

YSSP Report

Young Scientists Summer Program

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# Towards attributing climate-related displacement in Somalia to anthropogenic climate change

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This report represents the work completed by the author during the IIASA Young Scientists Summer Program (YSSP) with approval from the YSSP supervisor.

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## Abstract

Extreme weather events such as heat waves, droughts and floods pose risks to the environment and human societies. In East Africa, these events are well-known, reoccurring climate phenomena; however, their impacts and intensity vary across the region and require further study. The East African country of Somalia is highly vulnerable to climatic variability due to its geographic location, which in turn often leads to devastating droughts and floods. The climate impact on human wellbeing and livelihoods is further exacerbated by the absence of a central government coupled with poverty and civil conflict that can escalate – as currently seen – to famine-level situations and large-scale involuntary human mobility. Yet, the extent to which human mobility (measured by internal displacement) can be attributed to extreme weather events and in turn, whether and to what extent extreme weather events and consequently human mobility can be attributed to anthropogenic climate change, has been largely unexplored. Applying a framework based on probabilistic event attribution of extreme weather events, this paper, for the first time, investigates human mobility responses attributed to anthropogenic climate change, exemplifying the state of the art of this method in the context of the East African region. The study shows no attributable link of the April 2020 flood in Somalia (our case study) to anthropogenic climate change. Sparsity of climate observations reveal one of many reasons for a lack of a climate change signal.

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“Let everything happen to you

Beauty and terror

Just keep going

No feeling is final”

— **Rainer Maria Rilke**

## 1 Introduction

In the past decade, extreme weather events have become more frequent and intense leading to widespread and disastrous impacts (1). Extreme weather events such as droughts, floods and heatwaves impact populations globally, especially those who are already socioeconomically vulnerable. Whilst proactive migration can be used as adaptation response to the climate impact, reactive migration in response to unprecedented climatic shocks is often involuntarily and can seriously disrupt livelihoods (2).

In the existing literature, climate-related human mobility (see Appendix 6.1.1) is often portrayed as a key consequence of anthropogenic climate change. Despite a sharp surge in the past few years of quantitative evidence on climatic drivers of human migration in the form of extreme weather events, temperature and precipitation anomalies (3–5), surprisingly little research has quantitatively linked such evidence directly to anthropogenic climate change. Existing studies commonly rely on historical climate data and implicitly assume that extreme events identified in the data are linked to anthropogenic climate change. Causal, quantitative evidence on the attributable influence of anthropogenic climate change on human mobility is not sufficiently understood and suffers from disciplinary hurdles to date (5, 6). This paper addresses this knowledge gap and adds to the literature by asking:

*To what extent does anthropogenic climate change play a role in extreme weather which in turn adversely affect vulnerable people and instigate migration response?*

To date, climate scientists have assessed how anthropogenic climate change alters the frequency and intensity of extreme weather events. In recent years, methods that enable attributing these events to anthropogenic climate change have been devised (7). Indeed, these attribution studies show that global warming is the culprit behind many extreme events ranging from 2019 heatwaves in Western Europe , wildfire in California (8) to the 2017 Bangladesh floods (9). To address the increasing calls for a diversified understanding of how people react to new or changing migration pressures under extreme weather and climatic changes, the environmental and migration scholarship has increasingly paid attention to the framework suggested by Black et al., 2011 (11). Such a framework provides a starting point for a better understanding of human mobility in the context of extreme weather events, which this paper proposes to advance with an application probabilistic event attribution.

Despite the importance of extreme weather on human mobility, research to date has not combined the fields of climate science and environmental migration to empirically assess the impacts of anthropogenic climate in this context. Making use of the emerging science of probabilistic event attribution (PEA), the aim of this paper is to assess whether and how PEA allows to identify attributable links between climate change and recent human mobility in East Africa. An empirical case study on internal displacement in Somalia is used to exemplify the use of the method.

Human mobility can be affected by climatic factors in different ways. For example, individuals can be forced to leave their homes and communities due to sudden-onset events (such as storm surge, landslides, and flood events), or slow-onset processes (such as desertification and sea level rise). However, human mobility decisions, when not direct responses to extreme weather events in the form of sudden displacement, are multi-causal and rarely occur due to adverse climatic conditions alone (Figure 1).

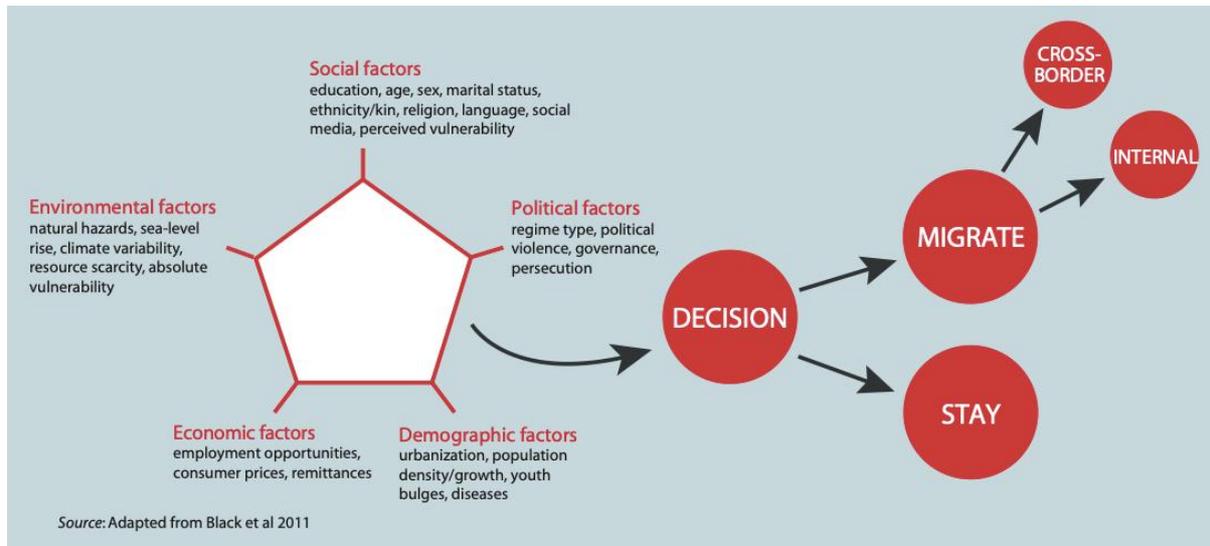


Figure 1: Human mobility decisions are multi-causal, with adverse climate being rarely the sole factor influencing human mobility. Source: Thalheimer & Webersik, 2020, adopted from Black et al., 2011.

Climate change is likely to influence human mobility through its effect on other drivers of migration. Push (e.g. unemployment or conflict) and pull (e.g. economic opportunities or better healthcare) factors of human mobility may change significantly with the inputs of anthropogenic climate change. It has been shown, for instance, that drought events can lead to forced migration through increasing violent conflict although the relationships hold only for certain countries and time period (6). With increased frequency and intensity of extreme weather, affected populations could run out of resources enabling them to migrate voluntarily. With an expected increase in average global temperature of at least 1.5 °C, there is little consensus regarding the direction and the extent to which these factors influence migration and other types of human mobility (5). Therefore, whether and to what extent human mobility will change under anthropogenic climate change is unknown.

East Africa is one of the regions most vulnerable to the impacts of extreme weather events, climate variability and climate change (12–14). In recent years, major extreme weather events involving floods and droughts have had significant social and economic impacts. The 2015 drought in Ethiopia put an estimated 22 million people in need of food aid (15). Relying on rain-fed agriculture (16) and the

predominance of hydroelectricity in the region means that rainfall is a key factor determining sustainable development progress for the populations in Kenya, Ethiopia and Somalia (17, 18).

Climate change therefore can pose serious threats to livelihoods in this region. Event attribution studies, mainly in the context of recent drought events, present some evidence on the impact of anthropogenic climate change: For the 2011 drought in East Africa, a study finds a human signal related to the probability increase of dry, or drier than 2011 long rains (19).<sup>1</sup> A number of East African countries are also affected by recurrent conflict and political instability (20). According to the UNHCR, over 8 million people are currently internally displaced in this part of the world (21). Climate change thus can directly and indirectly influence human mobility in East Africa.

To date, however, there is a paucity of research on the attributable link of anthropogenic climate change and human mobility in the region of East Africa. Given the impacts of anthropogenic climate change are projected to fall disproportionately upon countries in the Global South, with African countries particularly vulnerable (1, 22), this paper identifies a pressing need to better understand the links between human mobility and extreme weather events, and in turn anthropogenic climate change, their changes over time, and representation in models and the literature. By applying PEA to an internal displacement setting in a climate change hotspot region, attributable links between climate change and human mobility are explored for the first time, advancing the field of climate-related human mobility.

The knowledge of the links between human mobility and anthropogenic climate change can help clarify how mobility patterns will look like under future global warming. An improved scientific understanding of extreme weather events, regional climate, together with human mobility patterns around the world is expected to translate into better disaster preparedness and risk reduction to mitigate impacts of climate extremes and compound vulnerabilities associated with human mobility. Attribution studies of extreme events and human mobility will further help in the context of the Sustainable Development Goals (SDGs): to clarify policy debates and scientifically support ongoing and future vulnerability and disaster risk reduction work in the international community. The remainder of the paper is organised as follows. Section 2 lays the theoretical foundation by introducing probabilistic event attribution and recent applications in the East African context. Section 3 applies the attribution framework in a case study on the April 2020 flood in Somalia. Section 4 discusses the results, including limitations of the study and section 5 concludes with an outlook for future research.

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<sup>1</sup> Note however that the evidence is mixed. For a 2014 drought in the Horn of Africa region, no human-induced forcing is found (1).

## 2 The Attribution Question

### 2.1 An overview of Probabilistic Event Attribution

The emerging science of Probabilistic Event Attribution (PEA) could help bridge this research gap by outlining a framework which quantifies extreme weather impacts attributable to climate change on human mobility. Attribution science answers the question whether and to what extent climate change altered the likelihood of an extreme weather occurring. To answer such a question, we assess the likelihood of climate-induced human mobility occurring in today's climate and repeat this calculation in a counterfactual scenario without any emissions from burning fossil fuels. This assessment focuses on "attributable risk": quantifying whether and how much past emissions have contributed to the probability of an extreme event occurring.

Assessments of attributable risk are based on a large number of climate model experiments, called "ensembles". Large ensembles are needed to assess the frequency of extreme events - which are, by definition, rare, and assess how this frequency may change. PEA studies compare how often a particular extreme weather event occurs in model experiments representing "the world as it is" (with human influence on climate) with how often the same type of event occurs in experiments representing "the world that might have been" (with the estimated impact of human influence on climate removed, allowing for impact uncertainty). This is done by quantifying whether and how much past emissions have contributed to the probability of an extreme event occurring. In practice, event attribution studies are dynamic and flexible; however the framing of the event attribution statement is crucial (Hauser et al., 2017). Attribution studies have been carried out for a variety of extreme events across different geographic and climatic regions, although the focus has been in countries of the northern hemisphere due to issues such as data scarcity (15, 23).

A potential linkage between extreme weather events and human mobility has not been investigated in attribution studies yet. There remains a gap between the understanding of recent trends and the capacity to effectively plan for and address the impacts of climate and other drivers on human mobility which are likely to shift due to anthropogenic climate change. Introducing resilience measures to the development context may address some of the problems in the longer term; however, they may not suffice in the face of low mitigation climate change scenarios (e.g. RCP8.5 or a 4 °C scenario) or even under a 1.5 °C additional warming (24), especially in severely exposed regions in developing countries such as Somalia, Uganda or Djibouti.

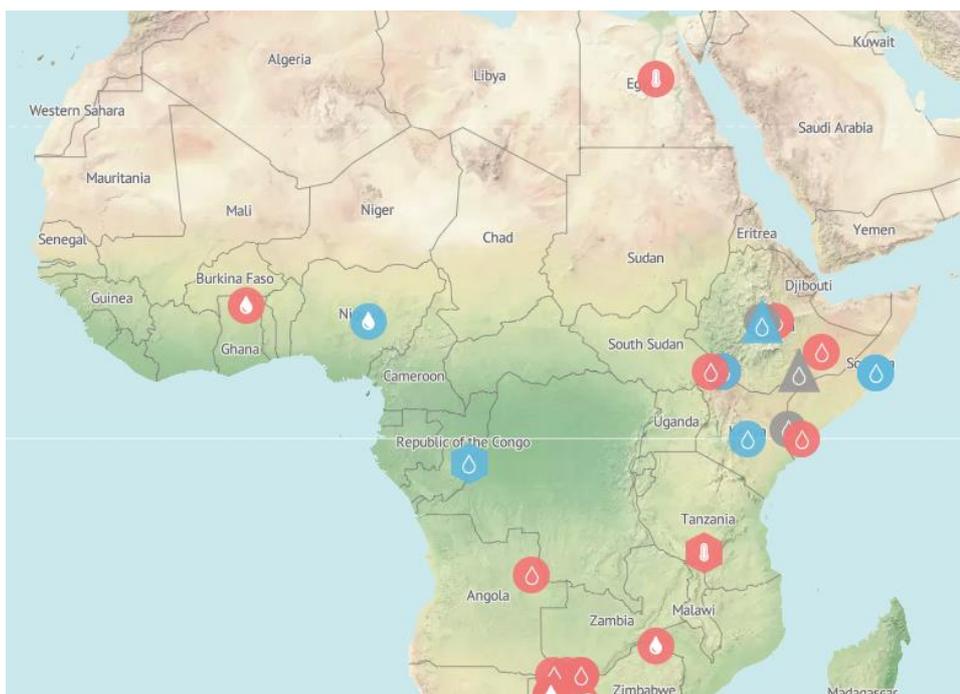


Figure 2: Map of climate change effects on extreme weather in Africa. Red icons indicate an anthropogenic influence was found in a particular extreme weather event, blue icons indicate no human influence was found and grey refers to inconclusive results. Source: Carbon Brief, 2020.

There exist some event attribution studies in the East African region, mainly in the context of recent drought events (25). The most prominent example is the study by Lott and colleagues (19) in which they investigate the role and extent of human-induced climate change for the 2011 drought in East Africa. The study finds a human signal related to the probability increase of dry, or drier than 2011 long rains (19). Studies employing probabilistic extreme event attribution techniques for East Africa evolved in the following years, resulting in a mixed picture in terms of anthropogenic signals in recent extreme events (Figure 2). For example, Marthews and colleagues (2019) investigate the 2014 East African long rains and find no human-induced forcing of the low precipitation levels. Results show that it is more likely to be a result of a natural variability in climate, which has led to failures in rainfall over parts of the Horn of Africa (26). Even though studies have been conducted in a region with similar event types, it is shown that contributing climate conditions are likely to be specific to individual events. This in turn would call for the importance to investigate extreme events carefully – case-by-case and avoid abstraction of results in comparable geo-climatic region (14).

## 2.2 Conceptualizing the links of extreme weather events and displacement

The lack of a common and linked approach to investigate long-term climate change and human mobility (27) implies that there is a need to advance knowledge about extreme weather events attribution and human mobility in the context of long-term climate changes on both conceptual and analytical level. From a conceptual standpoint, this paper seeks to synthesize knowledge and discussion of the two topics, which remain largely unconnected.

The attribution of extreme weather events and climate extremes has emerged as a climate science sub-discipline, outlining a novel approach to provide scientific evidence on the role of anthropogenic factors in individual extreme weather events (28). Attribution analyses are multi-methodological. Based on the principal idea of Allen (7), our approach applies methods and tools from the science of extreme weather event attribution (15, 29) with the objective of rapidly, objectively, and quantitatively assessing the changing nature of extreme weather risk at the country level, and then to translate this risk into mobility patterns in the East African region.

Since impacts of extreme events root in interacting multi-causal risk drivers (see Figure 1), including the meteorological hazard itself, attribution analyses would need to incorporate impacts of population and environmental vulnerabilities and the exposure of assets, livelihoods, and human lives to determine impact on a national and sub-national level. An impact-based approach, thus, requires observational and model data of high enough resolution to capture localized impacts. Country-by-country case studies could help in exemplifying research results of changing risk levels of extreme events and human mobility in this region.

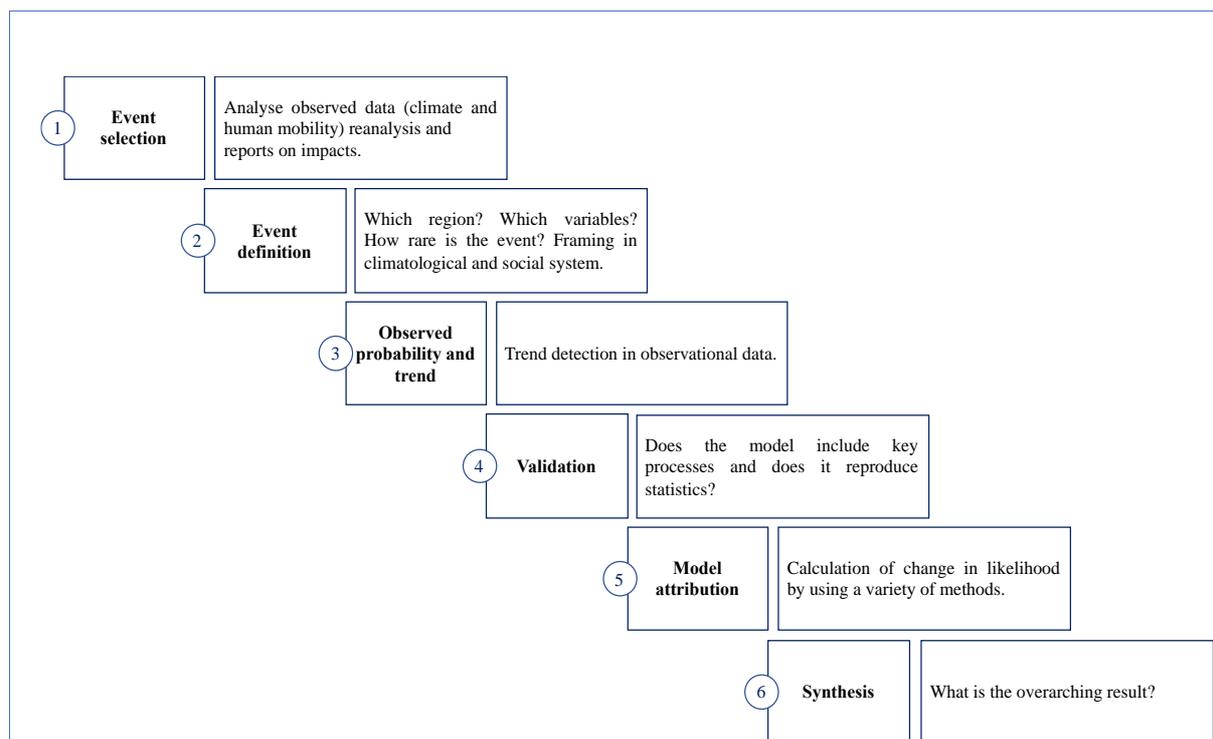


Figure 3: Extreme weather event and migration attribution schema following Otto et al., 2017 and Stott et al., 2015 (1, 2).

Attribution studies follow a common, six step approach: (1) event selection, (2) event definition and framing, (3) observed probability and trend, (4) validation and (5) model attribution and (6) synthesis and interpretation of these results (Figure 3).

Box 1: Probabilistic Event Attribution in a nutshell

### 3 Attribution study: Extreme rainfall in April 2020

We use the observed very high precipitation in Somalia in April 2020 as a case study in investigating the role of climate change based on both climate models and observational data. The methods applied here are similar to those performed on 2016 extreme rainfall in France (30) and 2017 flooding in Bangladesh (9).

#### *Event selection*

For this exercise, Somalia is chosen as a case study. Somalia's population faces recurring extreme weather and conflict events, disrupting existing migration and pastoralism routes. In Somalia, where poverty prevails, the resilience of the population is severely affected by compounding vulnerabilities (26), illustrating a diverse set of internal displacement drivers. At the same time, the country has a well-established war economy (31). In 2019, large parts of the Somali population have been newly displaced (flow: 514,000 - due to disasters and 189,000 from conflict according to IDMC) or live as internally displaced populations (stock: 2,648,000 - from conflict according to IDMC). The attribution procedure, illustrated in Box 1 for the case study is as follows. First, the extreme weather event to be attributed is selected. This is done by comparing internal displacement data from UNHCR and recorded disasters from the EM-Dat database to establish an initial index of impacts from droughts and floods on internally displaced populations in Somalia (see Appendix 6.1.2). Based on the number of displaced people, a respective extreme weather event is selected as recorded in EM-Dat for analysis (32). Here, the KNMI Climate Explorer is used to analyse climate data statistically for steps 2 to 5 (Figure 3). Such a procedure has been applied in previous attribution studies in the Horn of Africa region (33).

#### *Event definition*

Somalia is located in the Horn of Africa region and has two rainy seasons: when the intertropical convergence zone passes north in spring and when it passes south again in autumn. In central Somalia this is the *Gu* season (mainly in April-May) and the *Deyr* season (October-November/ December). Further north the rains start earlier, the *Gu* season starts in March and the *Deyr* season in August. Usually the periods in between are not completely dry. We use four-month seasons that encompass the peak of the rains both in the north and the south: March–June and September–December.

The northern part of Somalia (North Somalia or Somaliland) is characterised by a somewhat different climate from the rest of the country (South Somalia). The Juba and Shabelle rivers are located in the south. The maximum precipitation affected the region between southern Ethiopia and South Somalia (Figure 4). For this attribution study, both, the origin region of the heavy precipitation (Figure 4a) and the impact region are considered in this step (Figure 4b).

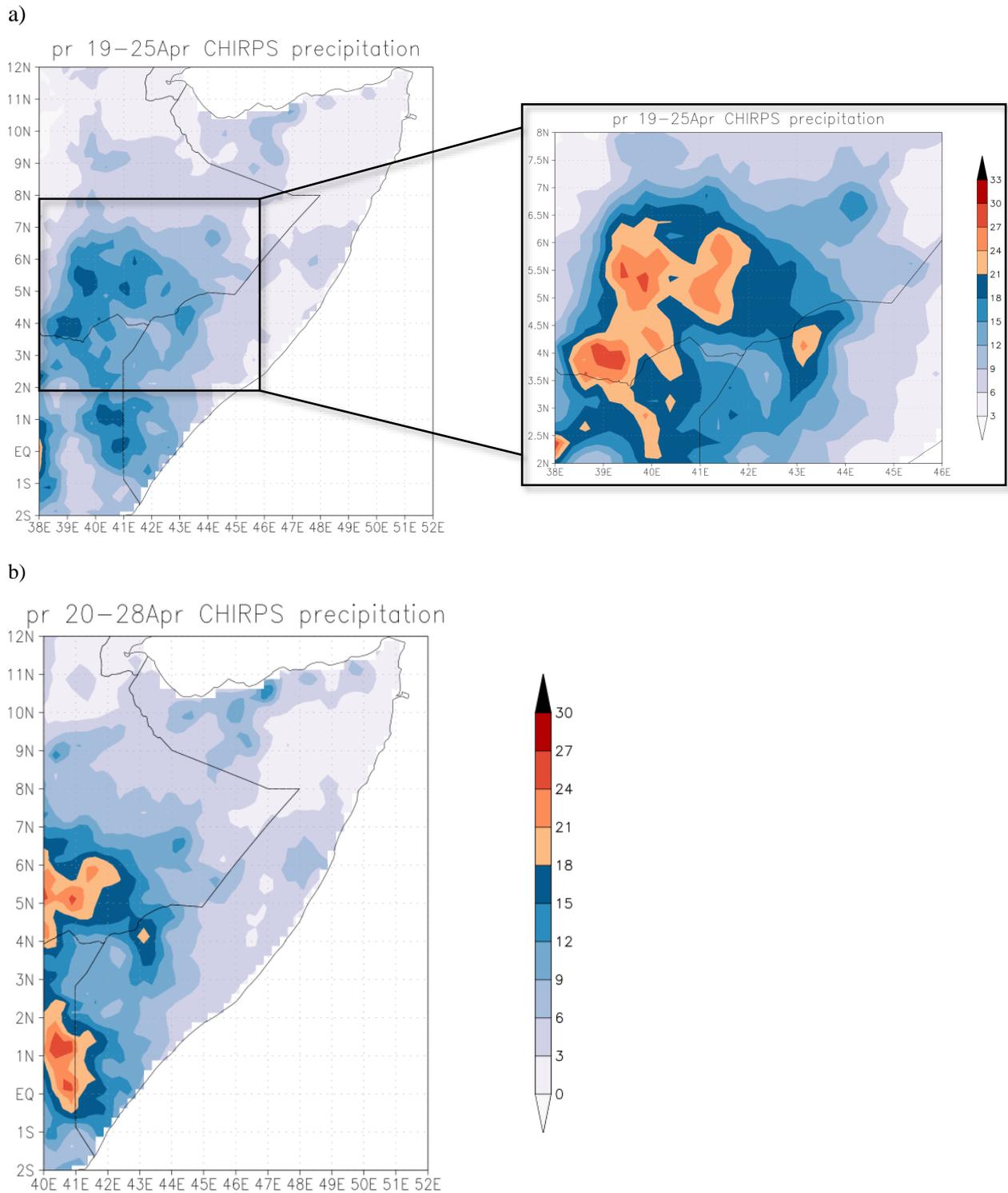


Figure 4: a) Map of event definition showing absolute rainfall over the time of maximum precipitation (19-25 April 2020). Orange and red areas indicate locations with highest rainfall. b) Same for the impact region in South Somalia during 20-28 April 2020.

#### *Defining impact relevant attributable events*

Based on the selection criteria, we identified the April 2020 floods in South Somalia which affected multiple Somalia States and territories: South West, Jubaland, Banadir, Puntland, and Somaliland, Belet

Weyne, Jowhar (Hirshabelle State). Extreme rainfall between 20-28 April 2020 resulted in flooding (mainly) of the Juba river and Shabelle river basins. The event has affected approximately 1 million people, displaced 283,000 and killed 26 people due to the resulting flood. As the origin of the flood is riverine, we also investigate the region of extreme rainfall (19-25 April 2020) which then led to flooding in the impact region.

### *Observed probability and trend*

First, historical observations of precipitation were investigated through three datasets: i) CRU TS4.0, ii) CenTrends and iii) CHIRPS. CRU TS4.0 and CenTrends contain the longer time series compared to the CHIRPS dataset which starts 1981. The CenTrends monthly dataset goes back to 1900 and is based on an extensive collection of station data in eastern Africa, containing more station data than other analyses for this data-sparse region (34). Figure 5 shows the rainfall variation from 1901 to 2019 using the CRU TS4.0 dataset. From the more granular resolution of the CHIRPS dataset (35), a ranking of the extreme precipitation is performed (Figure 6). Compared to recent years (2018 to mid-2020), the heavy precipitation in April 2020 ranks as the third largest event. Figure 7a shows the time series of CHIRPS precipitation averaged over the origin location for 30 days ending on 26 April 2020. The 7-day average at the beginning of April shows higher precipitation than the one in May 2020. Analysing 30 days prior to the event verifies the timeframe for the event definition (Figure 4a, Figure 7a).

The first step in an attribution analysis is trend detection (see step 3 in Figure 3). Observational data is fitted to a non-stationary statistical model to look for a trend outside the range of deviations expected by natural variability. Here, the trends of extreme high-precipitation are studied. In extreme value analysis, the generalised extreme value (GEV) distribution is often used to fit and model the tail of the empirical distribution for this type of event, the maximum daily or 7-daily value coinciding with the event duration (9).

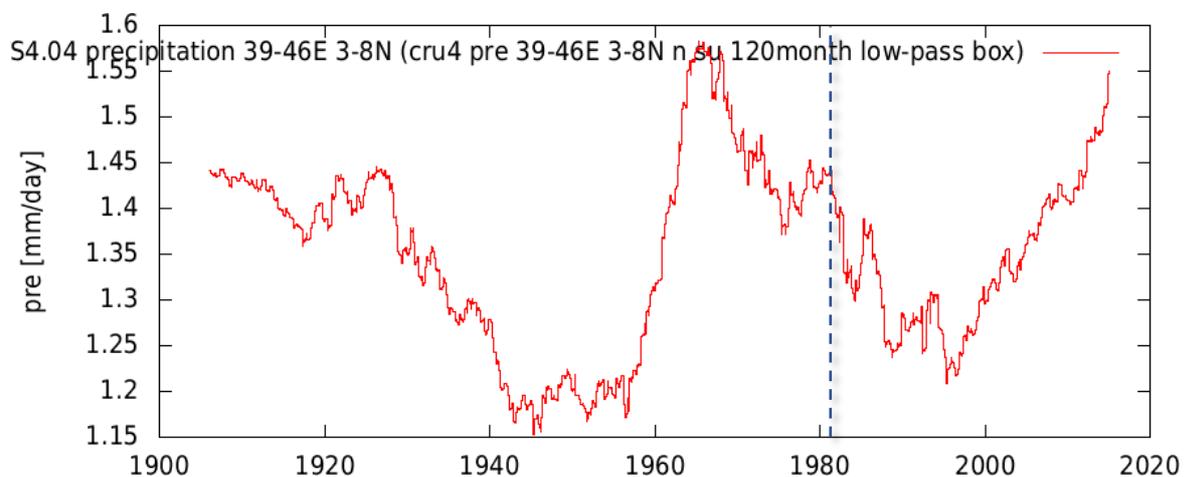


Figure 5: Rainfall time series 1901-2019 (Source: CRU TS4.0). Dashed line indicates the start of the CHIRPS timeseries.

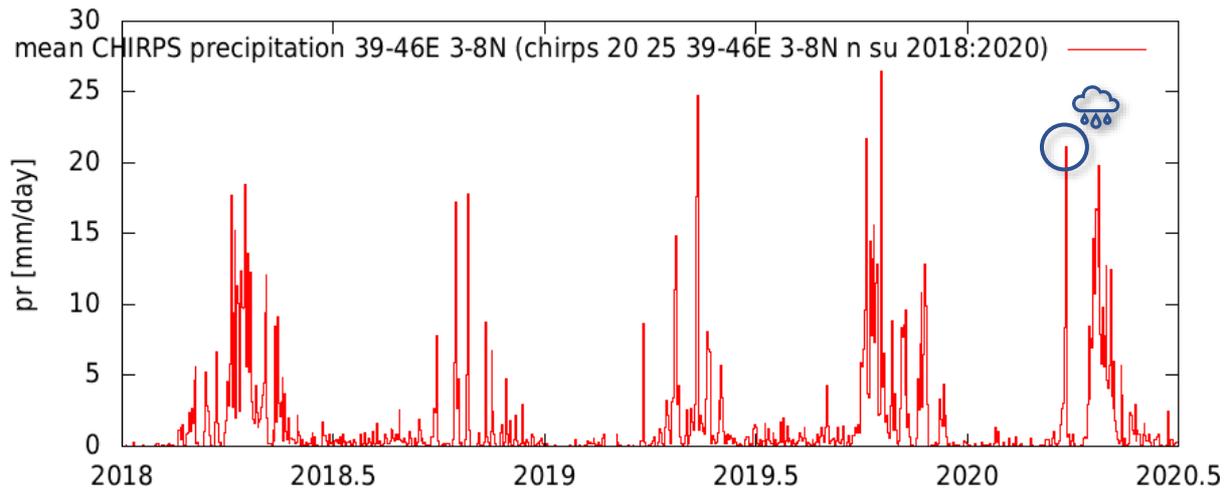


Figure 6: Mean precipitation over the study region over the period of 2018 to mid-2020 (source: CHIRPS)

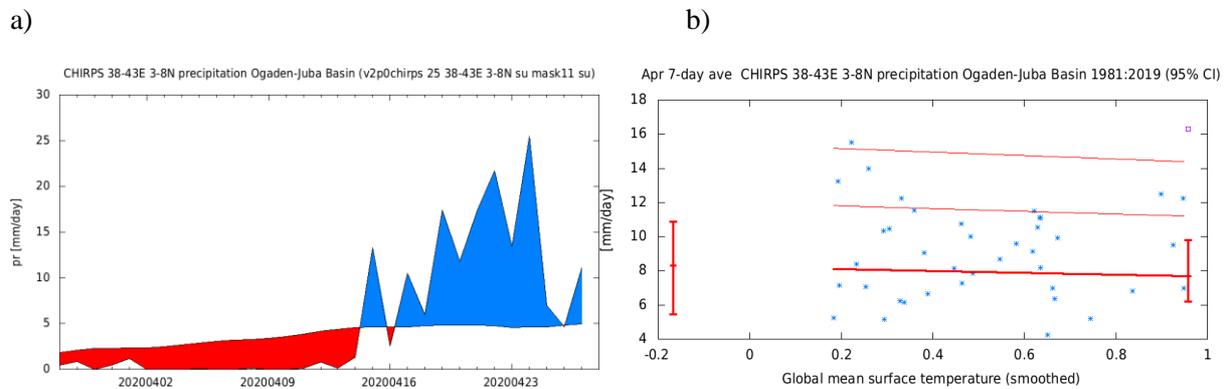


Figure 7: a) CHIRPS precipitation data and analysis over of the highest observed mean rainfall 30 days prior to the extreme event; b) The location parameter  $\mu$  (thick line),  $\mu+\sigma$  and  $\mu+2\sigma$  (thin lines) of the GEV fit of the 7-day averaged data.

### Observed return periods

#### i) Return periods in the origin location

The 7-day average annual maximum precipitation is fitted to a GEV distribution. The return period plots show that the distribution can be described by a GEV by overlaying the data points and fit for the present and a past climate (Figure 8). The return period calculated from this fit is 179 years (95 % CI – confidence interval, 15 to 78 years) for the current climate, indicating a relatively rare type of extreme event (see Table 2 in the Appendix for a results overview).

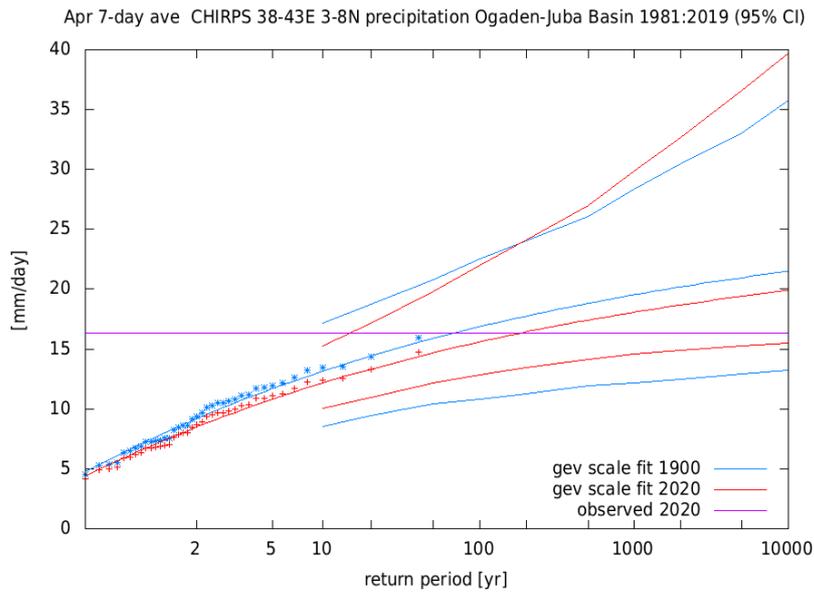


Figure 8: The GEV fit of the 7-day averaged data in 2020 (red) and 1900 (blue). The observations are drawn twice, scaled up with the trend (smoothed global mean temperature) to 2020 and scaled down to 1900. The purple line shows the observed value at present date (2020).

*b) Return periods in the impact region*

The same is done for the impact region. Note that a 9-day average is applied per the event definition. The return period calculated from this fit is 30 years (95 % CI, 12 to 452 years) for the current climate, so not an extremely rare event (see Table 3 in the Appendix for a results overview).

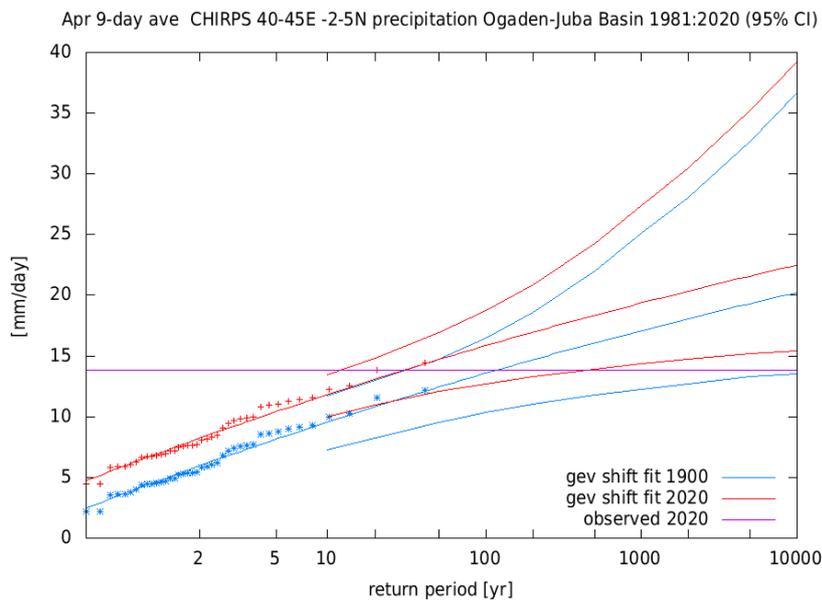


Figure 9: The GEV fit of the 9-day averaged data in 2020 (red) and 1900 (blue) at the flood impact region in Somalia. The observations are drawn twice, scaled up with the trend (smoothed global mean temperature) to 2020 and scaled down to 1900. The purple line shows the observed value at present date (2020).

### Modelled trends

This study applies the fully coupled EC-EARTH 2.3.16-member ensemble at a 150 km resolution using the CMIP5 historical/ RCP8.5 protocol that was used from the KMNI Climate Explorer. The spatial pattern indicates, a wettening trend in the region impacted by the extreme rainfalls, especially around the Juba river in South Somalia (Figure 10). When comparing with the year 2050, an event like the April 2020 flood would occur every 3.5 years instead of every 15.7 years under 2020 conditions (see Appendix Table 4).

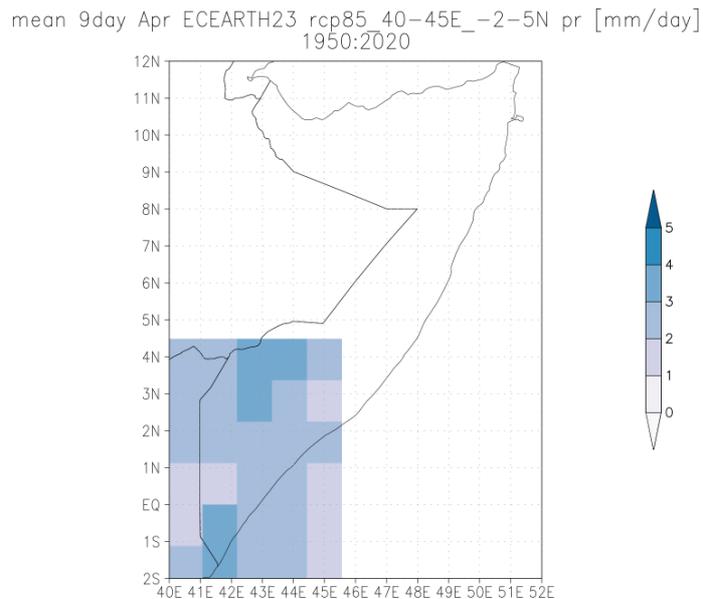


Figure 10: Spatial pattern indicating wetter conditions in South Somalia.

### Short Synthesis

Here, two regions of extreme rainfall are investigated: the origin region of heavy rainfalls in mid-April 2020 which have led to extreme flooding in the southern part of Somalia in late April 2020. With the current specification of the attribution model, no significant attributable links to anthropogenic climate change can be detected. In the following section the preliminary results are discussed along with possibilities of better detection and understanding of climate change impacts on displaced populations.

## 4 Towards a better understanding of the role of climate change in climate-related displacement events

This working paper shows that PEA is a well-suited starting point to explore attributable links between climate change and extreme events which may have contributed to population displacement. In this study, the usability and applicability of PEA for drawing causal conclusions on human-induced climate

change and human mobility in East Africa is shown. Although we have not detected the role of anthropogenic climate change in the Somalian April 2020 flooding event on displacement, we have shown the procedure and steps to perform such exercise. This can be applied straightforwardly to other events and contexts. However, there are limitations of this novel approach which deem further discussion.

First, there are limitations of attribution studies themselves. The results are very sensitive to the event definition. Data availability (or scarcity for that matter) in the study region are thereby key for in how the event can be defined and attributed, for example a extreme precipitation events (e.g., a flash flood) which could be measured better by hydrology models or secondary impacts (adaptation measures in past) such as dams versus heatwaves which have not been recorded on EM-Dat database due to data scarcity (36). In this study, a daily precipitation dataset (CHIRPS) starting from 1981 is used. This dataset has certain limitations, such as not accounting for the shift in the Intertropical Convergence Zone (ITCZ) as a result from the Sahel drought in the 1960s. The study region could have benefitted from wetter conditions and extreme events could be captured incorrectly in observational data. Reanalysis data such as ERA5 data could be used to compare and contrast the results from this study. Further, to overcome this limitation, it has been suggested to develop a comprehensive database for quantitative evidence on the impacts of climate change loss and damage (37).

The results of our study indicate that there is diversion between extreme weather impacts and whether these impacts actually lead to displacement. In the selected event, one million people have been affected by the flood event in Southern Somalia. However, a fraction of affected people has been displaced. This calls for incorporation of displacement impacts in addition to those from extreme weather events directly in the database. Moreover, emphasis should be put on sources of extreme weather damages databases and potential reporting biases. For example, there have been no heatwave impacts reported for the Africa region since 1900, despite the region having experienced multiple heatwaves (22). To date, attribution studies are conducted in an ad-hoc manner and apply a diverse set of methodologies which make any comparison difficult (38). Understanding changing risk of displacement due to extreme weather (vulnerability and exposure monitoring instead of ad-hoc studies) is crucial with people being affected disproportionately by extreme events under climate change.

Second, there are limitations concerning displacement data. With limited available granular data, any time series analysis is bound to the time frame set by the displacement data. In this study, we use a time series of five years (2016-2020) which draws a somewhat biased picture of climate-related displacement which can have some time lag depending on the type of extreme event: long-term drought versus a rapidly evolving extreme event such as flash floods. The data itself gives an indication about new displacements at origin and destination (flows) but does not give an indication on the movement of those who have been displaced in previous months (protracted displacement or returnees). In a similar vein, limited conclusions can be drawn on the stock of internally displaced people. To monitor the

displacement risk, especially in the fragility context, satellite imagery could be used to overcome these data challenges in the collection of continuous displacement data (39).

## 5 Conclusion

Somalia like many countries in sub-Saharan Africa is facing impacts from recurring extreme weather events displacing much of its population internally. Existing vulnerabilities and exposure to extreme weather are exacerbated through decades of conflict. This working paper provides a novel approach towards attributing human-induced climate change and migration in the context of Probabilistic Event Attribution, an emerging sub-discipline of climate science. The nature of event attribution is dynamic and flexible and can be used to study climate change signals in an extreme weather event that resulted in displacement. Results of existing attribution studies of extreme weather events and climate change can support the framing question within the framework and reduce potential biases. Future research has the potential to be useful for climate change adaptation, but there is a need to explore its application in fragile countries and those vulnerable to climate change, particularly those in Africa, since the majority of existing event attribution studies have focused on mid-latitude events.

## 6 Appendix

### 6.1 Further background material

#### 6.1.1 Typology of human mobility

There are different types of human mobility, ranging from voluntary to forced migration or displacement and refugees. Situations of immobility can also occur, voluntary immobility and entrapment. Contrary to modality in existing research (Adger et al., 2018; Boas, 2020; Farbotko et al., 2018), this paper does not use human mobility as a synonym for migration. *Table 1* provides a taxonomy of human mobility types.

Type	Definition
<b>Migration</b>	The voluntary movement of a person or a group of persons, either within a state or across a country's border. The reasons for such population movements are complex and multi-causal (Black, 2011; IOM, 2011)
<b>Displacement</b>	The involuntary movement, individually or collectively, of persons from their country or community, notably for reasons of armed conflict, civil unrest, or natural or man-made catastrophes (IOM, 2011).
<b>Refugee</b>	According to the 1951 UN Refugee Convention and the 1967 Protocol, refugees are persons who have fled their country because of a well-founded fear of persecution for reasons of race, religion, nationality, membership of a particular social group, or political opinions. Regional refugee conventions, e.g. the 1969 Organisation of the African Unity Convention and the 1984 Cartagena Declaration also regard groups of people as refugees who flee because of external aggression, occupation, foreign domination or events seriously disturbing public order.
<b>Climate-related human mobility</b>	Climate-related human mobility or short climate mobilities are population movements where adverse weather or climate conditions play a crucial factor in the decision to move (e.g. Boas et al., 2019).

*Table 1: Classification and definition of human mobility types*

## 6.1.2 Extreme weather events in Somalia

Year	Disaster Sub	Disaster Typ	Disaster Sub Entry	Criteria	Location	Origin	Dis	Maq	Val	Latitude	Longitude	River Basin	Start date	End date	Total Deaths	No Injured	No Affected	Total Affected	Source	New displac	Reason	Source
2016	Hydrological	Flood	Flash flood	Kill	Awdal, Gedo	Heavy rains							4/6/16	4/11/16	9				EM-Dat			
2018	Hydrological	Flood	Riverine floor	Affected	Gedo, Bakoc	Heavy rain							4/1/18	5/31/18	5		700,000	700,000	EM-Dat	267,000	flood	UNHCR
2019	Climatologica	Drought	Drought	Affected	Awdal, Woqo	Dry conditions							2/1/19	10/1/19			1,500,000	1,500,000	EM-Dat	127,000	drought	UNHCR
2019	Hydrological	Flood	Flash flood	Affected	Hirshabelle, Jubaland, South West, Banadir, Hiran, Gedo							Shabelle, Jub	10/1/19	10/1/19	17		500,000	500,000	EM-Dat	334,000	flood	UNHCR
2020	Hydrological	Flood	Riverine floor	Affected	Hirshabelle, South West, Jubaland, Mogadishu districts							Shabelle river	6/15/20	7/20/20	6		191,000	191,000	EM-Dat	137,000	flood	UNHCR
2020	Hydrological	Flood		Kill	Somalia Stat	Heavy rains	428331	614.157	470.848			Juba river, Sh	4/20/20	4/28/20	26	20	1,000,000	1,000,020	EM-Dat	283,000	flood	UNHCR

Figure 11: List of recent extreme weather events and associated internal displacement across Somalia. Source: UNHCR and EM-Dat.

### 6.1.3 Further details on the attribution results

This section of the Appendix presents additional results from the attribution study that are referred to in the main part of the paper.

#### *Observed trends*

Here, the trends in return times of extremes are estimated using the CHIRPS daily precipitation observations for 38-43E 3-8N in the Ogaden-Juba Basin (origin region). The return period of the 7-day rainfall maxima during April 2020 is estimated using the block maxima method, in which a generalised extreme value (GEV) distribution is fitted to the distribution of 7-day maxima observed within each time step. Then, the return periods are estimated by inverting the resulting GEV cumulative probability distribution of block maxima for a range of return periods. As such, the estimated return periods represent the probability of the 7-day maximum observed during April 2020 occurring within any April month, season, or year.

Apr 7-day ave CHIRPS 38-43E 3-8N precipitation Ogaden-Juba Basin pr [mm/day] dependent on Global mean surface temperature (smoothed)			
parameter	year	value	95% CI
covariate:	1900	-0.16667	
	2020	0.95792	
N:		39	
Fitted to GEV distribution $P(x) = \exp(-(1+\xi(x-\mu')/\sigma')^{-1/\xi})$			
with $\mu' = \mu \exp(\alpha T/\mu)$ and $\sigma' = \sigma \exp(\alpha T/\mu)$ and a Gaussian penalty on $\xi$ of width 0.2			
$\mu'$ :	1900	8.307	7.342... 9.120
$\sigma'$ :	1900	2.495	1.794... 2.899
$\mu'$ :	2020	7.687	6.721... 8.500
$\sigma'$ :	2020	2.309	1.642... 2.702
$\sigma/\mu$ :		0.300	0.222... 0.347
$\xi$ :		-0.134	-0.275... 0.102
$\alpha$ :		-0.547	-3.665... 3.691
return period event 2020 (value 16.312 )	1900	66.958	7.1544 ... $\infty$
probability	1900	0.14935E-01	0 ... 0.13977
return period event 2020 (value 16.312 )	2020	179.35	15.014 ... 0.77983E+06

probability	2020	0.55756E-02	0.12823E-05 ... 0.66606E-01
probability ratio		0.37333	0.55279E-04 ... $\infty$
inverse probability ratio		2.6786	0 ... 18090.
p-value probability ratio (one-sided)	$\neq 1$	0.4666	
change in intensity 1900-2020	diff %	-7.468	-40.832 ... 72.730

Table 2: Results of the GEV distribution fitting for origin region. The table lists statistical methods and properties.

Apr 9-day ave CHIRPS 40-45E -2-5N precipitation Ogaden-Juba Basin pr [mm/day] dependent on Global mean surface temperature (smoothed)			
parameter	year	value	95% CI
covariate:	1900	-0.16667	
	2020	0.95792	
N:		40	
Fitted to GEV distribution $P(x) = \exp(-(1+\xi(x-\mu')/\sigma')^{-1/\xi})$			
with $\mu' = \mu + \alpha T$ and $\sigma' = \sigma$ and a Gaussian penalty on $\xi$ of width 0.2			
$\mu'$ :	1900	5.218	4.562... 5.990
$\sigma'$ :	1900	2.035	1.398... 2.428
$\mu'$ :	2020	7.491	6.834... 8.262
$\sigma'$ :	2020	2.035	1.398... 2.428
$\xi$ :		-0.050	-0.224... 0.162
$\alpha$ :		2.021	-0.715... 4.895
return period event 2020 (value 13.832 )	1900	117.08	31.923 ... 24612.
probability	1900	0.85409E-02	0.40630E-04 ... 0.31326E-01
return period event 2020 (value 13.832 )	2020	30.128	12.045 ... 452.69
probability	2020	0.33192E-01	0.22090E-02 ... 0.83024E-01

probability ratio		3.8862	0.48422 ... 586.20
p-value probability ratio (one-sided)	$\neq 1$	0.0769	
change in intensity 1900-2020	diff	2.273	-0.804 ... 5.504

Table 3: Results of the GEV distribution fitting for the impact region.

### Observed return periods

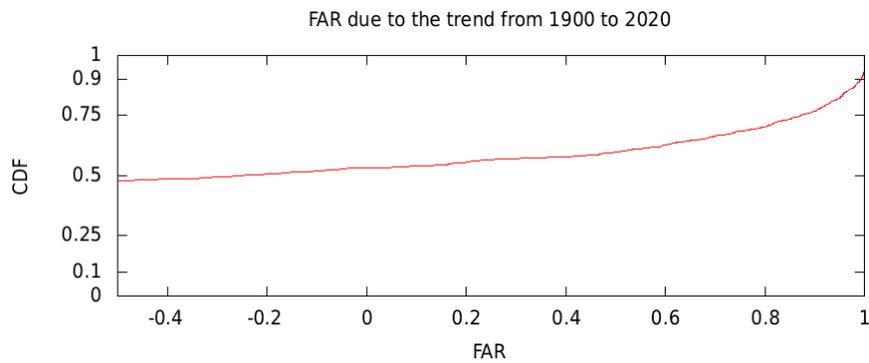


Figure 12: Fraction of attributable risk of the extreme event

### Model attribution

Return value for this event is 15.721.

Apr 9-day ave CHIRPS 40-45E -2-5N precipitation Ogaden-Juba Basin pr [mm/day] dependent on t Tglobal EC-Earth23 mean			
parameter	year	value	95% CI
covariate:	1900	12.502	
	2020	13.970	
N:		40	
Fitted to GEV distribution $P(x) = \exp(-(1+\xi(x-\mu')/\sigma')^{-1/\xi})$			
with $\mu' = \mu + \alpha T$ and $\sigma' = \sigma$ and a Gaussian penalty on $\xi$ of width 0.2			
$\mu'$ :	1900	5.124	4.461... 5.930
$\sigma'$ :	1900	2.039	1.386... 2.506
$\mu'$ :	2020	7.318	6.655... 8.124
$\sigma'$ :	2020	2.039	1.386... 2.506

$\xi$ :		-0.049	-0.245... 0.167
$\alpha$ :		1.496	-0.660... 3.848
return period event 2020 (value 12.517 )	1900	54.542	14.732 ... 2876.9
probability	1900	0.18335E-01	0.34760E-03 ... 0.67877E-01
return period event 2020 (value 12.517 )	2020	15.721	6.8467 ... 96.117
probability	2020	0.63609E-01	0.10404E-01 ... 0.14605
probability ratio		3.4693	0.51371 ... 215.35
<i>p</i> -value probability ratio (one-sided)	$\neq 1$	0.0896	
change in intensity 1900- 2020	diff	2.194	-0.968 ... 5.647

Table 4: Using threshold return period of 100 yr the return value in 2050 is estimated.

#### 6.1.4 List of Acronyms

CI	Confidence Interval
FAR	Fraction of attributable risk
IDMC	Internal Displacement Monitoring Centre
IPCC	International Panel on Climate Change
ITCZ	Intertropical Convergence Zone
KMNI	Royal Netherlands Meteorological Institute
PEA	Probabilistic Event Attribution
SDG	Sustainable Development Goals
UNHCR	United Nations High Commissioner for Refugees

## 7 References

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