvrlvlrsbnkbrst*~Dryspell*~Heatshock*~Fdinscrty: Burundi (1,0.11), CentralAfricanRepublic (1,0.2), Liberia (1,0.05), Mauritania (1,0.12),
                                                                       Rwanda (1,0.82), Senegal (1,0.08), SouthAfrica (1,0.07)
Cases with greater than 0.5 membership in term
Flood*~Storm*~Cyclone*~Heavyrain*~Landslides*~Dryspell*~Heatshock*~Fdinscrty: Angola (1,0.12), Benin (1,0.52), Botswana (1,0.06), Djibouti (1,0.06), Guinea (1,0.05),
                                                                              Gambia (1,0.05), Mali (1,0.08), Niger (1,0.66), Sudan (1,0.31), SouthSudan (1,0.35),
                                                                              Seychelles (1,0.05), Chad (1,0.12), Togo (1,0.09)
Cases with greater than 0.5 membership in term
Flood*~Storm*Cyclone*~Landslides*~Rvrlvlrsbnkbrst*~Dryspell*~Heatshock*~Fdinscrty: Guinea-Bissau (1,0.05),  Madagascar (1,0.78), Namibia (1,0.07)
Cases with greater than 0.5 membership in term
Storm*Cyclone*~Heavyrain*~Landslides*~Rvrlvlrsbnkbrst*~Dryspell*~Heatshock*~Fdinscrty: Comoros (1,0.09), Malawi (1,0.51), Swaziland (1,0.05), Zimbabwe (1,0.96)
Cases with greater than 0.5 membership in term
Flood*~Storm*~Cyclone*Heavyrain*Landslides*~Dryspell*~Heatshock*~Fdinscrty: RepublicofCongo (1,0.25), Zambia (1,0.09)
Cases with greater than 0.5 membership in term
Flood*~Storm*~Cyclone*Heavyrain*Landslides*~Rvrlvlrsbnkbrst*~Heatshock*~Fdinscrty: Ethiopia (1,0.74), Zambia (1,0.09)
Cases with greater than 0.5 membership in term
Flood*~Storm*~Cyclone*~Landslides*~Rvrlvlrsbnkbrst*Dryspell*~Heatshock*Fdinscrty: Ghana (1,0.26), Somalia (1,0.83)
Cases with greater than 0.5 membership in term
Flood*Storm*~Cyclone*Heavyrain*Landslides*~Rvrlvlrsbnkbrst*~Dryspell*~Fdinscrty: Burundi (1,0.11), Uganda (1,0.52)
Cases with greater than 0.5 membership in term
Flood*Storm*Cyclone*Heavyrain*Landslides*~Dryspell*~Heatshock*~Fdinscrty: DemocraticRepublicoftheCongo (1,0.43), Mozambique (1,0.84)
Cases with greater than 0.5 membership in term
Flood*~Storm*Cyclone*~Heavyrain*Landslides*~Rvrlvlrsbnkbrst*~Dryspell*Heatshock*~Fdinscrty: Tanzania (1,0.19)
Cases with greater than 0.5 membership in term
Flood*Storm*~Cyclone*~Heavyrain*Landslides*Rvrlvlrsbnkbrst*~Dryspell*Heatshock*~Fdinscrty: Nigeria (1,0.73)
Cases with greater than 0.5 membership in term
Flood*~Cyclone*~Heavyrain*~Rvrlvlrsbnkbrst*~Dryspell*~Heatshock*~Fdinscrty: Angola (1,0.12), Benin (1,0.52), Botswana (1,0.06), Côted'Ivoire (1,0.05), Cameroon (1,0.07),
                                                                            Djibouti (1,0.06), Guinea (1,0.05), Gambia (1,0.05), Kenya (1,0.06), Liberia (1,0.05), Mali (1,0.08),
                                                                            Niger (1,0.66), Rwanda (1,0.82), Sudan (1,0.31), Senegal (1,0.08), SouthSudan (1,0.35),
                                                                            Seychelles (1,0.05), Togo (1,0.09), SouthAfrica (1,0.07)
Cases with greater than 0.5 membership in term
Flood*~Cyclone*Landslides*~Rvrlvlrsbnkbrst*~Dryspell*~Heatshock*~Fdinscrty: Burundi (1,0.11), Côted'Ivoire (1,0.05), Cameroon (1,0.07), Kenya (1,0.06), Rwanda (1,0.82), Zambia (1,0.09)
Cases with greater than 0.5 membership in term
Flood*~Storm*~Cyclone*~Heavyrain*~Landslides*~Rvrlvlrsbnkbrst*~Heatshock*~Fdinscrty: Angola (1,0.12), Benin (1,0.52), BurkinaFaso (1,0.1), Botswana (1,0.06), Djibouti (1,0.06), Guinea (1,0.05),
                                                                                     Gambia (1,0.05), Mali (1,0.08), Niger (1,0.66), Sudan (1,0.31), SouthSudan (1,0.35), Seychelles (1,0.05), Togo (1,0.09)
Cases with greater than 0.5 membership in term
Flood*~Storm*~Cyclone*~Heavyrain*~Landslides*~Rvrlvlrsbnkbrst*Dryspell*~Heatshock: BurkinaFaso (1,0.1), Ghana (1,0.26)
```

Figure S15: Complex solution (** = and   ~ = absence of   : = is equal to*)

The first row Flood*Storm*~Cyclone*~Rvrlvlrsbnkbrst*~Dryspell*~Heatshock*~Fdinscrty implies the combination of migration driver's presence and absence: flood and storm and cyclone and absence of river water level rise and bank bursting and absence of dry spell and absence of heat shock and absence of food insecurity have raw coverage of 0.1214, unique coverage of 0.0268 and consistency of 0.207. Where: **Raw *coverage*** conveys the extent to which the outcome is addressed by this causal pathway. It expresses the 12.14% share of cases that are explained by this causal pathway. The countries with environmental migration under the same pathway are Burundi, Central African Republic, Liberia, Mauritania, Rwanda, Senegal, and South Africa.

Unique coverage conveys the extent to which an individual causal pathway only explains the outcome/migration. It expresses a 2.68% share of cases that are explained by this causal pathway alone. ***Solution coverage*** explains the extent to which outcome is described by the solution term or the share of cases described by the solution. In the above complex solution, the casual pathways explain 97.48% of the solution.

Solution consistency describes the extent to which empirical evidence confirms the claim that a set-theoretic relationship (sufficiency) exists (Groth, 2020; Ragin, 2017). A value close to 1.00 entails that there were no contradictory truth table rows included in the logical minimization process. In this case, the value 0.2839 explains the contradictory truth table rows which are minimized in the analysis to give us the parsimonious solution.

Standard Analyses: Parsimonious solution

The solution indicates the two paths to migration and 'flood' & 'storm and cyclone' when analyzing all extreme events. Countries within this membership are listed below. A parsimonious solution is developed based on the concept of Boolean minimization. When two or more Boolean expressions differ in just one causal condition but produce a similar outcome, then the causal condition that differentiates the two expressions can be removed and considered irrelevant (Ragin, 2017). The following example from figure 15 explains the Boolean minimization on the Boolean equation as follows:

Storm*Cyclone (Storm and Cyclone) parsimonious solution

Migration (Comoros, Malawi, Swaziland, Zimbabwe) = Storm * Cyclone * ~Heavyrain * ~Landslides * ~Rvrlvlrsbnkbrst * ~Dryspell * ~Heatshock * ~Fdinscrty … Line 4 in figure 15

Migration (Democratic Republic of the Congo, Mozambique) = Flood * Storm * Cyclone* Heavyrain * Landslides * ~Dryspell * ~Heatshock * ~Fdinscrty … Line 9 in figure 15

Migration in Comoros, Malawi, Swaziland, and Zimbabwe is caused by (presence of) Storm and Cyclone, and absence of heavy rain, landslides, river water level rise, riverbank bursting, dry spell, heat shock, and food insecurity. Migration in DRC and Mozambique is caused by (presence of) floods, storms, cyclones, heavy rain, and landslides and with the absence of dry spells, heat shock, and food insecurity. After combining both the causal pathways, we will remove the absent causes to produce an expression with reduced terms.

Migration = Migration (Democratic Republic of the Congo, Mozambique) * Migration (Comoros, Malawi, Swaziland, Zimbabwe)

Migration = Storm * Cyclone * Storm * Cyclone * Flood

In the second round the expression is further reduced to produce the following outcomes by selecting the only common causes for both pathways:

Migration = Storm * Cyclone … (Parsimonious solution)

Migration (Democratic Republic of the Congo, Mozambique, Comoros, Malawi, Swaziland, Zimbabwe) = Storm * Cyclone

```
*********************
*TRUTH TABLE ANALYSIS*
*********************

File:  G:/
Model: Prmry = f(Flood, Storm, Cyclone, Heavyrain, Landslides, Rvrlvlrsbnkbrst, Dryspell, Heatshock, Fdinscrty)
Algorithm: Quine-McCluskey

--- PARSIMONIOUS SOLUTION ---
frequency cutoff: 1
consistency cutoff: 0.06
                     raw       unique
                   coverage    coverage    consistency
                  ----------  ----------  ----------
Flood             0.963149    0.733668    0.294872
Storm*Cyclone     0.241206    0.0117254   0.48
solution coverage: 0.974874
solution consistency: 0.283902


Cases with greater than 0.5 membership in term Flood:Angola (1,0.12), Burundi (1,0.11), Benin (1,0.52), BurkinaFaso (1,0.1),
                                                     Botswana (1,0.06), CentralAfricanRepublic (1,0.2), Côted'Ivoire (1,0.05),
                                                     Cameroon (1,0.07), DemocraticRepublicoftheCongo (1,0.43), RepublicofCongo (1,0.25),
                                                     Djibouti (1,0.06), Ethiopia (1,0.74), Ghana (1,0.26), Guinea (1,0.05),
                                                     Gambia (1,0.05), Guinea-Bissau (1,0.05), Kenya (1,0.06), Liberia (1,0.05),
                                                     Madagascar (1,0.78), Mali (1,0.08)
Cases with greater than 0.5 membership in term Storm*Cyclone: DemocraticRepublicoftheCongo (1,0.43), Comoros (1,0.09),
                                                             Mozambique (1,0.84), Malawi (1,0.51), Swaziland (1,0.05), Zimbabwe (1,0.96)
```

Figure S16: Parsimonious solution

The process explained above is applied for each causal pathway in figure 15 to select the most parsimonious solution. The fsQCA software runs this algorithm within a fraction of seconds to produce the results in figure 16.

When running Standard Analyses on many variables the algorithm for selecting prime implicants cannot fully reduce the truth table, the Prime Implicant Window will appear as follows:

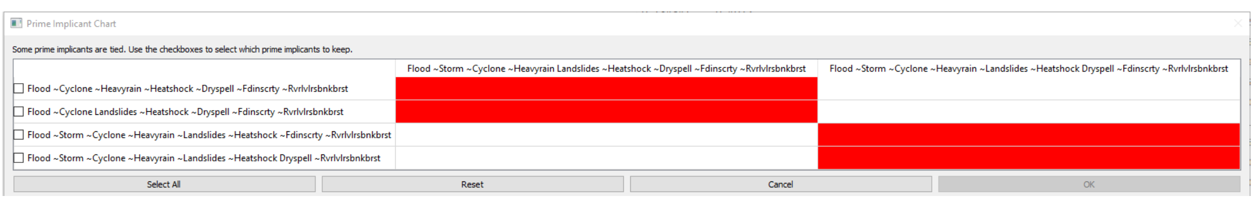


Figure S17: Prime implicant chart for complex solution

Prime implicants are important tools to minimize products of primitive expressions. The process reduces redundancy by using an expression with the selection of the logically minimal number of prime implicants as shown below in figure 18.

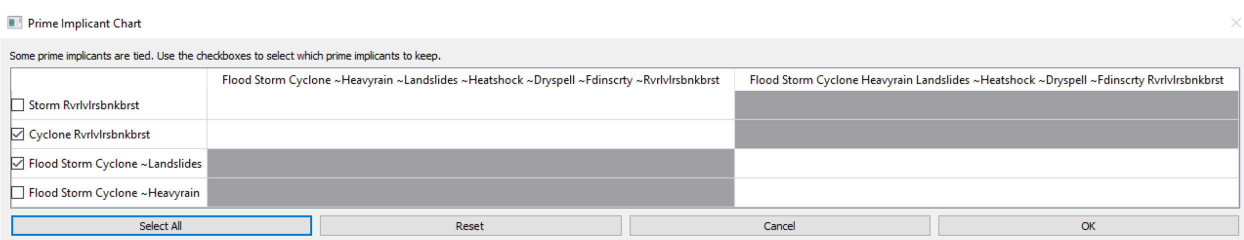


Figure S18: Prime implicant chart for complex solution

Standard Analyses: Intermediate solution

An intermediate solution is a result of "thought experiments" of researchers imagining counterfactual cases (i.e., when some combinations of causal conditions are absent) and hypothesizing the outcomes (Weber, 1949). Theoretical and substantive knowledge normally dictates that all casual conditions must be present for an outcome to exist in other words, all environmental migration drivers must exist for migration to occur in SSA. the intermediate solution brings the important concept of counterfactual cases by raising the critical question of what if some of the drivers are absent? Is it necessary for migration to happen? Are all environmental drivers (direct, indirect, sudden/slow on-set, and accumulated events) equally responsible for migration? The analysis allows counterfactual cases into the equation resulting parsimonious which will be discussed in the next paragraph.

When performing Standard Analyses, a dialogue box for deriving the intermediate solution shown below comes out. The author selected the option of "Present or Absent" to allow all causal conditions to contribute to the outcome. In this specific research, the presence of one or more causal conditions/drivers directly produces an outcome /migration and the selection below emphasizes that. When all condition is coded as "Present or Absent", the intermediate solution will be the same as the complex solution.

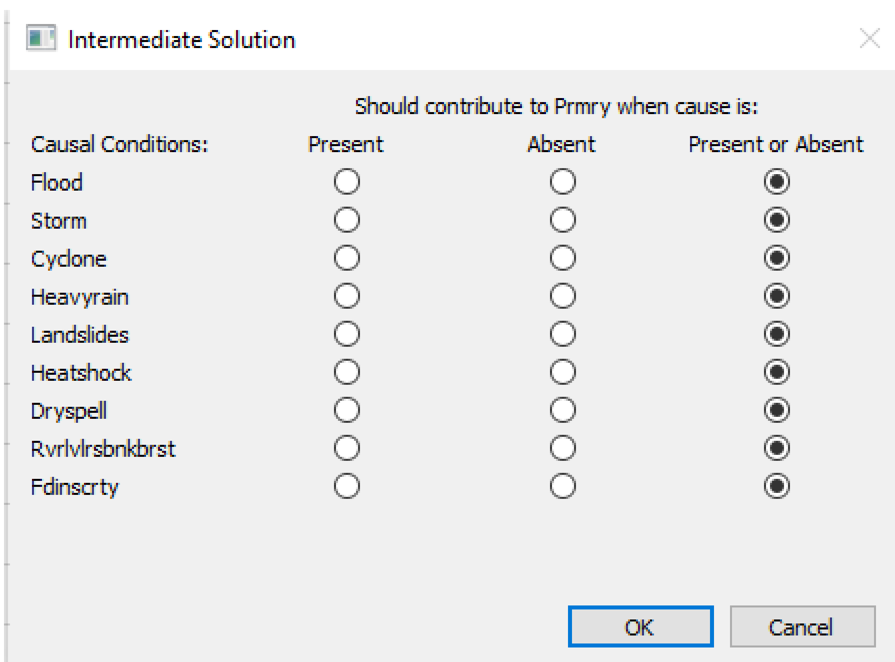


Figure S19: intermediate solution

III. Consideration of the 'logical remainders' cases

"Logical remainders" are cases that are not observed (Ragin, 2017; Rihoux, 2009). To achieve more parsimonious, we could allow the fsQCA software to include the non-observed cases. This step isn't useful for the research as it focuses on non-observed values.

IV. Interpretation

QCA was used to analyze 6 main combinations of environmental migration drivers (Please refer to the excel table tab QCA_1).

All slow-onset events: This category is constituted by events that slowly start to induce changes on the environment. It includes Flood, Storm, Cyclone, Heavy rain, Drought, Landslides, Heat shock and Dry spell.

All rapid extreme events: This category is constituted by events that suddenly induce changes on the environment leading to direct migration. It includes Flood, Storm, Cyclone, Heavy rain, Landslides, Riverbank bursting & River Water level rise (Rvrlvlrsbnkbrst), Dry spell, Heat shock, and Food insecurity (Fdinscrty).

Both rapid extreme and slow onset events: This category is constituted by events that can slowly or rapidly induce changes on the environment. It includes Riverbank bursting & River Water level rise (Rvrlvlrsbnkbrst), Flood, Dry spell, and Food insecurity (Fdinscrty).

Accumulated events: This category is constituted by events that were not harmful at the beginning but evolved to become serious threats over time. It includes Locust invasion, Forest fire (Frstfire), Ecological degradation, arable/ grazing land degradation, Soil erosion, Desertification & Deforestation (Dgrdtndtfdst), Land infertility (Lndinfrtl), Agricultural intensification (Agrint) and land scarcity (lndscrty).

Slow onset events: This category is constituted by events that slowly start to induce changes on the environment. It includes Drought, Famine and water scarcity & rainfall season shortening (Wtrscrty).

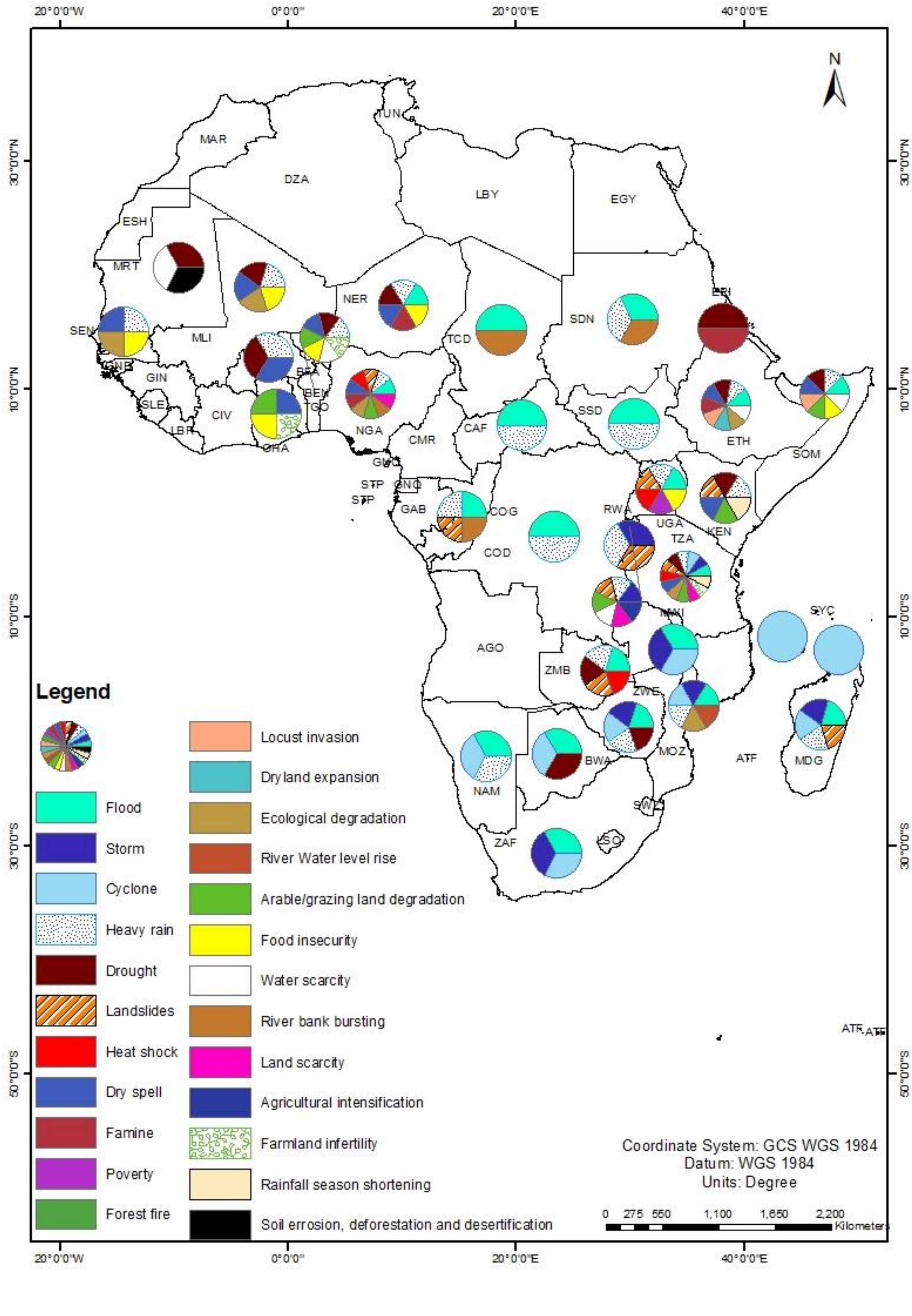
Extreme events: This category is constituted by events that are more frequent and intense. It includes Heat shock, Storm, Cyclone, Heavy rain, Riverbank bursting & River Water level rise (Rvrlvlrsbnkbrst), Landslides.

The final output below on table s20

Table s20: QCA output

	Complex solution						Parsimonious solution			Intermediate solution					
Countries	StCyHr*Fl*Lsd*Hs	Fl*~Dr*~Lsd*~Hs*~Ds	StCyHr*~Dr*Lsd*~Hs*~Ds	StCyHr*Fl*Dr*~Lsd*~Hs	~StCyHr*~Fl*Dr*~Lsd*~Hs*~Ds	StCyHr*~Fl*Dr*Lsd*~Hs*Ds	Fl	Lsd	Dr*~Ds	StCyHr*Fl*Lsd*Hs	Fl*~Dr*~Lsd*~Hs*~Ds	StCyHr*~Dr*Lsd*~Hs*~Ds	StCyHr*Fl*Dr*~Lsd*~Hs	~StCyHr*~Fl*Dr*~Lsd*~Hs*~Ds	StCyHr*~Fl*Dr*Lsd*~Hs*Ds
Burundi			■					■				■			
Benin															
Burkina Faso															
Botswana				■			■		■				■		
Central African Republic		■					■				■				
Democratic Republic of the Congo		■					■				■				
Republic of Congo			■				■	■				■			
Comoros															
Eritrea					■				■					■	
Ethiopia				■			■						■		
Ghana															
Kenya						■		■							■
Madagascar			■				■	■				■			
Mali															
Mozambique		■					■				■				
Mauritania					■				■					■	
Malawi		■					■				■				
Mayotte															
Namibia		■					■				■				
Niger				■			■						■		
Nigeria	■						■	■		■					
Rwanda			■					■				■			
Sudan		■					■				■				
Senegal															
Somalia				■			■						■		
South Sudan		■					■				■				
Chad		■					■				■				
Tanzania	■						■	■		■					
Uganda	■						■	■		■					
South Africa		■					■				■				
Zambia	■						■	■	■	■					
Zimbabwe				■			■		■				■		

Annex 4: Map of all environmental drivers in Sub-Sharan countries (1990-2021)



Annex 5: Statistical correlation results from IBM SPSS statistics viewer

Table s21: Statistical correlation result from literature-based case studies

Descriptive Statistics

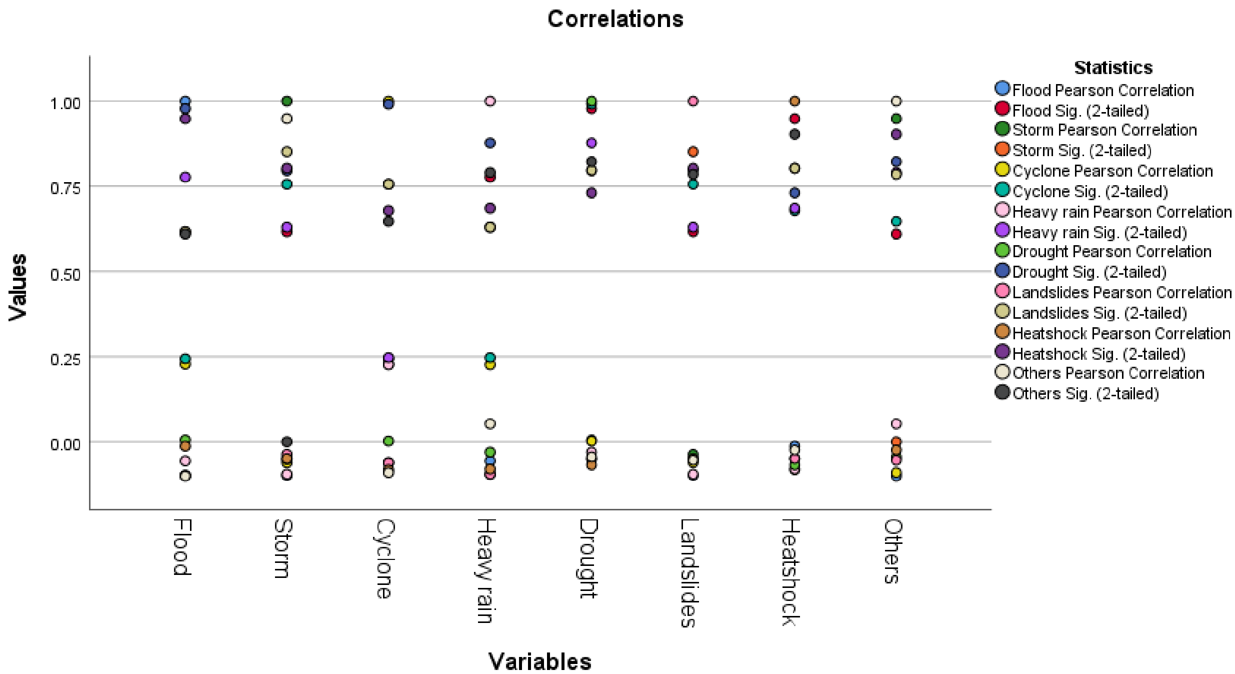
	Mean	Std. Deviation	N
Flood	63333.46	125552.010	28
Storm	214.29	1133.893	28
Cyclone	37336.46	119176.235	28
Heavy rain	53035.71	109106.296	28
Drought	151092.93	578408.650	28
Landslides	717.86	3798.543	28
Heatshock	235.14	932.319	28
Others	92480.86	332096.022	28

Correlations[b]

		Flood	Storm	Cyclone	Heavy rain	Drought	Landslides	Heatshock	Others
Flood	Pearson Correlation	1	-.099	.228	-.056	.005	-.099	-.013	-.101
	Sig. (2-tailed)		.617	.244	.777	.978	.617	.948	.610
Storm	Pearson Correlation	-.099	1	-.061	-.095	-.051	-.037	-.049	.949**
	Sig. (2-tailed)	.617		.756	.630	.796	.852	.803	.000
Cyclone	Pearson Correlation	.228	-.061	1	.226	.002	-.061	-.082	-.090
	Sig. (2-tailed)	.244	.756		.247	.991	.756	.678	.647
Heavy rain	Pearson Correlation	-.056	-.095	.226	1	-.031	-.095	-.080	.053
	Sig. (2-tailed)	.777	.630	.247		.877	.630	.685	.790
Drought	Pearson Correlation	.005	-.051	.002	-.031	1	-.051	-.068	-.044
	Sig. (2-tailed)	.978	.796	.991	.877		.797	.731	.822
Landslides	Pearson Correlation	-.099	-.037	-.061	-.095	-.051	1	-.049	-.054
	Sig. (2-tailed)	.617	.852	.756	.630	.797		.803	.785
Heatshock	Pearson Correlation	-.013	-.049	-.082	-.080	-.068	-.049	1	-.024
	Sig. (2-tailed)	.948	.803	.678	.685	.731	.803		.903
Others	Pearson Correlation	-.101	.949**	-.090	.053	-.044	-.054	-.024	1
	Sig. (2-tailed)	.610	.000	.647	.790	.822	.785	.903	

**. Correlation is significant at the 0.01 level (2-tailed).

b. Listwise N=28



Graphical representation of statistical correlation result

Table s22: Statistical correlation result from literature-based case studies and international dataset combined.

Descriptive Statistics

	Mean	Std. Deviation	N
Flood	149321.76	253630.742	46
Storm	2888.37	6347.921	46
Cyclone	60049.80	266100.235	46
Heavy rain	32282.61	88472.384	46
Drought	91969.61	454194.146	46
Landslides	1193.43	3597.188	46
Heatshock	143.13	731.433	46
Others	56292.70	261256.693	46

Correlations[b]

		Flood	Storm	Cyclone	Heavy rain	Drought	Landslides	Heatshock	Others
Flood	Pearson Correlation	1	-.118	.046	.203	.041	-.068	.089	.071
	Sig. (2-tailed)		.436	.762	.177	.784	.653	.555	.637
Storm	Pearson Correlation	-.118	1	-.010	.059	-.083	.039	-.039	.036
	Sig. (2-tailed)	.436		.947	.698	.585	.797	.795	.810
Cyclone	Pearson Correlation	.046	-.010	1	.186	-.008	-.010	-.044	-.050
	Sig. (2-tailed)	.762	.947		.216	.960	.946	.773	.743
Heavy rain	Pearson Correlation	.203	.059	.186	1	.020	-.003	-.029	.101
	Sig. (2-tailed)	.177	.698	.216		.896	.986	.850	.503
Drought	Pearson Correlation	.041	-.083	-.008	.020	1	-.066	-.040	-.014
	Sig. (2-tailed)	.784	.585	.960	.896		.662	.791	.924
Landslides	Pearson Correlation	-.068	.039	-.010	-.003	-.066	1	-.012	.327*
	Sig. (2-tailed)	.653	.797	.946	.986	.662		.936	.027
Heatshock	Pearson Correlation	.089	-.039	-.044	-.029	-.040	-.012	1	.004
	Sig. (2-tailed)	.555	.795	.773	.850	.791	.936		.977
Others	Pearson Correlation	.071	.036	-.050	.101	-.014	.327*	.004	1
	Sig. (2-tailed)	.637	.810	.743	.503	.924	.027	.977	

*. Correlation is significant at the 0.05 level (2-tailed).

b. Listwise N=46