

Methods of Attributing Human Mobility to Climate Change: Evidence from East Africa



LISA THALHEIMER

Christ Church

A Thesis submitted for the degree of Doctor of Philosophy

University of Oxford

Trinity Term 2021

In memory of Simon J. Abele

To Luisa Werner

Born 412.46ppm

Abstract

East Africa's population is vulnerable to weather and climate-related events because of its reliance on pastoralism for livelihoods, economic security, and development. Recent weather and climatic extremes have included both recurring droughts and floods. This is paired with an ongoing humanitarian crisis, poverty, and conflict prompting changes in existing human mobility. However, the processes involved in these changes and the extent to which human-induced (anthropogenic) climate change plays a role are not yet understood. Despite awareness of climate impacts on society and the economy, weather and climate-related events and attributable links to anthropogenic climate change have received limited attention in research and policy. To circumvent this issue, an integrated attribution approach is developed which assesses the full chain of causality with human mobility as outcome, weather and climate-related events as human mobility drivers and potential inputs of anthropogenic climate change. This thesis focusses on the concepts, tools and techniques needed for the attributability of weather and climate-related events and human mobility in East Africa to anthropogenic climate change. It emphasizes the need for general models to account for the complexities of human mobility and how these can be applied in the context of a range of weather and climate-related events facing this region. These range from disentangling the diverse drivers of human mobility, to characterising climate-related human mobility, to modelling the probability and attributability of anthropogenic climate change. There is a need and responsibility to redesign climate science outputs to be proactive, agile, and socially just when confronted with increasingly likely compounding risks. New approaches must be utilised to feed into this need of science for society and regional decision-makers alike. Here, several examples of such approaches are presented which outline practical steps to improve our understanding of climate-related human mobility in East Africa and attributable links to anthropogenic climate change. This thesis concludes that an integrated attribution approach can be used to attribute weather and climate-related events and human mobility to anthropogenic climate change and is a promising method for modelling future implications of climate-related human mobility.

Table of Contents

<i>Abstract.....</i>	<i>ii</i>
<i>Table of Contents.....</i>	<i>iii</i>
<i>Acknowledgements.....</i>	<i>viii</i>
<i>List of Figures.....</i>	<i>x</i>
<i>List of Tables.....</i>	<i>xvi</i>
<i>List of Acronyms.....</i>	<i>xix</i>
1 Introduction.....	1
1.1 Background and rationale	2
1.2 Typology of human mobility	5
1.3 Study area	9
1.4 Key challenges and knowledge gaps	10
1.5 Detailed research questions.....	12
1.5.1 Research questions.....	14
1.5.2 Thesis Structure.....	15
2 Data and Methods	22
2.1 Introduction.....	23
2.2 Data	23
2.2.1 Displacement data	23

2.2.2	Conflict data	25
2.2.3	Weather and climate reanalysis, gauge, and satellite data.....	25
2.2.4	Climate model data.....	27
2.3	Methods.....	29
2.3.1	Characterising climate-related human mobility.....	30
2.3.2	Disentangling human mobility drivers.....	32
2.3.3	Attributable links to anthropogenic climate change.....	35
3	<i>Deciphering Impacts and Human Responses to a Changing Climate in East Africa</i>	43
	Abstract.....	46
3.1	Introduction.....	47
3.2	The climate change and human mobility debate.....	47
3.3	Methods.....	50
3.3.1	Study area	50
3.3.2	Analytical framework	51
3.3.3	Case study approach	52
3.3.4	Topic model approach.....	53
3.4	Results	54
3.4.1	Drivers of human mobility	54
3.4.2	The role of climate data.....	58
3.4.3	Human mobility data	63
3.4.4	Implication of anthropogenic climate change	64
3.5	Discussion and conclusions.....	66
	Supplementary Material	71

A Sampling strategy and selection	71
B Case study analysis.....	74
C Topic modelling approach.....	77
 4 <i>Advancing the evidence base of future warming impacts on human mobility in African drylands</i>	82
Abstract.....	85
Plain language summary.....	85
4.1 Introduction.....	86
4.2 Climate-related human mobility	89
4.3 Mapping climate change effects on African drylands.....	90
4.4 Climate change impact sectors and their relation to human mobility in African drylands.....	92
4.5 Systems approaches to advance the current evidence	98
4.6 Outlook.....	99
 5 <i>Disentangling the effects of climate and conflict on displacement: Evidence from Somalia</i>	101
Abstract.....	104
5.1 Main Text	105
5.2 Methods and Data.....	107
5.3 Results	113
5.4 Discussion.....	122

Supplementary Material	124
S1 Supplementary Text	124
S2 Detailed description of Data	125
S3 Identification, model specification, and estimation methods.....	128
6 <i>Towards attributing climate-related displacement to anthropogenic</i>	
<i>climate change</i>	137
Abstract.....	140
6.1 Introduction.....	141
6.2 Human mobility in the context of climate change.....	144
6.3 Conceptualising and operationalising the analysis	148
6.4 Extreme precipitation as displacement trigger in Somalia	152
6.4.1 Event selection	152
6.4.2 Event definition	153
6.4.3 Observed probability and trend.....	155
6.4.4 Observed return periods	156
6.4.5 Modelled trends and synthesis.....	158
6.5 Towards a better understanding of the role of climate change in climate-	
related displacement events.....	160
6.6 Conclusions	162
Supplementary Material	165
A. Typology of human mobility	165
B. Flood as displacement trigger in Somalia.....	166
C. Descriptive Statistics.....	167

6.6.1	D. Model attribution	171
7	<i>Conclusions</i>	184
7.1	The value of integrated attribution approaches.....	186
7.2	Characterising climate-related human mobility	188
7.3	Disentangling human mobility drivers and attributability to anthropogenic climate change	193
7.4	Causal links to anthropogenic climate change.....	194
7.5	Policy implications.....	197
7.6	Avenues for future research.....	198
7.7	Concluding remarks.....	201
	<i>References</i>	202

Acknowledgements

Given the moderate gestation period of this thesis, I have accumulated a vast debt to many colleagues, friends, my family, and mentors, which it gives me great pleasure to acknowledge: The first thank you goes to my supervisor, Friederike (Fredi) Otto. I am grateful for her support, guidance, and advice throughout my time in Oxford. I cannot count the many times I left her office being inspired. I thank Fredi for her ability to stay relaxed and light-hearted in the academic setting of Oxford. Most importantly, Fredi has shown me that obstacles are not as impenetrable as they might have appeared initially. Danke!

Without extensive intellectual, moral, and financial support, none of this work would have been possible to achieve. I was awarded the opportunity to study in Oxford from the Evangelisches Studienwerk Villigst, and for that I am forever indebted. As an organisation, they were ceaselessly supportive and accommodating, especially during the COVID-19 pandemic. Thank you to Climate Econometrics and Nuffield College, for providing me with partial funding (and lunches) through my research assistantship. Further thanks go to the International Institute for Systems Analysis (IIASA) where I was able to participate in the Young Scientists Summer Program (YSSP) in 2020.

Throughout the DPhil, colleagues at the Environmental Change Institute have provided invaluable advice on science and life: James King, David Crowhurst, Thomas Caton Harrison, Meredith Li, Marcia Zilli, Raghav Pant, Jose Luis Ramirez Mendiola, and Alex Black. A special mention deserves Karsten Haustein for organising weekly Climate Pubs, bringing together colleagues from the Climate Research Lab and AOPP in Oxford, and most importantly, for being a true friend.

Over the years, many kind and insightful colleagues in Oxford have commented constructively and helpfully on my work, and in addition to those already mentioned, grateful thanks go to the members of my college, Christ Church: my tutor Simon Dadson, as well as Alex Vasudevan and Neil Hart. I am grateful for science chats with researchers from the humanities and theoretical physics; in particular thanks go to Alice Freeman, Alannah Jeune and Jane Chaffey, and August Malinauskas. Thank you to the Climate Econometrics core team, David Hendry, Felix Pretis, Angela Wenham, Moritz P. Schwarz, Xiyu Jiao, Jonas Kurler and Susana Martins.

Throughout my DPhil experience, I have been ably supported by a various friends and mentors across the globe, who have boosted my productivity, lowered my stress levels, and simply made me stay grounded: in geographical order; Germany - Mainz: Tala Mera, Michaela Werner; Salem: Christina Hansen and her partner Caspar Hopstock; Iserlohn: Andrej Berschauer and Bronislaw Nieradzick. Landau: Thank you to Wiltrud Eisenblätter (and her husband Volker Eisenblätter), who had been my geography

teacher during my secondary education and who has remained a dear pen pal for over fifteen years. New Zealand: My thanks travel to Christine Moore and Conrad Zorn in Auckland; for cheering me up, moral support and an amazing sense of humour. Many thanks to friends in my second home, the USA: to Tess Doeffinger for her endless support, for always believing in me and teaching me to take care of myself; also, to Darcy Jones and Sophia Rhee for remote support and friendship, as well as to Susan Swart for her mentorship throughout the years.

During the Coronavirus times, I have been fortunate to share my accommodation in Oxford with two of Christ Church's Junior Deans, Emily Swift and Nader Raafat, who have made the remainder of my DPhil studies an absolute blast. I am forever grateful to them for building me up, nerdy science conversations, art projects and Ready Steady Cook Saturdays; it was a true delight! The completion of this thesis benefitted from bi-weekly Deep Work sessions, which emerged from the IIASA YSSP program and that have been a constant companion over much of the past pandemic year; many thanks to my YSSP colleagues Maarten Brinkerink and Janet Molina Maturano for their continued company during these sessions.

I am indebted to Patryk Prężyna for his endless energy and wittiness helping me to finalise this thesis. I owe great debt to family: my parents, Mechthild Kratz and Frank Thalheimer, and my grandmother Margarete Thalheimer. My dear Mama thought my formal education would not see an end, but I am certain she is the first to be pleased that her prediction proved incorrect. Thank you for all the unconditional love and support, and for letting me explore the world. Finally, I would like to thank Michael Oppenheimer who risks hiring me as a post-doctoral research associate before the submission of my doctoral thesis.

List of Figures

Figure 1-1: Multi-causality of human mobility decisions, adapted from Black et al., 2011.....	8
Figure 1-2: Map showing the study area, including political boundaries and East African geographical region used in Chapter 3 and 4 (orange; 29°E to 52°E, 27°S to 15°N), Chapter 5 (blue; 41°E to 52°E, 2°S to 12°N) and Chapter 6 (green; 38 to 45°E, 2 to 7°N).	10
Figure 2-1: Timescale of attribution studies by selected types of extreme weather and climate-related event (heat, drought and precipitation and flooding). Data was obtained from the Carbon Brief Attribution Database (https://docs.google.com/spreadsheets/d/1aaAELrWlFQjmg_Gvwqjg5y6g4aXq7tMmJ3sPBm3R1xs/edit#gid=503631799).....	37
Figure 2-2: Geographical distribution of attribution studies. Data was obtained from the Carbon Brief Attribution Database (https://docs.google.com/spreadsheets/d/1aaAELrWlFQjmg_Gvwqjg5y6g4aXq7tMmJ3sPBm3R1xs/edit#gid=503631799).....	39
Figure 3-1: Conceptual framework of the dual-method framework.	51
Figure 3-2: Map of case study locations across East Africa. Dark grey indicates country case studies included in the review.	56

Figure 3-3: Heatmap of word frequency illustrates the distribution of mobility types, climate and contextual factors across the selected case studies. Contextual factors include four topics: conflict, economy, food security and social norms. Each topic consists of five to eight keywords derived from a list of the 100 most frequent words.	58
---	----

Figure S 3-1: PRISMA diagram illustrating the steps of the systematic literature review and case study selection.	73
---	----

Figure S 3-2: Distribution of topics across the case study corpus. The colour scale is normalised by topic keywords across the corpus and by individual topic per document. Note that publications containing the term climate change and climate are counted once. Normalised colour scale indicates the level of term-document association (a) and document-topic scores (b) indicate case studies where words associated with the topic appear.	81
--	----

Figure 4-1: Schematic illustration of the interactions between climate change effects in the six climate change impact sectors and different types of human mobility in a systems approach framework.	87
---	----

Figure 5-1: Internal displacement flows in Somalia 2016-2018, broken down by region and reason for displacement (circos plots: i, ii and network graph: iii). Lower right panel (iv) shows possible channel of effects across climate, conflict, and displacement.	111
--	-----

Figure 5-2: Climate effects on total displacement (Top) and displacement due to droughts (Bottom). Top panels show the temperature left) and precipitation right)	
---	--

effects on displacement over all temporal lags in the model. Shaded region shows the 95% confidence interval accounting for parameter uncertainty of lags and non-linear terms jointly. Arrows indicate the predicted percentage change in displacement in response to a one standard deviation change in temperatures or precipitation respectively at the base level indicated by the start of the arrow. A 95% confidence range of effects is shown in parentheses. 117

Figure 5-3: Climate effects on total displacement (Top, Relative Model) and displacement due to droughts (Bottom, Relative Model). Top panels show the effects of the relative differences in temperatures and precipitation on relative displacement aggregated over all temporal lags in the model. Shaded region shows the 95% confidence interval accounting for parameter uncertainty of lags and non-linear terms jointly. Arrows indicate the predicted percentage change in displacement in response to a one standard deviation change in temperatures or precipitation respectively at the base level indicated by the start of the arrow. A 95% confidence range of effects is shown in parentheses..... 118

Figure 5-4: Effect of conflict on total displacement (Top, controlling for climate) and effect of conflict on displacement due to conflict (Bottom, not controlling for climate). Histograms show the in-sample distribution of conflict events. Arrows indicate the predicted percentage change in displacement in response to a one standard deviation change in temperatures, precipitation, or conflict events respectively at the base level indicated by the start of the arrow. A 95% confidence range of effects is shown in parentheses..... 119

Figure 5-5: Linear probability model estimates for varying magnitude of conflict. Top panel shows the probability of any conflict occurring, middle panel shows the climate impact on the probability of exceeding 10 conflict events. Arrows indicate the predicted change in the probability of conflict events in response to a one standard deviation change in temperatures, precipitation, or conflict events respectively at the base level indicated by the start of the arrow. A 95% confidence range of effects is shown in parentheses. 120

Figure 5-6: Linear probability model estimates for varying magnitude of conflict while controlling for climate. Top panel shows the probability of any conflict occurring, lower panel shows the in-migration impact on the probability of exceeding 10 conflict events. Arrows indicate the predicted change in the probability of conflict events in response to a one standard deviation change in temperatures, precipitation, or conflict events respectively at the base level indicated by the start of the arrow. A 95% confidence range of effects is shown in parentheses. 121

Figure S 5-1: Lagged effects of temperature (top) and precipitation (bottom) on origin displacement. We show lags 0 to 4. 134

Figure S 5-2: Lagged effects of conflict on origin displacement. We show lags 0 to 4. 135

Figure 6-1: Probabilistic event attribution applied to human mobility. Extreme weather event and human mobility attribution schema (Otto, 2016; Philip et al., 2020). Event attribution studies follow a common, six step approaches: (1) event selection, (2) event

definition and framing, (3) observed probability and trend, (4) model validation and (5) model attribution and (6) synthesis and interpretation of these results. 151

Figure 6-2: a) Map of event definition showing absolute rainfall anomalies over the time of maximum precipitation (19-25 April 2020) in the origin region. Orange and red areas indicate locations with highest rainfall. b) Same for the impact region in South Somalia during 20-28 April 2020. 154

Figure 6-3: a) CHIRPS precipitation data and analysis over of the highest observed mean rainfall 30 days prior to the extreme event in the origin region. b) GEV fit where the location parameter μ (thick line), $\mu+\sigma$ and $\mu+2\sigma$ (thin lines) of the GEV fit of the 7-day averaged data. The same analyses are performed with a 9-day averaged data for the impact region, see 6-3c and 6-3d. 156

Figure 6-4: a) 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) 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). ... 157

Figure 6-5: Estimates of the change in risk, between preindustrial conditions (the year 1900 or ‘natural’ scenario) and the present conditions (the year 2020 or ‘current’ climate scenario) for the origin region with observations in blue, models in red and the

averaged synthesis in purple. For each bar, the black marker indicates the best estimate, and the shading depicts the range given by the 95% confidence interval. 159

Figure S 6-1: Rainfall time series 1901-2019 (Source: CRU TS4.0). The dashed line indicates the start of the CHIRPS timeseries in 1981. 168

Figure S 6-2: Mean precipitation over the study region over the period of 2018 to mid-2020 (source: CHIRPS)..... 168

Figure S 6-3: Fraction of attributable risk of the extreme event..... 171

Figure 7-1: Schematic of the integrated attribution approach (IAA), including the methods used in Chapter 5 (blue box) and Chapter 6 (green box)..... 186

List of Tables

Table 1-1: Classification and definition of human mobility types.....	6
Table 1-2: Overview of data sources on human mobility estimates for East Africa ..	12
Table 2-1: Reanalysis, gauge, and satellite data used in this thesis	27
Table 2-2: Historical and climate model data used in this thesis.....	29
Table 3-1: Climate data used in case studies. N/S indicates that no climate data is used for the analysis.	60
Table S 3-1: Search query for climate-related human mobility literature across five databases	72
Table S 3-2: Research sample with key factors of population mobility and spatio-temporal dimensions East Africa. N/S indicates insufficient information available; x indicates variable applicable. None of the case studies employed agent-based modelling. Therefore, we excluded this last variable from the classification matrix.....	74
Table 4-1: Summary of regional projected climatic changes and their effects in African drylands (including confidence levels). We distinguish between effects listed in SR15 and new research published since.	90

Table S 5-1: Summary statistics of the level models, listed individually for temperature, precipitation, total and drought displacement, and conflict.....	136
Table S 5-2: Summary statistics of the relative models, listed individually for relative temperature, precipitation, total and drought displacement, and conflict.	136
Table S 6-1: Classification and definition of human mobility types	165
Table S 6-2: Results of the GEV distribution fitting for the origin region. The table lists statistical methods and properties.	169
Table S 6-3: Results of the GEV distribution fitting for the impact region.	170
Table S 6-4: 7-day average EC-Earth23 RCP8.5 precipitation ensemble at the origin location.	172
Table S 6-5: 7-day average HadGEM2-ES RCP8.5 precipitation ensemble at the origin location.	173
Table S 6-6: Using threshold return period of 100 yr the return value in the year 2020 is estimated at the origin region.	174
Table S 6-7: Using threshold return period of 100 yr the return value in 2020 is estimated for the origin region with the HadGEM2-ES model.	175
Table S 6-8: Using threshold return period of 100 yr the return value in 2050 is estimated with EC-Earth 2.3 at the origin location.	177

Table S 6-9: Using threshold return period of 100 yr the return value in 2050 is estimated with HadGEM3-A at the origin location.	178
Table S 6-10: 9-day average EC-Earth23 RCP8.5 precipitation ensemble at the impact location.	179
Table S 6-11: Using threshold return period of 100 yr the return value in the year 2020 is estimated at the impact region.	180
Table S 6-12: Using threshold return period of 100 year the return value in 2050 is estimated at the impact region.	182
Table S 6-13: Synthesis of attribution results of precipitation at the origin region with a probability ratio of 1.62 (0.880E-01, 17.5), using common interval 1900-2020, with reference values -0.1621 0.9488.	183

List of Acronyms

AR5	IPCC Fifth Assessment Report
CENTRENDS	Centennial Trends
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station
CHIRTS	Climate Hazards Center Infrared Temperature with Stations
CMIP5	Coupled Model Intercomparison Project 5
CRU	Climate Research Unit (University of East Anglia)
EC-EARTH	EC-Earth Consortium: European Centre for Medium-Range Weather Forecasts (ECMWF) and other European institutes
ECMWF	European Centre for Medium-Range Weather Forecasts
ENSO	El Niño–Southern Oscillation
ERA5	Fifth generation ECMWF atmospheric reanalysis
FBF	Forecast-based Financing
GCM	Global Climate Model
GEV	Generalised Extreme Value
GMST	Global Mean Surface Temperature
HADGEM	Hadley Centre Global Environmental Model
HOA	Horn of Africa
IDMC	Internal Displacement Monitoring Centre
IDP	Internally Displaced Person
IHS	Inverse-Hyperbolic Sine
IOM	International Organization for Migration
IPCC	Intergovernmental Panel on Climate Change
NGO	Non-Governmental Organisation

OCHA	United Nations Office for the Coordination of Humanitarian Affairs
PEA	Probabilistic Event Attribution
PRMN	Protection and Return Monitoring Network
RCCC	Red Cross/ Red Crescent Climate Centre
RCP	Representative Concentration Pathway
SR15	IPCC Special Report on the Global Warming of 1.5 °C
SST	Sea Surface Temperature
TWFE	Two-Way Fixed Effects
UN	United Nations
UNHCR	United Nations High Commissioner for Refugees

1 Introduction

1.1 Background and rationale

East Africa is one of the most vulnerable regions to climate change and climate variability and the impacts from weather and climate-related events (Collier et al., 2008; Kew et al., 2021). The region is characterised by a traditionally mobile population, consisting of pastoralists and herders; human mobility is part of many livelihoods across East Africa, with populations in Kenya, Ethiopia, and Somalia heavily relying on rain-fed agriculture (Lyon, 2014b; Puma et al., 2018). In recent years, major weather and climate-related events, including floods and droughts have had significant social and economic impacts in this region. The 2015 drought in Ethiopia put an estimated 22 million people in need of food aid (Philip et al., 2017), and the 2016 Kenya drought led to over three million people in need of food aid (Uhe et al., 2018).

Political and economic factors are well-known drivers of migration. Indeed, migration is also a traditional adaptation strategy in the context of weather and climate-related events (Groth et al., 2020a; Owain & Maslin, 2018; Rigaud et al., 2018). The aim of this thesis is to identify the relative role of climate in driving human mobility. In the context of recent droughts in the region, several studies assessed whether and to what extent human-induced climate change played a role in the hazards with mixed results: For the 2011 drought in East Africa, a study found a contribution of climate change to the increase in probability of dry or drier than 2011 long rains (Lott et al., 2013). In contrast, no human-induced influence was found for a 2014 drought in the Horn of Africa (HOA) region (Marthews et al., 2019). A number of East African countries are also affected by recurrent conflict, internal displacement and political instability

(Internal Displacement Monitoring Centre, 2020), with the United Nations High Commissioner for Refugees (UNHCR) estimating that over 8 million people are currently internally displaced in the HOA region alone (UNHCR, 2020).

Globally, many weather and climate-related events have become more frequent and intense leading to widespread and disastrous impacts for populations globally (Hoegh-Guldberg et al., 2019); changes in the climate might enhance or reduce human mobility flows (Benveniste et al., 2020). For example, weather and climate-related events are estimated to have caused 30 million new internal displacements in 2020 (Internal Displacement Monitoring Centre, 2021c). In extreme cases, populations have previously migrated away from locations frequently impacted by weather and climate-related events (Gray & Mueller, 2012). However, populations in Bangladesh are projected to migrate towards coastlines affected by sea level rise (Bell et al., 2021).

In the existing literature, climate-related human mobility (see Section 1.2) is often portrayed as a key impact of anthropogenic climate change (e.g., Biermann & Boas, 2008; Myers, 2002; Rigaud et al., 2018). Despite the increasing abundance of qualitative evidence (e.g., Groth et al., 2020; Wiederkehr et al., 2018) on how and where populations migrate due to the impacts of weather and climate-related events, surprisingly little research has causally linked such evidence to anthropogenic climate change (Borderon et al., 2019; Cattaneo et al., 2019a). Causal evidence on attributable influences from anthropogenic climate change on human mobility is therefore not well understood and has suffered from disciplinary hurdles to date (Abel et al., 2019).

Since 2003, climate scientists assess how anthropogenic climate change alters the frequency and intensity of extreme weather events by applying probabilistic event attribution methods simulating the likelihood and intensity of weather and climate-related events with and without human-caused climate drivers (Otto, 2016). The impacts of anthropogenic climate change are projected to fall disproportionately upon countries in the ‘Global South’, with African countries particularly vulnerable to socio-economic effects from weather and climate-related events (Harrington & Otto, 2020; Hoegh-Guldberg et al., 2019). Progress on analytical techniques which include qualitative empirical research methods or ethnographies (e.g., Morrissey, 2013), mixed-method and meta-analysis approaches (e.g., Hoffmann et al., 2020; Scheffran et al., 2012) and statistical approaches (e.g., Bohra-Mishra et al., 2014; Hsiang, 2016) have improved our understanding of environmental drivers for human mobility (Klepp, 2017). To date, little to no research has been conducted on the attributable link between anthropogenic climate change and human mobility in the region of East Africa.

There is a clear need to better quantify the role of anthropogenic climate-change on weather and climate related events which adversely affect vulnerable people leading to migration and displacement. Together with the importance of human mobility, there is a pressing need to better understand different types of human mobility and the push-pull factors influencing human mobility.

This thesis advances this understanding with new empirical research from quantitative social science (climate econometrics), thus providing a new, dynamic methodological approach, the Integrated Attribution Approach (IAA), to address the gap between human mobility research and climate attribution. Making use of probabilistic event

attribution, alongside climate econometrics and qualitative social science methodologies, this thesis aims to assess to what extent these methods allow the identification of attributable links between anthropogenic climate change and recent human mobility in East Africa. A key contribution of this thesis is the use of observed data on human mobility with weather observations, climate model data and conflict variables for this region.

The rest of this chapter provides a more detailed overview of the state-of-the-art research on human mobility and climate change and the relevance and challenges for East Africa. It begins with the typology of human mobility (Section 1.2) before describing the study region and outlining its importance for human mobility in a changing climate (Section 1.3). Next, key challenges facing the climate-related human mobility research in the study area are highlighted (Section 1.4), which are used as motivation for this research. Finally, the specific research questions to be addressed and the thesis structure are outlined (Section 1.5).

1.2 Typology of human mobility

Human mobility takes different form across East Africa and is influenced by various factors ranging from weather and climate-related events to poverty and conflicts (Afifi et al., 2012, 2014; Owain & Maslin, 2018). It is important that there is some prior understanding of which processes influence decisions to move or stay, as this will help assess the extent to which weather and climate-related events contribute to such processes. Therefore, it is critical for this thesis to lay a foundation of the term ‘human

mobility’. There are three main types of human mobility, including (i) voluntary, (ii) forced migration or displacement and (iii) refugees. Situations of immobility can also occur, such as voluntary immobility and entrapment; however, these exceed the focus of this thesis. Contrary to modality in existing research (Adger et al., 2018; Boas, 2020; Farbotko et al., 2016), human mobility is not a synonym for migration in this thesis. Table 1-1 provides a taxonomy of human mobility types adopted herein.

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

Type	Definition	Relevant papers in this thesis
Migration	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 et al., 2011; International Organization for Migration, 2011).	Paper 1 and 2 (Chapters 3 and 4)
Displacement	The involuntary or forced 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 (International Organization for Migration, 2011). Displacement due to weather and climate-related events (disaster displacement) or conflicts (conflict-induced) are key trends within the theme of internal displacement (Internal Displacement Monitoring Centre, 2020).	Papers 1 to 4 (Chapters 3 to 6)
Refugee	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, for example, 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	Paper 1 (Chapter 3)

	order (United Nations High Commissioner for Refugees, 2019).	
Climate-related human mobility	Climate-related human mobility refers to population movements where adverse weather or climate conditions play a crucial factor in the decision to move (Boas et al., 2019).	Paper 2 and 4 (Chapters 3 and 6)

Human mobility decisions are often multi-causal and rarely due to weather and climate-related events alone. Climate change may influence human mobility both directly and indirectly through various channels ranging from economic, demographic, social, political and environmental factors as illustrated in Figure 1-1 (Black et al., 2011). These factors ultimately lead to a decision between staying or going – and where to migrate to if needed. In this context, there are several climatic factors that can both enhance and reduce human mobility (Cattaneo et al., 2019a; Hoffmann et al., 2020). Individuals can be forced to leave their homes and communities due to sudden-onset events such as tsunamis, landslides, and flood events, or slow-onset processes such as desertification and sea level rise (Bell et al., 2021; Feng et al., 2010a). 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; however, whether and to what extent these changes may manifest is unknown.

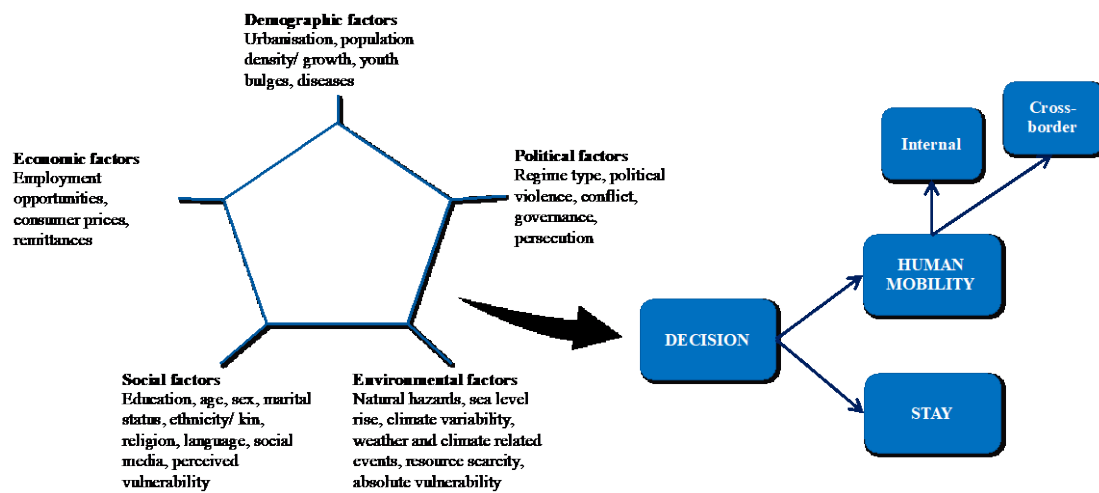


Figure 1-1: Multi-causality of human mobility decisions, adapted from Black et al., 2011.

In regions such as East Africa, which experience recurring weather and climate-related events, affected populations could run out of resources requiring them to migrate voluntarily. Taking migration, a form of human mobility as an example, recent literature (Abel et al., 2019) discusses mixed evidence on the extent to which climatic factors drive economic and socio-political crises and in turn, influence migration. Further, with an expected increase in average global temperature by 2100, there is little consensus regarding the direction and the extent to which these factors will influence migration and other types of human mobility (Hoffmann et al., 2020). Reemphasising the gaps in the evidence landscape and the potential large-scale impacts from climate change, it is critical to assess implications for climate-related human mobility based on empirical data-driven evidence now; inertia is not an option.

1.3 Study area

East Africa as referred to in this thesis, covers an area that contains part or all of the following countries: Ethiopia, Kenya, Mozambique, Somalia, Tanzania and Uganda (Figure 1-2). Each of the research chapters use different geographical extents depending on the specific research and data availability. The largest geographical area used in this thesis spans 29°E to 52°E and 27°S to 15°N, covering the broad East African region. The geographical area used in Chapters 5 and 6 in contrast is much smaller, accounting for the granular data of internal displacement in Somalia, which is the focus of these chapters. For simplicity, this thesis will use ‘East Africa’ to describe the broad region and ‘Somalia’ to describe a country case area or feasibility study.

East Africa has recently experienced a series of extreme weather and climate-related events ranging from droughts to extreme precipitation and flooding, for example, the Ethiopia drought in 2015 (Philip et al., 2017), the 2016/2017 drought (Uhe et al., 2018) and 2018 extreme precipitation (Kilavi et al., 2018) in Kenya. For simplicity, this thesis will use the term ‘weather and climate-related events’ to describe extreme weather and associated events and climate variability. Around 17.5 million people are at risk from food shortages in Ethiopia, Somalia, and Kenya (Funk, 2020) and interlinks have been suggested between drought and conflict in Somalia (Maystadt & Ecker, 2014; Thalheimer & Webersik, 2020).

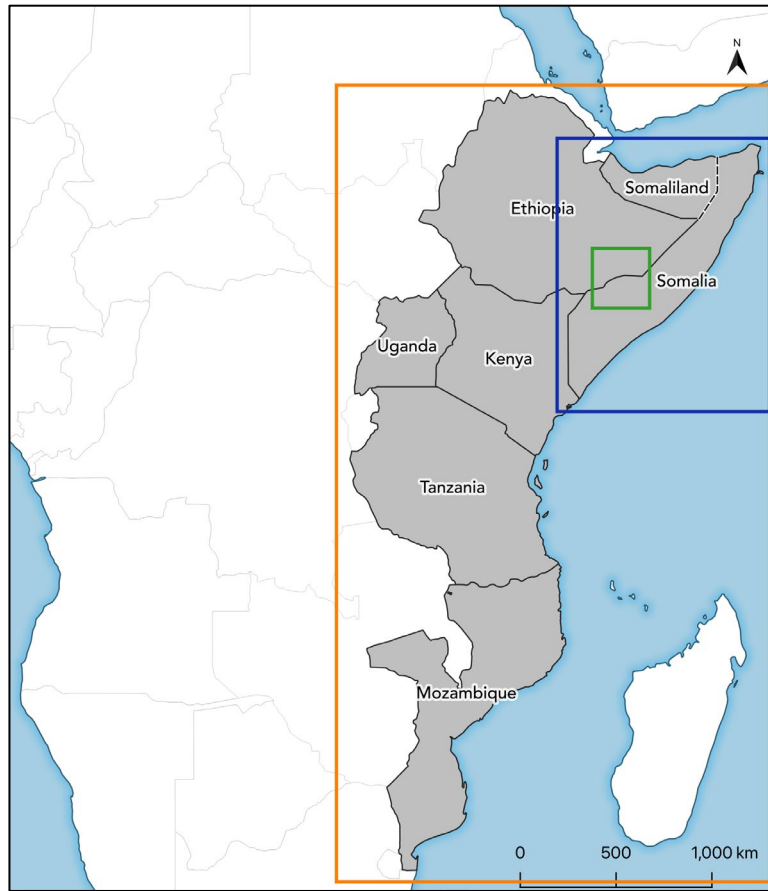


Figure 1-2: Map showing the study area, including political boundaries and East African geographical region used in Chapter 3 and 4 (orange; 29°E to 52°E, 27°S to 15°N), Chapter 5 (blue; 41°E to 52°E, 2°S to 12°N) and Chapter 6 (green; 38 to 45°E, 2 to 7°N).

1.4 Key challenges and knowledge gaps

Globally, nearly 1,900 weather and climate-related events triggered 24.9 million new displacements across 140 countries and territories in 2019; these are the highest figures that have been recorded since 2012 (Internal Displacement Monitoring Centre, 2020). Collecting such data is a key challenge facing the research on climate-related human mobility given the extreme scarcity of recent observational data in the study area. In terms of climate data, Africa is considered a data scarce region with key weather and

climate-related events having been consistently underreported (Otto, Harrington, Frame, et al., 2020). This is particularly stark in East Africa, which has some of the lowest reporting rates globally (Dinku et al., 2018). In Somalia, there have been no reporting rain gauges since the outbreak of the civil war in the 1990s (Dinku et al., 2011). Overall, the density of rain gauge clusters is sparse across East Africa with the number of reporting rain gauges across tropical Africa having decreased by a factor of 10 over the last 40 to 50 years (James et al., 2018; J. King et al., 2020). Consequently, the analyses in this thesis make use of gridded rainfall and temperature datasets, further described in Section 2.2.3.

Different types of human mobility data are collected in the study region by international organisations, such as the International Organization for Migration (IOM), the Internal Displacement Monitoring Centre (IDMC) and the United Nations High Commissioner for Refugees (UNHCR); Table 1-2 provides an overview of the data sources. A key challenge of the available data lies in its spatio-temporal characteristics: Most human mobility data available is aggregated to yearly observations at national scales; only one dataset focused on internal displacement in Somalia provides disaggregated, monthly-subnational datapoints. There have also been efforts to develop methods using remotely sensed images to overcome methodological challenges in environmentally motivated human mobility and the ability to calibrate and expand the limited or sparse ground-truthed data (Heslin & Thalheimer, 2020). The scarcity of observational data points has hampered progress on the quantification of complex drivers in human mobility in the context of weather and climate-related events and resulted in an overall lack of understanding of attributable links to climate change.

Table 1-2: Overview of data sources on human mobility estimates for East Africa

Type	Countries/ Region	Level	Timeseries	Data collection
Migrant stock	Global	National	Yearly	IOM Global Migration Data Portal
Refugees	Somalia, Uganda, Kenya, Djibouti, Eritrea, Ethiopia, Yemen	National	Yearly	UNHCR Open Data Portal
Internal displacement due to conflict and disasters	Global	National	Yearly	IDMC
Internal displacement	Somalia	Puntland; South Central; Somaliland	Yearly	UNHCR Open Data Portal
Migrant death	Horn of Africa	Region	Monthly, 2014-2021	IOM Missing Migrants Project
Internal displacement (reported drought, flood, or conflict as key reason)	Somalia	Subnational	Monthly, 2016-2021	UNHCR Somalia

1.5 Detailed research questions

The preceding section justifies the geographical focus on East Africa in this thesis. It summarises what is already known about human mobility of this region and the challenges towards attributing climate-related human mobility. The lack of recent, homogenous weather, climate and human mobility observations and attention to link these to climate change, has hampered efforts to observe any linkages between climate effects and human mobility. In turn, producing reliable projections of climate change impacts on human mobility is lacking. Given that data availability is unlikely to

improve in the near future, perhaps exacerbated by the COVID-19 pandemic, focus needs to be placed on providing methods for disentangling drivers in climate-related human mobility and improving models which investigate links to anthropogenic climate change. Recent efforts have highlighted the importance of “effective, rigorous, and scientifically defensible analysis” (National Academies of Sciences, Engineering, and Medicine et al., 2016, p. ix) of weather and climate-related events to climate change with a focus on Africa (Otto et al., 2020); taking into account particular challenges in the region ranging from food insecurity to drought affecting populations (Funk, 2020; Puma et al., 2018).

Sections 1.2 and 1.3 outlined the important regional processes which are known to contribute to human mobility in the study area, highlighting the role of multi-causal drivers of human mobility. In addition, previous research into drivers of human mobility across space and time indicates an important role for dynamical processes contributing to human mobility, as well as highlighting that future warming often relates to more forced types of human mobility. These findings indicate that attributing human mobility to anthropogenic climate change should start by exploring causal pathways that underlie these processes.

Important dynamics in the human mobility processes include weather and climate-related events (Cattaneo et al., 2019a). This thesis will focus on the representation of multi-causality in human mobility (see Figure 1-1) and on the recognition that impacts from weather and climate-related events are time and space-dependent. It also focusses on the applicability of the attribution methodology in a feasibility study on internal displacement in Somalia. Applying the attribution methodology for East Africa herein

will provide useful insights and a readily transferrable procedure for other data scarce regions.

1.5.1 Research questions

The aims of this thesis are twofold. First, it aims to contribute to an improved understanding of the impacts of weather and climate-related events on human mobility - voluntary and involuntary forms - in East Africa and links to anthropogenic climate change. This work will assess the differences amongst East African countries and will attempt to elucidate existing evidence and develop methodologies towards providing such evidence. An understanding of the representation of these methods and data across East Africa will be used to try to determine the scientific credibility of different lines of evidence on the links between weather and climate-related events, human mobility, and anthropogenic climate change, in light of the sparsity of observational climate and human mobility data.

To achieve this aim, the first overarching research questions for this thesis are therefore:

- i. *To what extent can weather and climate-related events in the form of droughts and floods explain human mobility in East Africa?*
- ii. *What is the current understanding of the implications for human mobility under future warming in East Africa?*

The second aim of this thesis is to determine the marginal contribution of weather and climate-related events in human mobility. Data on weather and climate and conflict-

related drivers of internal displacement are the primary data available to investigate causalities in human mobility drivers, but there has been limited research into their attributability to anthropogenic climate change in understudied and poorly observed regions such as Somalia. This work will contribute towards a better understanding of why people become displaced in East Africa, how this differs regionally and will be an important initial step towards providing usable information for regional decision makers and climate change impact researchers.

In light of this aim, two further research questions are therefore:

- iii. *How can we disentangle and quantify the drivers of human mobility in the study area?*
- iv. *Whether and to what extent does anthropogenic climate change alter the likelihood of climate-related human mobility today?*

1.5.2 Thesis Structure

The analysis of this thesis falls into two parts. The first part, comprising Chapters 3 and 4, assesses the existing literature for links between weather and climate-related events and human mobility in the historical period using a mixed-method methodology (Chapter 3), and a content analysis (Chapter 4) of the existing literature concerning the implications of future warming on human mobility in the study area.

The second part, comprising Chapters 5 and 6, first applies quantitative methods from social science to analyse the effects of climate on human mobility and then attempts to

attribute human mobility associated with weather and climate-related events to anthropogenic climate change. The results provide insights to what extent the attribution of climate changes human mobility in the study region. The overall methodological aim of this thesis is thus to develop and test a framework for attributing climate-related human mobility to anthropogenic climate change. The end product of this thesis is an integrated attribution approach.

This thesis has been submitted via the “paper route”, whereby the research chapters (Chapters 3 to 6) take the form of academic papers that have been submitted to peer-reviewed journals. The minimum requirement is that three papers are submitted. This thesis includes four articles, all of which have been submitted. The first paper (Chapter 3) and the fourth paper (Chapter 6) are under review, the second one (Chapter 4) is in revision, and the third paper is submitted (Chapters 5). The research papers’ supplementary material is included at the end of the relevant research chapters. The details of the papers are below, together with an outline of the research questions for each research chapter. Each paper includes the statement on the authorship preceding the content of the research chapter. The content of each research chapter is the same as appears in the submitted version of the paper. However, figure and table numbers have been altered to provide coherency throughout the thesis. In addition, the internal layout of some figures has been adapted to improve readability.

Chapter 3: Deciphering Impacts and Human Responses to a Changing Climate in East Africa

Thalheimer, L., Otto, F.E.L. and Abele, S. Deciphering Impacts and Human Responses to a Changing Climate in East Africa, *Frontiers in Climate* (accepted 8th July 2021)

Chapter 3 aims to answer the first research question in Section 1.5.1:

- i. To what extent can weather and climate-related events in the form of droughts and floods explain human mobility in East Africa?*

Previous research has suggested the relationship between human mobility and climate change can help to explain the links and regional differences of such links. The analysis in Chapter 3 addresses all East African countries and is as such the first comprehensive assessment of human mobility and climate change in the study region. Specifically, Chapter 3 asks:

- Which methods are used to investigate complex linkages between weather and climate-related events and human mobility within the relevant literature?
 - o How is human mobility defined and classified, and how are weather and climate-related events defined?
 - o Does the literature specify the theoretical-conceptual approach?
- Which human mobility drivers, e.g., socio-economic, demographic, and environmental, does the literature assess?
- To which extent is anthropogenic climate change inferred?

Chapter 4: Advancing the evidence base of future warming impacts on human mobility in African drylands

Thalheimer, L., Williams, D.S., Van der Geest, K., Otto, F.E.L. Advancing the evidence base of future warming impacts on human mobility in African drylands, *Earth's Future* (submitted 30th December 2020, in revision since 2nd April 2021)

Chapter 4 addresses the second research question:

- ii. *What is the current understanding of the implications for human mobility under future warming in East Africa?*

This chapter uses a content analysis to review the current and future impacts of climate change on African drylands considering the evidence from the IPCC 1.5 Special Report and more recent literature, with a focus on the implications for population mobility.

The specific research questions in Chapter 4 are:

- To what extent does the IPCC 1.5 Special Report investigate climate change impacts for human mobility in African drylands?
 - o Which are the climate change impact sectors most relevant for human mobility?
 - o What are cross-sectoral implications for human mobility under future warming?
- How can we address the interconnectedness of climate change impacts and the cascading risk of future warming?

Chapter 5: Disentangling the effects of climate and conflict on displacement: Evidence from Somalia

Thalheimer, L., Schwarz, M. P., Pretis, F. Disentangling the effects of climate and conflict on displacement: Evidence from Somalia, *Science* (submitted 01st June 2021)

Chapter 5 will address the third research question:

- iii. How can we disentangle and quantify the drivers of human mobility in the study area?*

This chapter focusses on the modelling of effects of weather and climate-related events and conflict and insecurity events on forced population movements in the form of internal displacement in Somalia. It uses econometric methods (two-way fixed effects) to attribute reported displacement reasons with climate observational data and conflict data from 2016 to 2018. Specifically, Chapter 5 asks:

- What effects from weather and climate related events and conflict result in internal displacement in Somalia?
 - o What is the relative effect of weather and climate-related events on internal displacement?
 - o What is the relative effect of conflict on internal displacement?
- What are the methodological advantages and limitations of climate econometric methods for assessing weather and climate-related human mobility?

Chapter 6: Towards attributing climate-related displacement in Somalia to anthropogenic climate change

Thalheimer, L., Li, S., Muttarak, R., Crespo Cuaresma, J. Mechler, R., Otto, F.E.L.
Towards attributing climate-related displacement in Somalia to anthropogenic climate change, *Scientific Reports* (submitted 17th April 2021)

Finally, Chapter 6 will address the fourth research question:

- iv. Whether and to what extent does anthropogenic climate change alter the likelihood of climate-related human mobility today?*

This chapter uses probabilistic event attribution (PEA) techniques to explain attributable links between extreme rainfall in Ethiopia (origin area of the extreme event) which led to riverine flooding and internal displacement in southern Somalia (impact area). In line with previous research and the previous chapters, the representation of rainfall impacts is assessed, and the extent to which changes in these processes are attributable to anthropogenic climate change. The event assessed is the April 2020 flooding in Somalia, which exhibits the strongest rainfall signal across models, and for which assessing the likelihood of rainfall changes is particularly important to the population affected. The specific research questions in this chapter are:

- In how far is the PEA framework applicable and feasible to investigate attributable links between weather and climate-related events and associated displacement?
- What is the physical process related to flood-related displacement, and where does it originate and impact populations in the form of internal displacement?

- Based on this assessment, can we determine whether there is an attributable link between extreme precipitation in the origin area that resulted in flooding and flood-related displacement in Somalia?

2 Data and Methods

2.1 Introduction

This section outlines the observational and model data used in the analysis in this thesis, as well as the methods used to analyse human mobility and attribution of climate change. Individual research chapters also include a Data and Methods section which details the respective data choices and methods employed.

2.2 Data

There are four main types of data used in the analysis of the research chapters: internal displacement data (2.2.1), conflict data (2.2.2), weather and climate-related data (2.2.3) and climate model data (2.2.4).

2.2.1 Displacement data

The observational human mobility data used in this thesis is taken from the United Nations High Commissioner for Refugees (UNHCR) initiative Protection & Return Monitoring Network (PRMN), an open-source dataset available via UNHCR's GitHub repository (<https://github.com/unhcr/dataviz-somalia-prmn>). PRMN identifies and reports on new internal displacements including returns of populations in Somalia. The monthly data is available from January 2016 to near present and is updated monthly. PRMN collects the primary reason for monthly new internal displacements of populations at the destination region as well as their point of departure (i.e., origin

region). The reported reasons geographically cover all 18 regions of Somalia and are divided into the four categories (1) drought, (2) flood, (3) conflict / insecurity and (4) other and geographically covers all 18 regions of Somalia. The data collection approach follows a monitoring of internal displacements and movements, such as returns by targeting strategic points such as transit sites, established internal displacement persons (IDP) settlements, border crossings and other ad-hoc locations which are not further described. To obtain data points, interviews are carried out with displaced persons generating “household-level” reports primarily at points of arrival or with key informants generating “group reports” (UNHCR Somalia, 2017).

The limitations of this dataset are discussed in Chapter 5 and can be summarised as follows: The data collected captures the main reason for displacement, while secondary reasons or a combination of reasons leading to the displacement of populations are undisclosed. The observational data does not allow for counting the stock of IDPs at a given time, nor does it allow for tracking population’s return or integration into host communities. The main advantage of the PRMN dataset for this thesis is that it comprises the geographical granularity as well as the primary reason of displacement. The analysis in Chapter 5 utilised the granularity of this dataset to disentangle internal displacement reasons associated with weather and climate-related events as well as conflict and insecurity, and attribute these reasons with observational data on conflict, weather, and climate. The data is arranged in panel data format. Chapter 6 used data on flood-related internal displacement to support the event definition of the attribution study.

2.2.2 Conflict data

Georeferenced, disaggregated events-level conflict data is used in Chapter 5 of this thesis. The Armed Conflict Location and Event Dataset (ACLED) measures conflict in several regions globally, including 55 countries in Africa (Raleigh et al., 2010). ACLED contains geo-coded, point-level data with the date and the type of conflict for all reported conflict events. Other conflict datasets such as the Uppsala Conflict Data Programme Georeferenced Event Dataset were not used as they contain a reporting threshold of fatalities or a limited spatial coverage (Raleigh & Kishi, 2019). For this thesis, the dataset has two main advantages: it provides almost-global spatial coverage, and it provides outputs on a number of conflict-related variables, including location, date, type of conflict, conflict actors and persons affected. Chapter 5 uses the dataset to analyse the effects of conflict, measured by the count of conflict events, on internal displacement in Somalia. The data utilised contains the location, actors involved, fatalities and conflict event counts; data points were aggregated to monthly conflict events at the regional level. The monthly timeseries used in the analysis of this thesis includes the data from 2016 to 2018.

2.2.3 Weather and climate reanalysis, gauge, and satellite data

Reanalysis, gauge, and satellite data are used to assess extreme dry and wet events in Chapters 5 and 6. Two main datasets are used in these research chapters of the thesis (Table 2-1): the Climate Hazards Group Infrared Precipitation with Stations version 2.0 (CHIRPS) (Funk, Peterson, et al., 2015) and Berkeley Earth (Rohde et al., 2013).

The CHIRPS dataset, a high-resolution dataset combining rain gauge and satellite data, is used for rainfall estimates in Somalia. There are no currently active rain gauges in Somalia contributing to CHIRPS (Dinku et al., 2018). However, this dataset has been extensively evaluated and validated over the wider Horn of Africa (HOA) region by researchers independent of its developers. Consistently, it has been found to provide the best-performing gridded rainfall dataset with regards to its initial development purpose of drought monitoring (e.g., Philip et al., 2017; Uhe et al., 2018), and also for analysing precipitation extremes (e.g., Fučkar et al., 2020). CHIRPS rainfall data was obtained from the Climate Hazards Group at the University of California, Santa Barbara (ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/global_monthly/netcdf/).

Chapter 5 uses observational temperature data from Berkeley Earth to analyse the effects of regional temperature anomaly extremes on internal displacement. Berkeley Earth is a land-only product that contains a monthly gridded temperature and a daily gridded homogenized temperature anomaly field. The dataset draws from a wide set of data sources, including the Colonial Era Weather Archive and the Global Climate Observing System (Funk et al., 2019). New algorithms reduce inhomogeneities identified in station time series caused by events such as station movement and instrument changes and measure their impact. Each daily time series is then transformed into a series of temperature anomalies. This is done by subtracting from each daily observation the corresponding monthly average (with respect to the 1951 to 1980 climatology time frame) at the same station. These daily anomaly series are then combined using a statistical method to interpolate data (kriging) from stations to arbitrary locations on the Earth. The daily maximum temperature anomaly field is available from 1880 to 2020. Observational input data and gridded spatial-temporal

fields are provided at the Berkeley Earth website (<http://berkeleyearth.lbl.gov/regions/somalia>). None of the satellite and gauge datasets have been interpolated and therefore, retain their native resolution in the analyses of Chapters 5 and 6.

Table 2-1: Reanalysis, gauge, and satellite data used in this thesis

Dataset	Type of data	Resolution	Variables used	Dates used
CHIRPS	Merged satellite and gauge	0.05°x 0.05°	Rainfall (Pr) anomalies: $Pr_{\min}$, Pr_{mean} , $Pr_{\max}$	1981-2020
Berkeley	Reanalysis	1°x 1°	Temperature (T) anomalies: $T_{\min}$, T_{mean} , $T_{\max}$	1880-2018

2.2.4 Climate model data

Two main climate model datasets are used in this thesis: EC-Earth (Hazeleger et al., 2010) and HadGEM3-A (Ciavarella et al., 2018); Table 2-2 provides details of these datasets. The analysis in this thesis focussed mainly on historical weather and climate-related events. It also incorporates climate model data from the 5th generation Coupled Model Intercomparison Project (CMIP5; Taylor et al., 2012).

Chapter 6 utilised observational data from CHIRPS and model data from monthly CMIP5 scenario runs. The analysis in Chapter 6 followed the World Weather Attribution methodology (Philip et al., 2020) and focussed on historical and future simulations of the climate. To do this, two sets of runs were utilised: the first one

comprising historical runs using CHIRPS and HadGEM2-ES data. Then, two scenario runs were performed: the fully coupled EC-EARTH 2.3.16-member ensemble at a 150 km resolution using the CMIP5 historical/ RCP8.5 protocol, and a 15-member ensemble from the HadGEM3-A model, the atmospheric component of the Met Office's Global Environment Model version 6. HadGEM2-ES runs (Collins et al., 2011; Jones et al., 2011) was utilised to develop historical runs for the HadGEM3-A model attribution simulations.

RCP8.5 scenario runs (1930-2050) are forced with the most extreme representative concentration pathway (RCP). RCP8.5 represents a radiative forcing greater than 8.5 W m⁻² by 2100. This scenario is chosen over less extreme scenarios due to the high vulnerability of the study region under such conditions. Another reason lies in practicability: EC-Earth 2.3 and HadGEM3-A RCP8.5 scenario data used for the analysis in Chapter 6 was chosen in part as it is readily available on The Royal Netherlands Meteorological Institute (KNMI) Climate Explorer and as the datasets effectiveness have been confirmed in recent attribution studies of East Africa (Kew et al., 2021; Otto et al., 2018). Each scenario run compares the period 2020-2050 in the RCP8.5 scenario runs to the period 1930-2020 in the historical runs. The EC-Earth 2.3 data was obtained via the KNMI Climate Explorer (<http://climexp.knmi.nl/>).

Table 2-2: Historical and climate model data used in this thesis

	Historical and model runs	Variable used	Years available (used)
EC-Earth	CHIRPS	Pr	1981-2020 (2020)
	EC-Earth 2.3 RCP8.5		1860-2100 (1930-2050)
HadGEM	HadGEM2-ES RCP8.5	Pr	1981-2020 (2020)
	HadGEM3-A		1859 to 2299 (1930-2050)

2.3 Methods

This section will first describe the methods used to characterise weather and climate-related human mobility throughout this thesis. It will then explain the primary method of analysis used to disentangle drivers of human mobility, before describing the techniques used within this thesis to attribute anthropogenic climate change, both in the historical and future period. Given the limited amount of observational data over East Africa, the analysis in this thesis starts broadly, covering a range of human mobility types and drivers, before narrowing to focus on a country case study on Somalia and internal displacement. The remainder of the thesis develops an integrated attribution approach for disentangling human mobility drivers (Chapter 5) and for attributing anthropogenic climate change in weather and climate-related event driven human mobility (Chapter 6) which by extension, may be producing the most plausible fractions of risk of forced population movements in this region. This overarching method is developed to be of particular use in regions affected by conflict and vulnerable to

climate change impacts, as it assesses the full causality, from emissions to socio-economic impacts.

2.3.1 Characterising climate-related human mobility

Reviews on human mobility in East Africa tend to focus on environmental factors instead of climatic factors. Given the scale of differences in human mobility across the study region and the limited understanding of weather and climate-related drivers due to the lack of incorporation of climate data, the analysis in this thesis will start broadly by characterising climate-related human mobility in East Africa. This is predicated on the understanding that the process of human mobility is in part linked to weather and climate and a lack of climate observations and data in evidence would likely not be credible to corroborate statements about climate change-induced human mobility.

The first research chapter (Chapter 3) presents a broad overview on multi-causal factors relating to human mobility in East Africa, in particular climate variability and extreme weather events, which have previously been identified as important factors in the complexity of human mobility in Africa (Borderon et al., 2019; Rigaud et al., 2018). Chapter 3 focuses on a review of the literature, as a first step in understanding the which weather and climate-related events as a motivation behind differences in human mobility, as well as the data landscape presented in the literature. This is done through a mixed-method approach of a case study analysis and a topic modelling approach.

The first step in characterising the complexity of human mobility in the study region is to select relevant evidence through a systematic literature review. Once the evidence is selected, a qualitative case study analysis is performed to categorise the literature according to various factors including the type of human mobility, weather and climate data used, and the contextual factors contributing to human mobility. To explore the relationship of multi-causal factors of human mobility within each case study and across the selected literature, a supervised machine-learning approach in the form of topic modelling approaches is used. Topic modelling comprises machine learning techniques aiming to explore text collections thematically. Chapter 3 uses this approach to classify the selected literature after the initial categorisation through the case study analysis.

Chapter 4 follows directly from the findings of the previous chapter. It focuses on the IPCC (IPCC, 2018) special report on global warming of 1.5 °C, in this thesis abbreviated as ‘SR15’ to characterise climate-related human mobility under future warming. As quantitative evidence of the future warming impact on human mobility itself are presented as a knowledge gap in SR15, a content analysis is used in the first instance rather than more complicated modelling techniques. In this way, researchers can gain a more holistic understanding of climate-related human mobility and attempt to avoid implying *per se* causal links of human mobility to climate change. However, given the wider impacts of future warming on the complexity of human mobility, it is important to interrogate the attribution of anthropogenic climate change produced by models. The influence of local weather and climate-related events is specifically investigated in Chapter 5, and a further attribution study concerning human-induced climate change signals in Chapter 6.

There are some limitations to methods used to characterise human mobility, which have been considered in this thesis. First, topic modelling approaches are usually selected for larger collections of the literature (Lamb et al., 2019), so the inclusion of the method in a smaller collection can skew the sample. To guard against this and since the selected literature follows roughly the same theme – that being climate-related human mobility in East Africa, contextual clues are used to connect words with similar meanings and distinguish between uses of words with multiple meanings. Second, in the analysis of the literature, there are a small number of literatures that concerns East Africa (as acknowledged by (Guldberg et al., 2018)). To address this limitation, the geographical scope of Chapter 4 has been expanded to African drylands, including literature which has been published post IPCC SR15.

2.3.2 Disentangling human mobility drivers

To disentangle weather and climate-related factors from other factors, e.g., political tensions or conflict contributing to human mobility, this thesis utilises techniques from quantitative social science, climate econometrics, which are described in the following section.

2.3.2.1 *Climate econometrics*

Climate econometrics has emerged as a sub-discipline within the quantitative social sciences which aims to identify the effect of climate on societies, and vice versa (Castle & Hendry, 2020; Hsiang, 2016). Changes to weather and climate can affect societies in

miscellaneous ways; however, there are two primary impacts. First, direct effects from weather and climate-related events on populations; a simple example would be rain generating puddles, causing people to put on Wellington boots. Second, populations' beliefs about the weather, climate, and changes thereof may affect their decisions and resulting outcomes; for example, if people believe their climate is rainy, some will buy Wellington boots. The same two climate effects, direct and decision-based ones can be applied to investigate attributable links between human mobility and climatic factors such as the weather and climate-related events this thesis focusses on. Information on attributable links may also be utilised to inform projections of climate-related human mobility decision outcomes under future warming.

Recent evidence illustrates how key innovations of research design, the measurement of climatic factors, and the formulation of econometric models have contributed to identifying climate effects on socio-economic outcomes. These have in turn, reshaped and reemphasised the need to deepening our understanding of human responses in a changing climate (Carleton & Hsiang, 2016); taking into account the relative impacts of these changes (Pretis et al., 2018). Climate econometric tools are complementary and utilise a set of empirical techniques to identify common patterns and allow for direct linking of climate data and models with empirical data (Pretis, 2021).

Previous studies have applied climate econometric methods to examine the effect of weather, climate, and changes thereof on agricultural yields and responding cross-border migratory events between Mexico and the United States (Feng et al., 2010a) and within South Africa (Mastrorillo et al., 2016). In Indonesia, a microlevel study investigates the effect of precipitation and temperature changes on permanent migration

outcomes (Bohra-Mishra et al., 2014). The effect of climate on conflict and asylum-seeking persons is explored in a global study that uses aggregated data of yearly asylum flows with climate and conflict observations (Abel et al., 2019).

2.3.2.2 The effects of weather and climate-related events on human mobility

To disentangle and study how weather and climate-related events affect populations; this thesis relies on panel data (observed data on climate, conflict, and human mobility for multiple regions over time) and uses two-way fixed effects (TWFE) panel models. An understanding of the functionality of the panel model and its underlying concept are crucial to the methods applied.

This thesis utilises panel data (also called longitudinal data) to better understand internal displacement over time. TWFE linear regression models are considered a standard method for estimating causal effects from panel data (Imai & Kim, 2020). The TWFE model allows for unit-specific intercepts and common time effects to estimate the effect of climate and conflict on internal displacement in Somalia. This methodological approach allows for a detailed understanding of when and where climate effects are the driving factors of internal displacement over time. While such panel estimators allow for individual fixed effects and common time effects, models of displacement of conflict may still suffer from endogeneity due to feedback: the effect of conflict on conflict-related displacement may occur contemporaneously with immigration causing conflict at the destination region.

The identification strategy aiming at exploiting the granular nature of the displacement data, allows us to disentangle the three reasons of displacement reported in the dataset, which are explained in detail in Section 2.2.1. The study in Chapter 5 considers the following base model (Eq. 1), where i refers to the region for response category c (aggregate climate, drought, or conflict as the reported displacement reason) in time t (capturing each month-year),

$$\log(Displ)_{c,i,t} = \alpha_{c,i} + \lambda_{c,t} + Clim_{i,t}\beta_c + Conf_{i,t}\gamma_c + \epsilon_{c,i,t} \quad [1]$$

for $i = 1, 2, \dots, N$, and $t = 1, 2, \dots, T$. Region fixed effects $\alpha_{c,i}$ account for different baselines of out-migration across regions, while time fixed effects $\lambda_{c,t}$ capture common features affecting all regions. Coefficients on climate variables are given by $\beta_c = (\beta_1, \dots, \beta_{K_{clim}})'$, $\gamma_c = (\gamma_1, \dots, \gamma_{K_{conf}})'$, with K_{clim} denoting the total number of climate variables in the model, and K_{conf} refers to total conflict variables.

2.3.3 Attributable links to anthropogenic climate change

There are compelling reasons to study attributable links between weather and climate-related events that affect populations and climate change. The physics behind our climate system is generally well understood, and so are the broad-scale impacts of additional greenhouse gases on this system. However, much can still be learned about the impact of a changing climate on weather and climate-related events affecting populations. The integration of societal impacts, including the predictions of associated extreme weather and climate-related events, may showcase a more nuanced and

sophisticated understanding of the climate-human-interface. This section first describes the method of probabilistic event attribution before outlining its opportunities in the context of human mobility and the attribution approaches utilised in this thesis.

2.3.3.1 Probabilistic event attribution

Attribution studies describe the process of causally evaluating relative contributions from a range of factors to changes in the climate or weather and climate-related events with an assignment of statistical robustness (Hegerl et al., 2010). Probabilistic Event Attribution (PEA) comprises process-based and statistical methods to assess whether and to what extent the likelihood, frequency and intensity of weather and climate-related events are changing compared to its natural climate variability, and conversely, how much of that change is attributable to anthropogenic climate change (Stott et al., 2016).

Recent decades have seen an increase in interest from the public and scientific advancement in the field of attribution science (Figure 2-1), an evolving methodology that has repeatedly been shown to be robust (Kew et al., 2019; Otto et al., 2018; Philip et al., 2018).

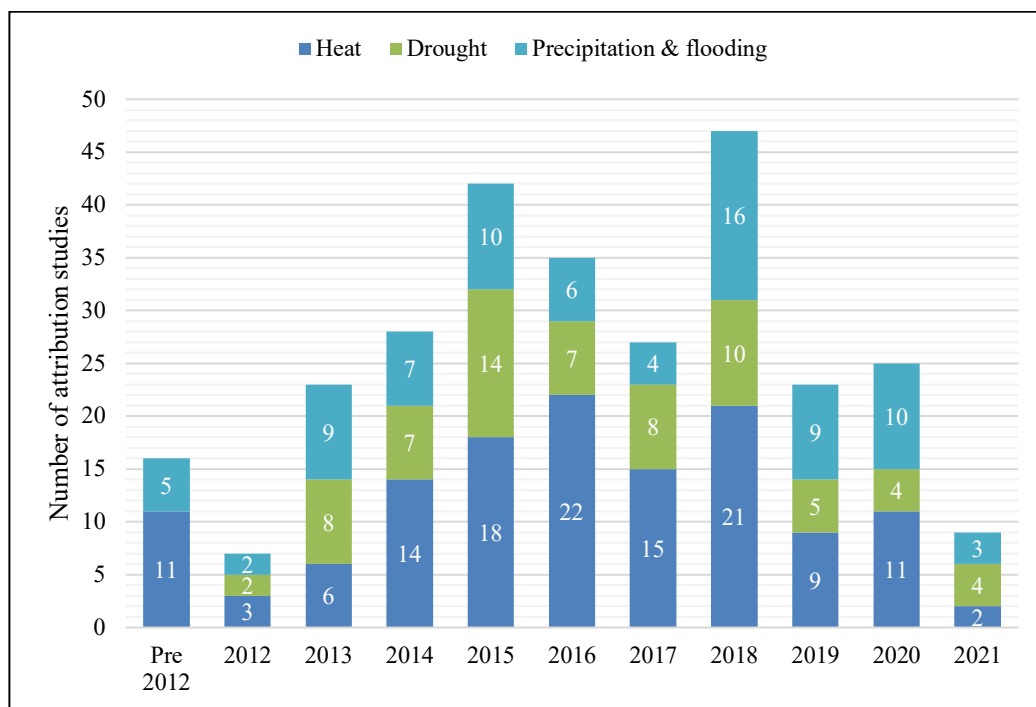


Figure 2-1: Timescale of attribution studies by selected types of extreme weather and climate-related event (heat, drought and precipitation and flooding). Data was obtained from the Carbon Brief Attribution Database (https://docs.google.com/spreadsheets/d/1aaAELrWIFQjmg_Gvwqjg5y6g4aXq7tMmJ3sPBm3R1xs/edit#gid=503631799).

Figure 2-1 provides an overview of attribution studies concerning heat, drought, precipitation, and flooding events. The discipline's main challenge is the estimation of how much anthropogenic climate change affects an event's intensity and frequency of occurrence. To overcome this challenge, a reoccurring theme in PEA is the importance of framing any research question in an attribution study. Questions have evolved from asking about the liability of climate change impacts (Allen, 2003) and contributions to the hydrological cycle (Philip et al., 2020), to the contribution of climate change to recent bushfires in Australia (van Oldenborgh et al., 2021), and glacier retreat in Peru (Stuart-Smith et al., 2021). Beyond the climate modelling aspects of PEA, the attribution approaches have been expanded towards attributing the economic costs of

Hurricane Harvey (Frame et al., 2020) and health outcomes of populations (Ebi et al., 2020).

Several approaches of attribution studies have been developed to address the question “Was this event influenced by climate change?” (Jézéquel et al., 2018, p. 374). The two main approaches being the ‘storyline-approach’ (Shepherd, 2016) and the widely-used ‘risk-based-approach’ (Haustein et al., 2019; Philip et al., 2019; Rimi et al., 2019; van Oldenborgh et al., 2021). This thesis (Chapter 6) utilises the step-by-step framework of the risk-based-approach and is explained below in Section 2.3.3.4.

2.3.3.2 *PEA assessments in East Africa*

Considerably less work has been undertaken to assess the link between extreme weather and climate-related events within Africa and anthropogenic climate change from an attribution perspective (Figure 2-2). Even though attribution studies are effective tools to extract information on recent human activities contributing to weather and climate-related events, studies remain sparse for the East African region, which is in part due to the short instrumental observations (Section 1.4) that ultimately limited confidence in the assessment (Herring et al., 2014; Marthews et al., 2019).

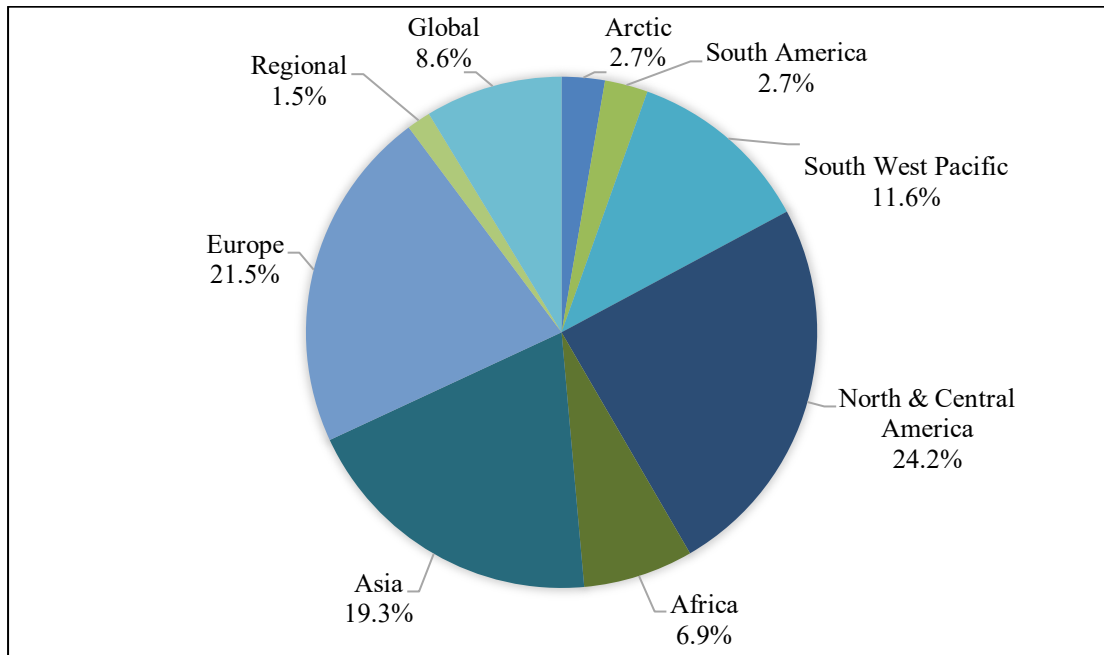


Figure 2-2: Geographical distribution of attribution studies. Data was obtained from the Carbon Brief Attribution Database (https://docs.google.com/spreadsheets/d/1aaAELrWIFQjmg_Gvwqjg5y6g4aXq7tMmJ3sPBm3R1xs/edit#gid=503631799).

2.3.3.3 Opportunities for PEA in the human mobility context

Little is currently known about the influence climate change may have on human mobility in the study region. Identifying the interlinkages between weather and climate-related events and displacement is therefore an opportunity to guide the development of models towards disentangling the underlying reasons of such forced population flows which may worsen under future warming, for example, in magnitude and frequency.

In East Africa, the investigations of the weather and climate-related events (Kew et al., 2021; Marthews et al., 2019; Otto et al., 2020) affecting populations using event

attribution methods would be well justified. Given its importance of studying the methods' relationships to disaster risk reduction, human mobility provides an appropriate field of application to assess risks under future warming. As human behaviour can exacerbate or mitigate impacts from weather and climate-related events, an understanding of the social, ethical, and human responses to a changing climate is an important research topic. PEA will guide research into important features of climate change impacts, as well as suggesting locations and climate variables that could be integrated with observational human mobility data to model historic and future linkages of climate change.

There has been previous research with a limited evidence base of the contribution of anthropogenic climate change to extreme weather in East Africa. Assessing the Ethiopia drought in 2015, Funk et al. (2016) found a human influence resulting from increased El Niño sea surface temperatures (SSTs) and air temperature, which led to reductions in rainfall and contributed to food insecurity. However, Philip et al. (2017) found no clear detectable trend and concluded that anthropogenic climate change has not contributed to the probability of this drought. This thesis will test the hypothesis that PEA approaches might further deepen our understanding of possible future impacts from climate change on populations, including population movements in the region. Given the growth and frequency of attribution studies not only in East Africa, but globally (Figure 2-1), Otto et al. (2020) highlight the need for a database that includes attributable changes in observed and projected climate hazards. Probabilistic event attribution assessments of climate-related human mobility in the region can therefore be expected to add scientific value in two ways. First, by offering an understanding of the contribution of changes in the observed climate and projections of future change to

populations and human mobility. Second, by identifying the changes in the regional climate which contribute most to the human mobility outcomes and assessing the likelihood of these changes under future warming. Previous work has identified that future warming could lead to additional climate-related migration (Rigaud et al., 2018), and work on climate-related human mobility has indicated that human mobility outcomes associated with climate change remain largely difficult to determine (Boas et al., 2019). This further justifies a focus on attribution methods, combining probabilistic event attribution and climate econometrics, in this thesis.

2.3.3.4 Attribution method applied in this thesis

Chapter 6 follows the step-by-step attribution approach suggested by Philip et al (2020): (i) analysis trigger, (ii) event definition, (iii) observed probability and trend, (iv) model evaluation, (v) model attribution and (vi) synthesis. To do so, two sets of ensemble simulations were used for an extreme flooding event in April 2020 (Chapter 6): one factual simulation run using climate models with present-day greenhouse gases and observed GMST from the period assessed and one counterfactual simulation run excluding higher greenhouse gas emissions (Otto et al., 2015). The counterfactual simulation runs used in Chapter 6 are generated using the same climate models but with pre-industrial greenhouse gases and GMST. Comparisons between these two ensembles through synthesis allow us to quantify the fraction of attributable risk, a metric which describes the fraction of the event probability that is attributable to anthropogenic climate change as opposed to natural drivers. The ensembles were derived from ensemble runs of the Met Office Hadley HadGEM3-A and EC-Earth 2.3

(Ciavarella et al., 2018; Hazeleger et al., 2010). The four-year smoothed global mean surface temperature (GMST) anomaly was calculated to remove El Niño–Southern Oscillation (ENSO)-related fluctuations in the global mean temperature, following Step 3 in the protocol for probabilistic event attribution analysis (Philip et al., 2020). These simulations were then analysed on the KMNI Climate Explorer.

3 Deciphering Impacts and Human Responses to a Changing Climate in East Africa

Preamble

The previous chapter detailed some methods to characterise climate-related human mobility. The recent advancement of machine learning, and success of other studies using machine learning approaches to classify the literature indicates that this approach could provide significant insight. This research chapter addresses the first research question: *To what extent can weather and climate-related events in the form of droughts and floods explain human mobility in East Africa?*

The findings are presented in the paper “Deciphering Impacts and Human Responses to a Changing Climate in East Africa” which is published in the journal *Frontiers of Climate*. It finds that weather and climate-related events affect human mobility in the study region differently. The first distinction is the type of human mobility affected; then the scale of populations affected as well as the duration needs distinction. The lesson-learnt from this chapter is that human mobility is complex and requires quantitative methods to assess the contribution from weather and climate-related events.

Deciphering Impacts and Human Responses to a Changing Climate in East Africa

L. THALHEIMER¹, F.EL. OTTO¹ and S. ABELE²

¹ Environmental Change Institute, University of Oxford, Oxford, UK

² School of Geography and the Environment, University of Oxford, Oxford, UK

Published in *Frontiers in Climate*

DOI: 10.3389/fclim.2021.692114

Manuscript received 07 April 2021

Accepted 08 July 2021

Published online 03 August 2021

Authorship Declaration

I conducted all of the analysis and writing for this paper. Simon Abele and Friederike Otto discussed the methodology, results, and structure of the paper with me, and edited the manuscript.

Abstract

Climate-related human mobility (climate mobilities) is often portrayed as a key impact of human-induced climate change. Yet, causal, quantitative evidence on this link remains limited and suffers from disciplinary hurdles. One reason for this is that existing case studies do not incorporate insights from climate science methods and pay little attention to contextual factors in climate mobilities. We use a dual-method approach to categorise and classify. By combining a qualitative case study analysis with statistical approaches from topic modelling in an innovative dual-method framework, we show current empirical evidence on weather and climate-related impacts and human mobility in East Africa, an alleged hot-spot of climate change. We find that although climate change is referred to, implicitly and explicitly, as a tipping point for human mobility, studies imply a causal link between human mobility and climate change while under or misrepresenting evidence in climate science. A map of evidence allows studies to be matched with human mobility types and contextual factors influencing such mobilities in a changing climate with a novel and more ambitious form of synthesis, carving out the multi-causal nature of human mobility. Our findings show that climatic influences on human mobility are not independent. Rather, climate factors influencing human mobility are closely connected with contextual factors such as social norms, economic opportunities, and conflict. The findings suggest that there is currently low confidence in a climate change-human mobility nexus for East Africa. As a way forward, we propose emerging methods to systematically research causal links between climate mobilities and anthropogenic climate change globally.

3.1 Introduction

Throughout history, environmental and climatic changes have played a role in human mobility, but decisions to stay or move are multi-faceted; if any, climate and weather have been factors among many (Black et al., 2011; Hoffmann et al., 2020; Piguet, 2010). With growing concerns about the impacts of anthropogenic climate change, such factors are expected to grow in importance (Kelley et al., 2015; Lugli et al., 2019). Despite recent advancements, empirical evidence on the proportional impacts of a changing climate on human mobility is scant and currently thin on quantitative assessment (Abel et al., 2019; Cattaneo et al., 2019b; Groth et al., 2020b). Crucially, comprehensive evidence is missing for places vulnerable to a changing climate and potentially hot-spots of increasing hazards such as East Africa (Otto, Harrington, Frame, et al., 2020).

3.1.1 The climate change and human mobility debate

Observed climatic change, independent of the cause of such change, human-induced climate change and various forms of human mobility such as migration are discussed widely, and connect discussants from the public, policymakers and academic researchers across disciplines (Gray & Mueller, 2012; Randall, 2015). Leading, in part, to a perceived causal chain between anthropogenic climate change, extreme events - often labelled as “climate change event”, and associated mobility suggested in the migration literature portray an over-simplified picture of climate-related human mobility (Hastrup & Olwig, 2012; Hoffmann et al., 2020). Most of the debate, or at

least a noisy part, has been framed by apocalyptic thinking or anti-immigrant sentiments (Haas, 2008; White et al., 2011), which construe particularly migration as a problem that needs to be solved. International organisations outline that migration will increase in so-called climate change hot-spots, or places where communities are already vulnerable to the physical and ecological effects of climate change (Rigaud et al., 2018).

Despite their prevalence in climate migration rhetoric, such perceptions that problematise climate change-induced human mobility have been criticized for their insufficient scientific robustness, for example, in the context of conflict research (Abel et al., 2019; Ide et al., 2020). The migration-development literature provides a more nuanced understanding of human mobility (Klepp, 2017). Scholars in social science and development studies (e.g., Bakewell, 2008, 2010; Flahaux & De Haas, 2016; Haas, 2008, 2010) break down and clarify the often-misunderstood debate on migration and development: because human mobility requires financial capital, poverty reduces out-migration; and in turn, economic development and increased financial means lead to *more* migration (Bastia & Skeldon, 2020).

With currently little consensus on appropriate research methods to identify whether and to what extent climate change affect human mobility, it is not clear what role human induced climate change plays in this nexus at present and in the future. Research that attempts to juxtapose the vast heterogeneity of topical perspectives have resulted in different concepts and terminologies (Borderon et al., 2019; Hoffmann et al., 2020; Piguet, 2010).

3.1.2 Review approach and contributions

This Review is guided by the question: How sound are the lines of evidence for a causal link between human-mobility and a changing climate in East Africa? Here, we provide a dual-method evidence approach, consisting of a qualitative case study analysis and a quantitative topic model that are set to disentangle the complex drivers of climate-related human mobility. Through the dual-method, we can reveal connections between climate mobilities and contextual factors (e.g., food security and livelihoods) which a single-method approach would have otherwise masked.

To this aim, we systematically review the literature and explore the lines of evidence on the link between weather and climate-related events and human mobility (climate mobilities). We focus on the methodological compatibility (or lack thereof) from climate mobilities research stemming from different disciplinary spheres in a potential climate change hot-spot region (Byers et al., 2018). We show that climate data finds little application in existing climate mobilities literature in East Africa. This might lead to an oversimplified picture of human responses to weather and climate-related events. From the analysis, we can infer there is not yet a framework that allows for a disentangling of weather and climate-related human mobility drivers from non-climatic, contextual drivers, assessing the probability of climate change impacts and outcomes. Our key takeaway is that the problematic use of climate and weather data is not limited to East Africa, but points to a wider problem in this field of climate change impact research which requires truly interdisciplinary research. Therefore, we outline the applicability of quantitative methods from econometrics and extreme event

attribution to support the development of a more comprehensive understanding on human responses to weather and climate-related events and attributable links to climate change in future research. This analysis contributes to the ongoing effort of assessing the probability of climate change impacts and human responses to a warming climate.

3.2 Methods

3.2.1 Study area

East Africa (Figure 3-2) is one of the regions which is most vulnerable to climate change and variability and the impacts from extreme weather and compound events (Marthews et al., 2019). The region is characterised by a traditionally mobile population, consisting of pastoralists and herders. Human mobility is part of many livelihoods across East Africa (Collier et al., 2008; Funk, 2020; Shongwe et al., 2011; Uhe et al., 2018). In recent years, a number of extreme weather events involved floods and droughts which have had significant social and economic impacts. To illustrate, the 2015 drought in Ethiopia put an estimated 22 million people in need of food aid (Philip et al., 2017). In Somalia, 26 different flood, drought and storm events have been recorded between 2010 and 2020 by the disaster database EM-DAT (Guha-Sapir et al., 2016).

3.2.2 Analytical framework

The analytical framework consists of three elements: a systematic literature review, a resulting case study analysis and a topic model evaluation (Figure 3-1). While setting out to qualitatively analyse the case studies, we use a topic modelling approach to augment the understanding on the range and significance of contextual and climatic influences on human mobility in the study region. This dual-method approach allows us to synthesise and quantify the current evidence in the field.

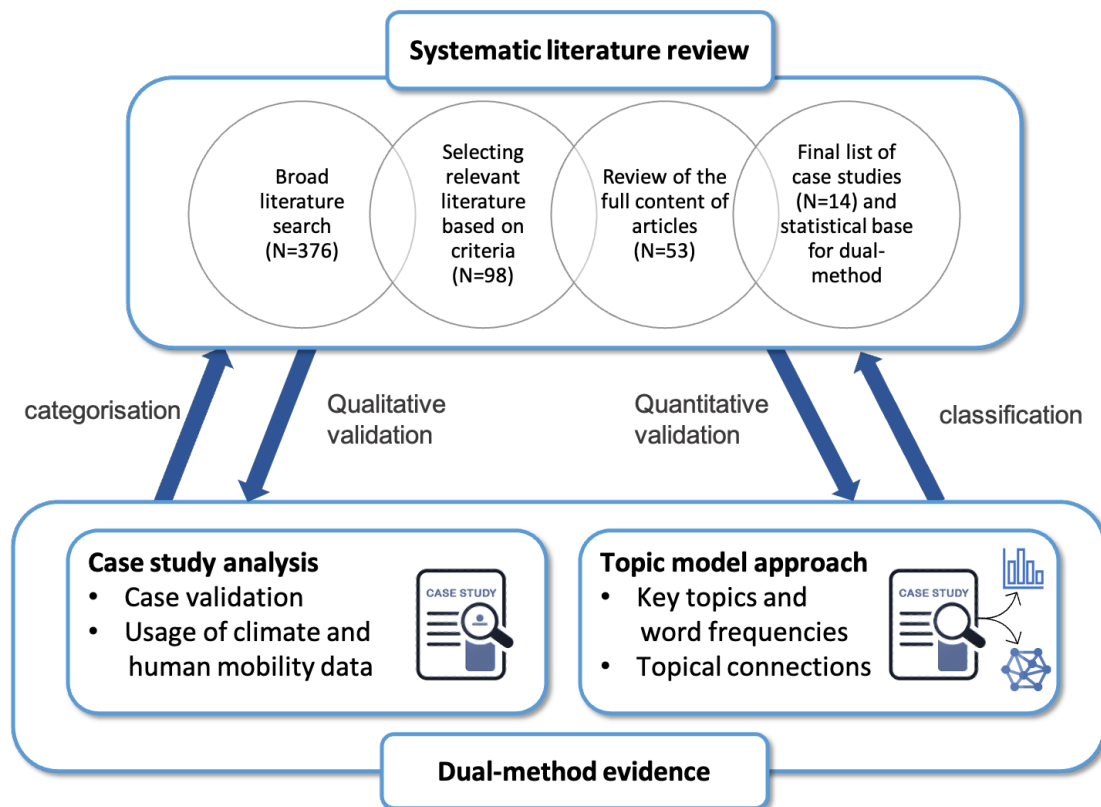


Figure 3-1: Conceptual framework of the dual-method framework.

3.2.3 Case study approach

In a broad and systematic search of the literature (Supplementary Section A), we identified qualitative and quantitative studies that investigate the link between a variety of climatic change factors and human mobility in East Africa. Applying the inclusion-exclusion criteria, the systematic literature review yields in 14 case studies published between 2000 and 2019 (see Supplementary Figure S4-1). For the analysis, we focus on country studies to cover large geographical areas in East Africa (Supplementary Table S4-1).

We apply a set of categories to the selected case studies, well-established in climate mobility research to systematically categorise the studies (Piguet, 2010). We synthesised evidence on socio-economic and political drivers which we hereafter refer to as contextual drivers as well as weather and climate-related drivers of human mobility. We then categorised the case studies according to the type of weather and climate-related event studied. To better understand the spatio-temporal dynamics of human mobility, we separately list the departure and arrival regions, and the analytical time horizon covered in the case studies. We also separately marked case studies which refer to multi-causality as a theoretical concept of human mobility (Supplementary Table S4-2).

3.2.4 Topic model approach

In a second analytical step, we apply a topic model approach on the selected case studies to classify them according to their key topics and word frequencies. The systematic literature review serves as statistical base for our model. Topic models are unsupervised machine learning techniques aiming at exploring text collections thematically. Our approach allows to generate topics through a set of statistical models that depict common occurrences of words within and across the case studies. From the systematic literature review, we gather that all selected case studies are broadly about the topic of climate mobilities. Using the topic model approach, it is generally assumed that a text collection consists of different topics with a topic being understood to be a cluster of words; in this case words such as “climate”, “migration” and “household” frequently occur together. Broadly, a topic can be regarded as a statistical phenomenon and therefore some correspondence, but not exactly the same as a (content-defined) theme. However, topic modelling methods are typically used to analyse large text collections (Supplementary Section C). We overcome the challenge of working with a smaller sample size by using contextual clues to connect words with similar meanings and distinguish between uses of words with multiple meanings. Topic models are therefore well-suited to explore the thematic contexts of a smaller sample size (Griffiths & Steyvers, 2004). Expanding on the results from the case study approach, topic models can help to discover hidden topical patterns that may be present across the case studies and might have been hidden otherwise. Hidden topical patterns can be revealed by annotating documents according to key topics; results of which we show in Figure 3-3. Using these annotations, topic modelling helps to organise, search and summarise the

case studies. The method illustrates both the quantity and relevance of key terms. Thus, it is a well-suited approach to expand our understanding on the vast parameters contributing to climate mobilities.

3.3 Results

Here, we use a dual-method evidence approach to investigate the drivers of human mobility, the role of climate data used, which could allow for any attributable links between extreme weather, human mobility, and anthropogenic climate change. Employing a diverse range of qualitative and quantitative methods, the case studies frame the influence of extreme weather on human mobility through basic plausible assumptions of push-pull factors: climatic stress conditions typify a push factor, and better economic opportunities a pull factor, for example. Showing multiple spatial and temporal dimensions of human mobility, these studies currently provide the best evidence on whether anthropogenic climate change and natural variability are currently influencing human mobility in East Africa.

3.3.1 Drivers of human mobility

As a region, East Africa is considered a hot-spot of compound events due to increased population exposure resulting from extreme weather and population growth (Weber et al., 2020). Although parts of the region are well-represented in the literature, the evidence on drivers of climate-related human mobility beyond voluntary migration,

direct and indirect factors, and their interlinkages remain inconclusive and context-specific (Groth et al., 2020a; Romankiewicz et al., 2018).

Apart from the very diverse temporal (including permanent migration) and geographical scales on which human mobility takes place, there are different forms human mobility can take. We find that the case studies distinguish between voluntary forms of mobility i) migration and ii) pastoralism, and involuntary mobility iii) displacement and iv) refugees, v) asylum seekers and vi) resettlement (Table 3-1).

Conversely, we find large differences on how studies analyse and describe a country or regional context (macro-level studies), e.g., employing models to control for specific socio-economic and contextual political variables to isolate the specific impact of climate on migration or investigating climate change perceptions of affected populations on the move through interviews. GM12 for example, investigates drought effects on local populations in Ethiopia through multivariate regressions (Gray & Mueller, 2012). AG12 (Afifi et al., 2012) provides evidence on climate change perceptions and vulnerability from the perspective of refugees based in camps in Ethiopia and Uganda.

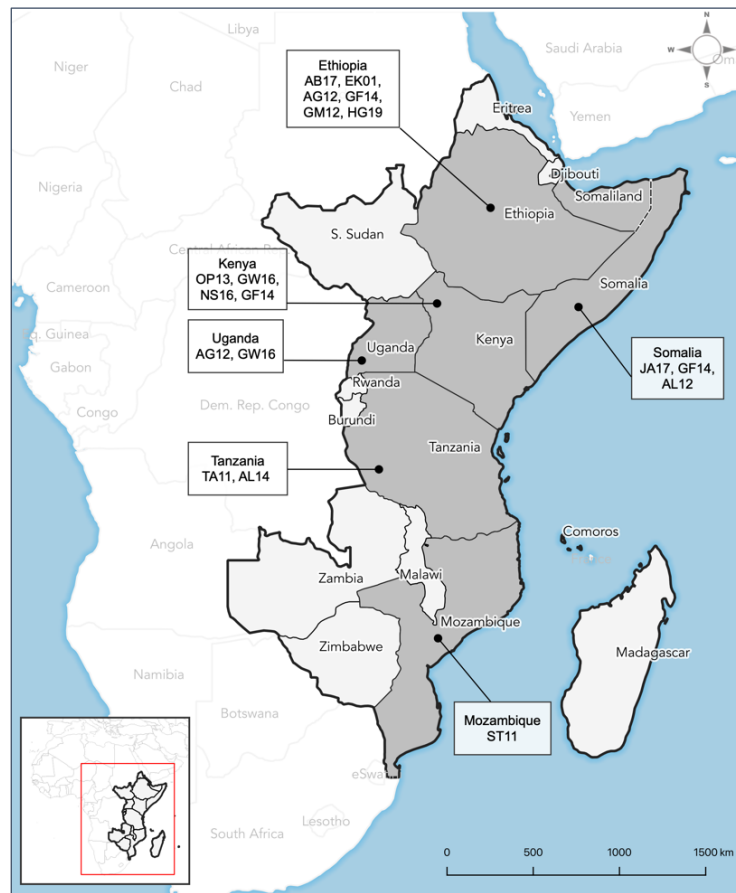


Figure 3-2: Map of case study locations across East Africa. Dark grey indicates country case studies included in the review.

Table 3-1: Topic map showing the distribution of mobility types and contextual factors across countries. For each country, the mobility types identified from the literature are summed up and the most frequent types are shown.

	Ethiopia	Kenya	Mozambique	Somalia	Tanzania	Uganda
Contextual topics by country	Drought, climate, household	Environment, land, development	Environment, climate, land	Climate, drought, risk	Environment, conflict, rural	Climate, climate change, environment
Mobility types by country	migration	migration	migration	displacement	migration	refugees

Our topic model allows to disentangle weather and climate-related drivers in human mobility from contextual drivers. By adding this approach, we can further infer that the studies document and discuss various types, drivers, and impacts (sub-themes) of human mobility in the study region (Figure 3-3, Supplementary Figure S4-2). The topic model reveals structures highlighting that a range of factors regarding food security, economy, conflict, and social norms influence human mobility in addition to climate factors. Within these contextual factors armed conflict, social norms, and livelihoods, e.g., pastoralism, and community stand out (Figure 3-3).

Interestingly, the studies OP13 (Opondo, 2013), ST11 (Stal, 2011), AB17 (Alemayehu & Bewket, 2017) focus on single factor influencing human mobility, whereas the other case studies use a framework proposed by Black et al. (2011), acknowledging the multi-causality in human mobility drivers. This framework proves to be well-suited to conceptualises different geographical and temporal dimension of direct and indirect factors influencing human mobility (Groth et al., 2020a), here, to theorise the links between human mobility and weather and climate-related events, often in the context of loss and damages or economic vulnerability, e.g., EK01 (Ezra & Kiros, 2001), TA11 (Tacoli, 2011) and HG19 (Hermans & Garbe, 2019).

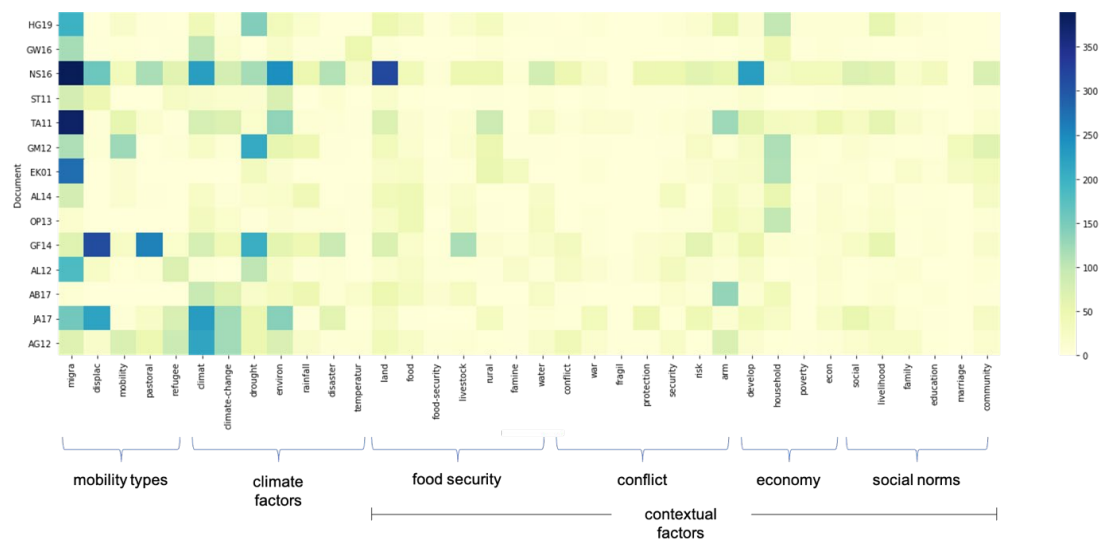


Figure 3-3: Heatmap of word frequency illustrates the distribution of mobility types, climate and contextual factors across the selected case studies. Contextual factors include four topics: conflict, economy, food security and social norms. Each topic consists of five to eight keywords derived from a list of the 100 most frequent words.

3.3.2 The role of climate data

In light of limitations on human mobility data (Hauer et al., 2020), the role of widely-available climate data takes a profound role in drawing conclusion on the effects of weather and climate-related events on human mobility and the role of anthropogenic climate change.

We find that at minimum, if at all, studies only use basic climate indicators to investigate climatic determinants of mobility. For example, publications around the Same-Kilimanjaro region in Tanzania (Afifi et al., 2014): AL14) or in (Nyaoro et al., 2016): NS16) use annual rainfall trends but forego to take the complexity of seasonality into account. One third of the case studies include climate data in their analysis or rely on previous publications of climate data assessments in the region, for example GF14

(Ginnetti & Franck, 2014), AG12 (Afifi et al., 2012) and AB17 (see Table 3-2). Of those, several use just a single aspect of climatic change, such as rainfall anomalies (e.g., HG19) or temperature change (e.g., AB17) while others use historical precipitation data on different temporal scales such as monthly rainfall or minimum and maximum temperature (e.g., AB17, data from 1981–2013).

One case, Afifi et al. (AL14), uses monthly mean precipitation observations from the Tanzania Meteorological Agency (TMA) to describe changes in climate variability. They however refer to annual mean temperature of 1992–2011 as a drought indicator of the 2011 East African drought. Alemayehu and Bewket (AB17) link their findings to rainfall and temperature variability observations on results from their previous study in which they analysed average annual maximum and minimum temperatures for the period of 1981–2013 (Alemayehu & Bewket, 2016). However, neither of these publications justify how temperature anomalies are linked to the occurrence of drought in the area. Instead, by analysing temperatures, the authors seem to imply that changing temperatures are a defining factor of drought. Yet, in an arid region it is usually rainfall that determines drought (Coughlan de Perez et al., 2019; Manning et al., 2018) and recent scientific studies suggest that in this region in particular temperature changes play a negligible role compared to other drivers of drought (Kew et al., 2019; Philip et al., 2017).

Table 3-2: Climate data used in case studies. N/S indicates that no climate data is used for the analysis.

Ref	Climate data used	Time series	Weather and climate-related event	Dataset source
HG19	Daily precipitation data	1985-2015 (excluding 2014)	2015 Ethiopian drought	East Amhara Meteorology Service Center
GW16	Gridded climate data products from weather stations and reanalysis data (a) Climatic Research Unit (CRU) time series 3.21 for monthly rainfall and temperature data (b) Modern Era-Retrospective Analysis for Research and Applications (MERRA) for monthly mean land surface temperature and total surface precipitation	2009-2014 (Base period 1981-2010)	Climate variability	(a) UEACRU (b) NASA
GM12	Global daily precipitation from Prediction of Worldwide Energy Resources (POWER) data	1997-2009	2002 + 2008 Ethiopian drought	NASA
AL14	(a) Mean monthly absolute rainfall values and anomalies (b) number of rain days per annum for the Same district.	(a) 1950-2010 (b) 1950-2000	Climate variability	Tanzania Meteorological Agency
OP13	N/S			
ST11	N/S			
AB17	(a) monthly, seasonal and annual rainfall totals (b) temperature (maximum and minimum)	(a) 1983-2013 (b) 1981-2011		weather stations and meteorological satellite observations
JA17	N/S			
EK01	N/S			

GF14	Monthly rainfall	2008-2013	Drought	N/S
NS16	N/S			
AG12	Annual absolute, max and min temperature	1992-2011	Drought	Weather stations: Ethiopia: Addis Ababa Bole weather station; Uganda: Entebbe Airport
AL12	N/S			
TA11	N/S			

Instead of analysing climate data, three studies use country-level records from the disaster statistics database EM-DAT (Guha-Sapir et al., 2016) to define an extreme weather event, for example, the 2002 and 2008 Ethiopian drought (GM12). Based on these records, NS16 lists the impacts of drought and flood disasters on affected populations from 1964 to 2015, whereas Stal (ST11) uses the database to define the two flood events investigated in the Zambezi River Valley. By incorporating satellite imagery of the 2001 flood and a risk assessment map for the 2007 flood, ST11 supports the characterisation of the event through physical characteristics of an extreme weather event (Stal, 2011).

Hermans and Garbe (HG19) investigate direct livelihood strategies, migration experiences and perceptions of the 2015 Ethiopian drought with household-level and individual information from a household survey and focus group discussions in early 2016, shortly after the drought ended. Despite framing the start and end of the drought by using a time series of 30-year daily rainfall observations (a triplet of 10-year blocks from 1985-1994, 1995-2004 and 2005-2014), the authors use the rainfall data to illustrate an increasingly variable start of the *Belg* rainy season across the time series through basic descriptive statistics.

Gridded climate datasets are used by a single case study of our document corpus. Gray and Wise (GW16) use observed monthly temperature and rainfall data from the Climatic Research Unit (CRU) in combination with NASA's MERRA reanalysis data on land surface temperature to address limitations identified in previous studies. They criticise the usage of a single climate dataset to explore links between climate variability and human migration (Gray & Wise, 2016).

All case studies focus on past weather and human mobility; only GF14 also models future displacement by using a systems dynamics model aiming to improve the understanding of the underlying system that drives pastoralists to lose their livelihoods. Along livestock and displacement statistics, Ginnetti and Franck (GF14) compare 2008 to 2013 mean annual rainfall over Somalia, Kenya, and Ethiopia with anecdotal, national-level monthly displacement records in a system dynamics model. This data serves as a proxy for drought and is mapped with socio-economic data such as agriculture productivity. On this basis, the model produces estimates of drought-related displacement by 2040 that can be compared to empirical evidence of past displacement due to drought. However, there is no justification for the choice of data, or a drought definition characterise the extreme weather event. The study relies on existing reports for defining drought impacts on livestock during 1991 to 2010 rather than using drought indicators. It remains unclear why such data was chosen instead of metrics such as the Standardized Precipitation Evaporation Index (SPEI) or precipitation anomalies for which the CHIRPS dataset is well suited (Dinku et al., 2018). Crucially, we find that the case studies that do employ climate data rather use a diverse set of spatial and temporal variables that is justified more by availability and ease of use than by the significance in defining weather and climate-related events.

3.3.3 Human mobility data

All studies use a single mobility dataset for their analysis (Supplementary Table S4.2). A fact primarily resulting from the very limited availability of datasets on combined mobility types or simply due to time and budget constraints (e.g., ST11, EK01, AG12). Ezra and Kiros (2001) for example, list a range of data limitations to their household survey implementation, such as spatial and temporal elements of their survey design (EK01).

In terms of data sources, the four grey literature studies rely on locally collected mobility data over the span of a few weeks. NS16 use UNHCR-collected country-level data from 2016 on refugees from various East African countries, most of them originating from Somalia (71%) and South Sudan (16%). Similarly, Jayawardhan (JA17) uses the same data source for annual displacement from 2009–2012 to show a peak in drought-related displacement during the 2011 drought in Somalia (Jayawardhan, 2017). Ten case studies collected empirical mobility data through household surveys and interviews with government officials and population affected by extreme weather using common combinations of sample surveys and qualitative research methods (Supplementary Table S4.2) at either the source or destination area (e.g., OP13, AG12, AL14 and GM12). Only Tacoli (TA11) interviewed Maasai men, an increasingly mobile group, in both the origin (rural) and destination (urban) across Tanzania. AL14 uses a combination of empirical data that includes a survey of 165 households, expert interviews and focus group discussions. Herman and Garbe (HG19) differentiate between participants who return after a month or longer (temporary

migrants), and those unlikely to return (permanent migrants) in their dataset and contextualizes migration decisions of male household heads with focus group discussions of farmers in northern Ethiopia.

The empirical studies use a combination of complementing methodologies to support the time frame of the analysis. The combination of sample surveys and qualitative research methods is common. AG12 use a mixed-method approach of expert interviews, household survey together with six participatory research methods to understand the interrelation between rainfall and mobility. Among affected populations, reported perceptions of climate stressors are fundamental for the definition and scope of extreme weather and help understand climate impacts experienced. These qualitative studies do not incorporate observational or reanalysis climate data, solely relying on perceived and self-reported observations on climatic changes (see Table 3-2). This use of complimentary datasets on human mobility in AG12 is unique and sets apart the analytical validation. In contrast, three papers solely rely on secondary statistics from international organizations or non-governmental organizations such as UNHCR or FEWS Net (JA17, NS16, (Achour & Lacan, 2011): AL12).

3.3.4 Implication of anthropogenic climate change

To some extent, the studies base their analyses on the assumption of the occurrence of human-induced climate change affecting mobility patterns in case study locations. It is however usually not clear whether they indeed mean human-induced climate change and so adopting the UNFCCC usage of the term (UNFCCC, 1992), only or the evolution

of the local climate independent of its drivers which represents the IPCC usage of the term (IPCC, 2018). The term is often discussed in the context of drought (e.g., JA17, AG12 and NS16). In particular, grey literature contextualizes adverse impacts of climate change on sectors such as forestry (for example, ST11), agriculture, and livelihoods, like JA17 (Figure 3-3).

From a theoretical standpoint, the studies refer to indirect and direct drivers of human mobility as suggested by Black et al. (2011) in the context of climate change (Supplementary Table S 3-2; Figure 3-3). For example, GF14 uses intervening facilitators for drought-related displacement in a dynamic model of livestock and market trends and estimates future dynamics of such displacement under climate change. AG12 specifically add the climate change component to migration in the initial data collection by including the perceptions of climate change across different groups of interviewees to understand its (perceived) role in outmigration. They find that refugees affected by climate variability directly link changes in climate to increases in political conflict and violence occurrences. Direct links are similarly made in the Ethiopia case study (HG19) regarding migration as a form of human mobility as an adaptation strategy for climate change in their conclusions. GF14 make it clear that the study only links to trends in the climate independent of the cause by defining the term according to the definition provided by the Intergovernmental Panel on Climate Change (IPCC). Synthesizing the results of their systems dynamics model, emphasis is put on the multi-causality of human mobility drivers, particularly that drought and climate change (and/or variability) are not the only drivers of displacement.

3.4 Discussion and conclusions

Our dual-method Review aimed at identifying whether the existing academic literature provides causal evidence for linking human mobility in East Africa with anthropogenic climate change. Our analysis consisting of a classical review of the existing literature and a topic model approach to further analyse published case studies leads us to the conclusion that this is not the case.

There are several reasons for this conclusion. To assess the existing literature, it is important to highlight that those contextual factors affecting human mobility are not evenly distributed across the study region but primarily exist in areas that experience drought and conflict; often reflecting the prominence of such reporting by humanitarian agencies: 75% of new displacements in 2019 are associated with weather and climate-related events and 25% with conflict and violence. Regionally, Sub-Saharan Africa tends to experience more conflict-related displacement than displacement triggered by extreme weather events (Internal Displacement Monitoring Centre, 2020). This further shows that the links between weather and climate-related events, contextual factors and human mobility are complex, defying simplistic reasoning according to which climate change would 'lead' to human mobility. In fact, depending on the circumstances, climatic variability or extreme weather can lead to more, or less human mobility (Wiederkehr et al., 2018).

Furthermore, in many cases, regardless of the exact location investigated, the fact that human mobility is part of societies is not mentioned in the reviewed analyses. As such,

displacement is discussed in conflict-affected Somalia, a country consisting of circa 60% pastoralists, a traditionally mobile part of the population that has long used migration as a coping mechanism in times of water scarcity or prolonged heat (Kassahun et al., 2008; Leal Filho et al., 2020). We find that the case studies are based on the implicit assumption that, generally, most people in a given location would prefer to stay where they live, as long as they have sufficient freedoms, are safe, and have economic opportunities. The results from the topic model emphasise that factors other than climate and weather, such as conflict, land use practices, and social norms, are believed to be important factors which contribute to forced migration flows in East Africa. Social science data, such as household surveys, are frequently used to support these claims. Despite nods to multi-causality, data on contextual drivers of human mobility are not further analysed. This lack of contextual data suggests an oversimplified conclusion on climate mobilities, an aspect that has also been identified in a review on environment-related migration in West Africa (Romankiewicz et al., 2018).

Crucially, we find that the use of climate data in all studies is inconsistent if data is used at all. Those case studies that employ climate data use a diverse set of spatial and temporal variables motivated more by availability and ease of use than by the significance in defining the weather and climate-related events affecting the region. No climate data assessment in the reviewed studies provides causal evidence for a link between observed events and human-induced climate change.

Collectively, our results are consistent with evidence on contextual factors contributing to environment-related migration (Groth et al., 2020b; Hoffmann et al., 2020) and

expand the scope of findings by investigating links to anthropogenic climate change. While the lack of contextual data is often driven by availability, such limitations also exist for climate data (Otto, Harrington, Frame, et al., 2020). However, the relatively random or even unjustified choice of climate and weather data used in the reviewed case studies is still to question.

Our results shows that none of the ways this climate and human mobility data has been used allows to single out or disentangle anthropogenic drivers of changes in the data. Thus, there is not yet a basis to causally link anthropogenic climate change to human mobility in this region. However, all case studies published after 2010 (13 out of 14) mention or refer to human-induced climate change in a way that is very ambiguous and tends to imply a causal connection. The grey literature studies depict (Achour & Lacan, 2011; Nyaoro et al., 2016) climate change as a tipping point for forced migration and conflict but uses inadequate methods and data to support such claims. Conversely, this suggests there is currently no evidence for a causal link between extreme events motivating human mobility in East Africa and anthropogenic climate change.

We acknowledge the geographical limitation of our results. Even though East Africa is vulnerable to the effects of future climate changes and also population developments, it has remained notoriously understudied (Harrington & Otto, 2020). Even with the results of the dual-method analysis in hand, the reviewed studies are also limited in scope and data used, often relying on secondary data.

What this review shows is that the evidence for East Africa is unfit to attribute human mobility to anthropogenic climate change. We do not show that such evidence is

principally impossible to obtain but highlight that a comprehensive understanding of the contribution of climatic factors influencing human mobility can only be achieved through a broad range of different, complimentary data. In turn, we argue, these data can only be understood and integrated by combining knowledge from very different disciplines. Whereas we acknowledge the restrictions in human mobility data available, we propose to expand the integration of climate data in future studies on climate mobilities to capture impacts and human responses to weather and climate-related events.

Thus, to better understand the extent to which anthropogenic climate change plays a role in existing population movements in East Africa and globally, a new framework of interdisciplinary research is needed, which integrates diverse data into models that simulate how human mobility is impacted by contextual and climate change-related factors. From other parts of the world examples exist how climate and mobility data can be jointly assessed, using e.g., econometric methods to quantify the probability of climate change impacts (Castle & Hendry, 2020), outmigration as a result of disasters in multiple regions (Bohra-Mishra et al., 2014; Feng et al., 2010b) or even to explore the climate-conflict-migration (Abel et al., 2019). Descriptive statistical methods allow for quantifying the link between past extreme weather events and human mobility. However, the second step, to identify whether and to what extent anthropogenic climate change was a driver of the extreme is missing across all studies and world regions (Beine & Jeusette, 2018). One promising way toward such a framework could be to combine the statistical methods to link weather and climate-related events and human mobility with extreme event attribution (EEA) (Horton et al., 2021). EEA comprises methodologies to understand whether and by how much anthropogenic climate change

has contributed to the intensity and likelihood of extreme events (Stott et al., 2016). With extreme event attribution and econometric methods in hand, the ensuing decade is likely to bring new insights and further changes to our understanding on complex causalities and paradigms of human mobility and for the first-time causal evidence for the link between anthropogenic climate change and human mobility.

Supplementary Material

This Supplementary Materials consists of three sections:

- A) Sampling strategy and selection
- B) Case study analysis
- C) Topic modelling approach

A Sampling strategy and selection

To identify a relevant sample, a systematic search for qualitative and quantitative empirical studies was carried out on five databases and information portals: (i) CliMig (Université de Neuchâtel, 2020), (ii) PERN (PERN, 2020) and (iii) Scopus (Elsevier, 2020) for of peer-reviewed academic journal articles. We obtained grey literature from search results on the (iv) Environmental Migration Portal (IOM, 2020) research database and (v) ReliefWeb (OCHA, 2020). We used the following key search terms in combination: “climate change”; “displacement”; “drought”; “East Africa”; “Ethiopia”; “extreme weather”; “flood”; “human mobility”; “Kenya”; “migration”; “Mozambique”; “Somalia”; “Tanzania”; “Uganda” across databases (see Supplementary Table S 3-1).

Since some of the databases have a focus on the broader environment or human mobility already (i.e., i, ii, and v), we also performed country keyword and free text searches. For example, our country specific key word search on the CliMig database resulted in

a total of 68 hits: 12 hits for “Kenya”, 6 hits for “Somalia”, 5 hits for “Uganda”, 21 hits for “Ethiopia”, 11 hits for “Mozambique” and 13 hits for “Tanzania”.

Table S 3-1: Search query for climate-related human mobility literature across five databases

Mobility synonyms	Climatic change synonyms	East Africa synonyms
(‘migration’ or ‘displacement’ or ‘human mobil*’	‘drought’ or ‘extreme weather’ or ‘flood’ or ‘climat*’	‘ethiopia’ or ‘kenya’ or ‘mozambique’ or ‘somalia’ or ‘tanzania’ or ‘uganda’

Our inclusion strategy involved a search setting to peer-reviewed academic and grey full-text manuscripts. An initial search resulted in 376 papers published in English. Based on key search terms in the abstracts, 98 papers published between 2000 and 2019 were selected for further assessment. An in-depth paper assessment was performed for those publications, which indicate that a link between extreme weather events and human mobility types (with focus on displacement, migration, or refugees) is explicitly made (Supplementary Figure S 3-1). The sample was updated in 2020 with the final list of case studies for review consists of 14 case studies, consisting of 8 journal papers and 6 grey literature pieces; these disperse across six countries (see Supplementary Table S 3-2).

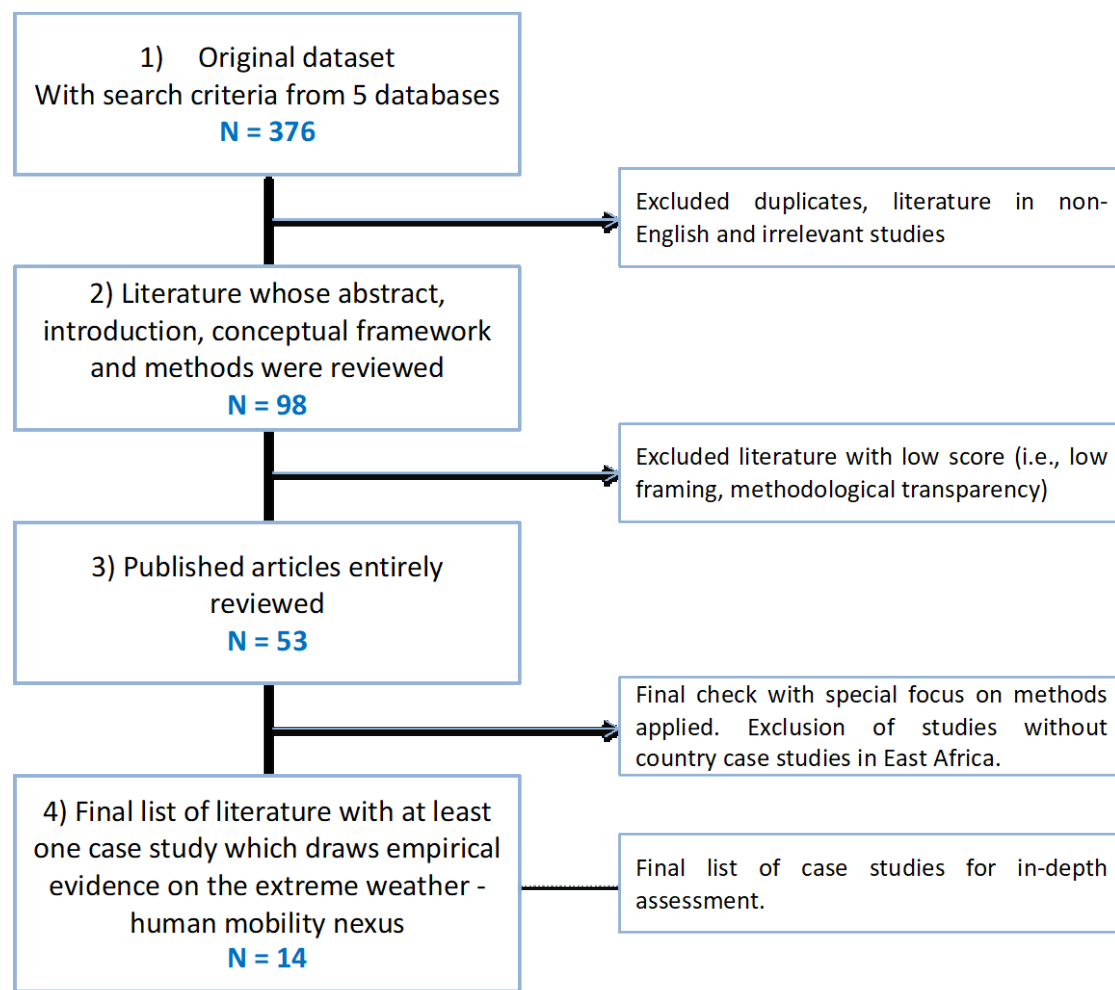


Figure S 3-1: PRISMA diagram illustrating the steps of the systematic literature review and case study selection.

B Case study analysis

Table S 3-2: Research sample with key factors of population mobility and spatio-temporal dimensions East Africa. N/S indicates insufficient information available; x indicates variable applicable. None of the case studies employed agent-based modelling. Therefore, we excluded this last variable from the classification matrix.

Ref.	Author(s)	Title	Research approach indicators (Piguet, 2010)							Mobility-related indicators			Spatio-temporal indicators		Analytical time frame		
			Ecological inference	Surveys	Time Series	Multi-level	Qualitative research	Quantitative research	Type of extreme weather event	Types of human mobility	Sub-types of human mobility	Previous region	Current region	Past or present	Future	Multi-causality	
OP13	Opondo, DO	Erosive coping after the 2011 floods in Kenya	x	x			x	x	December 2011 River Nzoia flood	migration	temporary relocation, mainly rural	Kenya	N/S	x			
ST11	Stal, M.	“Flooding and Relocation: The Zambezi River Valley in Mozambique		x			x		2000, 2001 and 2007 floods of Zambezi River	displacement, resettlement	rural-urban	Zambezi River Valley (Mozambique)	resettlement centres in Zambezi a, Tete and Sofala (Mozambique)	x			
AB17	Alemayehu, A. & Bewket, W.	Smallholder farmers’ coping and adaptation strategies to climate change and variability in the central highlands of Ethiopia		x	x		x		N/S	migration	N/S	Central highlands Ethiopia	Central highlands Ethiopia	x			
JA17	Jayawardhan, S.	Vulnerability and Climate Change Induced Human Displacement.					x		2011 East African drought (Somalia)	displacement	environmental	Somalia	Kenya, Ethiopia	x		x	
EK01	Ezra, M. & Kiros, G.	Rural Out-Migration in the Drought Prone Areas of Ethiopia: A		x		x	x		drought	migration	rural	Ethiopia	urban areas in Ethiopia	x		x	

		Multilevel Analysis														
AG12	Afifi et al.	Climate change, vulnerability and human mobility: Perspectives of refugees from the East and Horn of Africa	x	x			x		2011 East African drought	refugees	N/S	Ethiopia, Uganda	Ethiopia, Uganda	x		x
GF14	Ginnetti, J. & Franck, T.	Assessing drought displacement risk for Kenyan, Ethiopian and Somali pastoralists			x			x	drought	displacement	drought-induced	Ethiopia, Kenya, Somalia	Yemen, Ethiopia, Kenya, Somalia	x	x	x
NS16	Nyaoro, D., Schade, J. & Schmidt, K.	Assessing the Evidence: Migration, Environment and Climate Change in Kenya					x		overview of different types of extreme weather	migration, displacement	N/S	Kenya	N/S	x		x
GM12	Gray, C. & Mueller, V.	Drought and population mobility in rural Ethiopia		x		x	x	x	2002, 2008 drought	migration	N/S	Ethiopia, central and northern plateau	Ethiopia	x		x
AL14	Afifi et al.	Rainfall-Induced Crop Failure, Food Insecurity and Out-Migration in Same-Kilimanjaro, Tanzania		x		x	x		five extreme lowest rainfall events in 1952, 1975, 1993, 1996 and 2005	migration	out-migration	Same District, Kilimanjaro (3 villages)	Tanzania, Kenya	x		x
AL12	Achour, M. & Lacan, N.	Drought in Somalia: a migration crisis					x		2011 East African drought (Somalia)	displacement	internal, international and cross border	Somalia	Somalia, Kenya, Yemen	x		x

TA11	Tacoli, C.	Not Only Climate Change: Mobility, Vulnerability and Socio-economic Transformations in Environmentally fragile Areas of Bolivia, Senegal and Tanzania	x	x			x		reported drought in 2009/10 and 1998 floods by interviewees	migration	temporary rural-urban	Tanzania: Arusha, Monduli and Dar es Salaam	urban	x		x
GW16	Gray, C. & Wise, E.	Country-specific effects of climate variability on human migration		x				x	N/S	migration	Internal and international	Kenya, Uganda	N/S	x		
HG19	Herman, K. & Garbe, L.	Droughts, livelihoods, and human migration in northern Ethiopia		x			x	x	2015 drought in Ethiopia	migration	Internal	Ethiopian northern highlands	N/S	x		x
	Total	14	3	10	2	3	12	5						14	1	11

C Topic modelling approach

In essence, topic modelling is an unsupervised machine learning technique to discover the relationships between a collection of documents (corpus) and words (terms) within each document. We use the Python library *gensim* (Řehůřek & Sojka, 2011; Schreiber, 2018) to produce a set of 5 to 40 topic models from our corpus. In particular, we use two complimentary natural language processing (NLP) models to produce the optimum number of well-distributed topics. We apply Latent Dirichlet Allocation (LDA), a generative probabilistic model to produce the appropriate number of well-distributed topics across our corpus (Blei et al., 2003; Cheng et al., 2018). As we have a confined set of documents, we also use Latent Semantic Analysis (LSA) to cross-validate our set of topics (Dumais, 2004). We manually curate a range of 5–10 main topics by evaluating 'goodness of fit' of the LSA and LDA model.

To measure how well our model predicts topics, we calculate the perplexity score of documents. We do so by dividing the corpus into two batches with one batch set aside serving as a holdout set. One constraint of our model is that classic topic models and their associated keywords reveal insufficient information regarding keyword variation per topic to allow their input to the NLP analysis in an unmodified way. However, applying the topic models to each document to classify them reinforces that the documents are highly similar. We manually label topic names and their composite terms. This process produced six topics - CLIMATE, CONFLICT, HUMAN MOBILITY, FOOD SECURITY, ECONOMY, SOCIAL NORMS - each comprising 5-10 keywords. We use the resulting topics to refine the unfiltered text analysis through

the frequency and the distribution of terms and the relative importance of each topic and its composite terms (Supplementary Figure S 3-2).

As a next step, we investigate the common occurrences of topics with a term frequency analysis by counting the word frequency for recurring words in the study collection. Term frequency analysis assumes the more common a term is within a study, the greater its significance and the more relevant it must be in explaining its content. It quantifies commonness of terms within a single document. This involved extracting a set of unique words (terms) from the text of each case study (document). We pre-process terms to remove stop-words, punctuation, convert numbers to text form and normalise the text. We prepare composite terms to be counted as single terms for example climate change denotes as climate-change and 'a change in the climate' filters climate and, change individually. We derive a word frequencies rank, selecting the top one hundred for simplicity. In this part of the analysis, we further subset through subjective choice, reducing the number of times they appear from 10,637 times to 36 keywords distributed across six topic models.

However, such an approach does not quantify the relevance or meaningfulness of document terms only their frequency with the inferred assumption that high frequency is more significant than low frequency. To analyse in which relation the high-frequent words are, we compute the inverse term frequency (tf-idf). We do so for both topic terms and all unique terms to summarise the content of a document based on its relevance (Supplementary Figure S 3-2a). In particular, this information retrieval technique weights relevant search results of document terms based on the weighted

document term frequency (tf), and the term frequency across a whole corpus of documents (idf), its product resulting in a score per term:

$$TF - IDF_{(t,d,D)} = tf_{(t,d)} * idf_{(t,D)}$$

where [t] denotes the terms, [d] denotes each document, [D] denotes all corpus documents. We expanded the tf-idf score for all documents across the text collection by

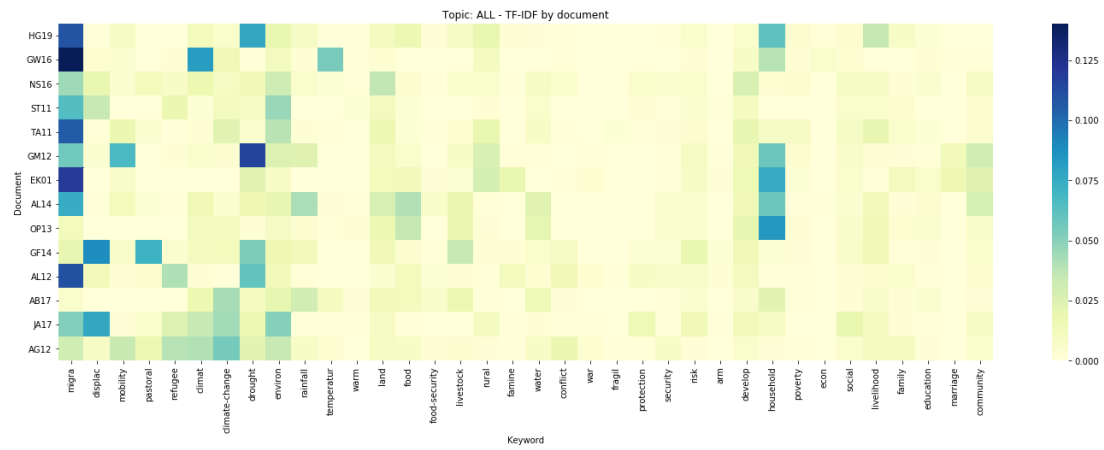
$$(1) \left| TF_{(t,d)} = \frac{n}{N} TF_{(t,d)} = \frac{n}{N} \right|$$

Where n refers to the number of occurrences of terms (t) in a document (d) and N refers to the number of occurrences of terms across all documents (D).

$$(2) \left| IDF_{(t,d)} = \log\left(\frac{D}{\{d \in D / t \in d\}}\right) IDF_{(t,d)} = \log\left(\frac{D}{\{d \in D / t \in d\}}\right) \right|$$

Here, IDF is the inverse document frequency supplied by term t and document d, $\{d \in D : t \in d\}$ denotes the number of documents in which t occurs.

a)



b)





Figure S 3-2: Distribution of topics across the case study corpus. The colour scale is normalised by topic keywords across the corpus and by individual topic per document. Note that publications containing the term climate change and climate are counted once. Normalised colour scale indicates the level of term-document association (a) and document-topic scores (b) indicate case studies where words associated with the topic appear.

4 Advancing the evidence base of future warming impacts on human mobility in African drylands

Preamble

The previous chapter detailed some methods to characterise climate-related human mobility in the literature. As outlined in Chapter 2, there are quantitative and qualitative ways to study past links between weather and climate-related events and various forms of human mobility. Chapter 4 focusses on human mobility under future warming and addresses the second research question: *What is the current understanding of the implications for human mobility under future warming in East Africa?*. In seeking to consolidate and synthesise the available evidence listed in the IPCC SR15, this research chapter uses a content analysis to address knowledge gaps outlined in SR15 and update these with more up to date evidence if such exists.

The findings of this study are presented in the paper entitled “Advancing the evidence base of future warming impacts on human mobility in African drylands” which is in revision with the journal *Earth’s Future*.

**Advancing the evidence base of future warming impacts on human mobility in
African drylands**

L. THALHEIMER¹, WILLIAMS, D.S.², VAN DER GEEST, K.³ and F.EL. OTTO¹

¹ Environmental Change Institute, University of Oxford, Oxford, UK

² Istanbul Policy Center, Sabanci University, Istanbul, Turkey

³ United Nations University, Bonn, Germany

Submitted to *Earth's Future*

Manuscript received 30 December 2020

In revision since 02 April 2021

Authorship Declaration

I conducted all of the analysis and writing for this paper. David Williams, Kees van der Geest and Friederike Otto discussed the methodology, results, and structure of the paper with me, and edited the manuscript.

Abstract

A better understanding of climate change impacts and resulting human responses (climate-related human mobility) have been identified as a research priority by the climate science community. Here, we provide the basis for future research efforts by identifying knowledge gaps and consolidating published evidence in the IPCC 1.5 Special Report (SR15) with recent evidence from climate science and the literature on human mobility in African drylands, a region where migrants are particularly vulnerable to climate change. We first synthesise climatic changes and their projected impacts across the region to then contextualize the projected impacts with current knowledge regarding the effect of anthropogenic climate change on human mobility. We discuss these often-indirect impact channels and argue that a systems approach is needed to address the interconnectedness of climate impacts and the cascading risks of adverse consequences for human mobility.

Plain language summary

The Paris Agreement recognises that climate change and extreme weather events alter human mobility patterns. Even under an optimistic scenario, an increase in global temperature of 1.5 °C above pre-industrial levels is likely to increase the numbers of people vulnerable to climatic stress while limiting the capacity for effective climate change adaptation. Under a less optimistic scenario the disruption is expected to be worse. Yet, the impacts of different warming scenarios, including observed warming, on human mobility remain insufficiently understood and discussed in policymaking. A

synthesis of empirical evidence from the IPCC Special Report on Global Warming of 1.5 °C and subsequently published literature on climate change effects in African drylands highlight implications of warming scenarios on human mobility in this region, where climatic change is a defining feature of local communities and predominantly agricultural economies. Adverse effects of climate change on African dryland communities may not necessarily cause mass migration but are likely to alter human mobility from more voluntary towards more forced displacement or entrapment. A systems approach can be used as a starting point to address the urgent challenges of climate-related human mobility.

4.1 Introduction

Stipulating the goal of capping global warming at 1.5 °C above pre-industrial levels, the Paris Agreement recognises links between climate change and human mobility (Hoffmann et al., 2020; Task Force on Displacement, 2018; UNFCCC, 2015). The importance of addressing climate-related human mobility has been increasingly recognized in a range of legal and policy frameworks (Intergovernmental Authority on Development, 2020; International Organization for Migration, 2019; United Nations Office for Disaster Risk Reduction, 2015). The Task Force on Displacement, established under the Warsaw International Mechanism for Loss and Damage, aims to develop recommendations for integrated approaches to avert and minimise internal displacement from extreme weather events and slow-onset adverse effects of climate change (Oakes et al., 2019; Task Force on Displacement, 2018). Climate change will impact a wide range of sectors (Dasgupta et al., 2014). The most significant impact

sectors of climate-related human mobility are covered by the Intergovernmental Panel on Climate Change (IPCC) Special Report on Global Warming of 1.5 °C (SR15). While more recent IPCC reports have been released, including the Special Report on the Oceans and Cryosphere in a Changing Climate and the Special Report on Climate Change and Land (IPCC, 2019a, 2019b), SR15 was commissioned specifically with decision-makers and policy planners in mind. The report scientifically assesses the implications of pursuing efforts to implement the Paris Agreement by outlining sector-specific transitions and policy actions (Tokarska et al., 2019), as well as the expected societal impacts in six climate change impact sectors (Figure 4-1).

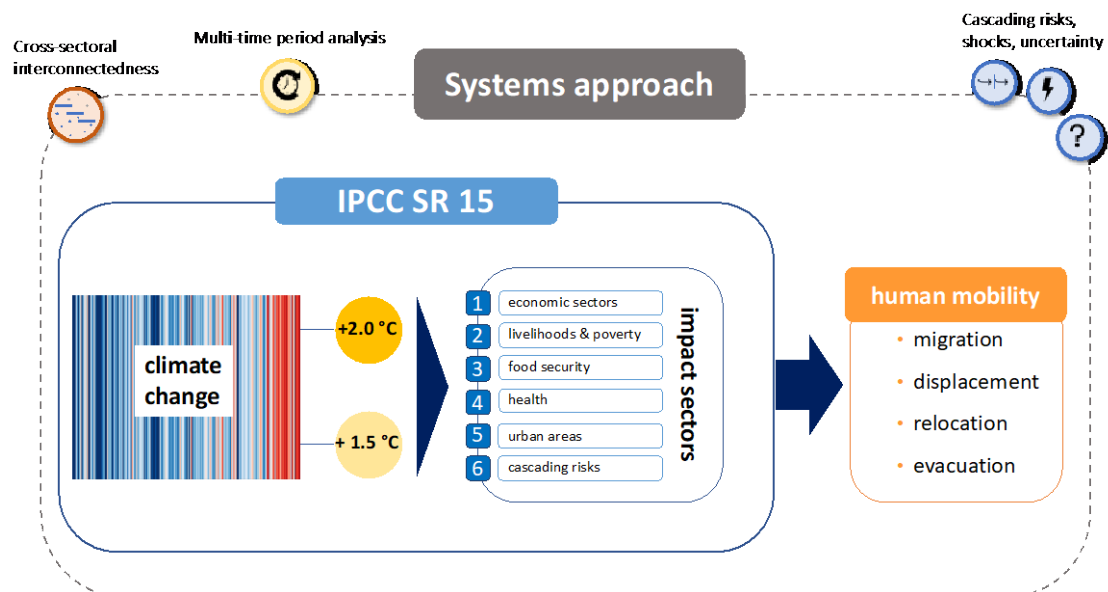


Figure 4-1: Schematic illustration of the interactions between climate change effects in the six climate change impact sectors and different types of human mobility in a systems approach framework.

Human mobility in the form of migration provides a coping mechanism when facing extreme weather events and anomalous seasons (Geest & Warner, 2014; Harrington & Otto, 2018; King et al., 2018). However, without concrete climate and development

action, situations of entrapment can become more prevalent globally (Adger et al., 2015; Ayeb-Karlsson et al., 2015). This is particularly relevant in regions where vulnerability and exposure are already high and even small changes in hazards amplify consequences on populations in situ (Harrington & Otto, 2018).

Here, we focus on one of the largest regions where such conditions apply. Home to over 38% of the earth's population (Burrell et al., 2020; Huang et al., 2017), dryland communities are disproportionately affected and vulnerable to the impacts of climate change. Dryland regions are projected to experience a 3.2 °C to 4 °C warming under a 2 °C global warming scenario by 2050 (IPCC, 2018). This is particularly crucial for African dryland regions, where regional climate models further project increases in frequency and intensity of heatwaves, droughts and floods, and adaptation is additionally hindered by high uncertainties and poor data availability (Harrington & Otto, 2020; Wartenburger et al., 2017). Therefore, we seek to answer: What is the current understanding of the implications for human mobility in African drylands under future warming?

In this paper, we provide a comprehensive discussion of the impact channels through which future warming affects human mobility (climate-related human mobility). This Commentary contributes to the ongoing, global effort toward a better understanding of climate-related human mobility (Boas et al., 2019) and constitutes a directly usable approach for policy-makers. To this aim, we propose a systems approach to address the interconnectedness of climate impacts and cascading risks of future warming on human mobility in African drylands.

4.2 Climate-related human mobility

Many weather and climate-related events have become more frequent and intense leading to widespread and disastrous impacts for populations globally (Hoegh-Guldberg et al., 2019). In extreme cases, populations have migrated away from locations frequently impacted by extreme weather events (Gray & Mueller, 2012) or are projected to move towards coastlines affected by sea level rise (Bell et al., 2021). At the same time, human mobility decisions are often multi-causal and rarely due to extreme weather events alone. Climate change may influence human mobility both directly and indirectly through various channels ranging from economic, demographic, social, political and environmental factors (Black et al., 2011). These factors ultimately lead to a decision between staying or going – and where to migrate to if needed. In this context, there are several climatic factors and cascading risks that can enhance and reduce human mobility, or even entrap populations (Cattaneo et al., 2019a; Hoffmann et al., 2020).

In existing literature, climate-related human mobility is often portrayed as a key impact of anthropogenic climate change (e.g., Biermann & Boas, 2008; Myers, 2002; Rigaud et al., 2018). Despite the increasing abundance of qualitative evidence (e.g., Groth et al., 2020; Wiederkehr et al., 2018) on how and where populations migrate due to the impacts of environmental change, surprisingly little research has linked such evidence to anthropogenic climate change (Borderon et al., 2019; Cattaneo et al., 2019a); quantitatively or qualitatively. As the impacts of anthropogenic climate change are projected to fall disproportionately upon African countries (Harrington & Otto, 2020;

Hoegh-Guldberg et al., 2019), this paper focusses on climate-related human mobility in African drylands. To do so, an understanding of climate change effects and cascading risks in this region is needed.

4.3 Mapping climate change effects on African drylands

SR15 lists projected climatic changes in a variety of climatological areas. We adopt the report's regional structure for Western, Southern and Eastern Africa in which drylands are the predominant land zone (Cervigni & Morris, 2016), and summarise projected climatic changes (Table 4-1). The table updates findings from SR15 with recently published literature. The focus is on precipitation extremes and temperature extremes as they comprise the predominant natural hazards in African drylands.

Table 4-1: Summary of regional projected climatic changes and their effects in African drylands (including confidence levels). We distinguish between effects listed in SR15 and new research published since.

	African drylands regions		
	Western Africa	Southern Africa	Eastern Africa
Precipitation and related extremes	SR15		
	Overall decrease in mean rainfall, stress in water availability (SR15, p. 197) (<i>medium confidence</i>).	Overall decrease annually, increased water stress while less water available (SR15, p. 197, 213) (<i>medium confidence</i>); Increase in heavy precipitation events (<i>low confidence</i>), while region as a whole will experience precipitation decrease (SR15, p. 197, 204) (<i>high confidence</i>).	Increase in heavy precipitation events especially over Somalia and river flooding (SR15, p. 197, 201) (<i>low - medium confidence</i>); Increase in number of consecutive dry days (SR15, p. 199) (<i>high confidence</i>).

	Post-SR15		
	Observed increase in heavy precipitation events (Barry et al., 2018) which is likely to increase in frequency and intensity by 2100 (Akinsanola & Zhou, 2019; Dosio et al., 2019). Attribution studies on late onset of rain and heavy rain do not find a significant change (Gaetani et al., 2020; Lawal et al., 2019; Parker et al., 2017).	Drying is likely to increase (Dosio et al., 2019; Maure et al., 2018), especially under Regional Climate Models (RCM) (Ahmadalipour et al., 2019) and recent droughts have been attributed to climate change (Herring et al., 2019; Nangombe et al., 2020; Otto et al., 2018).	Insufficient evidence from recent projections of rainfall over East Africa (Finney et al., 2020) to draw confident conclusions. Several attribution studies suggest no significant attributable link to climate change in observed drying trend (Herring et al., 2019; Kew et al., 2019; Otto et al., 2018; Uhe et al., 2018).
Temperature and related extremes	SR15		
	Increase in heatwaves and number of hot nights (SR15, p. 259, 261). <i>Low confidence.</i>	Rise in extreme temperature causing more frequent heatwaves and aridity, especially at +2 °C (SR15, p. 177, 178, 190, 200, 261). <i>High confidence.</i>	No findings for East Africa specified.
	Post-SR15		
	Throughout Sub-Saharan Africa: Exposure to dangerous heat projected to increase (Rohat et al., 2019).		
	Observed frequencies of warm extremes are likely to increase.	increases in frequency of warm days and decrease in cold days.	East Africa is a hotspot of increasing trends in heatwaves (Perkins-Kirkpatrick & Lewis, 2020). Lack of research on compound heat and drought events (Raymond et al., 2020).

In a warmer world, drylands are expanding globally (IPCC, 2018) while high population growth in drylands exposes more people to climate hazards (Koutroulis, 2019). Despite sparse literature, the current evidence concerning African dryland regions suggests that heat extremes will become more frequent in the region (Perkins-

Kirkpatrick & Lewis, 2020; Rohat et al., 2019). For dry and wet extremes, the influence of climate change is less clear and varies across the continent, with a significant signal only in observed, attributed, and projected drying in Southern Africa, and an increase in heavy precipitation in Western Africa. In East Africa, increases in temperature have been found to be linked to anthropogenic climate change, while current rainfall deficits and subsequent droughts do not show a strong anthropogenic climate signal. Uncertainties are significant though, as is vulnerability to natural climate variability (Kew et al., 2019).

4.4 Climate change impact sectors and their relation to human mobility in African drylands

There is growing evidence that climate change and extremes primarily affect human mobility indirectly (Black et al., 2011; Hoffmann et al., 2020; Romankiewicz et al., 2018). With a focus on interconnectedness of climate impacts and cascading risks, this section consolidates and expands on the evidence provided in SR15 with relevant implications for human mobility in African drylands.

We find that the effects from interacting and cascading risks could imperil migration as an adaptation or coping mechanism across the region. Cascading risks are spatially compounding risks that involve multiple interacting hazards in the same location. Cascading risks lead to increased exposure and raising adaptation pressure (Piontek et al., 2014). The amount of people exposed to cascading risks is projected to double from a 1.5 °C to a 2 °C warmer world, with almost the entire global population affected either

directly or indirectly under a 3 °C warming scenario; the exposure in African regions to cascading risks is amongst the highest (IPCC, 2018). Poor communities affected by drought and water-stress, as well as political instability and growing conflicts, could find themselves forced to move as a response to climate thresholds (Tol, 2018; C. Xu et al., 2020). Cascading risks are a cross-cutting theme and particularly impactful on people living in poverty (IPCC, 2018), highlighting the urgent need for a systems approach as a bridging framework.

Accessibility, trade and distribution of food crops and livestock form an interconnected variable between human mobility and climate change (Adams & Adger, 2013; Afifi et al., 2016). Drylands have already experienced lower agricultural productivity and recurring weather shocks (Geest & Warner, 2014). Even a warming of +1.5 °C accelerates adverse risks of reduced water and food availability (Betts et al., 2018; Cheung et al., 2016). Constraining warming levels to 1.5 °C can substantially minimise risks in crop yield losses in West Africa (Schleussner et al., 2016). Dryland areas, where rainfall levels are already increasingly uncertain, are projected to become less suitable for agricultural production (Läderach et al., 2013; Sultan & Gaetani, 2016; Zommers et al., 2016). As extreme events are projected to further increase in frequency and intensity, poor people and those with lower access to resources are likely to be adversely impacted (Hallegatte & Rozenberg, 2017; IPCC, 2018).

Further, food insecurity is projected to disproportionately affect poor populations in African drylands (Byers et al., 2018; Puma et al., 2018; Thalheimer et al., 2019). Related increases in local, regional, and global food prices could put an additional 122 million people in extreme poverty by 2030 (Guldberg et al., 2018). Climate change

could adversely impact the livelihood security of seasonal migrants and pastoralists (Fanzo et al., 2018; Rademacher-Schulz et al., 2014). In regions with increased risk of water stress, pastoralists and their livestock will have to alter mobility patterns in the search for water and livestock fodder (Boone et al., 2018).

Despite limited research on the effects of a current and near term warming, variabilities in rainfall and temperature extremes are associated with higher levels of internal migration in agriculture-dependent communities (Cai et al., 2016; Rigaud et al., 2018) highlighting wider economic implications for affected populations. In poorly endowed communities, climate change impacts can further amplify conflict over scarce resources (Serdeczny et al., 2017). In some cases, a warming up to 1.5 °C (expected by 2030s, independent of scenarios) already significantly increases the risk of inter-group conflicts, which in turn can generate reinforced involuntary mobility (Hsiang et al., 2013). Climate change impacts on agriculture highlight wider economic implications for affected populations.

For instance, while drought increases economic-related internal migration, it is important to consider that financial capital is needed to pursue mobility (Cattaneo et al., 2019a; Gray & Wise, 2016). Even though there are major gaps in quantifying climate change impacts from the transportation sector (IPCC, 2018; Tol, 2018), many migrants depend on infrastructure and public transport for work and to secure income. With more frequent heat waves, the demand for cooling devices will rise (Khosla et al., 2020). Resulting increases in household spending for electricity will adversely affect the world's poorest – many of those living in African drylands. However, major capital expenditures to secure the provision of energy remain at risk under climate change and

are highly uncertain. In Ethiopia, climate impact models indicate a decrease in capital expenditure by 3% under extreme wet scenarios and an increase by 4% in extreme dry scenarios by 2050 (Block & Strzepek, 2012).

In addition, climate change is likely to damage agricultural yields whilst adversely impacting workers' health conditions and their ability to perform labour intensive work outdoors. Climate change has already increased the exposure and vulnerability to climate-related stress and related health issues (Haines & Ebi, 2019). Heatwaves in particular have shown adverse effects on occupational health (Rey et al., 2007). Among vulnerable populations, climate change can reduce food security and labour productivity, which has adverse health outcomes, while the functioning of healthcare systems may be reduced in the event of weather extremes. Together, heatwaves and long-term climate change can limit the physical work capacity, leading to diminished agricultural productivity and causing undernutrition in drylands. Droughts contribute to biodiversity loss and ecosystem collapse, increasing the likelihood and occurrence of vector-borne diseases (Watts et al., 2017). A half-degree temperature increase to 2°C adversely impacts health conditions globally (Haines & Ebi, 2019). SR15 states with very high confidence that heat-related mortality and morbidity will be higher under 2°C than under 1.5 °C.

While there is some evidence of climate-related health impacts influencing human mobility decisions, the extent to which out-migration will increase remains uncertain and needs further empirical research (McMichael, 2020; Schwerdtle et al., 2018). Initially, negative impacts on human health may decrease the likelihood of migration due to reduced personal capacity for relocation. However, studies have demonstrated

migrants willing to move into sites with increased exposure to natural hazards and potentially cascading risks for their health (McMichael, 2020) during stages of the migration journey (Schwerdtle et al., 2018; Schwerdtle et al., 2019). The western African region (Byers et al., 2018) and drylands in Ethiopia (Piontek et al., 2014) are potential hotspots for such cascading risks. The combination of various vector-borne diseases, especially malaria, and climate-induced socio-economic disruption is projected to have significant regional impacts such as increased outward migration (Piontek et al., 2014) to areas with less exposure to extreme weather events. Systemic shocks like the COVID-19 pandemic show that access to health care is limited during relocation processes which may undermine global health goals (Schwerdtle et al., 2019).

With an increasing number of people from rural dryland areas pursuing urban migration in the search for alternative occupation, there is a higher vulnerability to heatwaves and poor urban air quality exacerbated by climate change. Even under a 1.5 °C of warming, the incidence of heat waves is projected to increase, doubling the number of megacities affected by heat stress and exacerbating urban heat island effects. Under a 2 °C warming scenario, a significant rise in heat stress-related mortality is projected, particularly for low-income countries in sub-Saharan Africa. Given the lack of reporting on current heat impacts this provides particular challenges to adaptation (Harrington & Otto, 2020). Climate projections further indicate a decrease in the number of consecutive wet days, and an increase in consecutive dry days for sub-Saharan Africa. Despite large uncertainties in projections (King et al., 2020), if the amount of annual precipitation is to stay constant, it will increase the intensity of hydrological extremes in the form of floods, droughts, and water scarcity (IPCC, 2018).

Drought and water scarcity already prompt internal and cross-border migration flows (Adams & Kay, 2019; Nawrotzki & DeWaard, 2016), while there is little evidence for heatwaves (Harrington & Otto, 2020). In some cases, climate-related migration can lead to further risk accumulation in urban areas (Ayeb-Karlsson, 2020; Wilkinson, 2016). Increased rural-urban migration accelerates rapid urbanization, which is compounded by the inability of already overstretched cities and municipalities to provide affordable and safe housing (D. S. Williams et al., 2019). The resulting number of people residing in environmentally precarious areas rises, meaning they experience higher exposure to natural hazards. Most arriving migrants lack financial resources to relocate to areas with a significant level of access to basic services and less exposure to hazards (Adams & Kay, 2019; D. S. Williams et al., 2019). They are thus trapped in environmentally precarious areas in which the climatic risks under future warming scenarios are significantly more precarious (Adger et al., 2015; IPCC, 2018).

We find that climate change effects adversely impact African dryland communities and are likely to alter human mobility in different ways. In some cases, climate change can lead to more population displacement, whereas in other cases it can lead to less human mobility for instance when people become trapped. Overall, climate change can shift more voluntary human mobility to more forced flows. There is consistent evidence on the relationship between climate change impacts on economic development and human mobility through economic losses in agriculture and food insecurity from droughts (Nawrotzki & Bakhtsiyarava, 2017), changes in temperature (Gray & Wise, 2016) and precipitation (Mastrorillo et al., 2016). Cascading risks and compound events interlink all sectors and therefore indicate the biggest impact on human mobility under future warming. In East Africa, the ongoing locust spread and survival due to climatic stresses

and socio-economic activities is yet another example that shows the importance of such cascading risks (Salih et al., 2020).

4.5 Systems approaches to advance the current evidence

In this paper, we highlighted that climate change impacts on African drylands mobility are not just a result of potential disruptions of a single impact sector, rather showcasing shocks to multiple sectors, cascading or even compounding risks. Given the increasing relevance of cascading risks from connected and compound events (Raymond et al., 2020), it thus seems reasonable to propose a systems approach as a starting point to address future warming impacts on human mobility in research and policy.

A first option to effectively respond to sectoral climate change impacts is to take a system-wide approach (Ratter, 2013), which requires decision-makers, policy planners and various sectors to undertake a co-ordinated and concerted effort. The advantage of this method is that a holistic understanding of the interface between climate change and human mobility can be gained. Resulting interlinked concepts, dynamic relationships, and feedback behaviour, can be useful for enhancing co-operation and guidance, and for identifying resilience-enhancing pathways. However, a systems approach deems a form of co-operation which is currently constrained by a lack of cross-sectoral integration and political instrumentalization prevalent across regions affected by climate change (D. S. Williams et al., 2019). Further limitations lie in the governance context; in much of dryland Africa fragile states are prevalent and high poverty levels.

Conversely, a systems approach could also be a bridging framework to address interlinked challenges.

Clearly, it is crucial to investigate and derive policy conclusions holistically, beginning with the interconnectedness of climate change, impact sectors and human mobility. Climate change policies are likely to have significant impacts in economic, environmental and social domains and on a wide range of stakeholders (Tol, 2018). It is therefore essential to take potential and unintended side-effects of the policy on other sectors into account. We have highlighted the importance of accounting for cascading risks, shocks, and uncertainties. Various policy alternatives and their trade-offs have to be accounted for. Cascading risks, and ways to deal with them, as well as risk criteria have to be included from a systems dependency perspective. Management of risk also entails to capture uncertainty in the strength or in the direction of cross-sectoral interconnectedness. Short, medium, and long-term impacts of a policy need to be defined, for example, a trade-off between various types of proactive long-term (ex-ante) measures and reactive short term (ex-post) measures. Uncertain futures of climate change, including possible occurrence of extreme weather events affecting human mobility versus lifespans of adaptation measures have to be taken into consideration.

4.6 Outlook

We find ourselves at a crossroads. More research is needed on all aspects of the interface between human mobility and climate change, and the cascading risks associated with it. Evidence on the link between climate change and current extreme

weather and slow-onset events as well as research on near-term changes at 1.5 °C and 2 °C warming could provide ground-truthing of the above-described findings and be transformative in understanding human mobility if enhanced by a deeper understanding of the cross-sectoral interconnectedness of climate impacts that drive human mobility. From a research perspective, this requires global collaboration and truly transdisciplinary approaches that can inform policy aimed at preventing forced migration and facilitating safe and dignified human mobility in a changing climate.

5 Disentangling the effects of climate and conflict on displacement: Evidence from Somalia

Preamble

The previous chapters formed the first part of this thesis characterising climate-related human mobility and evidence of respective implications under warming. Chapter 5 starts the second part of this thesis and addresses the third research question: *How can we disentangle and quantify the drivers of human mobility in the study area?*. This chapter presents a country case study on Somalia and uses quantitative social science methods (climate econometrics) to disentangle climate and conflict-related internal displacement drivers and attribute reported reasons of respective displacement dynamics. This chapter emphasises on the uniqueness of the dataset used and the methodology applied.

The findings of the study are presented in the paper “Disentangling the effects of climate and conflict on displacement: Evidence from Somalia”, which has been submitted for publication to *Science*.

**Disentangling the effects of climate and conflict on displacement: Evidence from
Somalia**

L. THALHEIMER¹, M. P. SCHWARZ² and F. PRETIS³

¹Environmental Change Institute, University of Oxford, Oxford, UK

² Smith School, University of Oxford, Oxford, UK

³ Department of Economics, University of Victoria Canada

Submitted to *Science*

01 June 2021

Authorship Declaration

I conducted all of the analysis and writing for this paper. Moritz P. Schwarz and Felix Pretis both discussed the methodology with me, contributed to the interpretation of the results, and provided comments on the manuscript.

Abstract

Weather, climate, and conflict-related events may drive forced displacement. However, their individual contribution to displacement is not fully understood due to challenges around isolating individual channels of causality. Here, we use novel disaggregated data on displacement in all of Somalia's 18 regions from 2016-2018 broken down by reason of displacement and combine it with weather and conflict data to isolate the effects of climate and conflict on forced displacement, as well as the effects of climate and displacement on conflict itself. We find large non-linear lagged effects of weather on displacement and immediate effects of conflict on displacement, which are masked when the data is aggregated. We also show that reduced precipitation increases the probability of armed conflict, however, migration itself has no effect on the probability of conflict events.

One-Sentence Summary

Climate and conflict have non-linear effects on population displacement in a climate change vulnerable country, with climate affecting conflict directly and in-migration itself not increasing the probability of conflict.

5.1 Main Text

Globally, weather and climate-related events displaced 30 million people in 2020 alone, with armed conflict leading to an additional 9.8 million of internally displaced persons (IDPs) (Internal Displacement Monitoring Centre, 2021a). In order to allocate aid and resources to the growing number of displaced people optimally, the causal drivers of displacement need to be understood. While the impacts of a changing climate and conflict on communities have been well documented in other fields, the quantification of climate effects on displacement has been severely limited by highly-aggregated data, limiting the literature's ability to disentangle the individual drivers of displacement (Abel et al., 2019; Cattaneo et al., 2019a; Rigaud et al., 2018). Aggregate data may reflect multi-causal drivers of displacement (text S1) but complicate capturing the individual contribution of local weather, climate or conflict-related events (Hoffmann et al., 2020; Internal Displacement Monitoring Centre, 2019). Whether people are displaced due to climate or conflict-related events has major implications for global sustainable development and inclusive growth, especially given the significant effects of further climate change (IPCC, 2018).

In this study, we study displacement in Somalia between 2016 and 2018 to empirically assess the interaction between drought, conflict, and displacement. The humanitarian crisis in Somalia is one of the most long-standing and complex ones since the end of the Cold War (World Bank Group, 2018). We investigate human responses to drought and conflict by statistically analysing monthly displacement of 18 administrative regions using a novel disaggregated dataset (Figure 5-1).

To illustrate, the scale of displacement, Figure 5-1 (iii) shows a network of arriving IDPs, most of them in the southern parts. The data shows that respondents indicated drought to be their primary displacement motivation twice as often as conflict across all regions (Figure 5-1, i and ii). Conversely, conflict appears to displace populations in the south sporadically, despite drought occurrences. Here, we study how and to what extent climate and conflict displace communities, and how climate and displacement affect the potential for conflict.

Our results show significant non-linear impacts of temperatures and precipitation on internal displacement, where above-average temperatures and below average precipitation increase displacement with a lag of 3-4 months with IDPs moving to more favourable regions, however, below average temperatures or precipitation show no effect. When focusing on displacement data of IDPs reporting that conflict was their prime motivation to leave, we find significant effects of conflict on forced migration as expected. These effects, however, are masked in aggregate data, suggesting that data aggregation may explain the absence of conflict-induced displacement effects in earlier studies (Kelley et al., 2015; Missirian & Schlenker, 2017). We further show there is evidence of direct effects of climate on conflict itself, where decreasing precipitation increases the probability of conflict, potentially due to resource scarcity. Using the unique structure of our dataset, we are able to bypass simultaneity concerns to investigate the effect of displacement itself on the probability of armed conflict, where we do not find statistically significant effects.

5.2 Methods and Data

For this study, we combine disaggregated data collected by UNHCR/PRMN on internal displacement (Figure 5-1, (UNHCR, 2021)) broken down by reported displacement reason (drought and conflict) with data on prevailing climatic conditions and the number of conflict events (see supplementary sections in S2) for 18 Somali regions from January 2016 to September 2018 (for a total of 594 monthly observations). We combine this dataset with weather and conflict data. UNHCR/PRMN capture this detailed information at the regional level by conducting interviews with IDPs. This is done primarily at points of arrival or by interviewing key informants at IDP settlements, transit centres, and other strategic locations (UNHCR Somalia, 2017). Modelling absolute displacement (rather than relative between regions) allows us to take such intra-region population movements into account. Beyond isolating individual channels of effects, the level of disaggregation (by reason of displacement) also allows us to study the degree to which aggregation of data masks underlying causes.

We model five channels through which climate and conflict directly or indirectly could influence displacement (labelled A–E in Figure 5-1, iv) using well-established two-way fixed effect (TWFEs) models (de Chaisemartin & D’Haultfœuille, 2020; Maystadt & Ecker, 2014) allowing for non-linearities and dynamic effects over time. Climate may directly drive displacement (e.g., due to droughts) (channel A), or indirectly by leading to increased conflict (e.g., due to resource scarcity, channel E and subsequent conflict driven displacement, channel B). Conflict at the origin region may drive displacement (e.g., fleeing from a warzone, channel B), but conflict itself may be driven by in-

migration at the destination (e.g., mixing of ethnic groups/ intra clan rivalry, channels D and C). Much of the previous literature on climate, conflict, and migration had to rely on aggregate data of displacement, making it difficult to disentangle individual channels due to possible feedback between conflict and migration (Abel et al., 2019).

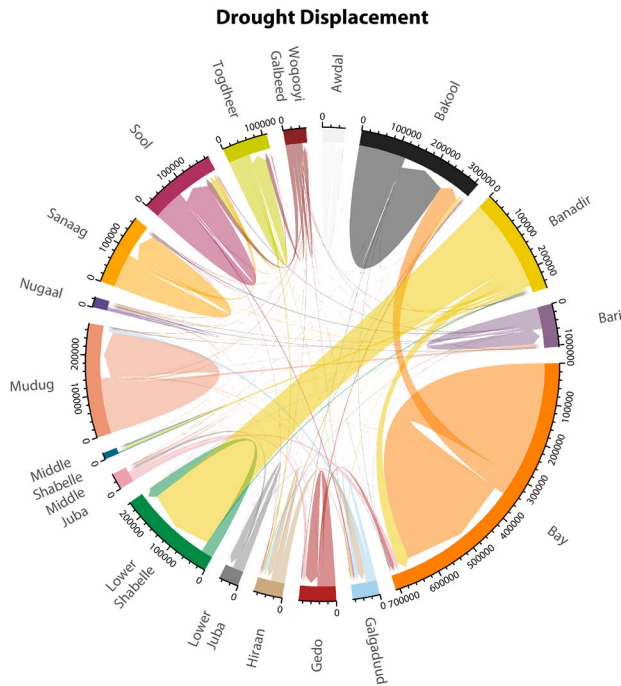
Here we observe displacement and conflict both at the origin and departure region, broken down by the primary reason for displacement, which allows us to identify individual channels of effects. We rely on two identifying assumptions to isolate these channels. First, we assume that IDPs truthfully declare the primary reason of displacement, as indicated in the PRMN data collection methodology (UNHCR Somalia, 2017). As the surveys are anonymous and released with a substantial lag, there is no obvious reason for IDPs not to truthfully report their reason at each checkpoint. Second, we assume that IDPs from the origin region do not affect the occurrence of conflict at the origin region. Although the degree to which people are forced to leave due to conflicts might differ, the literature does not suggest that out-migration itself causes conflict at the origin (Borderon et al., 2019; Collier & Hoeffler, 2005; Ide & Scheffran, 2014); thus we consider our assumptions reasonable.

Under these two assumptions, we can identify the following channels of effects, illustrated in Figure 5-1 (iv). First, we assess the net effect of climate on migration (channels A, E and B) by modelling total displacement as a function of climate conditions at the origin (or relative climate between origin and destination). Second, we identify the sole-climate effect by modelling climate-driven displacement as a function of the observed climate. This identifies channel A by only focusing on IDPs reporting only climate (i.e., drought) to be the reason for displacement. Third, we

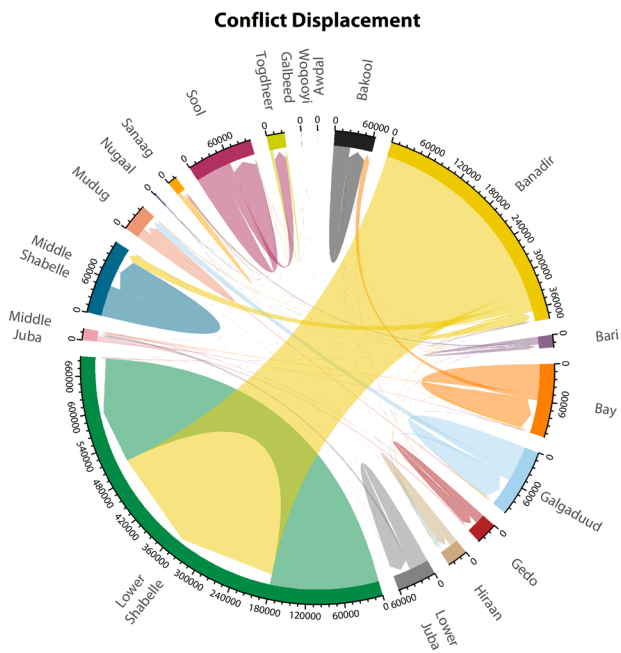
identify the effect of conflict on displacement in absence of climate by modelling out-migration specifically reported due to conflict as a function of conflict at the origin (isolating channel B). Fourth, we can assess the net effect of climate on conflict, which aggregates direct effects (E) as well as indirect effects through migration (channels A–D). In the context of poor governance and political fragility, weather and climate-related events can create and maintain conflict over scarce resources (Cattaneo et al., 2019a; Missirian & Schlenker, 2017). Fifth, we can isolate the effect of displacement on conflict by studying conflict at the destination as a function of in-migration (channels D–C), where we model the probability of the occurrence of armed conflict events as a function of local weather and in-migration into each destination region. We discuss our estimation approach further in the Supplementary material (S3).

We model each possible channel of effect using two-way fixed effects panel models. We control for region and time fixed effects while allowing for dynamics using distributed lags and non-linear effects through second-order polynomial functional forms. We consider two general model specifications. In the first one, we model the level of displacement (and probability of conflict) in each region. In the second one, we model the relative displacement between regions making use of the fact that we have information on the origin and destination of IDPs. The first approach allows us to answer whether climate (or conflict) has any measurable effect on displacement, and accounts for displacement within the same region. This is crucial given the large number of IDPs moving within their origin region (see Figure 5-1, i and ii). The second (relative) approach allows us to assess whether people move to more favourable regions where they might be better off as suggested in the literature (Benveniste et al., 2020; Collier et al., 2008). In contrast to a recent study (Owain & Maslin, 2018), our research

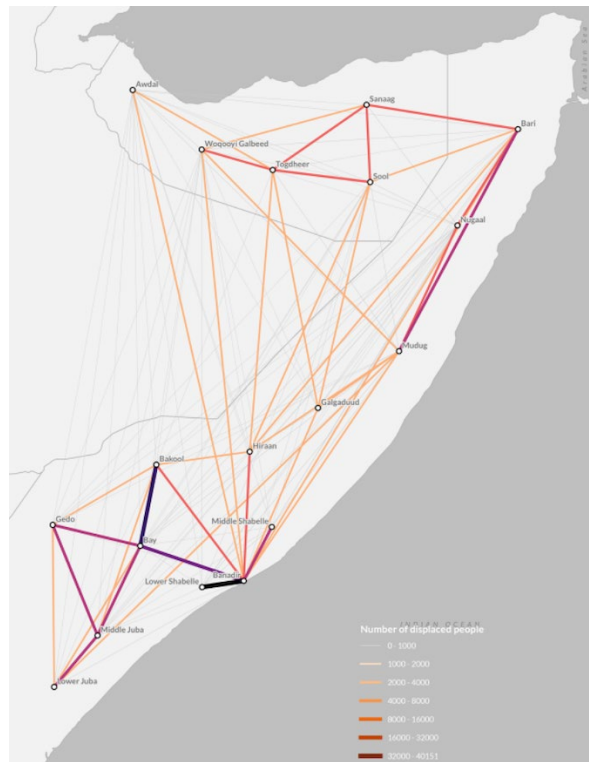
design allows to explicitly disentangle effects through which climate influences internal displacement and to estimate non-linear effects of climate on displacement and conflict, and the effects of conflict on displacement, and *vice versa*.



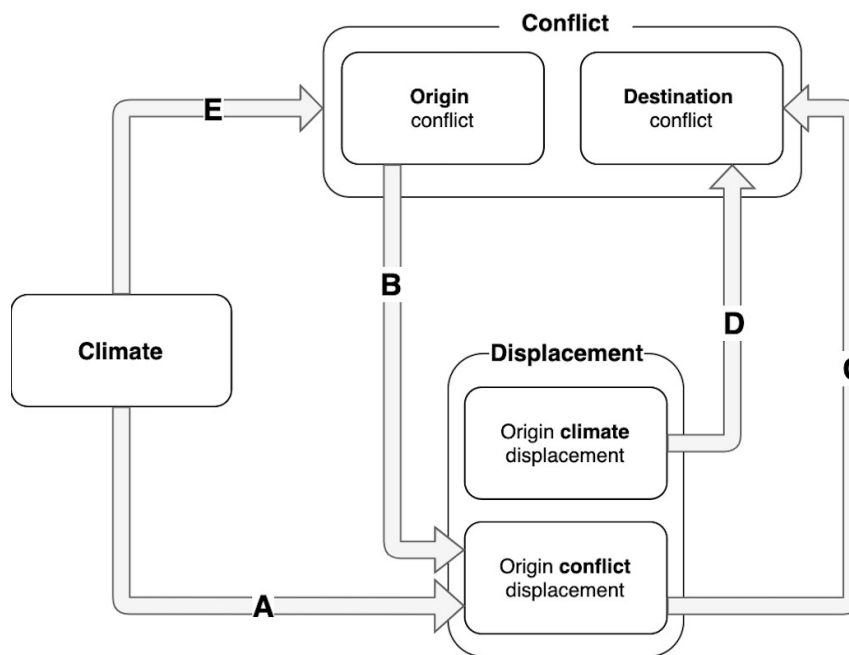
(i)



(ii)



(iii)



(iv)

Figure 5-1: Internal displacement flows in Somalia 2016-2018, broken down by region and reason for displacement (circos plots: i, ii and network graph: iii). Lower right panel (iv) shows possible channel of effects across climate, conflict, and displacement.

Notes:

Top panels: Circos plots (i, ii) depicting cumulative regional links for IDPs in the period 2016 to 2018. We show drought and conflict displacement separately to illustrate two key aspects: 1) most displacement occurs in southern Somalia and 2) high level of within-region displacement occur independent of the displacement reason reported. Displacement due to conflict (over 0.6 million) remains a persisting factor in the southern regions. Drought is reported to displace more people in the period (over 1.2 million), largely affecting the southern regions of Bay, Bakool and Lower Shabelle. Bottom left panel (iii): Displacement network across 18 administrative regions in Somalia. We computed weighted centroids for each region to generate a base network and visualise regional differences in displacement frequency. Lower right panel (iv): shows the range of possible interactions between climate, displacement, and conflict, where we observe both in and out migration in each region, as well as conflict and climate at both the origin and destination of IDPs.

5.3 Results

We find significant non-linear effects of both temperatures and precipitation on internal displacement (see Figure 5-2, which shows the cumulative effects over all 4 lags for level models, estimated coefficients and tables S 5-3 to S 5-6 in the supplementary materials). Above-average temperatures and below average precipitation increase displacement, while below average temperatures or above average precipitation have no notable effect. Despite large estimation uncertainties, our results suggest that as temperatures increase to 1.5-2°C above the regional long-time average, we find significant increases of around 1.7% (95CI: 0-22%) in-migration of drought-related IDPs for a one-standard deviation increase in temperatures (0.6°C) relative to the sample mean. In turn, we find no reduction in migration for cooler than average periods. Increased precipitation leads to a reduction in migrants for precipitation levels below

50-100mm relative to regional averages, where a one SD increase in precipitation (at low levels of precipitation) reduces conflict-related IDPs by around 0.3% (95% CI: -9-0%). Both the temperature and precipitation signals are consistent with IDPs migrating in response to drought-like conditions, where temperatures and precipitation induce a migration decision only after tipping points of high levels of warming and low levels of precipitation. This effect is detectable in both aggregate displacement as well as IDPs who report to have migrated due to droughts, although expectedly the effect is lower in aggregate displacement. Our dynamic models suggest that this drought-related displacement does not occur instantaneously but occurs with a lag of 3 to 4 months (Figure S 5-1). This complements previous findings on the role of drought in East Africa as a ‘risk multiplier’ by exceeding populations’ resilience to dry conditions (Owain & Maslin, 2018).

When assessing the estimated relative models (S3.2, table S2), our results suggest that IDPs move to regions with more ‘favourable’ weather (Figure 5-3). As temperatures at the destination region increase relative to the origin, fewer people are displaced. Similarly, as the precipitation difference between two regions increases, more people are displaced. Combining level and relative results shows that IDPs respond to climate conditions at their origin and at the respective destination: IDPs move due to challenging drought conditions at their origin, sometimes even within their region. When IDPs move to a different region, they are more likely to go to places where relative temperatures are lower and where relative precipitation is higher, although the size of the absolute effect seems to dominate the relative effect (Figure 5-3).

Modelling the displacement response to conflict at the origin, we find a positive significant effect, with increased armed conflict leading to an increase in IDPs. However, the conflict signal is only detectable when measuring the response of conflict-reported displacement (Figure 5-4 lower panel). When testing for an effect of conflict on total displacement, the signal is masked, suggesting that data aggregation may lead to a spurious conclusion that conflict has no effect on displacement (Figure 5-4 upper panel). Unlike drought-induced displacement which occurs with a lag, conflict effects take place at a more rapid pace, with the largest estimated effect of conflict on displacement occurring contemporaneously (i.e., in the same month given our monthly frequency of observations) – see Figure S 5-1 and Figure S 5-2.

The estimated conflict-displacement relationship appears weakly non-linear, with decreasing marginal impacts for higher levels of conflict. For “low” levels of conflict (<25 events per month) the effects are positive and large (increasing conflict increases displacement) where a one SD increase in conflict events is associated with a 1.5% increase in IDPs (90% CI: 0-20%), however, once conflict events rise to high levels (> 25-50 events per month), additional conflict events do not lead to a statistically significant change in conflict-induced displacement. This may suggest that migration is only a feasible adaptation strategy to conflict for comparatively low levels of conflict. High levels of conflict may preclude the local population from removing themselves out of harm’s way, although the number of available observations in this range is scarce and so effects can only be estimated with significant uncertainty.

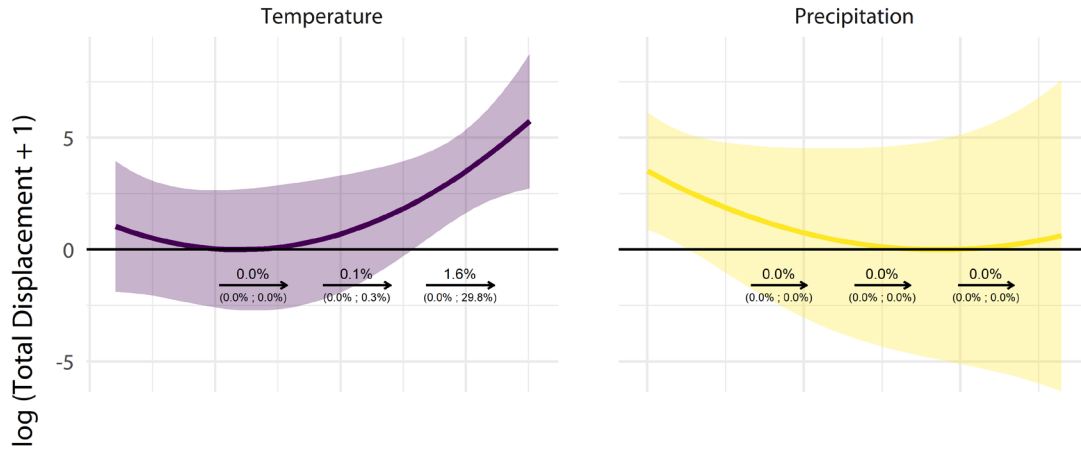
Our analysis of the climate effects on conflict shows that the probability of observing armed conflict events decreases with additional above-average regional precipitation

(Figure 5-5). This effect is strongest for observing any conflict (i.e., observing no conflict to at least one), suggesting that drought-like conditions increase the probability of conflict events. We cannot find an increase in probability of observing large conflict events conditional on having pre-existing conflict situations.

As we observe both origin and destination of IDPs, we can identify the effect of in-migration onto conflict at the destination, asking the question whether an arrival of IDPs could lead to further disputes in the region they arrive in. We find no effect of in-migration on the probability of conflict events at the destination (Figure 5-6). This holds both for the probability of observing any conflict as well as the probability of observing a larger number of conflict events.

Effect on Total Migration (Level)

Effect predicted across the variable range.
Arrows indicate predicted difference of one SD change.
Effect standardised with observed Mean = 4,090.



Effect on Drought Migration (Level)

Effect predicted across the variable range.
Arrows indicate predicted difference of one SD change.
Effect standardised with observed Mean = 2,303.

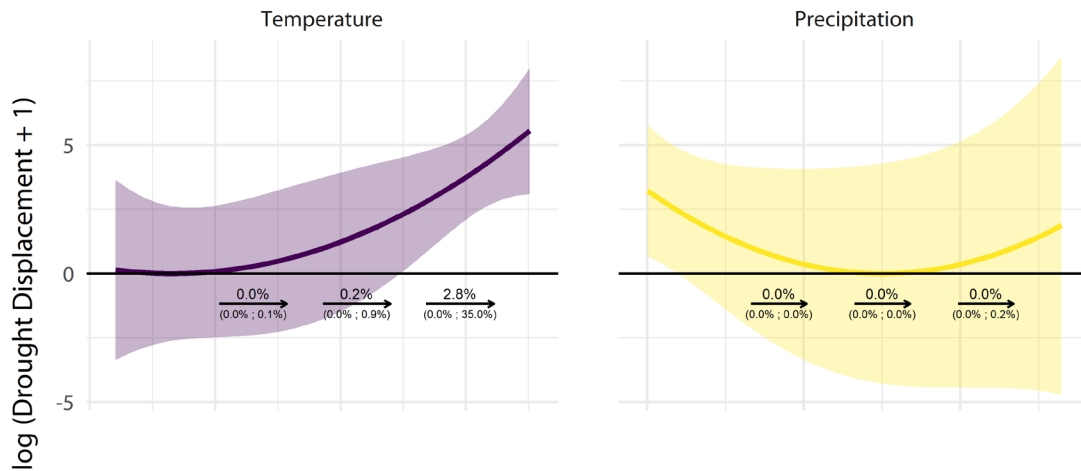
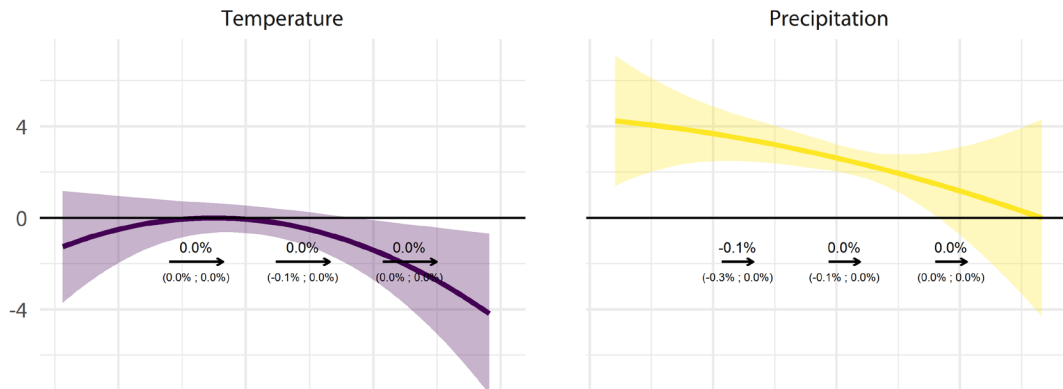


Figure 5-2: Climate effects on total displacement (Top) and displacement due to droughts (Bottom). Top panels show the temperature (left) and precipitation (right) effects on displacement over all temporal lags in the model. Shaded region shows the 95% confidence interval accounting for parameter uncertainty of lags and non-linear terms jointly. Arrows indicate the predicted percentage change in displacement in response to a one standard deviation change in temperatures or precipitation respectively at the base level indicated by the start of the arrow. A 95% confidence range of effects is shown in parentheses.

Effect on Total Migration (Relative)

Effect predicted across the variable range.
Arrows indicate predicted difference of one SD change.
Effect standardised with observed Mean = 723.



Effect on Drought Migration (Relative)

Effect predicted across the variable range.
Arrows indicate predicted difference of one SD change.
Effect standardised with observed Mean = 263.

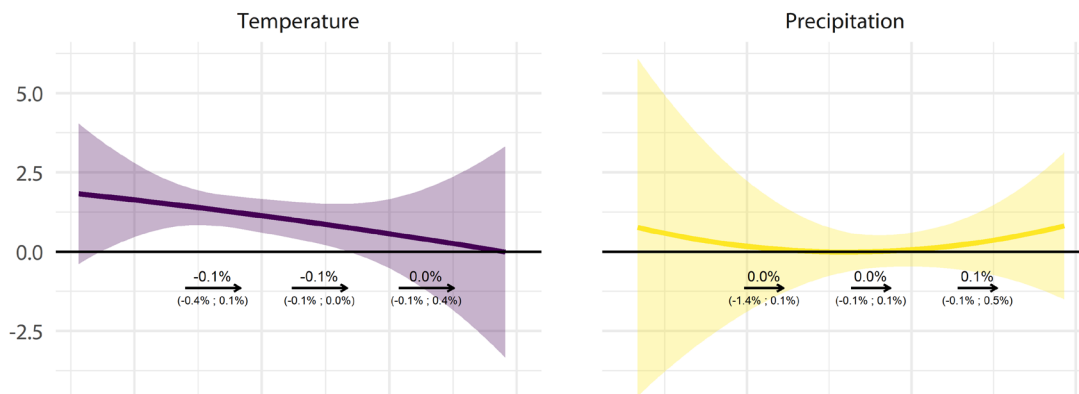


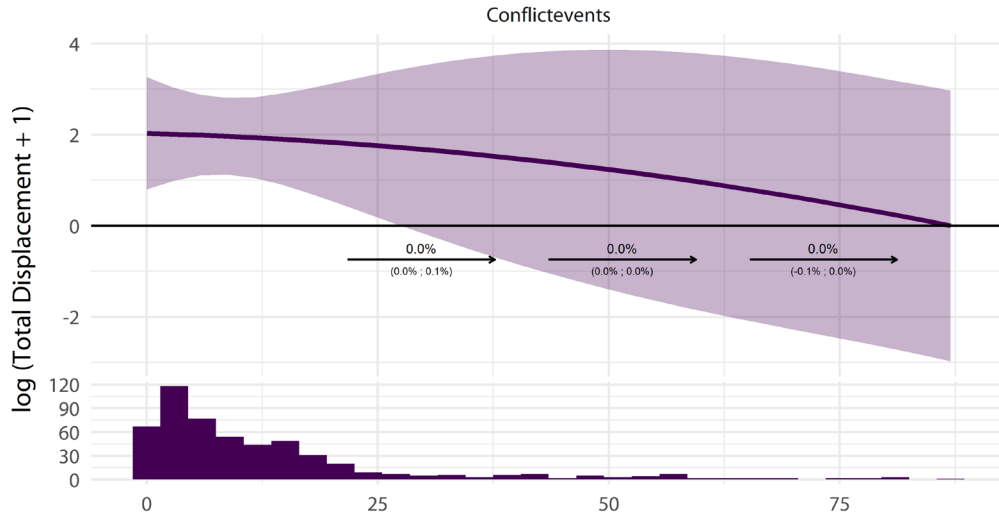
Figure 5-3: Climate effects on total displacement (Top, Relative Model) and displacement due to droughts (Bottom, Relative Model). Top panels show the effects of the relative differences in temperatures and precipitation on relative displacement aggregated over all temporal lags in the model. Shaded region shows the 95% confidence interval accounting for parameter uncertainty of lags and non-linear terms jointly. Arrows indicate the predicted percentage change in displacement in response to a one standard deviation change in temperatures or precipitation respectively at the base level indicated by the start of the arrow. A 95% confidence range of effects is shown in parentheses.

Conflict Effect on Total Migration (Level)

Effect predicted across the variable range.

Arrows indicate predicted difference of one SD change.

Effect standardised with observed Mean = 3,954.



Conflict Effect on Conflict Migration (Controlling for Climate - Level)

Effect predicted across the variable range.

Arrows indicate predicted difference of one SD change.

Effect standardised with observed Mean = 1,132.

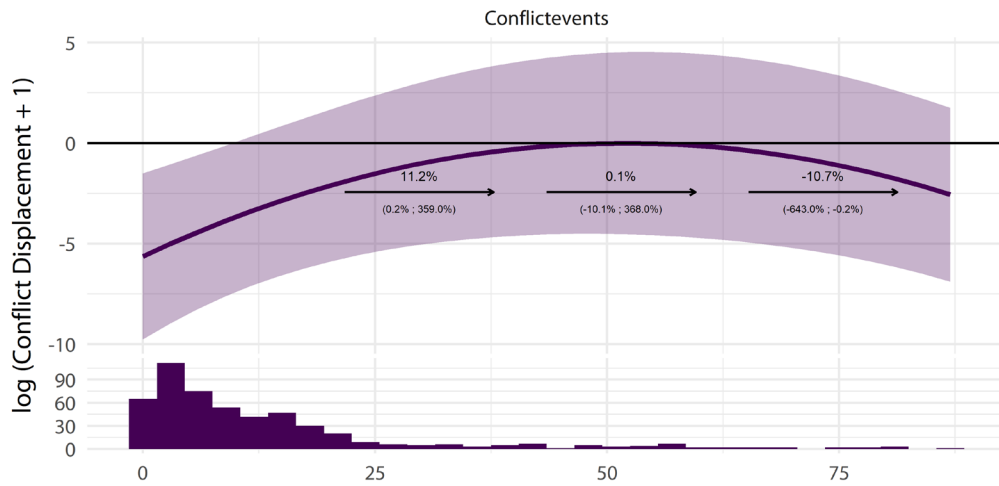


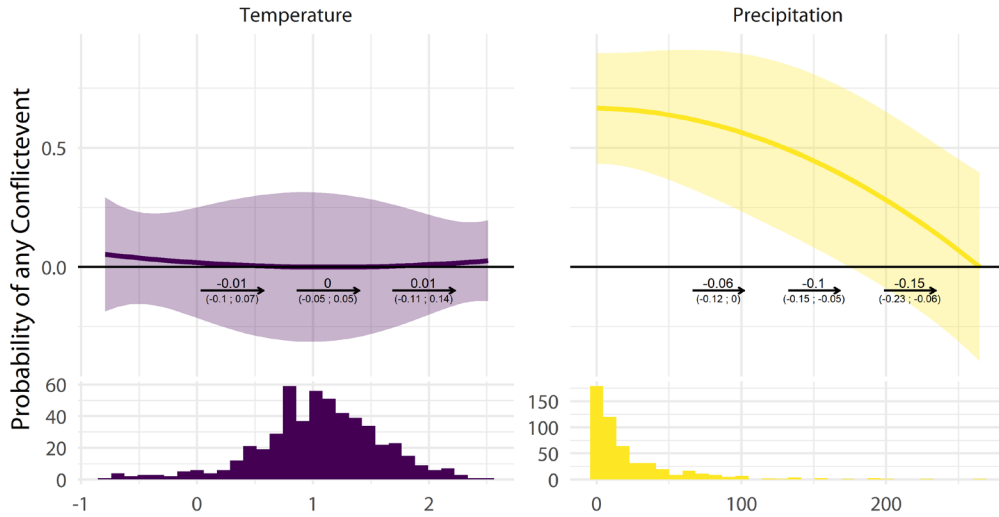
Figure 5-4: Effect of conflict on total displacement (Top, controlling for climate) and effect of conflict on displacement due to conflict (Bottom, not controlling for climate). Histograms show the in-sample distribution of conflict events. Arrows indicate the predicted percentage change in displacement in response to a one standard deviation change in temperatures, precipitation, or conflict events respectively at the base level indicated by the start of the arrow. A 95% confidence range of effects is shown in parentheses.

Climate Effect on Conflict events (LPM-0 - Level)

Effect predicted across the variable range.

Arrows indicate predicted difference of one SD change.

Effect standardised with observed Mean = 0.05.



Climate Effect on Conflict events (LPM-10 - Level)

Effect predicted across the variable range.

Arrows indicate predicted difference of one SD change.

Effect standardised with observed Mean = 0.44.

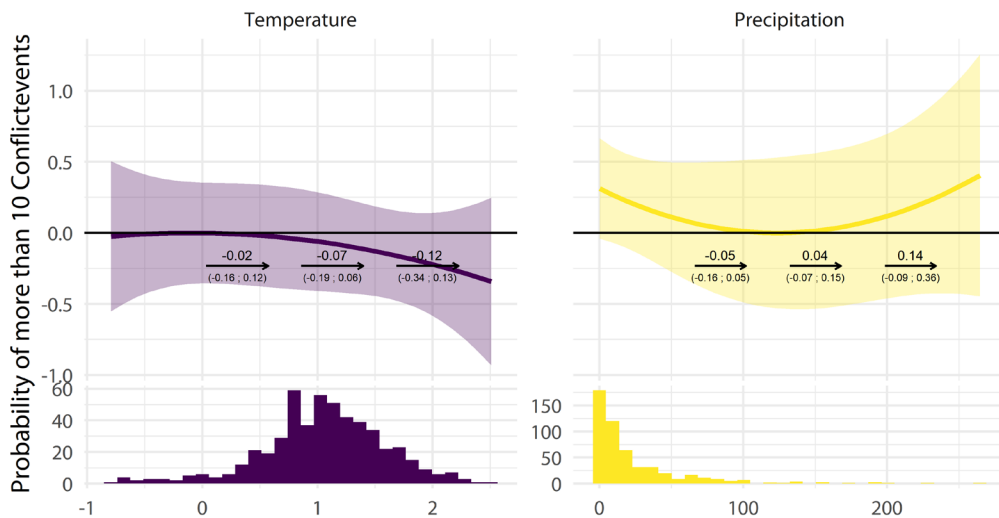
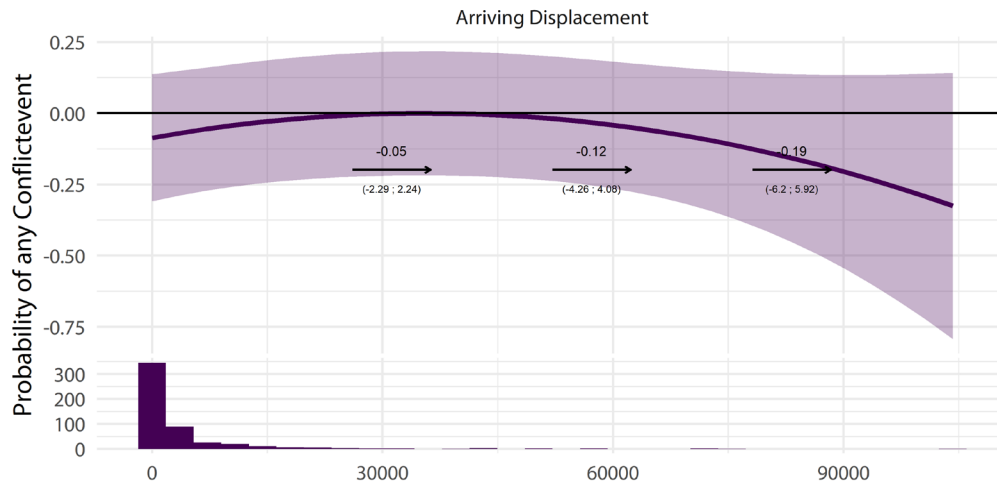


Figure 5-5: Linear probability model estimates for varying magnitude of conflict. Top panel shows the probability of any conflict occurring, middle panel shows the climate impact on the probability of exceeding 10 conflict events. Arrows indicate the predicted change in the probability of conflict events in response to a one standard deviation change in temperatures, precipitation, or conflict events respectively at the base level indicated by the start of the arrow. A 95% confidence range of effects is shown in parentheses.

Arriving Migrant Effect on Conflict events (Controlling for Climate - LPM-0 - Level)

Effect predicted across the variable range.
Arrows indicate predicted difference of one SD change.
Effect standardised with observed Mean = 0.05.



Arriving Migrant Effect on Conflict events (Controlling for Climate - LPM-10 - Level)

Effect predicted across the variable range.
Arrows indicate predicted difference of one SD change.
Effect standardised with observed Mean = 0.44.

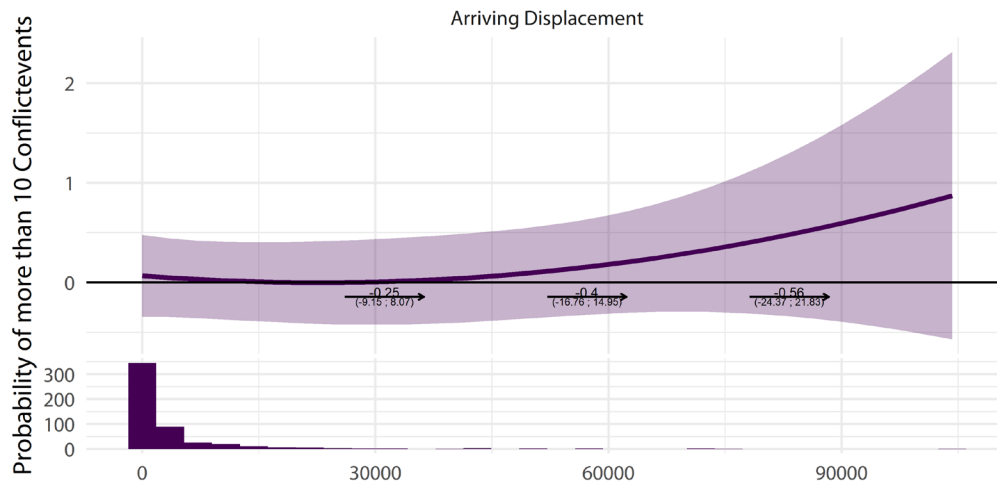


Figure 5-6: Linear probability model estimates for varying magnitude of conflict while controlling for climate. Top panel shows the probability of any conflict occurring, lower panel shows the in-migration impact on the probability of exceeding 10 conflict events. Arrows indicate the predicted change in the probability of conflict events in response to a one standard deviation change in temperatures, precipitation, or conflict events respectively at the base level indicated by the start of the arrow. A 95% confidence range of effects is shown in parentheses.

5.4 Discussion

Our results show that climate through severe drought episodes displaces people at by about 38.5 (90%CI 0.659 - 505) IPDs for each standard deviation, however, drought effects do not occur instantaneously, indicated through a 4-month lag relative to significant drought events. Our results are highly non-linear, illustrated by the marginal effects of a one SD increase at the maximum of our sample, which is 2.5°C above the long-term monthly mean, leading to a best estimate increase of 1141 IDPs (90% CI - 1.24 – 456,223). This is in agreement with recent evidence (Owain & Maslin, 2018) that suggests climate change might exacerbate displacement conditions in the region. The lagged response to weather extremes, however, opens the door to policy responses – timely counter measures to droughts may be able to offset the negative impacts and thus not force people to migrate as a form of adaptation. Conflict has a strong immediate effect on displacement.

However, the effects of conflict on displacement are only apparent when using disaggregated data broken down by reason of displacement. This offers a cautious tale for related studies assessing the link between conflict and displacement – aggregate displacement data may well mask some displacement signals, potentially leading to the erroneous conclusion of conflict (or other drivers) having little effect on displacement. The unique nature of our data allowed us to assess some of the potential drivers of conflict itself. Contrary to earlier evidence of temperature contributing to conflict incidences in other geographies (Kelley et al., 2015), we predominantly find a precipitation effect (when controlling for temperatures), where a reduction thereof

raises the probability of armed conflict. This temperature-precipitation discrepancy may nevertheless simply capture the fact that drought-induced resource scarcity fuels conflict (Hsiang et al., 2013; Ide et al., 2020). It is worth noting that the channel of precipitation lowering the probability of conflict appears to act directly onto conflict and not through drought-induced migration, as we find no effect of displacement on conflict itself. Arriving IDPs do not appear to increase the probability of armed conflict at their destination, suggesting that concerns over migration-induced conflict (perhaps through migration-induced resource scarcity) may be unfounded.

Overall, our results highlight the nuances of the interactions between climate, conflict, and displacement in Somalia, both along temporal and non-linear dynamics. Beyond this study, the results further emphasize the need for granular disaggregated displacement and migration data for other regions affected by weather, climate and conflict extreme events. Detailed displacement information may tell a different story of the drivers of displacement when compared to aggregated measures available in many other regions. Adverse impacts of climate change could present compounding risks to already-vulnerable populations and sustainable ways for human mobility and societal outcomes.

Acknowledgments: We thank F.E.L. Otto for feedback on a first draft and acknowledge the contribution of S. Abele who provided excellent support in the data curation process.

Funding: This work was supported by the Robertson Foundation, award #9907422, as well as Nuffield College at the University of Oxford.

Supplementary Material

S1 Supplementary Text

Brief literature Review

Existing literature and policy debates often frame climate-related migration and displacement as threats to human security (Baldwin et al., 2014). However, the landscape of empirical evidence of weather, climate and conflict effects on various types of human mobility is mixed and varies depending on geography and time (Boas et al., 2019; Cattaneo et al., 2019a). Socio-economic impacts and human responses to weather and climate-related events are multi-faceted, with weather being able to exacerbate the competition for resources, by causing internal displacement flows that may increase the probability of political tensions. To illustrate, Ash & Obradovich (2020) and Kelley et al. (2015) find that extreme weather-related migration could have contributed to violence in Syria. Conversely, flood-related displacement has been posited not to have led to protests in Bangladesh by Petrova (2021). Bosetti et al. (2020), find no evidence that climate-induced migration leads to conflicts in receiving countries.

Our focus is on Somalia, a country in East Africa with a traditionally mobile population that has been exposed to the impacts of such events (Maystadt & Ecker, 2014). Somalia's population is estimated at 15.4 million in 2019 (World Bank, 2021a) with large parts displaced due to recent weather and climate-related events (514,000) and conflict (189,000); or live as IDPs (over 2.6 million) (Internal Displacement Monitoring

Centre, 2021b). For the past thirty years, Somalia has maintained its well-established war economy (Shortland et al., 2013) as result of civil war, poverty and climate stress (Collier et al., 2008). However, groups of violent actors such as Al-Shabaab have disrupted urban social and economic life in the Horn of Africa region since 2008. Armed conflict and climate stress increase pressure on Somalia's security institutions and forces in the region and beyond (Collier et al., 2008; Uhe et al., 2018) and its populations (Marthews et al., 2019), and create an ambiguous image of population pressures under future warming.

S2 Detailed description of Data

Displacement estimates

Internal displacement statistics for Somalia are collected by the Protection and Return Monitoring Network (PRMN) and the United Nations High Commissioner for Refugees (UNHCR) since 2016 (UNHCR, 2021). The UNHCR/PRMN dataset provides monthly estimates on the cumulative number of newly displaced people within 18 regions in Somalia (see Figure 5-1 in the main text). Our sample spans all 18 administrative regions from January 2016 to September 2018, for a total of 594 monthly observations. We note two caveats of the dataset. First, the data collected captures only the primary reason of displacement. Second, as those newly displaced are captured in the data, it does not allow us to count the stock of IDPs at a given time, tracking their return or a potential integration into host communities.

Naturally, there are limitations in the used dataset. The PRMN dataset itself gives an indication about new displacements at origin and destination localities (flows) but does

not give an indication on the movement of those who have been displaced in previous months (protracted displacement or returnees). Despite its recentness (UNHCR Somalia, 2017), the PRMN dataset offers a starting point for an in-depth analyse of the displacement-climate-conflict nexus. The dataset does not quantify current IDP populations accurately. However, the clear advantage of this dataset lies in its large spatial coverage and granular datapoints. Further, displacement data usually does not reveal displacement reasons in a straightforward way and thus requires multiple data inputs and statistical analysis to disentangle reasons of such forced human responses such as economic, socio-demographic, political and environmental drivers. Therefore, this dataset makes it possible to disentangle displacement drivers at the regional impact level of climate or conflict as well as at destination regions.

Conflict events

The Armed Conflict Location and Event Dataset (ACLED) measures conflict in 55 countries in Africa, including Somalia (Raleigh et al., 2010). ACLED contains geo-coded, point-level daily data with the date and the type of conflict for all reported conflict events. From 2010 to 2020, ACLED reported 10,811 organised conflict events, 8043 conflict events occurred during 2016 and 2018, and almost half of these (4,549) involved the extremist group al-Shabaab (Armed Conflict Location & Event Data Project, 2020). We created a monthly sum of daily conflict events in each of Somalia's administrative regions matching our displacement data.

Climatology

Weather and climate-related events are measured by regional monthly temperature and precipitation anomalies over the period 2016 to 2018 with a climatology baseline of

1981-2010. Minimum, mean and maximum temperature anomalies were obtained from the Berkeley Earth dataset, which offers a gridded temperature product (Rohde et al., 2013). Berkeley Earth also provides a daily gridded homogenized temperature anomaly field. Each daily time series is transformed into a series of temperature anomalies by subtracting the corresponding monthly average (with respect to 1951-1980) from each daily observation at the same station. The daily maximum temperature anomaly field is available from 1880 at a $1.00^\circ \times 1.00^\circ$ spatial resolution which we map to each of Somalia's 18 regions. We measure precipitation using the Climate Hazards Groups Infrared Precipitation with Stations dataset (CHIRPS). Given the data sparsity of weather observations in the East African region (Kew et al., 2019), CHIRPS combines satellite derived observations and weather station data. CHIRPS captures daily rainfall observations from 1981 to present (Funk, Peterson, et al., 2015). A combination of satellite and station data is not likely to be interrupted by conflict events, and therefore mitigates conflict issues of station loss during conflict (Schultz & Mankin, 2019). We use minimum, mean and maximum precipitation anomalies (2016-2018) mapped to each of Somalia's region as the temperature data. Our main results rely on models using the temperature and precipitation means. Results using the maximum and minimum are reported in the supplementary material.

Processing of climate data

We combine all datasets by spatially averaging the climatology data over the time 2016-2018 and across the subnational regions in Somalia. We then computed the minimum, maximum, and mean of temperature and precipitation anomalies for each centroid. This involved clipping the climatology grids with the regional polygons. In this step, the software Feature Manipulation Engine (FME) was used for data integration and

conversion (J.-Z. Xu & Zhu, 2005). The spatial averaging processing for conflict data is the same except for the computation of anomaly variables.

S3 Identification, model specification, and estimation methods

Our modelling framework aims to disentangle the dynamics of climate, conflict, and displacement. We focus on internal displacement dynamics at both origin and destination regions and analyse these with the set of primary reasons of displacement indicated in the UNHCR/PRMN data. To this aim, the analysis is based in part on the point of departure (origin region) and the reason for a departure – drought or conflict–recorded, and the point populations are moving to (destination region). We model various channels through which climate and conflict directly and indirectly influence displacement. Figure 5-1 (main text) outlines the five channels (labelled A–E) of effects between climate, conflict, and displacement under analysis.

S3.1 Modelling framework

We model each possible channel of effects using a fixed effects panel model controlling for region and time effects while allowing for dynamics using distributed lags and non-linear effects through flexible functional forms. We consider two general model specifications. In the first, we model the level of displacement (and probability of conflict) in each region. In the second, we model the relative displacement between regions exploiting the fact that we have information on both the origin and destination

of IDPs. The first approach allows us to answer the question whether climate (or conflict) has any measurable effect on displacement, and accounts for displacement within the same region (which is crucial given the large number of IDPs moving within their origin region – see Figure 5-1). The second (relative) approach allows us to assess whether people move to more favourable regions where they might be better off as suggested in the literature (Benveniste et al., 2020; Collier et al., 2008). In contrast to a recent study (Owain & Maslin, 2018), our research design allows to explicitly disentangle effects through which climate influences internal displacement and to estimate non-linear effects of climate on displacement and conflict, and the effects of conflict on displacement, and *vice versa*.

S3.2 Displacement models

Level Models

We consider models of displacement to estimate the degree to which internal displacement responds to climate and conflict. We model the level of displacement using the inverse-hyperbolic sine transformation (IHS – see e.g. Bellemare & Wichman, 2020) of the number of displaced people coming from region i for response category c (aggregate, drought, or conflict as the reported driver) in time t (capturing each month-year) as a function of climate and conflict at the origin region. We use the HIS transformation to approximate the natural logarithm of displacement while also allowing for observations taking the value of zero. The base model is given in Eq. 1:

$$D\tilde{is}pl_{c,i,t} = \alpha_{c,i} + \lambda_{c,t} + Clim_{i,t}\beta_c + Conf_{i,t}\gamma_c + \epsilon_{c,i,t} \quad [1]$$

Where $Displ_{c,i,t}$ denotes the HIS transformation given by $Displ_{c,i,t} = \ln(Displ + \sqrt{Displ^2 + 1})$. Note that the HIS approaches the natural log for large values of $Displ$, and thus the coefficients on linear covariates can approximately be interpreted as semi-elasticities (see (Bellemare & Wichman, 2020)). We vary the model specification for each specific channel of migration of interest (see discussion below). Region fixed effects $\alpha_{c,i}$ account for different baselines of out-migration in different regions, while time fixed effects $\lambda_{c,t}$ capture common features affecting all regions jointly. Coefficients on climate and conflict variables are given by $\beta_c = (\beta_1, \dots, \beta_{K_{clim}})'$, $\gamma_c = (\beta_1, \dots, \beta_{K_{conf}})'$, with K_{clim} denoting the total number of linear, non-linear, and lagged climate variables in model, and K_{conf} refers to total conflict variables. Climate variables for up to s_{clim} lags allow for dynamic and non-linear effects and are given by lagged linear and quadratic temperature and precipitation observations:

$$Clim_{i,t} = (Temp_{i,t}, \dots, Temp_{i,t-s_{clim}}, Temp_{i,t}^2, \dots, Temp_{i,t-s_{clim}}^2, \\ Precip_{i,t}, \dots, Precip_{i,t-s_{clim}}, Precip_{i,t}^2, \dots, Precip_{i,t-s_{clim}}^2)$$

To show the dynamic effects of temperatures and climate on displacement, we report both the estimated non-linear functions for each lag, as well as the cumulative effect by summing coefficients over all lags of each variable. Conflict variables are specified as the number of conflict events observed in each region i at time t using ACLED for up to s_{conf} lags allowing for non-linear effects using quadratic terms:

$$Conf_{i,t} = (Events_{i,t}, \dots, Events_{i,t-s_{conf}}, Events_{i,t}^2, \dots, Events_{i,t-s_{conf}}^2)$$

Relative Models

As we observe both origin and destination of displaced people, we can assess whether people move due to the relative difference of climate between two regions. In other words, this allows us to answer the question whether people move to places with more favourable climate conditions, as well as controlling for travel distance when considering displacement due to conflict at the origin region. The general relative model for displacement from region i to region j is given by:

$$D\tilde{s}pl_{c,i,j,t} = \alpha_{c,i,j} + \lambda_{c,t} + (Clim_{j,t} - Clim_{i,t})\beta_c + Conf_{i,t}\gamma_c + \epsilon_{c,i,j,t} \quad [2]$$

We only allow for origin conflict effects in region i (rather than the difference between origin and destination conflict) because incoming migration may affect conflict at the destination j (though when isolating this conflict channel, we find no evidence of this effect – see conflict model results below). When estimating relative models [Eq. 2] we restrict the sample to IDPs moving from one region to another region, not including those that migrate within their origin region (as the relative difference in climate would be uninformative when the origin region is identical to the destination region).

Identifying Climate Effects on Displacement

To estimate the overall (net) climate effect on displacement (channels A, E, B) which may act through conflict), we estimate Eq. 1 with aggregate migration as the dependent variable omitting all conflict variables. To isolate the sole-climate effect, we estimate channel A using climate (drought)-reported displacement as the outcome variable, again omitting conflict variables. To capture relative migration, we repeat this estimation approach using the model in Eq. 2.

Identifying Conflict Effects on Displacement

We estimate the effect of conflict on aggregate migration by estimating Eq. 1 including conflict variables while controlling for climate. We then estimate the direct conflict channel (B) by modelling conflict-reported displacement as a function of conflict featured in Eq. 1 (while omitting climate). We also estimate Eq. 2, assessing the impact of origin conflict on relative migration. Destination conflict is purposely omitted as we cannot rule out that in-migration leads to conflict at the destination region.

S3.3 Conflict Models

Beyond the impact of climate and conflict on displacement, our data allows us to consider the effects of climate as well as displacement on conflict itself. We assess the overall effect of climate on conflict (channels A–E in Figure 1) by modelling the probability of conflict events (of different minimum magnitudes) in region i as a function of climate in region i at time t using a linear probability model in Eqs. 3:

$$P(Events_{i,t} > 0) = \alpha_i + \lambda_t + Clim_{i,t}\beta + \epsilon_{i,t} \quad [3.1]$$

$$P(Events_{i,t} > 10) = \alpha_i + \lambda_t + Clim_{i,t}\beta + \epsilon_{i,t} \quad [3.2]$$

Using the fact that we observe the origin as well as the destination of displaced people, we isolate the migration channel on conflict (channels D and C in Main Text Fig. 1) by modelling conflict at the destination region as a function of in-migration (arriving at region i from any other region). As we can differentiate between in-migration and out-migration in each region, we avoid concerns about endogeneity of feedback between conflict and displacement if we meet the assumption that out-migration does not cause

conflict at the origin. Specifically, we model the probability of observing conflict events in region i at time t as a function of in-migration ($InDispl$) and its lags into region i (regardless of their origin) while controlling for climate in Eqs. 4:

$$P(Events_{i,t} > 0) = \alpha_i + \lambda_t + InDispl_{i,t}\beta + Clim_{i,t}\gamma + \epsilon_{i,t} \quad [4.1]$$

$$P(Events_{i,t} > 10) = \alpha_i + \lambda_t + InDispl_{i,t}\beta + Clim_{i,t}\gamma + \epsilon_{i,t} \quad [4.2]$$

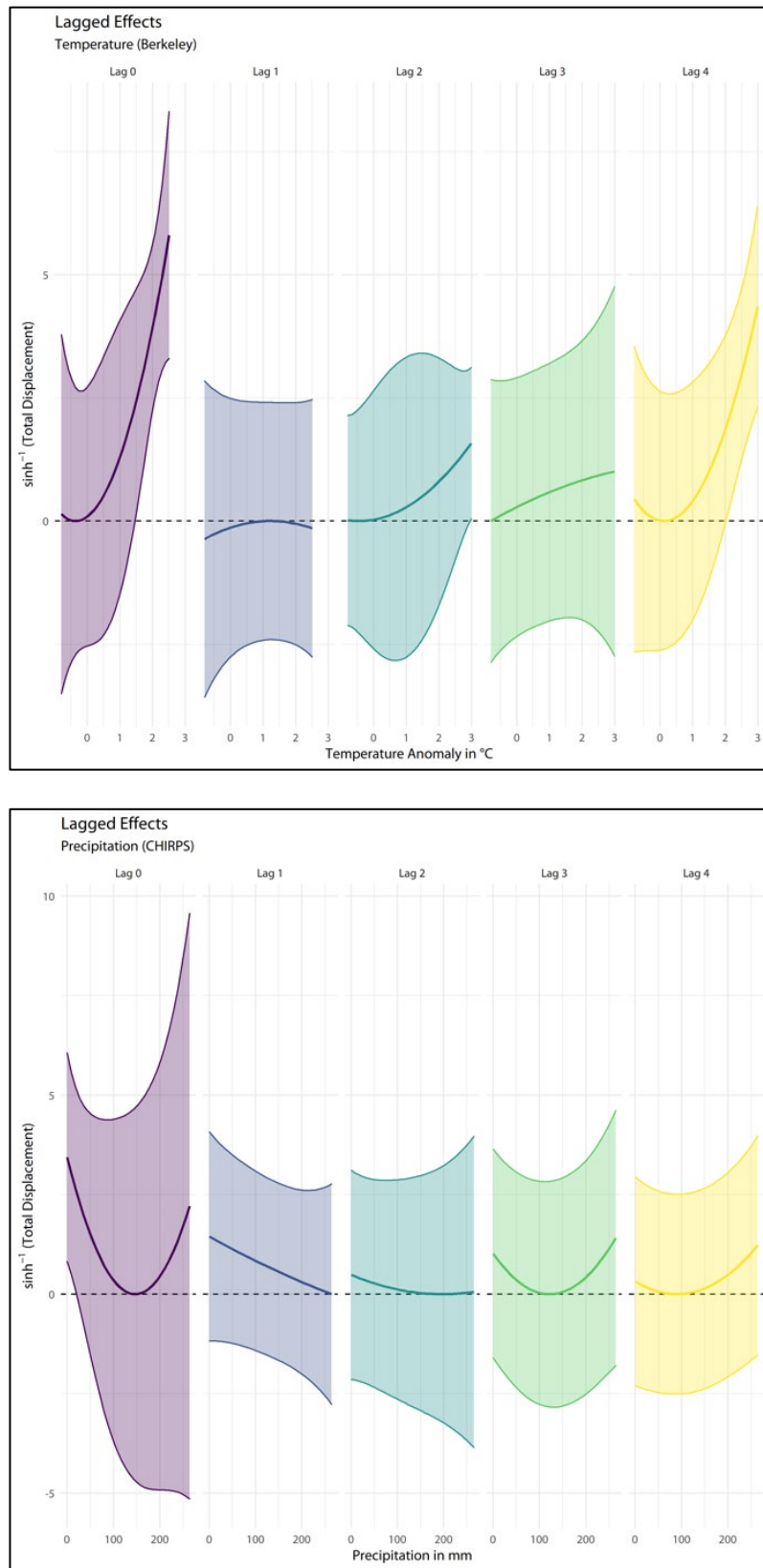


Figure S 5-1: Lagged effects of temperature (top) and precipitation (bottom) on origin displacement. We show lags 0 to 4.

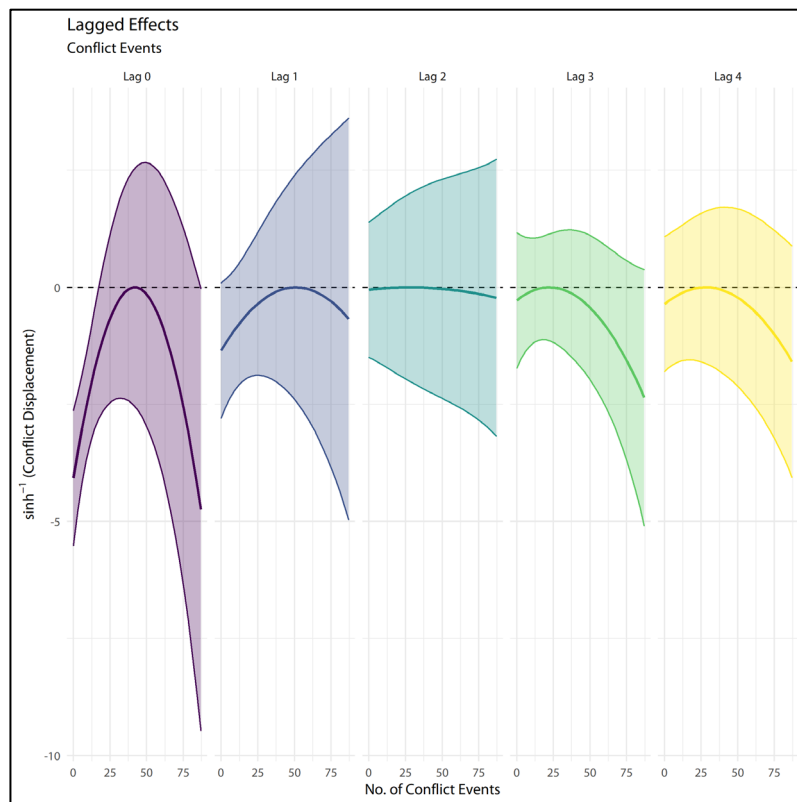


Figure S 5-2: Lagged effects of conflict on origin displacement. We show lags 0 to 4.

Table S 5-1: Summary statistics of the level models, listed individually for temperature, precipitation, total and drought displacement, and conflict.

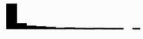
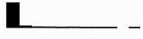
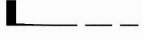
Summary Statistics: Level Data							
	N	Mean	SD	Min	Median	Max	
Temperature °C (Berkeley)	594	1.13	0.60	-0.79	1.10	2.99	
Precipitation mm (CHIRPS)	594	23	35	0.09	8.02	265	
Total Displacement	594	3,696	9,881	0	588	104,980	
Drought Displacement	594	2,044	6,671	0	234	73,403	
No. of Conflict Events	594	13	16	0	8.00	87	

Table S 5-2: Summary statistics of the relative models, listed individually for relative temperature, precipitation, total and drought displacement, and conflict.

Summary Statistics: Relative Data							
	N	Mean	SD	Min	Median	Max	
Displaced People	2148	346	2,261	1.00	19	58,576	
No. of Conflict Events	2148	-1.75	25	-86	-2.00	81	
Temperature °C (Berkeley)	2148	0.09	0.38	-1.44	0.03	1.91	
Precipitation mm (CHIRPS)	2148	-4.74	27	-180	-0.42	122	

Values represent the Difference between Arrival and Departure Region

Data S1. (separate file)

All data and code underlying this analysis are available at:

https://github.com/geoliz/Somalia-paper_internal

6 Towards attributing climate-related displacement to anthropogenic climate change

Preamble

The previous chapter has outlined how to disentangle drivers of displacement during weather and climate-related events, focusing on the past. This final chapter investigates the contribution of an extreme precipitation event to internal displacement in a country case study on Somalia. This chapter thus addresses the fourth research question: *Whether and to what extent does anthropogenic climate change alter the likelihood of climate-related human mobility today?*

This chapter uses probabilistic event attribution to test the methodological feasibility toward attributing changes in human mobility due to weather and climate-related events, and anthropogenic climate change. The findings of this research chapter are presented in the paper “Towards attributing climate-related displacement to anthropogenic climate change”, which is in review with the journal *Scientific Reports*.

**Towards attributing climate-related displacement to anthropogenic climate
change**

L. THALHEIMER¹, S. LI², J. CRESPO CUARESMA³, R. MUTTARAK, R.
MECHLER, F.E.L. OTTO¹

¹Environmental Change Institute, University of Oxford, Oxford, UK

² School of Geography and the Environment, University of Oxford, Oxford, UK

³ Vienna University of Economics and Business, Vienna, Austria

⁴ International Institute for Applied Systems Analysis, Laxenburg, Austria

Submitted to *Scientific Reports*

Manuscript received 17 April 2021

Under review since 24 April 2021

Authorship Declaration

I designed the research, conducted all of the analysis and writing for this paper. All authors discussed the methodology, results and structure of the paper with me, and edited the manuscript.

Abstract

As climate change is increasingly exacerbating the intensity and frequency of many hazards in vulnerable regions, ex situ responses to climate change including human mobility are starkly stepping into the spotlight. Whilst proactive migration is often used as an adaptation response to the impact of climate and extreme weather events, reactive migration following unprecedented climatic shocks is often involuntarily and can seriously disrupt livelihoods and undermine human security. Yet, the extent to which human mobility is attributable to extreme weather events and in turn, whether and to what extent extreme weather events and human mobility are attributable to anthropogenic climate change, is largely unexplored. In this paper, we apply a framework based on probabilistic event attribution (PEA), typically used to assess changes in the likelihood of an extreme event under climate change. To this aim, we investigate human mobility responses (measured by internal displacement) to anthropogenic climate change in a feasibility study in April 2020 in Somalia, a highly climate-vulnerable country with a longstanding history of migration and displacement. We find no attributable links to anthropogenic climate change in the event analysis even though the event displaced over 280,000 people. Sparsity of climate observations in the study region reveal one of many reasons for a lack of detectable climate change signal. The results show that better data and more research are required in this new field since it is possible that human mobility is attributable to anthropogenic climate change in other contexts. Crucially, this study demonstrates how PEA can be applied to quantitatively assess climate mobility and suggests that event attribution need to play a greater part in climate change impact research and policy.

6.1 Introduction

In the past decade, a range of natural hazards, in particular extreme weather events, have become more frequent and intense, often leading to widespread and disastrous impacts (Guldborg et al., 2018). Extreme weather events such as droughts, floods and heatwaves impact populations globally, especially those who are already socioeconomically vulnerable. Whilst proactive migration is sometimes used as an adaptation response to the impact of climate and extreme weather events, reactive migration following climatic shocks is often involuntary and can seriously disrupt livelihoods and undermine human security (Fussell, 2012).

Climate-related human mobility is often portrayed as a key consequence of anthropogenic climate change while discussing its multifactorial nature. 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 (Borderon et al., 2019; Cattaneo et al., 2019a; Hoffmann et al., 2020), surprisingly little research has empirically 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 attributable to anthropogenic climate change. Causal, quantitative evidence on the attributable influence of anthropogenic climate change on human mobility is not sufficiently understood and continues to suffer from disciplinary hurdles (Abel et al., 2019; Hoffmann et al., 2020). Using a feasibility case study of Somalia, a climate change and human mobility hotspot region (Rigaud et al., 2018), this paper empirically investigates

to what extent anthropogenic climate change plays a role in extreme weather events, which in turn instigate migration responses, and thus this study takes necessary steps to address this knowledge gap.

Climate scientists are increasingly able to assess how anthropogenic climate change alters the frequency and intensity of extreme weather events. In recent years, methods enabling the attribution of these events to anthropogenic climate change have been devised (Allen, 2003). These attribution studies show that global warming is an important driver of many extreme events ranging from the 2019 heatwaves in Western Europe (Vautard et al., 2020) and wildfires in California (A. P. Williams et al., 2019) to the 2017 Bangladesh floods (Philip et al., 2019). There is a need to investigate other climate change impacts that have an attributable signal baked into the setup, with extreme weather being the trigger lying in wait. 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). Black's framework provides a starting point for addressing the underlying complexities determining human mobility in the context of extreme weather events, by highlighting the interplay between different drivers of human mobility i.e., environmental, social, political, demographic, and economic ones at the individual, household, community, and macro-levels. Environmental and climate change influences migration directly and indirectly through affecting other drivers of migration.

The impacts of anthropogenic climate change are projected to fall disproportionately upon developing economies. Experiencing some of the fastest changing and deadliest climatic extremes, African countries are particularly vulnerable (Guldberg et al., 2018; Harrington & Otto, 2020). There is however a paucity of research on the attributable link of anthropogenic climate change and human mobility. The lack of empirical knowledge makes it difficult to engage in certain debates such as the legal recognition of ‘climate refugees’.

In this paper, we provide, for the first time, a quantitative assessment of the effect of climate change on flood-related displacement flows – along a causal chain from anthropogenic climate change and changing frequencies and intensities of extreme weather events to human mobility outcomes. This analysis contributes to the ongoing efforts of modelling the multi-causal links between human mobility and extreme weather events, their changes over time, and the role played by anthropogenic climate change. Making use of the emerging science of probabilistic event attribution (PEA), this analysis constitutes a directly usable approach for assessing attributable climate change and human mobility links.

Understanding and quantifying the links between human mobility and anthropogenic climate change can also help clarify how mobility patterns will look like under future global warming. An improved scientific understanding of extreme weather events and regional climate change and their linkages with human mobility patterns around the world, can translate into better disaster preparedness and risk reduction to mitigate the impacts of climate extremes and compound vulnerabilities associated with human mobility. Attribution studies of extreme events and human mobility will further

contribute to sustainable development, especially in clarifying policy debates and scientifically supporting ongoing work on reducing future vulnerability and disaster risk in the international community.

The remainder of the paper is organised as follows. Section 2 reviews existing evidence on the links between human mobility, extreme weather and climate change. Section 3 lays the theoretical foundation by introducing probabilistic event attribution and recent applications in the East African context. Section 4 applies the attribution framework as feasibility study. Section 5 discusses the results, including limitations of the study and section 6 concludes and provides further discussions on future research and policy implications.

6.2 Human mobility in the context of climate change

Human mobility is affected by climatic factors in many different ways (see Supplementary Section A). Individuals may 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, or long-term droughts). Human mobility decisions, when they are not direct responses to extreme weather events in the form of sudden displacement, are generally multi-causal and rarely occur due to adverse climatic conditions alone (Black et al., 2011; Cattaneo et al., 2019a).

Climate change is likely to influence human mobility through its effect on other drivers of migration (Benveniste et al., 2020). Push (e.g., unemployment or conflict at the place of origin) and pull (e.g., economic opportunities or better healthcare at the place of destination) factors driving human mobility can change significantly due to anthropogenic climate change. It has been shown, for instance, that drought events can lead to forced migration through increasing violent conflicts, although this relationship holds only for certain countries and time periods (Abel et al., 2019). With increased frequency and intensity of extreme weather events, in particular when manifested through compounding events (Raymond et al., 2020), affected populations could run out of resources that would enable them to migrate voluntarily. Vulnerable subgroups of the population, in particular, may lack capacity to move out of harm's way (Boas et al., 2019). With an expected increase in average global temperature of at least 1.5 °C by mid-century, there is little consensus regarding the direction and the extent to which these factors influence migration and other types of human mobility (Hoffmann et al., 2020). Therefore, whether and to what extent human mobility will change due to anthropogenic climate change remains largely unclear.

As one example, East Africa is one of the regions most vulnerable to the impacts of extreme weather events, climate variability and climate change (Collier et al., 2008; Shongwe et al., 2011; Uhe et al., 2018). 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 (Philip et al., 2017). A rain-fed agriculture (Lyon, 2014a) and the predominance of hydroelectricity in the region means that rainfall is vital for livelihoods and is a key

factor determining sustainable development progress for the populations in Kenya, Ethiopia and Somalia (Hirpa et al., 2019; Kaunda et al., 2012).

At the same time, there has been an increasing trend in frequency, duration and cumulative heat since the 1950s. Heat extremes will continue to become hotter with existing impacts such as excess mortality being exacerbated across the globe even if global warming is kept below 1.5 °C. Despite these risks, extreme heat events are not routinely monitored (Harrington & Otto, 2020). 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 impacts of anthropogenic climate change. For the 2011 drought in East Africa, a study finds an anthropogenic climate change signal related to the probability increase of long rains as dry or drier than those in 2011. The evidence is however mixed and depends on the framing. For a 2014 drought in the Horn of Africa region, no human-induced climate change factor is found (Marthews et al., 2019). A number of East African countries are also currently affected by recurrent conflict and political instability (Internal Displacement Monitoring Centre, 2020). There is consistent evidence showing that adverse climatic conditions, especially warmer temperatures and the reduction in rainfall can lead to conflict (Burke et al., 2009, 2015; Hsiang et al., 2013) and this can result in forced migration (Hayes et al., 2016; Ibáñez & Vélez, 2008). With over 8 million people currently internally displaced in this part of the world (UNHCR, 2020), it is possible that climate change directly and indirectly (such as through conflicts) influence human mobility in East Africa. How can we attribute extreme weather events that affect human mobility to climate change?

The framework of PEA (Philip et al., 2020) could help identifying whether there is a link between anthropogenic climate change and extreme events that in turn can potentially drive human mobility. Attribution science aims at answering the question whether and to what extent climate change altered the likelihood of an extreme weather event occurring. To answer this question in the context of East African mobility, we assess the likelihood of an extreme weather event that led to 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 quantifying whether and how much past emissions have altered the probability of an extreme event occurring by calculating probability ratios.

PEA studies compare the frequency of occurrence of a particular extreme weather event in model experiments representing “the world as it is” (with today's human influence on climate) with that in experiments representing the counterfactual “world that might have been” (with the estimated impact of human influence on the climate removed). In practice, event attribution studies are a multi-model process; 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 (Otto, Harrington, Frame, et al., 2020; Philip et al., 2017). Some event attribution studies for extremes in East Africa exist, mainly in the context of drought events (Carbon Brief, 2020). Results on an anthropogenic signal for these recent events is mixed (Lott et al., 2013; Marthews et al., 2019; Otto, Philip, et al., 2018; Philip et al., 2020). In turn, the results from previous studies underscore the importance to investigate extreme events

carefully, case-by-case and to avoid generalisation of the results to comparable geo-climatic regions (Uhe et al., 2018).

6.3 Conceptualising and operationalising the analysis

A potential linkage between extreme weather events and human mobility has not yet been investigated in the context of attribution studies. This leads to a significant gap in 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 and enhancing adaptive capacity may address some of the problems in the short- longer term. However, these measures may not suffice under low mitigation climate change scenarios (e.g., RCP8.5 leading to global and regional warming exceeding 4 °C) or even under a 1.5 °C additional warming (IPCC, 2018), especially in severely exposed regions in low-income countries.

This lack of a common approach to investigate long-term climate change and human mobility (Motesharrei et al., 2016) 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 at the conceptual, methodological and empirical level. From a conceptual standpoint, this paper seeks to synthesise knowledge on the two limbs of the chain of causality, which remain largely unconnected.

Since impacts of extreme events root in interacting multi-causal risk drivers, including the meteorological hazard itself, attribution analyses need to disentangle impact drivers of population and environmental vulnerabilities and the exposure of assets, livelihoods, and human lives to determine cause and effect in the context of climate impacts at national and sub-national levels. An impact-based approach, thus, requires observational and model data of high enough resolution to capture localized impacts. Country case studies could help in exemplifying research results of changing risk levels associated with extreme events and human mobility in this region.

Here, we apply multiple methods and tools from the science of extreme weather event attribution (Otto, 2016; Philip et al., 2017) with the objective of transparently, and quantitatively assessing the changing nature of extreme weather risk at the country level, and then to translate this risk into human mobility patterns in the region (see Figure 6-1). The reporting on human mobility statistics is getting increasingly common triggered, among others, by recent events such as the Syrian civil war and their spill over effects in neighbouring countries (Kelley et al., 2015). There are various initiatives that collect data on human mobility through surveys. Available datasets on internal displacement usually in the context of conflict and extreme weather events tend to focus on country-level displacement incidence. Such data are rarely available at state or district level. The Somalia Protection and Return Monitoring Network (PRMN) (UNHCR Somalia, 2017) provides a unique monthly dataset reporting the recent origin and destination regions of internally displaced persons (see Supplementary Section B). The dataset contains information on the key reason of displacement, specifying whether it was due to flooding, drought or conflict, and thus, allows for disentangling the nature of displacement drivers in the country.

To further allow for the general applicability of the framework beyond the dataset used for this feasibility study, approaches from social sciences can be used to disentangle reasons for displacement and projecting future human mobility. For example, econometric methods can be used to empirically assess the influence of climatic or non-climatic factors driving human mobility (Abel et al., 2019; Hauer et al., 2020; Hoffmann et al., 2020). The standard economic push and pull model of migration (Todaro, 1980) estimates worker movement occurring due to real income differences across locations. Spatially explicit bottom-up agent-based modelling has been used to understand the role of such push and pull factors in predicting the spatial and temporal emergence of migration post-disaster (Naqvi, 2017). Insights into the drivers of migration can be combined with a risk perspective grounded in observed data. The Internal Displacement Monitoring Centre (IDMC) has developed a displacement risk model to estimate the likelihood of future population movements (Internal Displacement Monitoring Centre, 2017). Such a conceptual framework allows us to decipher multiple interwoven mechanisms affecting human mobility drivers comprehensively.

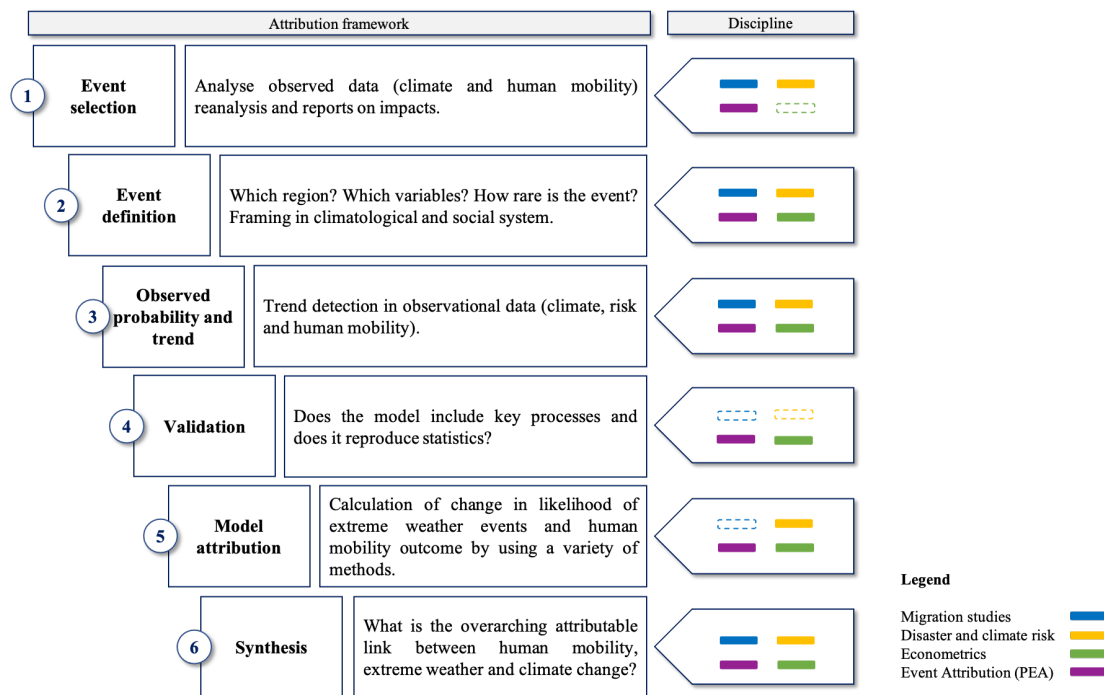


Figure 6-1: Probabilistic event attribution applied to human mobility. Extreme weather event and human mobility attribution schema (Otto, 2016; Philip et al., 2020). Event attribution studies follow a common, six step approaches: (1) event selection, (2) event definition and framing, (3) observed probability and trend, (4) model validation and (5) model attribution and (6) synthesis and interpretation of these results.

As our key contribution, we analyse to what extent flood-related displacement is attributable to anthropogenic climate change by expanding on the common six step approach, typically used in event attribution studies (Figure 6-1). For each step, we highlight the methodological contribution from i) migration studies, ii) disaster and climate risk, iii) econometrics and iv) event attribution science. Undoubtedly, PEA is key in the analysis of attributable links to climate change. Note that quantitative social science methods can be applied to disentangle underlying drivers of human mobility such as extreme weather events, conflicts, or economic opportunities, in line with the literature. Our analytical framework allows us to obtain a holistic view of the full causal chain.

For this exercise, Somalia is chosen as a feasibility study of the framework displayed in Figure 6-1. Somalia's population faces recurring extreme weather events and conflicts, disrupting existing migration and pastoralism routes. In Somalia, where poverty prevails, the resilience of the population is severely affected by compounding vulnerabilities (Marthews et al., 2019), illustrating a diverse set of internal displacement drivers. At the same time, the country has a well-established war economy (Shortland et al., 2013). In 2019, large parts of the Somali population were newly displaced (flow: 514,000 due to disasters and 189,000 from conflicts, according to IDMC) or lived as internally displaced populations (stock: 2,648,000 from conflicts, according to IDMC).

6.4 Extreme precipitation as displacement trigger in Somalia

6.4.1 Event selection

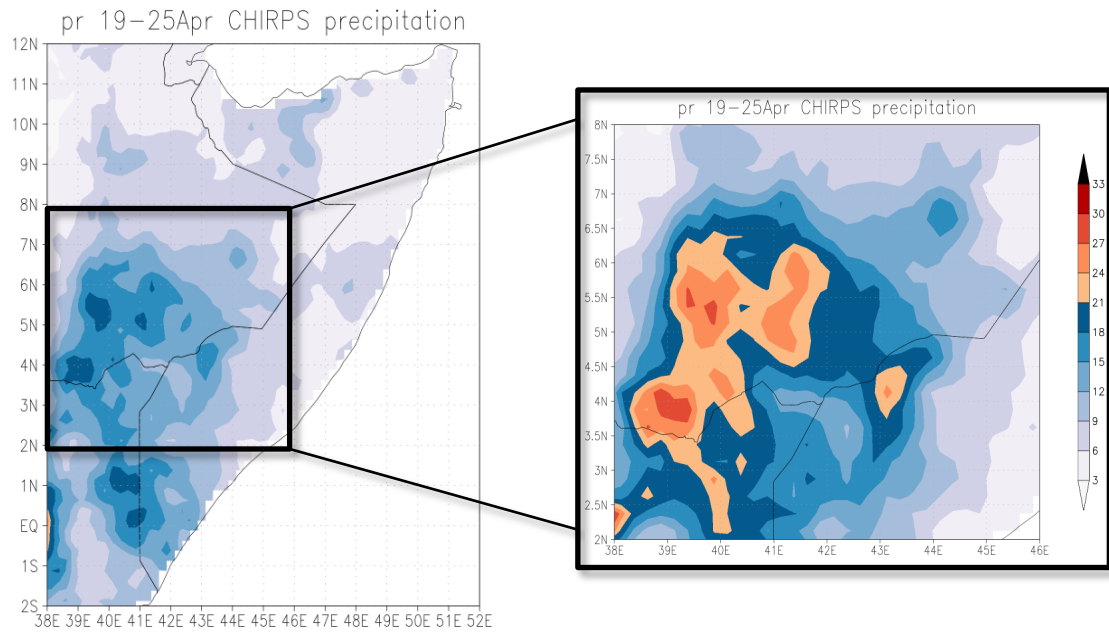
To select the extreme weather event to be attributed we compare internal displacement data from UNHCR and recorded disasters from the EM-DAT database to establish an initial index of impacts from droughts and floods on internally displacement in Somalia (see Supplementary Dataset 1). Based on the 283,000 flood-displaced people UNHCR (UNHCR, 2020) recorded, the corresponding extreme weather event, the April 2020 flooding in South Somalia as recorded in the global disaster database EM-DAT (Guha-Sapir et al., 2016), is selected for analysis. Applying EM-DAT statistics to the event selection is a common procedure in attribution studies and has been applied for the study region (Otto, Philip, et al., 2018).

6.4.2 Event definition

Somalia is located in the Horn of Africa and has two rainy seasons. In central Somalia this is the *Gu* season (mainly in April-May) and the *Deyr* season (October-November/December). Further north (Somaliland), the rains start earlier, with the *Gu* season beginning in March and the *Deyr* season in August. To capture both rainy seasons in the whole country, we use two four-month seasons that encompass the peak of the rains both in the north and the south: March–June and September–December.

Based on disaster and human mobility data applied in the event selection and climate observations, we identified the April 2020 floods in South Somalia (20-28 April 2020) that affected multiple states and territories *in situ*: South West, Jubaland, Banadir, Puntland, and Somaliland, Belet Weyne, Jowhar (Hirshabelle State). Between 19-25 April 2020, heavy rainfall (21 – 30 mm in anomalies) in southern Ethiopia resulted in flooding of the Juba river and Shabelle river basins (Figure 6-2a). Consecutive heavy rains lead to flooding along the Juba river (FAO SWALIM, 2020) and affected approximately 1 million people, displaced 283,000 and killed 26 people due to the resulting flood (see Supplementary Dataset 1). For this attribution study, both the origin region (southern Ethiopia) of the heavy precipitation and the impact region (South Somalia) of riverine flooding are considered in this step. We do so by investigating the region that experienced the 7-day extreme rainfall in the origin region (Figure 6-2a) which then led to a 9-day flooding event in the impact region (Figure 6-2b).

a)



b)

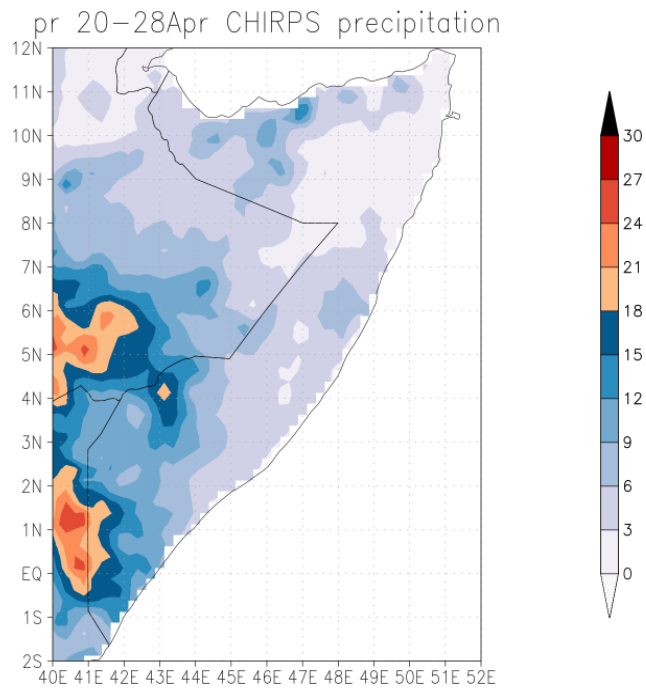


Figure 6-2: a) Map of event definition showing absolute rainfall anomalies over the time of maximum precipitation (19-25 April 2020) in the origin region. Orange and red areas indicate locations with highest rainfall. b) Same for the impact region in South Somalia during 20-28 April 2020.

6.4.3 Observed probability and trend

The observational analysis used 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 in 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 sources for this data-sparse region, with about four stations in 1900-1920 and 20 stations from 1920-2000 (Funk, Nicholson, et al., 2015). Compared to recent years, the heavy precipitation in April 2020 ranks as the third largest extreme rainfall event (Supplementary Figure S 6-1 and Figure S 6-2). Figure 6-3a shows the time series of CHIRPS precipitation averaged over the origin location for 30 days ending on 30 April 2020. In the impact region, the 9-day average at the beginning of April shows higher precipitation than the beginning of May 2020 (Figure 6-3c and 6-3d). Analysing 30 days prior to the event adds an additional layer of support to validate the time frame used for the event definition (Figure 6-2a, Supplementary Figure S 6-2).

We fitted a Generalized Extreme Value (GEV) distribution to the CHIRPS data that scales with global mean temperature as a proxy for climate change. For the trend detection, observational data is fitted to a non-stationary statistical model to look for a trend outside the range of deviations expected by natural variability alone. Here, the trends of extreme high precipitation are studied. In extreme value analysis, the GEV distribution is often used to model the tail of the empirical distribution. The GEV fit gives a local return time in the current climate (Figure 6-3 b and d). For this extreme

weather event, the 7-day running mean coincides with the event duration (Philip et al., 2019). The figure also shows that there is a small positive trend (a higher probability of extreme rainfall now) in the origin region (Figure 6-3 b, probability of 0.44 to 0.66) and the impact region (Figure 6-3 d, probability of 0.70 to 0.95).

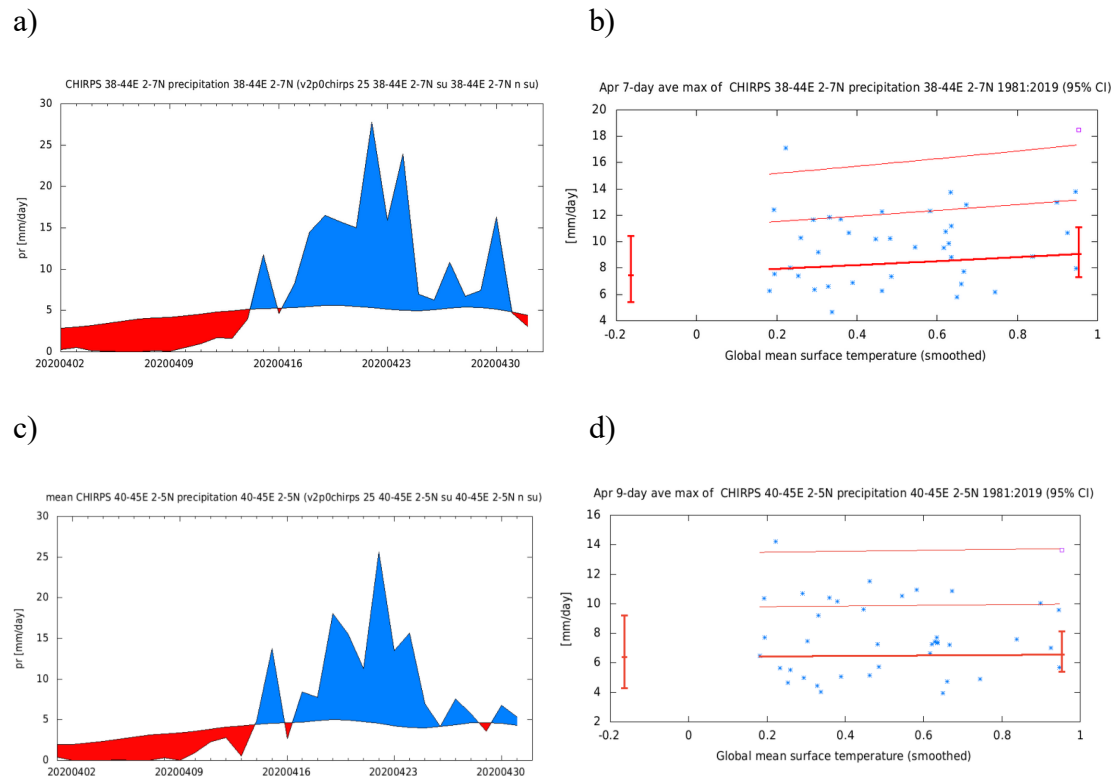


Figure 6-3: a) CHIRPS precipitation data and analysis over of the highest observed mean rainfall 30 days prior to the extreme event in the origin region. b) GEV fit where the location parameter μ (thick line), $\mu+\sigma$ and $\mu+2\sigma$ (thin lines) of the GEV fit of the 7-day averaged data. The same analyses are performed with a 9-day averaged data for the impact region, see 6-3c and 6-3d.

6.4.4 Observed return periods

i) Return periods in the origin location

In this step, the annual maximum of the 7-day running mean is fitted to a GEV distribution. Note that the GEV fit to quantify the return period does not include the event itself as the area was chosen as having an extreme event and the extreme value occurring in this year is therefore drawn from a much larger distribution than the historical time series. The return periods of the heavy rainfall in Figure 6-4a show that the distribution is described by a GEV by overlaying the data points and fit for the present and a past climate. The return period calculated from this fit is 71 years (15 to 23 years, 95 % CI – confidence interval) for the current climate, indicating a relatively rare extreme event in the current climate (see Supplementary Table S 6-2 for a results overview).

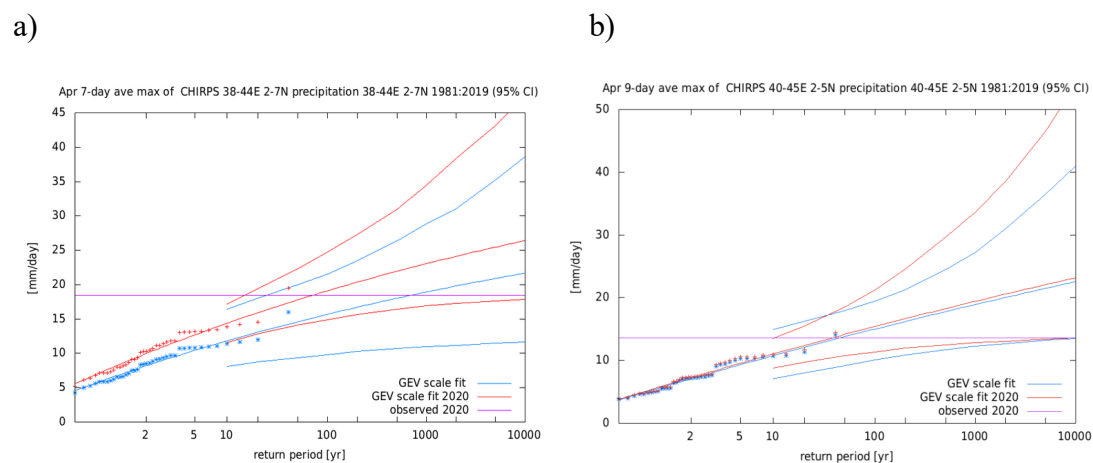


Figure 6-4: a) The GEV fit of the 7-day averaged data in 2020 (red) and 1900 (blue). The observations are drawn twice, scaled up with the trend (smoothed global mean temperature) to 2020 and scaled down to 1900. The purple line shows the observed value at present date (2020). b) The GEV fit of the 9-day 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).

The same analysis is carried out for the impact region in southern Somalia. A 9-day average is applied per the event definition (Figure 6-4b). The return period calculated from this fit is 38 years (11 to 14,331 years, 95 % CI) for the current climate, so the event cannot be categorised as extremely rare (see Supplementary Table S 6-3 for a results overview; Supplementary Figure S 6-3).

6.4.5 Modelled trends and synthesis

This study applies the fully coupled EC-EARTH (Hazeleger et al., 2010) 2.3.16-member ensemble at a 150 km resolution using the CMIP5 historical/ RCP8.5 protocol (see Supplementary Section D). This study also makes use of a 15 member ensemble from the HadGEM3-A (Christidis et al., 2013) model, the atmospheric component of the Met Office's Global Environment Model version 6. When comparing with the year 2050, an event like the April 2020 flood is 1.6-fold instead compared to the likelihood of occurrence under pre-industrial conditions in the year 1900 (see Supplementary Table S 6-13).

As defined in event definition, we investigate two regions of extreme rainfall, (i) the origin region of heavy rainfalls in mid-April 2020, and (ii) impact region (southern Somalia), which experienced extreme flooding in late April 2020 due to this rainfall episode. The results of the attribution analysis show that no significant attributable links to anthropogenic climate change can be detected.

We synthesise the observation and model results (see Supplementary Table S 6-4 to Table S 6-12 for a detailed model results) to provide an overall attribution result (as shown in Figure 6-5), following the most recent synthesis protocol (Philip et al., 2020), which in essence computes the weighted average (shown by the magenta bar in Figure 6-5) of observations and models. The results of observational analysis show an increase (although not statistically significant) of the likelihood of the event to occur under current 2020 climate conditions, with a best estimate of 9.95 for the probability ratio. On the other hand, both model results indicate a (statistically insignificant) decrease in occurrence probability, with a best estimate of 0.73 for EC-Earth and a best estimate of 0.58 for HadGEM3-A. The ranges of both models are compatible with each other. The discrepancy between observations and models seen here are perhaps due to the previously noted poor model representation (Munday et al., 2021) of precipitation over this region. Synthesising observation and model results leads to a probability ratio of 1.62 (0.0880, 17.5).

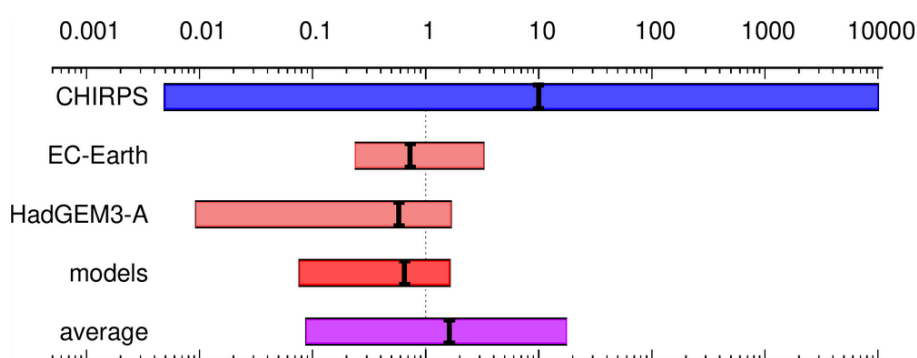


Figure 6-5: Estimates of the change in risk, between preindustrial conditions (the year 1900 or ‘natural’ scenario) and the present conditions (the year 2020 or ‘current’ climate scenario) for the origin region with observations in blue, models in red and the averaged synthesis in purple. For each bar, the black marker indicates the best estimate, and the shading depicts the range given by the 95% confidence interval.

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

PEA provides an important framework for unveiling causal connections between climate change and extreme events which may have contributed to population displacement. In this study, we have shown the procedure and steps to perform such an exercise. The analysis can be applied in a straightforward manner to other extreme events, regions, and contexts. However, the widely applied approach is not a panacea and several limitations apply which we discuss below.

First, there are limitations of attribution studies themselves. The results are very sensitive to the event definition. Data availability in the study region is furthermore key to determine how the event can be defined and attributed. For example, extreme precipitation events (e.g., a flash flood) can be better measured making use of hydrology models, and secondary impacts (adaptation measures carried out in the past) such as dams (Kew et al., 2019). The data used in this study contains certain limitations. The CHIRPS daily time series contains observations from 1981 onwards and presents a short time series. The development of a comprehensive database for quantitative evidence on the impacts of climate change has been suggested in order to overcome this limitation (Otto et al., 2020) and could provide an avenue for future studies.

The results of our study indicate that there is a discrepancy between extreme weather impacts and whether these impacts lead to displacement. In the selected event, one million people were affected by the flood event in Southern Somalia. However, only a

fraction of the affected people was displaced. This calls for the incorporation of displacement impacts in addition to those from extreme weather events directly in disaster databases like EM-DAT. Moreover, an emphasis could be put on quantitative sources of extreme weather damages, and potential reporting biases. For example, no heatwave impacts have been reported for the Africa region since 1900, despite the region having experienced multiple heatwaves (Harrington & Otto, 2020). To date, attribution studies are conducted in an ad-hoc manner and apply a diverse set of methodologies, which makes direct comparison difficult (Osaka & Bellamy, 2020). Understanding the changing risk of displacement due to extreme weather events (vulnerability and exposure monitoring instead of ad-hoc studies) is crucial given that people are affected disproportionately by extreme events under climate change.

Second, there are important data limitations concerning internal displacement. With limited available granular data, any time series analysis is bound to the time frame set by the displacement data used. In this study, we use a time series of five years (2016-2020), which may draw a biased picture of climate-related displacement since the time lag of the effects depends on the type of extreme weather events (e.g., long-term drought versus rapidly evolving flash floods). The PRMN dataset itself gives an indication about new displacements at origin and destination localities (flows) but does not give an indication on the movement of those who have been displaced in previous months (protracted displacement or returnees).

However, data usually does not reveal displacement reasons in a straight forward way and thus requires multiple data inputs and statistical analysis to disentangle reasons of such forced human responses such as economic, socio-demographic, political and

environmental drivers (Black et al., 2011). We show that PEA is a crucial element in the attribution process of extreme weather events, human mobility, and anthropogenic climate change (see Figure 6-1). The incorporation of interdisciplinary methods from econometrics, earth observation, migration studies and risk analysis (Abel et al., 2019; Bohra-Mishra et al., 2014; Feng et al., 2010a; Heslin & Thalheimer, 2020; Hoffmann et al., 2020; Hsiang et al., 2013) could help to decipher reasons of displacement if such data is not readily available, allowing for an application beyond Somalia. Furthermore, cross-national comparisons of similar displacement contexts are difficult due to the structure of the data, short time horizon of available data points as well as heterogeneity of the country context itself. 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 applied to overcome these data challenges in the collection of continuous displacement data (Heslin & Thalheimer, 2020).

6.6 Conclusions

In this paper, we propose a substantial methodological advancement for the study of human mobility in the context of climate change by including implicit displacement statistics in a widely used PEA framework. In doing so, we empirically assess the feasibility of event attribution in the climate mobility context. The benefit from the methodological advancement is twofold. First, by effectively combining the two disciplines, climate science and social-science migration scholarship, we contribute to the ongoing interdisciplinary effort towards modelling climate mobilities. Secondly, we propose a directly usable approach for assessing climate change impacts on human

mobility dynamics. This puts us into a position to fully assess the causal chain from anthropogenic climate change and changing frequencies and intensities of extreme weather and climate-related events to human mobility outcomes.

Furthermore, this study provides a quantitative assessment for a highly vulnerable area. Somalia, like many countries in sub-Saharan Africa, faces impacts from recurring extreme weather events displacing much of its population internally. Existing vulnerabilities and exposure to extreme weather events are exacerbated through decades of sustained conflicts. Using the unique insight into the key reasons associated with internal displacement in a country that experiences compounding extreme weather events and conflict-related vulnerabilities, we show existing exposure and vulnerabilities for a highly mobile population.

Using techniques from PEA, in combination with sub-national displacement data, we find no attributable link between the anthropogenic climate change and associated flood-related displacement investigated. Crucially, we show that PEA is an important component to advance climate change impact research despite the null result. This result only applies for the 2020 April flood and aligned with the quantitative assessment; our results suggest that a case-by-case analysis is needed to investigate possible contributions of climate change impacts in other extreme events. Therefore, our results confirm that the framework of attribution science can be applied to study anthropogenic climate change signals for extreme weather events that result in displacement.

These findings hold direct implications for the policy arena. First, future attribution research can inform climate change adaptation endeavours as well as the policy debate on loss and damage. Second, there is a need to explore its application in fragile countries and those vulnerable to climate change, particularly in Africa since the majority of existing event attribution studies have focused on mid-latitude events. Indeed, with warming proceeding and internal displacement becoming more likely, the study of and policy actions on climate mobility would benefit from methodological advancements climate science offers.

Supplementary Material

A. 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 using human mobility as a synonym for migration (Adger et al., 2018; Boas, 2020; Farbotko et al., 2016), this paper differentiates a set of human mobility types (Table S 6-1).

Table S 6-1: Classification and definition of human mobility types

Type	Definition
Migration	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)
Displacement	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).
Refugee	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.
Climate-related human mobility	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 (Boas et al., 2019).

B. Flood as displacement trigger in Somalia

In East Africa and Somalia, extreme weather events are well-known, reoccurring climate-related phenomena. However, their impacts and intensity vary across the region and require further study. The impact of climate on human wellbeing and livelihoods is further exacerbated by the absence of a central government coupled with poverty and civil conflict that can escalate to crisis-level food insecurity and large-scale involuntary human mobility. After the 2016/17 drought across Somalia, heavy rains during *Gu* season of 2018 led to episodes of flash floods. The UNHCR measured more than 200,000 flood-related IDPs in the regions of Juba and Shabelle in the aftermath of the disasters. The history of drought and flash flood displacement has continued. The numbers of displaced indicate that flash floods cause more harm than in part due to Somali population increase and continuing lack of preparation mechanisms.

Displacement data underlying flood-related displacement

The displacement statistics are based on data from the United Nations High Commissioner for Refugees (UNHCR) Protection and Return Monitoring Network (PRMN). The dataset consists of monthly records of internal displacement (IDP) flows at the regional level. According to the PRMN methodology, population displacements and movement are recorded by targeting strategic points including transit sites, established IDP settlements, border crossings and other ad hoc locations. Interviews are carried out with IDP generating ‘household-level’ reports at points of arrival or with key informants generating ‘group reports’. The point of departure and reason for departure (drought, conflict, flood) are recorded. A clear advantage of this dataset lies

in its large spatial coverage and datapoints. In South and Central Somalia, the project is implemented in Banadir, Bay, Bakool, Gedo, Lower Jubba, Hiraan, Lower Shabelle, Middle Shabelle, middle Juba and Galgaduud region. In Puntland, project operations focus on the regions of Galmaadug, Mudug and Bari. In Somaliland, geographic coverage includes Woqooyi Galbeed, Marodijeh, Sool and Awdal regions. Data is available from 2016 to 2021 (near today). Therefore, this dataset makes it possible to study flood-related displacement attribution at the regional impact level.

C. Descriptive Statistics

Observed trends

We used the Climate Research Unit time series data version 4.0 (CRU Ts4.0) (Harris et al., 2014) to expand the time series of the CHIRPS dataset. Rainfall variation from 1901 to 2019 using the CRU TS4.0 dataset show the suggested downward shift in the Intertropical Convergence Zone which is likely caused by atmospheric aerosols during the 1950 to 1960 period (Peterson et al., 2013).

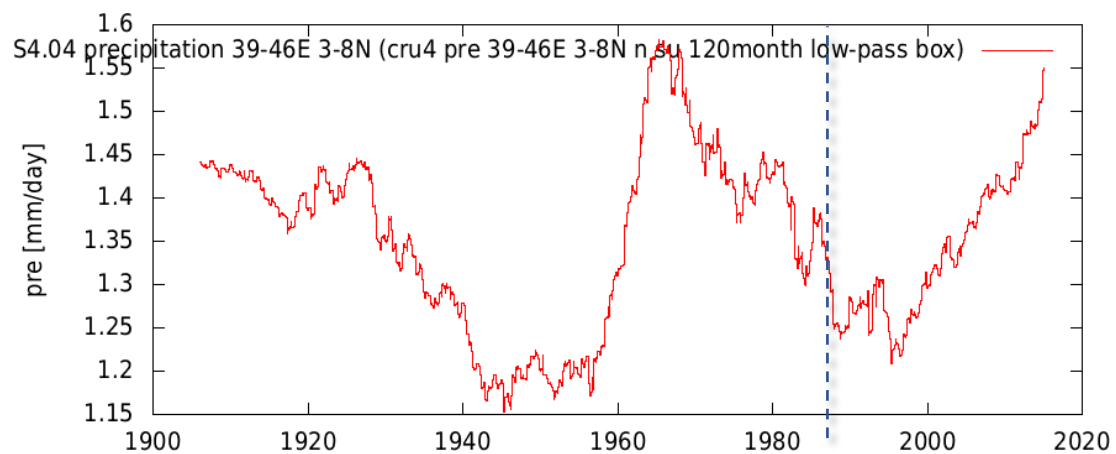


Figure S 6-1: Rainfall time series 1901-2019 (Source: CRU TS4.0). The dashed line indicates the start of the CHIRPS timeseries in 1981.

Here, we perform a ranking of the extreme precipitation for the time period 2018 to 2020 (Figure S 6-2). 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.

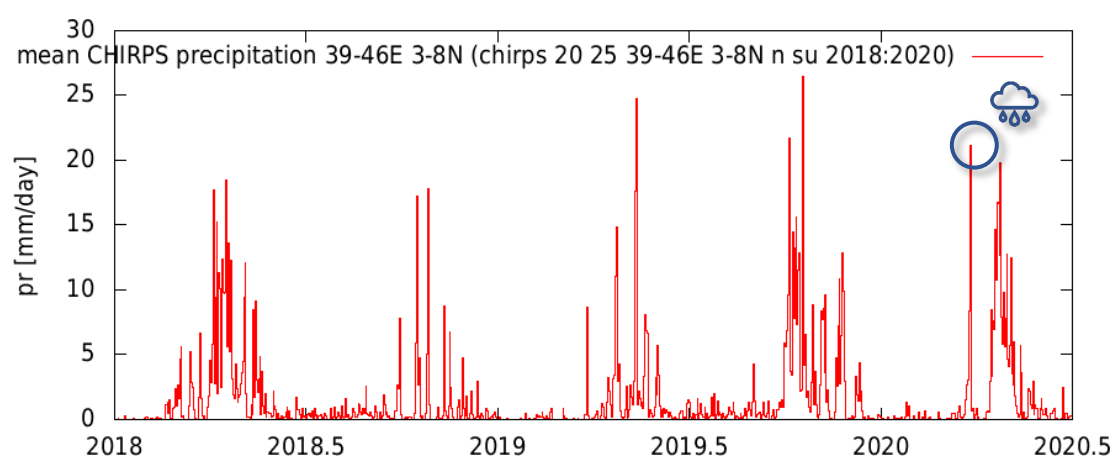


Figure S 6-2: Mean precipitation over the study region over the period of 2018 to mid-2020 (source: CHIRPS)

Here, the trends in return times of extremes are estimated using the CHIRPS daily precipitation observations in the origin region. 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.

i) Origin region

Table S 6-2: Results of the GEV distribution fitting for the origin region. The table lists statistical methods and properties.

Apr 7-day ave CHIRPS 38-44E 2-7N precipitation 38-44E 2-7N pr [mm/day] dependent on Global mean surface temperature (smoothed)			
parameter	year	value	95% CI
covariate:	1900	-0.16375	
	2020	0.95361	
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 ξ of width $2\sigma = 0.4$			
μ' :	1900	7.450	6.635... 8.335
σ' :	1900	2.097	1.520... 2.504
μ' :	2020	9.074	8.256... 9.961
σ' :	2020	2.554	1.891... 2.993
σ/μ :		0.281	0.212... 0.324
ξ :		-0.070	-0.289... 0.122
α :		1.480	-2.290... 5.171

return period event 2020 (value 18.475)	1900	708.80	24.440 ... ∞
probability	1900	0.14108E-02	0 ... 0.40916E-01
return period event 2020 (value 18.475)	2020	71.261	15.188 ... 0.22974E+06
probability	2020	0.14033E-01	0.43527E-05 ... 0.65843E-01
probability ratio		9.9465	0.49281E-02 ... ∞
p-value probability ratio (one-sided)	$\neq 1$	0.2057	
change in intensity 1900 -2020	diff %	21.794	-26.414 ... 101.355

ii) Impact region

Table S 6-3: Results of the GEV distribution fitting for the impact region.

Apr 9-day ave CHIRPS 40-45E 2-5N precipitation 40-45E 2-5N pr [mm/day] dependent on Global mean surface temperature (smoothed)			
parameter	year	value	95% CI
covariate:	1900	-0.16375	
	2020	0.95361	
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 ξ of width $2\sigma = 0.4$			
μ' :	1900	6.379	5.585... 7.276
σ' :	1900	2.012	1.433... 2.440
μ' :	2020	6.551	5.757... 7.448
σ' :	2020	2.066	1.477... 2.497
σ/μ :		0.315	0.238... 0.361
ξ :		-0.030	-0.264... 0.194

α :		0.154	-2.985... 3.328
return period event 2020 (value 13.636)	1900	46.075	5.8525 ... 14566.
probability	1900	0.21704E-01	0.68651E-04 ... 0.17087
return period event 2020 (value 13.636)	2020	37.844	10.506 ... 14331.
probability	2020	0.26424E-01	0.69779E-04 ... 0.95182E-01
probability ratio		1.2175	0.10033E-02 ... 439.47
p -value probability ratio (one-sided)	$\neq 1$	0.4365	
change in intensity 1900 -2020	diff %	2.697	-39.250 ... 80.904

Observed return periods

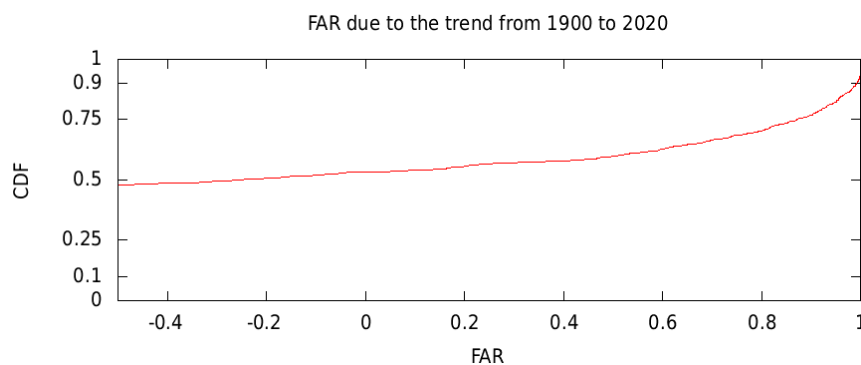


Figure S 6-3: Fraction of attributable risk of the extreme event

6.6.1 D. Model attribution

Model attribution in origin (D i) and impact (D ii) region calculated separately.

Synthesised model results can be found in section D iii.

i) Origin region

EC-Earth23 model (1981-2020)

Return value for this event is 73.021.

Table S 6-4: 7-day average EC-Earth23 RCP8.5 precipitation ensemble at the origin location.

Apr 7-day ave ECEARTH23 rcp85 38-44E 2-7N pr 38-44E 2-7N ensemble pr [mm/day] dependent on t Tglobal EC-Earth23 mean			
parameter	year	value	95% CI
covariate:	1900	12.500	
	2020	13.961	
N:		640	
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 ξ of width $2\sigma = 0.4$			
μ' :	1900	4.070	3.994... 4.228
σ' :	1900	1.298	1.245... 1.403
μ' :	2020	3.930	3.855... 4.088
σ' :	2020	1.254	1.201... 1.357
σ/μ :		0.319	0.305... 0.341
ξ :		-0.056	-0.103... -0.011
α :		-0.095	-0.450... 0.340
return period event 2020 (value 9.0148 at 000)	1900	73.021	32.157 ... 210.91
probability	1900	0.13695E-01	0.47414E-02 ... 0.31097E-01
return period 2020 (value 9.0148 at 000)	2020	100.00	46.139 ... 185.05
probability	2020	0.10000E-01	0.54039E-02 ... 0.21674E-01
probability ratio		0.73021	0.24008 ... 3.2299
inverse probability ratio		1.3695	0.30961 ... 4.1653
p-value probability ratio (one-sided)	$\neq 1$	0.3983	

return value 100 yr	1900	9.335	8.424 ... 10.429
	2020	9.015	8.508 ... 9.951
change in intensity 1900 -2020	diff %	-3.431	-15.209 ... 13.128

HadGEM2-ES model (1981-2020)

Return value is 58.045.

Table S 6-5: 7-day average HadGEM2-ES RCP8.5 precipitation ensemble at the origin location.

HadGEM2-ES rcp85 tas 0-360E -90-90N ensemble mean anomalies			
parameter	year	value	95% CI
covariate:	1900	-1.1872	
	2020	0.40771E-01	
N:		705	
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 ξ of width $2\sigma = 0.4$			
μ' :	1900	10.447	10.171... 10.664
σ' :	1900	2.340	2.290... 2.566
μ' :	2020	10.244	9.969... 10.462
σ' :	2020	2.295	2.244... 2.517
σ/μ :		0.224	0.216... 0.250
ξ :		-0.329	-0.401... -0.318
α :		-0.165	-0.814... 0.122
return period event 2020 (value 15.688 at 000)	1900	58.045	27.100 ... 170.79
probability	1900	0.17228E-01	0.58553E-02 ... 0.36900E-01
return period 2020 (value 15.688 at 000)	2020	100.00	61.885 ... 4377.7

probability	2020	0.10000E-01	0.22843E-03 ... 0.16159E-01
probability ratio		0.58045	0.93259E-02 ... 1.6551
inverse probability ratio		1.7228	0.60418 ... 107.23
p-value probability ratio (one-sided)	$\neq 1$	0.0579	
return value 100 yr	1900	15.998	15.491 ... 16.515
	2020	15.688	14.872 ... 15.940
change in intensity 1900 -2020	diff %	-1.936	-9.187 ... 1.462

Data up to 2020

EC-Earth 2.3 model (1930 – 2020 values)

Table S 6-6: Using threshold return period of 100 yr the return value in the year 2020 is estimated at the origin region.

Apr 7-day ave ECEARTH23 rcpr85 38-44E 2-7N pr 38-44E 2-7N ensemble pr [mm/day] dependent on t Tglobal EC-Earth23 mean			
parameter	year	value	95% CI
covariate:	1900	12.500	
	2020	13.961	
N:		1456	
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 ξ of width $2\sigma = 0.4$			
μ' :	1900	4.327	4.252... 4.402
σ' :	1900	1.360	1.308... 1.412
μ' :	2020	3.881	3.805... 3.956
σ' :	2020	1.220	1.171... 1.269
σ/μ :		0.314	0.302... 0.327

ξ :		-0.079	-0.118... -0.049
α :		-0.307	-0.508... -0.130
return period event 2020 (value 8.5832 at 000)	1900	36.958	27.171 ... 55.925
probability	1900	0.27058E-01	0.17881E-01 ... 0.36804E-01
return period 2020 (value 8.5832 at 000)	2020	100.00	62.983 ... 193.43
probability	2020	0.10000E-01	0.51697E-02 ... 0.15877E-01
probability ratio		0.36958	0.18134 ... 0.65630
inverse probability ratio		2.7058	1.5237 ... 5.5146
p-value probability ratio (one-sided)	$\neq 1$	0.0018	
return value 100 yr	1900	9.570	9.063 ... 10.033
	2020	8.583	8.113 ... 9.034
change in intensity 1900 -2020	diff %	-10.313	-16.327 ... -4.489

HadGEM2-ES model (1930 – 2020 values)

Table S 6-7: Using threshold return period of 100 yr the return value in 2020 is estimated for the origin region with the HadGEM2-ES model.

Apr 7-day ave HadGEM3-A-N216 historical 38-44E 2-7N pr 38-44E 2-7N ensemble pr [mm/day] dependent on HadGEM2-ES rep85 tas 0-360E -90-90N ensemble mean anomalies			
parameter	year	value	95% CI
covariate:	1900	-1.1872	
	2020	0.40771E-01	
N:		1020	
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 ξ of width $2\sigma = 0.4$			

μ' :	1900	10.613	10.454... 10.774
σ' :	1900	2.344	2.255... 2.461
μ' :	2020	10.176	10.018... 10.337
σ' :	2020	2.248	2.161... 2.362
σ/μ :		0.221	0.211... 0.233
ξ :		-0.323	-0.358... -0.298
α :		-0.358	-0.643... -0.084
return period event 2020 (value 15.560 at 000)	1900	35.125	25.301 ... 51.287
probability	1900	0.28470E-01	0.19498E-01 ... 0.39523E-01
return period 2020 (value 15.560 at 000)	2020	100.00	51.964 ... 364.48
probability	2020	0.10000E-01	0.27437E-02 ... 0.19244E-01
probability ratio		0.35125	0.91650E-01 ... 0.78911
inverse probability ratio		2.8470	1.2673 ... 10.911
p-value probability ratio (one-sided)	$\neq 1$	0.0101	
return value 100 yr	1900	16.227	15.936 ... 16.519
	2020	15.560	15.088 ... 15.961
change in intensity 1900 -2020	diff %	-4.111	-7.314 ... -0.984

Future projections origin region

EC-Earth 2.3 model (1930 – 2050 values)

Table S 6-8: Using threshold return period of 100 yr the return value in 2050 is estimated with EC-Earth 2.3 at the origin location.

Apr 7-day ave ECEARTH23 rcp85 38-44E 2-7N pr 38-44E 2-7N ensemble pr [mm/day] dependent on t Tglobal EC-Earth23 mean			
parameter	year	value	95% CI
covariate:	1900	12.500	
	2020	13.961	
N:		1936	
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 ξ of width $2\sigma = 0.4$			
μ' :	1900	4.176	4.115... 4.243
σ' :	1900	1.344	1.296... 1.389
μ' :	2020	4.037	3.976... 4.105
σ' :	2020	1.300	1.253... 1.344
σ/μ :		0.322	0.309... 0.333
ξ :		-0.056	-0.087... -0.028
α :		-0.094	-0.198... -0.000
return period event 2020 (value 8.5830 at 000)	1900	37.997	29.319 ... 51.227
probability	1900	0.26318E-01	0.19521E-01 ... 0.34108E-01
return period 2020 (value 8.5830 at 000)	2020	49.650	39.847 ... 66.881
probability	2020	0.20141E-01	0.14952E-01 ... 0.25096E-01
probability ratio		0.76529	0.57150 ... 0.99856

inverse probability ratio		1.3067	1.0014 ... 1.7498
p-value probability ratio (one-sided)	$\neq 1$	0.0248	
change in intensity 1900 -2020	diff %	-3.317	-6.837 ... -0.017

HadGEM2-EM model (1930 – 2050 values)

Table S 6-9: Using threshold return period of 100 yr the return value in 2050 is estimated with HadGEM3-A at the origin location.

Apr 7-day ave HadGEM3-A-N216 historical 38-44E 2-7N pr 38-44E 2-7N ensemble pr [mm/day] dependent on HadGEM2-ES rcp85 tas 0-360E -90-90N ensemble mean anomalies			
parameter	year	value	95% CI
covariate:	1900	-1.1872	
	2020	0.40771E-01	
N:		1020	
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 ξ of width $2\sigma = 0.4$			
μ' :	1900	10.613	10.450... 10.779
σ' :	1900	2.344	2.255... 2.459
μ' :	2020	10.176	10.014... 10.342
σ' :	2020	2.248	2.161... 2.359
σ/μ :		0.221	0.212... 0.233
ξ :		-0.323	-0.353... -0.298
α :		-0.358	-0.647... -0.052
return period event 2020 (value 15.560 at 000)	1900	35.123	25.227 ... 52.152
probability	1900	0.28471E-01	0.19175E-01 ... 0.39640E-01

return period 2020 (value 15.560 at 000)	2020	99.992	49.862 ... 292.61
probability	2020	0.10001E-01	0.34175E-02 ... 0.20056E-01
probability ratio		0.35126	0.10559 ... 0.86550
inverse probability ratio		2.8469	1.1554 ... 9.4706
p-value probability ratio (one-sided)	$\neq 1$	0.0066	
change in intensity 1900 -2020	diff %	-4.111	-7.301 ... -0.601

ii) Impact region

Return value for this event is 61.610.

Table S 6-10: 9-day average EC-Earth23 RCP8.5 precipitation ensemble at the impact location.

Apr 9-day ave ECEARTH23 rcp85 40-45E 2-5N pr 40-45E 2-5N ensemble pr [mm/day] dependent on t Tglobal EC-Earth23			
parameter	year	value	95% CI
covariate:	1900	12.522	
	2020	13.892	
N:		640	
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 ξ of width $2\sigma = 0.4$			
μ' :	1900	3.991	3.894... 4.123
σ' :	1900	1.345	1.271... 1.433
μ' :	2020	3.831	3.734... 3.963
σ' :	2020	1.291	1.218... 1.378
σ/μ :		0.337	0.314... 0.360

ξ :		-0.152	-0.195... -0.112
α :		-0.116	-0.498... 0.267
return period event 2020 (value 8.1065 at 000)	1900	61.610	23.457 ... 246.84
probability	1900	0.16231E-01	0.40511E-02 ... 0.42631E-01
return period 2020 (value 8.1065 at 000)	2020	100.00	46.765 ... 298.71
probability	2020	0.10000E-01	0.33477E-02 ... 0.21383E-01
probability ratio		0.61610	0.11788 ... 3.9093
inverse probability ratio		1.6231	0.25580 ... 8.4830
p-value probability ratio (one-sided)	$\neq 1$	0.2435	
return value 100 yr	1900	8.445	7.640 ... 9.411
	2020	8.107	7.547 ... 8.690
change in intensity 1900 -2020	diff %	-4.011	-16.016 ... 9.651

Data up to 2020

EC-Earth 2.3 model (1930 – 2020 values)

Table S 6-11: Using threshold return period of 100 yr the return value in the year 2020 is estimated at the impact region.

Apr 9-day ave ECEARTH23 rcp85 40-45E 2-5N pr 40-45E 2-5N ensemble pr [mm/day] dependent on t Tglobal EC-Earth23			
parameter	year	value	95% CI
covariate:	1900	12.522	
	2020	13.892	
N:		1456	
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 ξ of width $2\sigma = 0.4$			

μ' :	1900	4.185	4.117... 4.260
σ' :	1900	1.338	1.280... 1.392
μ' :	2020	3.825	3.757... 3.900
σ' :	2020	1.224	1.168... 1.274
σ/μ :		0.320	0.305... 0.334
ξ :		-0.156	-0.191... -0.132
α :		-0.263	-0.467... -0.063
return period event 2020 (value 7.8393 at 000)	1900	35.683	24.972 ... 59.363
probability	1900	0.28024E-01	0.16845E-01 ... 0.40044E-01
return period 2020 (value 7.8393 at 000)	2020	100.00	62.839 ... 214.71
probability	2020	0.10000E-01	0.46574E-02 ... 0.15914E-01
probability ratio		0.35683	0.14879 ... 0.75895
inverse probability ratio		2.8024	1.3176 ... 6.7208
p-value probability ratio (one-sided)	$\neq 1$	0.0047	
return value 100 yr	1900	8.575	8.153 ... 8.941
	2020	7.839	7.448 ... 8.140
change in intensity 1900 -2020	diff %	-8.584	-14.693 ... -2.145

Future projections impact region
EC-Earth 2.3 model (1930 – 2050 values)

Table S 6-12: Using threshold return period of 100 year the return value in 2050 is estimated at the impact region.

Apr 9-day ave ECEARTH23 rcp85 40-45E 2-5N pr 40-45E 2-5N ensemble pr [mm/day] dependent on t Tglobal EC-Earth23			
parameter	year	value	95% CI
covariate:	1900	12.522	
	2020	13.892	
N:		1936	
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 ξ of width $2\sigma = 0.4$			
μ' :	1900	3.994	3.933... 4.072
σ' :	1900	1.321	1.276... 1.369
μ' :	2020	3.974	3.913... 4.052
σ' :	2020	1.314	1.270... 1.362
σ/μ :		0.331	0.317... 0.344
ξ :		-0.125	-0.187... -0.103
α :		-0.015	-0.126... 0.077
return period event 2020 (value 6.2908 at 000)	1900	7.6157	6.6247 ... 8.8327
probability	1900	0.13131	0.11322 ... 0.15095
return period 2020 (value 6.2908 at 000)	2020	7.8390	7.0019 ... 9.2528
probability	2020	0.12757	0.10808 ... 0.14282
probability ratio		0.97151	0.77725 ... 1.1622
inverse probability ratio		1.0293	0.86046 ... 1.2866
p-value probability ratio (one-sided)	$\neq 1$	0.3107	
change in intensity 1900 -2020	diff %	-0.506	-4.246 ... 2.671

iii) Synthesis

Table S 6-13: Synthesis of attribution results of precipitation at the origin region with a probability ratio of 1.62 (0.880E-01, 17.5), using common interval 1900-2020, with reference values -0.1621 0.9488.

Data set	PR	PR lower bound	PR upper bound
Observations CHIRPS	9.95	0.493E-02	0.100E+08
EC-Earth	0.730	0.24008	3.2299
HadGEM3-A	0.580	0.93259E-02	1.6551
Models	0.651	0.767E-01	1.62
average	1.62	0.880E-01	17.5

7 Conclusions

The importance of human mobility in East Africa is undisputed. The media, politicians, international organisations, researchers, and climate activists increasingly claim that the effects of climate change on weather and climate-related events will lead to massive displacements of populations globally. Few papers have attempted to provide quantitative evidence, describe different methodologies and data to link weather and climate-related events, human mobility, and anthropogenic climate change. However, until this point, there has been little evidence to support causal links. The overall consequence of this is that our understanding of the link between climate, weather, and human mobility in this vulnerable part of the world is superficial at best. Thus, there is a dearth of credible and reliable evidence for decision-makers to use in long-term planning for climate-related human mobility in East Africa.

The papers (Chapters 3 to 6) presented in this thesis represent a logical approach to the outlined problem, focusing on the knowledge gaps and processes the existing literature has indicated as most crucial. This led to a particular focus on the methods to model societal impacts (climate econometrics) and attribute climate change impacts (probabilistic event attribution). This final chapter synthesises the research undertaken in this thesis and offers conclusions. The first section (Chapter 7.1) will tie together the conclusions that can be made from across the research chapters relating to the integrated attribution approach developed in this thesis to answer the question: how feasible is this methodology in data scarce regions such as East Africa? It will then synthesise the lines of evidence (Chapters 7.2–7.4) relating to the two overarching aims of the thesis (characterising climate-related human mobility and assessing causal links to anthropogenic climate change). Implications for research and policy are outlined before moving to discuss some limitations of the attribution approaches. This chapter

concludes with an outline of policy implications and avenues for future research (Chapters 7.5–7.6).

7.1 The value of integrated attribution approaches

As a main research contribution, this thesis developed an integrated attribution approach (IAA, Figure 7-1), a novel methodology to assess causal links between human mobility and weather and climate-related events to anthropogenic climate change. The IAA espoused in this thesis has been conducted in the context of increasing recognition within the climate science and policy community of the scientific value in understanding how populations respond in the aftermath of weather and climate-related events.

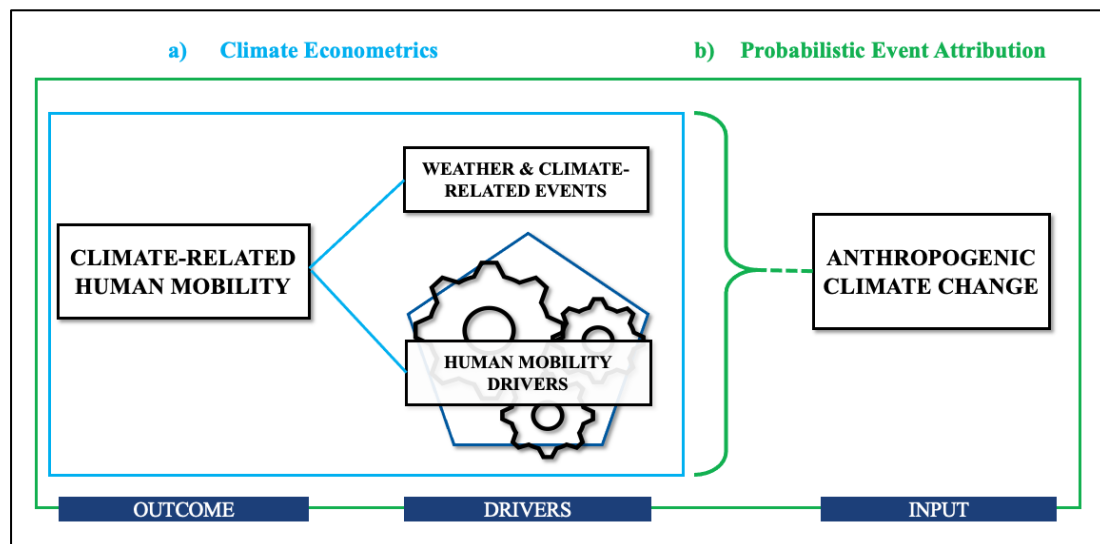


Figure 7-1: Schematic of the integrated attribution approach (IAA), including the methods used in Chapter 5 (blue box) and Chapter 6 (green box).

This is reflected in a number of recent initiatives to better understand the risks associated with the effects of anthropogenic climate change on weather and climate-related events, such as World Weather Attribution studies over Africa (World Weather Attribution, 2021) and special issues in the annual Bulletin of the American Meteorological Society collection (e.g., Herring et al., 2018, 2019) and the special collection on weather attribution in Climatic Change. There has also been increasing recognition of the importance of attribution studies to address society-relevant questions and implications for populations' wellbeing and climate adaptation (Swain et al., 2020).

In the context of such work, this thesis hypothesized that an integrated attribution approach would provide significant insights into the human responses to anthropogenic climate change in East Africa and sought to develop methods that are of particular use to data scarce regions. The ability of commonly used methods to investigate climate-related human mobility to provide insight into attributable links to anthropogenic climate change are severely limited (see Chapters 3 and 4) without utilising climate observations and data and quantitative approaches to do modelling with. The analysis in Chapter 5 filled this gap by providing a method for identifying climate-related human mobility drivers (green box in Figure 7-1), exemplified by drought-related internal displacement in Somalia.

It was hypothesized that IAA would offer greater clarity in determining the weather and climate-related drivers of human mobility, and in turn, the causal links to anthropogenic climate change. This was done for the first time in Chapter 6 through a feasibility study, which applied PEA to flood-related displacement in Somalia and

helped to determine causal links to anthropogenic climate change (blue box in Figure 7-1).

Overall, the analysis in this thesis showed that an integrated attribution approach to model the attributability of climate-related human mobility can add significant scientific value, particularly in regions such as East Africa where characterising climate-related human mobility lacks scientific rigour. Most attribution studies focus on climate impacts with a few going further by assessing financial components in the form of losses and damages, as outlined in Section 2.3.3. IAA goes beyond an analysis from emissions to impacts (Stone & Allen, 2005) as it adds an analysis of societal impacts such as climate-related human mobility. In this context, this thesis highlighted the importance of granular data and location-specific weather observations, as data which assess yearly or national level human mobility are not necessarily useable for the attribution of shorter-term weather and climate-related events, e.g., floods and heat waves. With an understanding of the value of IAA in hand, the four research questions of this thesis can be sufficiently answered. This is done in Chapters 7.2 through 7.4.

7.2 Characterising climate-related human mobility

This section discusses the research questions relating to the current evidence on climate-related human mobility in the past and under future warming, which were largely explored in Chapter 3 and Chapter 4.

- i. To what extent can weather and climate-related events in the form of droughts and floods explain human mobility in East Africa?*

ii. *What is the current understanding of the implications for human mobility under future warming in East Africa?*

The first step in better understanding climate-related human mobility was to examine in detail the representation of weather and climate-related events across a suite of human mobility types in the existing literature and to assess the quality of the evidence these provide. A mixed-method approach, consisting of a case study analysis and a topic modelling approach (Borderon et al., 2019; Lamb et al., 2019) was chosen in Chapter 3. To date, there has been very little research into the different types of human mobility and weather and climate-related events in East Africa, and even less aiming to understand potential links to anthropogenic climate change.

The analysis in Chapter 3 showed that droughts and floods have mainly led to involuntary population movements in the form of internal displacement across East Africa. Although climate change is referred to implicitly and explicitly as a driver of human mobility, the reviewed literature implied a causal link between human mobility and anthropogenic climate change. At the same time, climate data and evidence from attribution studies were either underrepresented or misrepresented, and do not support the implied links. The map of evidence developed allows case studies to be matched across human mobility types and climate and contextual factors influencing human mobility in a changing climate. Chapter 3 also carved out the multi-causal nature of human mobility in East Africa. Weather and climate influences on human mobility were not independent but were closely connected with social and economic factors as well as conflict events and political insecurity.

There are two related research and policy implications of Chapter 3. First, when studies are conducted on the contribution of weather and climate-related events to human mobility, there is currently low confidence in a climate change-human mobility nexus for East Africa. This has implications for the attribution between human mobility and climate change. Climate observations are sparsely used to base assumptions that weather and climate-related events contribute to individuals' mobility. However, the results in existing literature are likely to be misleading, as the causal link to climate change is implied without analysis corroborating such links. Second, this casts doubt on the utility of existing evidence in future projections of human mobility in East Africa and elsewhere, and its use for studying climate-related human mobility. Given that the contribution of weather and climate affecting human mobility may be better observed or modelled by using weather and climate data, it follows that an investigation of these data used in the literature may offer a starting point for understanding the evidence landscape of climate-related human mobility in the past and under future warming. Such an analysis was conducted in Chapters 3 and 4.

Given the paucity of evidence on causal links between human mobility and anthropogenic climate change in East Africa and the divergence in climate observations and data used to corroborate claims of existing links, this thesis sought to determine methods that could provide causal links should they exist; in other words, to develop a framework to attribute human mobility to anthropogenic climate change. Previous research has confirmed the importance of understanding the multi-causal drivers contributing to human mobility and clearly identifying weather and climate-related events in this context (Boas et al., 2019; Bohra-Mishra et al., 2014). Such a characterisation of location-specific climate-related human mobility is a useful starting

point for understanding the contribution of past weather and climate-related events. Understanding which of these events contributed to a specific form of human mobility and how human mobility might evolve under future warming could form a suitable framing (event definition) for the integrated attribution approach developed in this thesis.

Chapter 4, therefore, assessed the evidence on the links between human mobility and implications in climate change impact sectors in Eastern Africa with a content analysis. This was done to establish whether evidence exists to a) better understand weather and climate-related events affecting human mobility under future warming and b) constrain the type of human mobility most pressing to investigate under future warming in East Africa.

Chapter 4 showed that climate change impacts on human mobility are not just be a result of potential disruptions to one sector vulnerable to climate change. Indeed, shocks to multiple sectors or even compounding risks need further attention under future warming. This finding is in accordance with research on the increasing relevance of cascading risks from connected and compound events: Raymond et al. (2020) found that careful impact analyses, granular data and metrics will support a better understanding of climate change impacts on populations and society, and facilitate decision-making processes.

The analysis in Chapter 4 identified research and policy implications in the East African region. First, the sectoral interconnectedness and the reliance on human mobility highlights the importance of conducting climate-specific assessments of human

mobility drivers under future warming. Previous research into Eastern and Southern African countries indicates that the relative influence of weather and climate-related events on human mobility varies by country (Mueller et al., 2020). Chapter 4 found that the same regional differences occur across the existing literature. In particular, there is scarce evidence on future climate-related human mobility in East Africa further highlighting the importance of approaching this region with methods from social and climate science (Borderon et al., 2019; Zickgraf, 2021). It also raises the possibility that a systems analysis is needed to facilitate coordinated research and policy work on the human responses to climate change (Cradock-Henry et al., 2020).

Bringing together the gained knowledge from Chapter 3 and 4, flood and droughts only tell a fraction of the story of climate-related human mobility in East Africa, and even less is known for future warming scenarios. This work points out the importance of quantitatively analysing climate-related human mobility. Assessments of human mobility drivers usually focus on the contribution of past weather and climate-related events or the perception thereof. However, as noted by Hoffmann et al., (2020), a better understanding is needed of where people move to under future warming, as well as associated uncertainties. Thus, the advantage of analysing local impacts of weather and climate-related events on human mobility is that the contribution of past and future anthropogenic climate change to different forms of human mobility can be systematically elucidated. Given uncertainties remain in the contribution of different types of weather and climate-related events to human mobility, such an analysis is performed in a country case study in Chapter 5.

7.3 Disentangling human mobility drivers and attributability to anthropogenic climate change

The findings regarding the evidence landscape of human mobility drivers in East Africa in the historical period and under future warming in Chapters 3 and 4 were intended to feed directly into an examination of the ability of statistical methods to disentangle human mobility drivers. The research in Chapter 5 addressed the following research question:

- iii. How can we disentangle and quantify the drivers of human mobility in the study area?*

In responding to this question, the findings of Chapter 5 show that displacement outcomes are largely dependent on the type of weather and climate-related event. Populations were displaced differently when comparing drought- and conflict-related displacement. The study shows that weather and climate-related events trigger displacement and gives evidence on where people move to. Findings indicate that displacement impact are constant with drought input. If it matters in Somalia, it is likely that it matters in another region in East Africa as well. With the inputs of climate change making weather and climate-related events more frequent and extreme, this is something to worry about in the sustainable development context. Chapter 5 confirms that research should focus on neglected regions, and policy makers should pay attention to this theme of climate change impacts.

Recognising that the dataset used in Chapter 5 is unique (due to its granularity and the reported reasons of displacement), there are limitations for the replicability in regions where such data does not exist. However, the methods applied (two-way fixed effects models) can be easily transferred to other regions without requiring complicated models. Indeed, with the developed model, it is possible to work with less granular data. This allows to expand the geographical scale to other regions and presents a direct implication for future research. In terms of policy implications, findings from this study conclude that more investment should go towards subnational data collection including the main reason of mobility to help climate-related human mobility adaptation in East Africa.

7.4 Causal links to anthropogenic climate change

The contribution of weather and climate-related events to human mobility in East Africa is addressed in Chapter 5. To assess the attributability between human mobility and anthropogenic climate change, the research in Chapter 6 addressed research question 4:

- iv. Whether and to what extent does anthropogenic climate change alter the likelihood of climate-related human mobility today?*

Chapter 6 addressed this research question with an event attribution study as a feasibility study for the integrated attribution approach developed throughout this thesis. Research that attempts to determine the attributability between changes in the likelihood of weather and climate-related events and human mobility outcomes often

works on the assumption that anthropogenic climate change is a definitive driver of human mobility and will continue to do so in the future (Rigaud et al., 2018). This is the underlying assumption of the majority of studies conducting analyses on the nexus between human mobility and weather and climate-related events, as outlined in Section 1.4 and discussed in Chapters 3 and 4. However, it is not clear whether and to what extent anthropogenic climate change has already shifted human mobility or might do so in the future (IPCC, 2018). The hypothesis in Chapter 6 is that attributing internal displacement that is a result of weather and climate-related events may provide definitive insights into the attributability of anthropogenic climate change.

Chapter 6 thus focussed on identifying a potential contribution of anthropogenic climate change to recent flood-related internal displacement in Somalia. This is done by using granular internal displacement data in addition to probabilistic event attribution techniques. The result of the study is twofold: For one, the PEA framework is well suited to answer research question 3. Second, the study result itself found no contribution of anthropogenic climate change in the displacement event investigated.

The previous research that has been undertaken indicated that climate observations and models need to be considered for studies on climate-related human mobility (Hoffmann et al., 2020) and potential links to anthropogenic climate change carefully assessed (Mueller et al., 2020). However, such an approach has yet to be pursued to explore links between human mobility and anthropogenic climate change in East Africa. Chapter 6 provides the first comprehensive analysis to attribute a flood event to internal displacement over a) the origin region of the extreme precipitation event and b) the impact region of the flood, where populations were displaced from.

The analysis followed the common, six step approach of PEA studies, event selection; event definition and framing; observed probability and trend; model validation; model attribution; and synthesis and interpretation of these results. Internal displacement data by reported reason was used to select and define the event in Somalia. The PEA framework has proved to be a good starting point to explore the contribution of anthropogenic climate change to internal displacement and similar analysis should be conducted for other climate-related human mobility events in East Africa. The key take-away from this study is that for PEA to feed into IAA, it would depend on granular human mobility data. Integrating methods from climate econometrics, e.g., TWFE, could go a long way in characterising climate-related human mobility in such a way that granular data is not a requirement. Even if such data are available, the outcome of future studies may depend on the type of climate-related human mobility and weather and climate-related event. Nevertheless, further work, refining and testing the integrated attribution approach could add further value to these initial findings. Attribution analyses on socio-economic and humanitarian outcomes associated with floods and droughts may offer insights into which implications are plausible for climate-related human mobility, and in turn, attributable to anthropogenic climate change today and in the future. This is similar to new approaches called for to address complex emergencies (Kruczkiewicz et al., 2021). The findings in Chapter 6 could further be strengthened by an improved understanding of the attributability of drought-related internal displacement in recent years, the type of climate-related human mobility focused on in Chapter 5.

7.5 Policy implications

The outcomes of the research chapters yield a variety of implications for policy makers and are useful for governments, international organisations or funding agencies supporting human mobility in East Africa. The study results presented in Chapter 3 inform decision makers about the extent to which existing scientific evidence on climate-related human mobility in the region is plausible and indicates where weather and climate-related events have disrupted human mobility. The results of Chapter 3 informed both the technical and political economy analyses and policy recommendations of the report “Somalia Urbanization Review” (World Bank, 2021b).

The work in Chapter 4 is motivated by the outcomes of the IPCC SR15 report (2018). SR15 is set up specifically to inform policy makers about the implications for future warming scenarios in climate-sensitive sectors. The analysis in Chapter 4 showed that future warming influences sectors relevant to human mobility beyond the region of East Africa. The study suggests a systems approach to pool policy responses across sectors. As warming continues, the development of systems approaches to risk assessment and decision support are increasingly necessary to secure a safe way for populations to pursue human mobility.

Findings of Chapter 5 provide information to governments, international and humanitarian organisations to efficiently allocate resources to contingency plans and humanitarian aid to improve the resilience of populations, including those at risk of displacement and those already displaced. Climate and conflict effects on displaced

populations were identified and can help build early warning systems that incorporate displacement risks and pre-allocated funding to support those at risk of displacement and those displaced. The results of Chapter 5 informed new approaches of anticipatory action and financing for the Red Cross/ Red Crescent Climate Centre (RCCC). Results were included in an issue brief that outlines the existing and potential links between forecast-based financing (FbF) and weather and climate-related displacement (Thalheimer et al., 2020). This set of policy recommendations that aims to guide researchers and practitioners in this new field were presented at the Virtual Climate Summit in September 2020.

Chapter 6 is the first study to incorporate PEA methods to study the impacts of anthropogenic climate change on climate-related human mobility. As scientific studies have mostly concentrated on the climate change impact, little research on human responses to anthropogenic climate change exists. Using climate model outputs commonly used by the IPCC, the study provides useful information about future climate risks to societies in East Africa and contributes to current climate policy discussions.

7.6 Avenues for future research

The thesis has contributed a set of four research papers to the scientific literature on climate-related human mobility in East Africa, including two reviews on past and future warming, which has been understudied despite its importance in African dryland for climate-sensitive sectors relevant to human mobility. Nevertheless, there is still

important work to be done to improve the understanding of complex drivers of East African human mobility in a changing climate. Priorities for future research should focus on integrating societal data in attribution approaches, improved human mobility data, connecting with humanitarian actors and consider the complexity of climate-related human mobility.

Weather and climate-related events differ geographically, and in their impact on human mobility, as Chapter 3 addressed. While this thesis predominately focussed on past events, Chapter 4 also demonstrated that future impacts on human mobility could affect a wide array of climate change impact sectors such as agriculture and livelihoods. In light of this, further work should account for the resulting implications of food insecurity on human mobility, as discussed by Puma et al. (2018).

Populations do not stay in one place for various reasons. This thesis has highlighted that the current evidence landscape on climate-related human mobility is sparse for East Africa and sparser than the number of research studies might suggest. There is a need for more granular data on human mobility and reporting on reasons on why people move, as well as attribution approaches to determine the contributions from weather and climate-related events. Closely linked, the analysis of high resolution, limited area climate models will be important due to the local impact of weather and climate related events that impact populations. Expanding on drought and flood impacts on human mobility and its attributability to anthropogenic climate change, more research should be done on the impacts from heat waves across human mobility in the study region. An excellent new candidate for this sort of analysis is the high-resolution data from the

Climate Hazards Center Infrared Temperature with Stations (CHIRTS), as a recent publication indicates (Amou et al., 2021).

Conversely, this thesis has also highlighted the value of assessing granular data on human mobility with statistical methods, and future research should build on this. Whilst valuable data has been collected assessing the underlying reasons for internal displacement in Somalia (UNHCR Somalia, 2020), further data collection work needs to be done to expand such efforts across East Africa jointly from different UN entities and humanitarian actors like the Red Cross/ Red Crescent who are usually present in the aftermath of weather and climate-related events.

Future work should also focus on a stronger link between research and humanitarian actors such as the ones outlined above. Forecast based- financing (FbF) could be a first step in the direction of the usage of weather forecasts informing actions for practitioners and the humanitarian aid community on the ground. The Red Cross/ Red Crescent Climate Centre recently highlighted the usability of anticipatory action in the form of FbF for weather and climate-related displacement (Thalheimer et al., 2020). In the aftermath of such events and avoided humanitarian hardship, the integrated attribution approach of this thesis helps to determine the degree to which climate change is to blame for the remaining loss and damage. In turn, this would link to ongoing discussions about attribution studies for loss and damage research and policy work (James et al., 2019).

The COVID-19 pandemic has further complicated the landscape of human mobility in ways which have the potential to exacerbate the challenges already faced by

populations impacted by weather and climate-related events. There is a need to depict these complexities to test whether anthropogenic climate change might exacerbate the impacts from systemic risks such as pandemics. Understanding how populations move in the absence of UN or non-governmental agencies being present can help make more accurate decisions based on time and place. Remote sensing work offers valuable insights to ground-truth when and where populations move during weather and climate-related events (Heslin & Thalheimer, 2020).

7.7 Concluding remarks

In our mobile world that is always changing, ‘conclusions’ might appear an oxymoron. But a summary of the story of climate-related human mobility in East Africa can be done. First, human mobility data and observational weather and climate data are far from pervasive. Second, there are two main sources of attributability deriving from a) disentangling the drivers leading to and the characterising of climate-related human mobility, and b) attributable links to anthropogenic climate change that lead to a shift in probability and frequency of those weather and climate-related events affecting human mobility. Third, the resulting attributability not only radically alters the focus of climate-related human mobility research but can also have pernicious implications for migration scholarship and for policy. Fourth, methods for characterising and attributing climate-related human mobility should be an essential part of the modeller’s toolkit.

References

- Abel, G. J., Brottrager, M., Cuaresma, J. C., & Muttarak, R. (2019). Climate, conflict and forced migration. *Global Environmental Change*, 54, 239–249.
- Achour, M., & Lacan, N. (2011). *DROUGHT IN SOMALIA: A MIGRATION CRISIS*. 16.
- Adams, H., & Adger, W. N. (2013). The contribution of ecosystem services to place utility as a determinant of migration decision-making. *Environmental Research Letters*, 8(1), 015006. <https://doi.org/10.1088/1748-9326/8/1/015006>
- Adams, H., & Kay, S. (2019). Migration as a human affair: Integrating individual stress thresholds into quantitative models of climate migration. *Environmental Science & Policy*, 93, 129–138. <https://doi.org/10.1016/j.envsci.2018.10.015>
- Adger, W. N., Arnell, N. W., Black, R., Dercon, S., Geddes, A., & Thomas, D. S. G. (2015). Focus on environmental risks and migration: Causes and consequences. *Environmental Research Letters*, 10(6), 060201. <https://doi.org/10.1088/1748-9326/10/6/060201>
- Adger, W. N., Safra de Campos, R., & Mortreux, C. (2018). Mobility, displacement and migration, and their interactions with vulnerability and adaptation to environmental risks. In *Routledge Handbook of Environmental Displacement and Migration*. Routledge.
- Afifi, T., Govil, R., Sakdapolrak, P., & Warner, K. (2012). CLIMATE CHANGE, VULNERABILITY AND HUMAN MOBILITY: PERSPECTIVES OF REFUGEES FROM THE EAST AND HORN OF AFRICA. *Climate Change*, 1, 60.

- Afifi, T., Liwenga, E., & Kwezi, L. (2014). Rainfall-induced crop failure, food insecurity and out-migration in Same-Kilimanjaro, Tanzania. *Climate and Development*, 6(1), 53–60. <https://doi.org/10.1080/17565529.2013.826128>
- Afifi, T., Milan, A., Etzold, B., Schraven, B., Rademacher-Schulz, C., Sakdapolrak, P., Reif, A., Geest, K. van der, & Warner, K. (2016). Human mobility in response to rainfall variability: Opportunities for migration as a successful adaptation strategy in eight case studies. *Migration and Development*, 5(2), 254–274. <https://doi.org/10.1080/21632324.2015.1022974>
- Ahmadalipour, A., Moradkhani, H., Castelletti, A., & Magliocca, N. (2019). Future drought risk in Africa: Integrating vulnerability, climate change, and population growth. *Science of The Total Environment*, 662, 672–686. <https://doi.org/10.1016/j.scitotenv.2019.01.278>
- Akinsanola, A. A., & Zhou, W. (2019). Ensemble-based CMIP5 simulations of West African summer monsoon rainfall: Current climate and future changes. *Theoretical and Applied Climatology*, 136(3), 1021–1031. <https://doi.org/10.1007/s00704-018-2516-3>
- Alemayehu, A., & Bewket, W. (2016). Local climate variability and crop production in the central highlands of Ethiopia. *Environmental Development*, 19, 36–48. <https://doi.org/10.1016/j.envdev.2016.06.002>
- Alemayehu, A., & Bewket, W. (2017). Smallholder farmers’ coping and adaptation strategies to climate change and variability in the central highlands of Ethiopia. *Local Environment*, 22(7), 825–839. <https://doi.org/10.1080/13549839.2017.1290058>
- Allen, M. (2003). Liability for climate change. *Nature*, 421(6926), 891–892. <https://doi.org/10.1038/421891a>

- Amou, M., Gyilbag, A., Demelash, T., & Xu, Y. (2021). Heatwaves in Kenya 1987–2016: Facts from CHIRTS High Resolution Satellite Remotely Sensed and Station Blended Temperature Dataset. *Atmosphere*, 12(1), 37. <https://doi.org/10.3390/atmos12010037>
- Armed Conflict Location & Event Data Project. (2020, January 15). Al Shabaab in Somalia and Kenya. *ACLED Resources*. <https://acleddata.com/2020/01/15/acled-resources-al-shabaab-in-somalia-and-kenya/>
- Ash, K., & Obradovich, N. (2020). Climatic Stress, Internal Migration, and Syrian Civil War Onset. *Journal of Conflict Resolution*, 64(1), 3–31. <https://doi.org/10.1177/0022002719864140>
- Ayeb-Karlsson, S. (2020). ‘When we were children we had dreams, then we came to Dhaka to survive’: Urban stories connecting loss of wellbeing, displacement and (im)mobility. *Climate and Development*, 1–12. <https://doi.org/10.1080/17565529.2020.1777078>
- Ayeb-Karlsson, S., Tanner, T., van der Geest, K., Warner, K., Adams, H., Ahmed, I., Alaniz, R., Andrei, S., Barthelt, C., Bhargava, M., Bronen, R., Contreras, D., Cradock-Henry, N., Fernando, N., Henly-Shepard, S., Huq, S., Lawless, C., Lewis, D., Loster, T., ... Zommers, Z. (2015). *Livelihood resilience in a changing world – 6 global policy recommendations for a more sustainable future*. <https://collections.unu.edu/view/UNU:3339>
- Bakewell, O. (2008). ‘Keeping Them in Their Place’: The ambivalent relationship between development and migration in Africa. *Third World Quarterly*, 29(7), 1341–1358. <https://doi.org/10.1080/01436590802386492>

- Bakewell, O. (2010). Some Reflections on Structure and Agency in Migration Theory. *Journal of Ethnic and Migration Studies*, 36(10), 1689–1708. <https://doi.org/10.1080/1369183X.2010.489382>
- Baldwin, A., Methmann, C., & Rothe, D. (2014). Securitizing ‘climate refugees’: The futurology of climate-induced migration. *Critical Studies on Security*, 2(2), 121–130. <https://doi.org/10.1080/21624887.2014.943570>
- Barry, A. A., Caesar, J., Tank, A. M. G. K., Aguilar, E., McSweeney, C., Cyrille, A. M., Nikiema, M. P., Narcisse, K. B., Sima, F., Stafford, G., Touray, L. M., Ayilari-Naa, J. A., Mendes, C. L., Tounkara, M., Gar-Glahn, E. V. S., Coulibaly, M. S., Dieh, M. F., Mouhaimouni, M., Oyegade, J. A., ... Laogbessi, E. T. (2018). West Africa climate extremes and climate change indices. *International Journal of Climatology*, 38(S1), e921–e938. <https://doi.org/10.1002/joc.5420>
- Bastia, T., & Skeldon, R. (2020). *Routledge Handbook of Migration and Development*. Routledge.
- Beine, M. A. R., & Jeusette, L. (2018). *A Meta-Analysis of the Literature on Climate Change and Migration* (SSRN Scholarly Paper ID 3338771). Social Science Research Network. <https://papers.ssrn.com/abstract=3338771>
- Bell, A. R., Wrathall, D. J., Mueller, V., Chen, J., Oppenheimer, M., Hauer, M., Adams, H., Kulp, S., Clark, P. U., Fussell, E., Magliocca, N., Xiao, T., Gilmore, E. A., Abel, K., Call, M., & Slangen, A. B. A. (2021). Migration towards Bangladesh coastlines projected to increase with sea-level rise through 2100. *Environmental Research Letters*, 16(2), 024045. <https://doi.org/10.1088/1748-9326/abdc5b>

- Bellemare, M. F., & Wichman, C. J. (2020). Elasticities and the Inverse Hyperbolic Sine Transformation. *Oxford Bulletin of Economics and Statistics*, 82(1), 50–61. <https://doi.org/10.1111/obes.12325>
- Benveniste, H., Oppenheimer, M., & Fleurbaey, M. (2020). Effect of border policy on exposure and vulnerability to climate change. *Proceedings of the National Academy of Sciences*, 117(43), 26692–26702. <https://doi.org/10.1073/pnas.2007597117>
- Betts, R. A., Alfieri, L., Bradshaw, C., Caesar, J., Feyen, L., Friedlingstein, P., Gohar, L., Koutroulis, A., Lewis, K., Morfopoulos, C., Papadimitriou, L., Richardson, K. J., Tsanis, I., & Wyser, K. (2018). Changes in climate extremes, fresh water availability and vulnerability to food insecurity projected at 1.5°C and 2°C global warming with a higher-resolution global climate model. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 376(2119), 20160452. <https://doi.org/10.1098/rsta.2016.0452>
- Biermann, F., & Boas, I. (2008). *Protecting Climate Refugees: The Case for a Global Protocol*. 50(6), 11.
- Black, R., Adger, W. N., Arnell, N. W., Dercon, S., Geddes, A., & Thomas, D. (2011). The effect of environmental change on human migration. *Global Environmental Change*, 21, S3–S11. <https://doi.org/10.1016/j.gloenvcha.2011.10.001>
- Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet Allocation. *Journal of Machine Learning Research*, 3(Jan), 993–1022.
- Block, P., & Strzepek, K. (2012). Power Ahead: Meeting Ethiopia's Energy Needs Under a Changing Climate. *Review of Development Economics*, 16(3), 476–488. <https://doi.org/10.1111/j.1467-9361.2012.00675.x>

- Boas, I. (2020). Social networking in a digital and mobile world: The case of environmentally-related migration in Bangladesh. *Journal of Ethnic and Migration Studies*, 46(7), 1330–1347. <https://doi.org/10.1080/1369183X.2019.1605891>
- Boas, I., Farbotko, C., Adams, H., Sterly, H., Bush, S., van der Geest, K., Wiegel, H., Ashraf, H., Baldwin, A., Bettini, G., Blondin, S., de Bruijn, M., Durand-Delacre, D., Fröhlich, C., Gioli, G., Guaita, L., Hut, E., Jarawura, F. X., Lamers, M., ... Hulme, M. (2019). Climate migration myths. *Nature Climate Change*, 9(12), 901–903. <https://doi.org/10.1038/s41558-019-0633-3>
- Bohra-Mishra, P., Oppenheimer, M., & Hsiang, S. M. (2014). Nonlinear permanent migration response to climatic variations but minimal response to disasters. *Proceedings of the National Academy of Sciences*, 111(27), 9780–9785. <https://doi.org/10.1073/pnas.1317166111>
- Boone, R. B., Conant, R. T., Sircely, J., Thornton, P. K., & Herrero, M. (2018). Climate change impacts on selected global rangeland ecosystem services. *Global Change Biology*, 24(3), 1382–1393. <https://doi.org/10.1111/gcb.13995>
- Borderon, M., Sakdapolrak, P., Muttarak, R., Kebede, E., Pagogna, R., & Sporer, E. (2019). Migration influenced by environmental change in Africa: A systematic review of empirical evidence. *Demographic Research*, 41, 491–544. JSTOR. <https://doi.org/10.2307/26850658>
- Bosetti, V., Cattaneo, C., & Peri, G. (2020). Should they stay or should they go? Climate migrants and local conflicts. *Journal of Economic Geography*, lbaa002. <https://doi.org/10.1093/jeg/lbaa002>

- Burke, M., Hsiang, S. M., & Miguel, E. (2015). Climate and Conflict. *Annual Review of Economics*, 7(1), 577–617. <https://doi.org/10.1146/annurev-economics-080614-115430>
- Burke, M., Miguel, E., Satyanath, S., Dykema, J. A., & Lobell, D. B. (2009). Warming increases the risk of civil war in Africa. *Proceedings of the National Academy of Sciences*, 106(49), 20670–20674. <https://doi.org/10.1073/pnas.0907998106>
- Burrell, A. L., Evans, J. P., & De Kauwe, M. G. (2020). Anthropogenic climate change has driven over 5 million km² of drylands towards desertification. *Nature Communications*, 11(1), 3853. <https://doi.org/10.1038/s41467-020-17710-7>
- Byers, E., Gidden, M., Leclère, D., Balkovic, J., Burek, P., Ebi, K., Greve, P., Grey, D., Havlik, P., Hillers, A., Johnson, N., Kahil, T., Krey, V., Langan, S., Nakicenovic, N., Novak, R., Obersteiner, M., Pachauri, S., Palazzo, A., ... Riahi, K. (2018). Global exposure and vulnerability to multi-sector development and climate change hotspots. *Environmental Research Letters*, 13(5), 055012. <https://doi.org/10.1088/1748-9326/aabf45>
- Cai, R., Feng, S., Oppenheimer, M., & Pytlikova, M. (2016). Climate variability and international migration: The importance of the agricultural linkage. *Journal of Environmental Economics and Management*, 79, 135–151. <https://doi.org/10.1016/j.jeem.2016.06.005>
- Carbon Brief. (2020, April 15). *Mapped: How climate change affects extreme weather around the world*. Carbon Brief. <https://www.carbonbrief.org/mapped-how-climate-change-affects-extreme-weather-around-the-world>
- Carleton, T. A., & Hsiang, S. M. (2016). Social and economic impacts of climate. *Science*, 353(6304). <https://doi.org/10.1126/science.aad9837>

- Castle, J. L., & Hendry, D. F. (2020). Climate Econometrics: An Overview. *Foundations and Trends® in Econometrics*, 10(3–4), 145–322. <https://doi.org/10.1561/08000000037>
- Cattaneo, C., Beine, M., Fröhlich, C. J., Kniveton, D., Martinez-Zarzoso, I., Mastrorillo, M., Millock, K., Piguet, E., & Schraven, B. (2019a). Human Migration in the Era of Climate Change. *Review of Environmental Economics and Policy*, 13(2), 189–206. <https://doi.org/10.1093/reep/rez008>
- Cattaneo, C., Beine, M., Fröhlich, C. J., Kniveton, D., Martinez-Zarzoso, I., Mastrorillo, M., Millock, K., Piguet, E., & Schraven, B. (2019b). Human Migration in the Era of Climate Change. *Review of Environmental Economics and Policy*, 13(2), 189–206. <https://doi.org/10.1093/reep/rez008>
- Cervigni, R., & Morris, M. (2016). *Confronting Drought in Africa's Drylands: Opportunities for Enhancing Resilience*. The World Bank. <https://doi.org/10.1596/978-1-4648-0817-3>
- Cheng, X., Shuai, C., Liu, J., Wang, J., Liu, Y., Li, W., & Shuai, J. (2018). Topic modelling of ecology, environment and poverty nexus: An integrated framework. *Agriculture, Ecosystems & Environment*, 267, 1–14. <https://doi.org/10.1016/j.agee.2018.07.022>
- Cheung, W. W. L., Reygondeau, G., & Frölicher, T. L. (2016). Large benefits to marine fisheries of meeting the 1.5°C global warming target. *Science*, 354(6319), 1591–1594. <https://doi.org/10.1126/science.aag2331>
- Christidis, N., Stott, P. A., Scaife, A. A., Arribas, A., Jones, G. S., Copsey, D., Knight, J. R., & Tennant, W. J. (2013). A New HadGEM3-A-Based System for Attribution of Weather- and Climate-Related Extreme Events. *Journal of Climate*, 26(9), 2756–2783. <https://doi.org/10.1175/JCLI-D-12-00169.1>

- Ciavarella, A., Christidis, N., Andrews, M., Groenendijk, M., Rostron, J., Elkington, M., Burke, C., Lott, F. C., & Stott, P. A. (2018). Upgrade of the HadGEM3-A based attribution system to high resolution and a new validation framework for probabilistic event attribution. *Weather and Climate Extremes*, 20, 9–32. <https://doi.org/10.1016/j.wace.2018.03.003>
- Collier, P., Conway, G., & Venables, T. (2008). Climate change and Africa. *Oxford Review of Economic Policy*, 24(2), 337–353. <https://doi.org/10.1093/oxrep/grn019>
- Collier, P., & Hoeffler, A. (2005). Resource Rents, Governance, and Conflict. *Journal of Conflict Resolution*, 49(4), 625–633. <https://doi.org/10.1177/0022002705277551>
- Collins, W. J., Bellouin, N., Doutriaux-Boucher, M., Gedney, N., Halloran, P., Hinton, T., Hughes, J., Jones, C. D., Joshi, M., Liddicoat, S., Martin, G., O'Connor, F., Rae, J., Senior, C., Sitch, S., Totterdell, I., Wiltshire, A., & Woodward, S. (2011). Development and evaluation of an Earth-System model – HadGEM2. *Geoscientific Model Development*, 4(4), 1051–1075. <https://doi.org/10.5194/gmd-4-1051-2011>
- Coughlan de Perez, E., van Aalst, M., Choularton, R., van den Hurk, B., Mason, S., Nissan, H., & Schwager, S. (2019). From rain to famine: Assessing the utility of rainfall observations and seasonal forecasts to anticipate food insecurity in East Africa. *Food Security*, 11(1), 57–68. <https://doi.org/10.1007/s12571-018-00885-9>
- Cradock-Henry, N. A., Connolly, J., Blackett, P., & Lawrence, J. (2020). Elaborating a systems methodology for cascading climate change impacts and implications. *MethodsX*, 7, 100893. <https://doi.org/10.1016/j.mex.2020.100893>

- Dasgupta, P., Morton, J., Dodman, D., Karapinar, B., Meza, F., Rivera-Ferre, M. G., Toure Sarr, A., & Vincent, K. E. (2014). Rural areas. In C. Field & V. Barros (Eds.), *Climate Change 2014: Impacts, Adaptation, and Vulnerability: Vol. A* (pp. 613–657). Cambridge University Press. <https://gala.gre.ac.uk/id/eprint/14369/>
- de Chaisemartin, C., & D'Haultfœuille, X. (2020). Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. *American Economic Review*, 110(9), 2964–2996. <https://doi.org/10.1257/aer.20181169>
- Dinku, T., Ceccato, P., & Connor, S. J. (2011). Challenges of satellite rainfall estimation over mountainous and arid parts of east Africa. *International Journal of Remote Sensing*, 32(21), 5965–5979. <https://doi.org/10.1080/01431161.2010.499381>
- Dinku, T., Funk, C., Peterson, P., Maidment, R., Tadesse, T., Gadain, H., & Ceccato, P. (2018). Validation of the CHIRPS satellite rainfall estimates over eastern Africa. *Quarterly Journal of the Royal Meteorological Society*, 144(S1), 292–312. <https://doi.org/10.1002/qj.3244>
- Dosio, A., Jones, R. G., Jack, C., Lennard, C., Nikulin, G., & Hewitson, B. (2019). What can we know about future precipitation in Africa? Robustness, significance and added value of projections from a large ensemble of regional climate models. *Climate Dynamics*, 53(9), 5833–5858. <https://doi.org/10.1007/s00382-019-04900-3>
- Dumais, S. T. (2004). Latent semantic analysis. *Annual Review of Information Science and Technology*, 38(1), 188–230. <https://doi.org/10.1002/aris.1440380105>
- Ebi, K. L., Åström, C., Boyer, C. J., Harrington, L. J., Hess, J. J., Honda, Y., Kazura, E., Stuart-Smith, R. F., & Otto, F. E. L. (2020). Using Detection And Attribution

- To Quantify How Climate Change Is Affecting Health. *Health Affairs*, 39(12), 2168–2174. <https://doi.org/10.1377/hlthaff.2020.01004>
- Elsevier. (2020). *Scopus*. <https://www.scopus.com/>
- Ezra, M., & Kiros, G.-E. (2001). Rural Out-migration in the Drought Prone Areas of Ethiopia: A Multilevel Analysis¹. *International Migration Review*, 35(3), 749–771. <https://doi.org/10.1111/j.1747-7379.2001.tb00039.x>
- Fanzo, J., Davis, C., McLaren, R., & Choufani, J. (2018). The effect of climate change across food systems: Implications for nutrition outcomes. *Global Food Security*, 18, 12–19. <https://doi.org/10.1016/j.gfs.2018.06.001>
- FAO SWALIM. (2020). *Somalia Flood Update*. https://www.faoswalim.org/resources/site_files/Somalia_Flood_Update-27042020.pdf
- Farbotko, C., Stratford, E., & Lazrus, H. (2016). Climate migrants and new identities? The geopolitics of embracing or rejecting mobility. *Social & Cultural Geography*, 17(4), 533–552. <https://doi.org/10.1080/14649365.2015.1089589>
- Feng, S., Krueger, A. B., & Oppenheimer, M. (2010a). Linkages among climate change, crop yields and Mexico–US cross-border migration. *Proceedings of the National Academy of Sciences*, 107(32), 14257–14262. <https://doi.org/10.1073/pnas.1002632107>
- Feng, S., Krueger, A. B., & Oppenheimer, M. (2010b). Linkages among climate change, crop yields and Mexico–US cross-border migration. *Proceedings of the National Academy of Sciences*, 107(32), 14257–14262. <https://doi.org/10.1073/pnas.1002632107>
- Finney, D. L., Marsham, J. H., Rowell, D. P., Kendon, E. J., Tucker, S. O., Stratton, R. A., & Jackson, L. S. (2020). Effects of Explicit Convection on Future

- Projections of Mesoscale Circulations, Rainfall, and Rainfall Extremes over Eastern Africa. *Journal of Climate*, 33(7), 2701–2718. <https://doi.org/10.1175/JCLI-D-19-0328.1>
- Flahaux, M.-L., & De Haas, H. (2016). African migration: Trends, patterns, drivers. *Comparative Migration Studies*, 4(1), 1. <https://doi.org/10.1186/s40878-015-0015-6>
- Frame, D. J., Wehner, M. F., Noy, I., & Rosier, S. M. (2020). The economic costs of Hurricane Harvey attributable to climate change. *Climatic Change*, 160(2), 271–281. <https://doi.org/10.1007/s10584-020-02692-8>
- Fučkar, N. S., Otto, F. E. L., Lehner, F., Pinto, I., Sparrow, S., Li, S., & Wallom, D. (2020). On High Precipitation in Mozambique, Zimbabwe and Zambia in February 2018. *Bulletin of the American Meteorological Society*, 101(1), S47–S52. <https://doi.org/10.1175/BAMS-D-19-0162.1>
- Funk, C. (2020). Ethiopia, Somalia and Kenya face devastating drought. *Nature*. <https://doi.org/10.1038/d41586-020-02698-3>
- Funk, C., Harrison, L., Shukla, S., Korecha, D., Magadzire, T., Husak, G., Galu, G., & Hoell, A. (2016). Assessing the Contributions of Local and East Pacific Warming to the 2015 Droughts in Ethiopia and Southern Africa. *Bulletin of the American Meteorological Society*, 97(12), S75–S80. <https://doi.org/10.1175/BAMS-D-16-0167.1>
- Funk, C., Nicholson, S. E., Landsfeld, M., Klotter, D., Peterson, P., & Harrison, L. (2015). The Centennial Trends Greater Horn of Africa precipitation dataset. *Scientific Data*, 2(1), 150050. <https://doi.org/10.1038/sdata.2015.50>
- Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., & Michaelsen, J. (2015). The climate

- hazards infrared precipitation with stations—A new environmental record for monitoring extremes. *Scientific Data*, 2(1), 150066. <https://doi.org/10.1038/sdata.2015.66>
- Funk, C., Peterson, P., Peterson, S., Shukla, S., Davenport, F., Michaelsen, J., Knapp, K. R., Landsfeld, M., Husak, G., Harrison, L., Rowland, J., Budde, M., Meiburg, A., Dinku, T., Pedreros, D., & Mata, N. (2019). A High-Resolution 1983–2016 Tmax Climate Data Record Based on Infrared Temperatures and Stations by the Climate Hazard Center. *Journal of Climate*, 32(17), 5639–5658. <https://doi.org/10.1175/JCLI-D-18-0698.1>
- Fussell, E. (2012). Space, Time, and Volition: Dimensions of Migration Theory. In M. R. Rosenblum & D. J. Tichenor (Eds.), *Oxford Handbook of the Politics of International Migration* (pp. 25–52). Oxford University Press. <https://www.oxfordhandbooks.com/view/10.1093/oxfordhb/9780195337228.01.0001/oxfordhb-9780195337228-e-2>
- Gaetani, M., Janicot, S., Vrac, M., Famien, A. M., & Sultan, B. (2020). Robust assessment of the time of emergence of precipitation change in West Africa. *Scientific Reports*, 10(1), 7670. <https://doi.org/10.1038/s41598-020-63782-2>
- Geest, K. van der, & Warner, K. (2014). Loss and Damage from Droughts and Floods in Rural Africa. In *Digging Deeper: Inside Africa's Agricultural, Food and Nutrition Dynamics* (pp. 276–293). Brill. https://doi.org/10.1163/9789004282698_014
- Ginnetti, J., & Franck, T. (2014). *Assessing drought displacement risk for Kenyan, Ethiopian and Somali pastoralists* [Data set]. Norwegian Refugee Council (NRC) Internal Displacement Monitoring Centre (IDMC). https://doi.org/10.1163/2210-7975_HRD-9806-2014039

- Gray, C., & Mueller, V. (2012). Drought and Population Mobility in Rural Ethiopia. *World Development*, 40(1), 134–145. <https://doi.org/10.1016/j.worlddev.2011.05.023>
- Gray, C., & Wise, E. (2016). Country-specific effects of climate variability on human migration. *Climatic Change*, 135(3), 555–568. <https://doi.org/10.1007/s10584-015-1592-y>
- Griffiths, T. L., & Steyvers, M. (2004). Finding scientific topics. *Proceedings of the National Academy of Sciences*, 101(suppl 1), 5228–5235. <https://doi.org/10.1073/pnas.0307752101>
- Groth, J., Ide, T., Sakdapolrak, P., Kassa, E., & Hermans, K. (2020a). Deciphering interwoven drivers of environment-related migration – A multisite case study from the Ethiopian highlands. *Global Environmental Change*, 63, 102094. <https://doi.org/10.1016/j.gloenvcha.2020.102094>
- Groth, J., Ide, T., Sakdapolrak, P., Kassa, E., & Hermans, K. (2020b). Deciphering interwoven drivers of environment-related migration – A multisite case study from the Ethiopian highlands. *Global Environmental Change*, 63, 102094. <https://doi.org/10.1016/j.gloenvcha.2020.102094>
- Guha-Sapir, D., Below, R., & Hoyois, P. (2016, February 19). *EM-DAT: The CRED/OFDA International Disaster Database*. <https://wedocs.unep.org/handle/20.500.11822/16183>
- Guldberg, O. H., Jacob, D., Taylor, M., Bindi, M., Brown, S., Camilloni, I., & Zougmore, R. (2018). Chapter 3: Impacts of 1.5 C Global Warming on Natural and Human Systems. *Global Warming of 1.5 C: An IPCC Special Report on the Impacts of Global Warming of 1.5 C Above Pre-Industrial Levels and Related*

Global Greenhouse Gas Emission Pathways, in the Context of Strengthening the Global Response to the Threat of Climate Change.

- Haas, H. de. (2008). The Myth of Invasion: The inconvenient realities of African migration to Europe. *Third World Quarterly*, 29(7), 1305–1322. <https://doi.org/10.1080/01436590802386435>
- Haas, H. de. (2010). The Internal Dynamics of Migration Processes: A Theoretical Inquiry. *Journal of Ethnic and Migration Studies*, 36(10), 1587–1617. <https://doi.org/10.1080/1369183X.2010.489361>
- Haines, A., & Ebi, K. (2019). The Imperative for Climate Action to Protect Health. *New England Journal of Medicine*. <https://www.nejm.org/doi/10.1056/NEJMra1807873>
- Hallegatte, S., & Rozenberg, J. (2017). Climate change through a poverty lens. *Nature Climate Change*, 7(4), 250–256. <https://doi.org/10.1038/nclimate3253>
- Harrington, L. J., & Otto, F. E. L. (2018). Changing population dynamics and uneven temperature emergence combine to exacerbate regional exposure to heat extremes under 1.5°C and 2°C of warming. *Environmental Research Letters*, 13(3), 034011. <https://doi.org/10.1088/1748-9326/aaa99>
- Harrington, L. J., & Otto, F. E. L. (2020). Reconciling theory with the reality of African heatwaves. *Nature Climate Change*, 10(9), 796–798. <https://doi.org/10.1038/s41558-020-0851-8>
- Harris, I., Jones, P. D., Osborn, T. J., & Lister, D. H. (2014). Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 Dataset. *International Journal of Climatology*, 34(3), 623–642. <https://doi.org/10.1002/joc.3711>

- Hastrup, K., & Olwig, K. F. (Eds.). (2012). *Climate change and human mobility: Global challenges to the social sciences*. Cambridge University Press.
- Hauer, M. E., Fussell, E., Mueller, V., Burkett, M., Call, M., Abel, K., McLeman, R., & Wrathall, D. (2020). Sea-level rise and human migration. *Nature Reviews Earth & Environment*, 1(1), 28–39. <https://doi.org/10.1038/s43017-019-0002-9>
- Hauser, M., Gudmundsson, L., Orth, R., Jézéquel, A., Haustein, K., Vautard, R., van Oldenborgh, G. J., Wilcox, L., & Seneviratne, S. I. (2017). Methods and Model Dependency of Extreme Event Attribution: The 2015 European Drought. *Earth's Future*, 5(10), 1034–1043. <https://doi.org/10.1002/2017EF000612>
- Haustein, K., Otto, F. E. L., Venema, V., Jacobs, P., Cowtan, K., Hausfather, Z., Way, R. G., White, B., Subramanian, A., & Schurer, A. P. (2019). A Limited Role for Unforced Internal Variability in Twentieth-Century Warming. *Journal of Climate*, 32(16), 4893–4917. <https://doi.org/10.1175/JCLI-D-18-0555.1>
- Hayes, S., Lundy, B. D., & Hallward, M. C. (2016). Conflict-Induced Migration and the Refugee Crisis: Global and Local Perspectives from Peacebuilding and Development. *Journal of Peacebuilding & Development*, 11(3), 1–7. <https://doi.org/10.1080/15423166.2016.1239404>
- Hazeleger, W., Severijns, C., Semmler, T., Ștefănescu, S., Yang, S., Wang, X., Wyser, K., Dutra, E., Baldasano, J. M., Bintanja, R., Bougeault, P., Caballero, R., Ekman, A. M. L., Christensen, J. H., Hurk, B. van den, Jimenez, P., Jones, C., Kållberg, P., Koenigk, T., ... Willén, U. (2010). EC-Earth: A Seamless Earth-System Prediction Approach in Action. *Bulletin of the American Meteorological Society*, 91(10), 1357–1364. <https://doi.org/10.1175/2010BAMS2877.1>

- Hegerl, G., Hoegh-Guldberg, O., Casassa, G., Hoerling, M., Kovats, S., Pierce, D., Stott, P., & Stone, D. (2010). *Good Practice Guidance Paper on Detection and Attribution Related to Anthropogenic Climate Change*. 9.
- Hermans, K., & Garbe, L. (2019). Droughts, livelihoods, and human migration in northern Ethiopia. *Regional Environmental Change*, 19(4), 1101–1111. <https://doi.org/10.1007/s10113-019-01473-z>
- Herring, S. C., Christidis, N., Hoell, A., Hoerling, M. P., & Stott, P. A. (2019). *Explaining Extreme Events of 2017 from a climate perspective*. 11.
- Herring, S. C., Christidis, N., Hoell, A., Kossin, J. P., Schreck, C. J., & Stott, P. A. (2018). Explaining Extreme Events of 2016 from a Climate Perspective. *Bulletin of the American Meteorological Society*, 99(1), S1–S157. <https://doi.org/10.1175/BAMS-ExplainingExtremeEvents2016.1>
- Herring, S. C., Hoerling, M. P., Peterson, T. C., & Stott, P. A. (2014). *EXPLAINING EXTREME EVENTS OF 2013 FROM A CLIMATE PERSPECTIVE*. 105.
- Heslin, A., & Thalheimer, L. (2020). *The Picture from Above: Using Satellite Imagery to Overcome Methodological Challenges in Studying Environmental Displacement*. 8(2). <https://core.ac.uk/download/pdf/286269512.pdf#page=81>
- Hirpa, F. A., Alfieri, L., Lees, T., Peng, J., Dyer, E., & Dadson, S. J. (2019). Streamflow response to climate change in the Greater Horn of Africa. *Climatic Change*, 156(3), 341–363. <https://doi.org/10.1007/s10584-019-02547-x>
- Hoegh-Guldberg, O., Jacob, D., Taylor, M., Bolaños, T. G., Bindi, M., Brown, S., Camilloni, I. A., Diedhiou, A., Djalante, R., Ebi, K., Engelbrecht, F., Guiot, J., Hijikata, Y., Mehrotra, S., Hope, C. W., Payne, A. J., Pörtner, H.-O., Seneviratne, S. I., Thomas, A., ... Zhou, G. (2019). The human imperative of

- stabilizing global climate change at 1.5°C. *Science*, 365(6459).
<https://doi.org/10.1126/science.aaw6974>
- Hoffmann, R., Dimitrova, A., Muttarak, R., Crespo Cuaresma, J., & Peisker, J. (2020). A meta-analysis of country-level studies on environmental change and migration. *Nature Climate Change*, 1–9. <https://doi.org/10.1038/s41558-020-0898-6>
- Horton, R. M., Sherbinin, A. de, Wrathall, D., & Oppenheimer, M. (2021). Assessing human habitability and migration. *Science*, 372(6548), 1279–1283.
<https://doi.org/10.1126/science.abi8603>
- Hsiang, S. M. (2016). *Climate Econometrics*. 35.
- Hsiang, S. M., Burke, M., & Miguel, E. (2013). Quantifying the Influence of Climate on Human Conflict. *Science*, 341(6151).
<https://doi.org/10.1126/science.1235367>
- Huang, J., Yu, H., Dai, A., Wei, Y., & Kang, L. (2017). Drylands face potential threat under 2 °C global warming target. *Nature Climate Change*, 7(6), 417–422.
<https://doi.org/10.1038/nclimate3275>
- Ibáñez, A. M., & Vélez, C. E. (2008). Civil Conflict and Forced Migration: The Micro Determinants and Welfare Losses of Displacement in Colombia. *World Development*, 36(4), 659–676. <https://doi.org/10.1016/j.worlddev.2007.04.013>
- Ide, T., Brzoska, M., Donges, J. F., & Schleussner, C.-F. (2020). Multi-method evidence for when and how climate-related disasters contribute to armed conflict risk. *Global Environmental Change*, 62, 102063.
<https://doi.org/10.1016/j.gloenvcha.2020.102063>
- Ide, T., & Scheffran, J. (2014). On climate, conflict and cumulation: Suggestions for integrative cumulation of knowledge in the research on climate change and

- violent conflict. *Global Change, Peace & Security*, 26(3), 263–279.
<https://doi.org/10.1080/14781158.2014.924917>
- Imai, K., & Kim, I. S. (2020). On the Use of Two-Way Fixed Effects Regression Models for Causal Inference with Panel Data. *Political Analysis*, 1–11.
<https://doi.org/10.1017/pan.2020.33>
- Intergovernmental Authority on Development. (2020). *Protocol on Free Movement of Persons*.
<https://disasterdisplacement.org/wp-content/uploads/2020/03/Communique-on-Endorsement-of-the-Protocol-of-Free-Movement-of-Persons.pdf>
- Internal Displacement Monitoring Centre. (2017). *Global Displacement Risk Model*. IDMC. <https://www.internal-displacement.org/database/global-displacement-risk-model>
- Internal Displacement Monitoring Centre. (2019). *Global Internal Displacement Database*. IDMC. <https://www.internal-displacement.org/database/displacement-data>
- Internal Displacement Monitoring Centre. (2020). *Global Report on Internal Displacement*. <https://www.internal-displacement.org/sites/default/files/publications/documents/2020-IDMC-GRID.pdf>
- Internal Displacement Monitoring Centre. (2021a). *2021 Global Report on Internal Displacement*. <https://www.internal-displacement.org/global-report/grid2021/>
- Internal Displacement Monitoring Centre. (2021b). *Somalia*. IDMC. <https://www.internal-displacement.org/countries/somalia>

- Internal Displacement Monitoring Centre. (2021c). *GRID2021*. https://www.internal-displacement.org/sites/default/files/publications/documents/grid2021_idmc.pdf
- International Organization for Migration. (2011). *World Migration Report 2011—Communicating Effectively about Migration*. <https://publications.iom.int/books/world-migration-report-2011>
- International Organization for Migration. (2019). *Global Compact for Migration*. International Organization for Migration. <https://www.iom.int/global-compact-migration>
- IOM. (2020). *Research Database | Environmental Migration Portal*. <https://environmentalmigration.iom.int/research-database>
- IPCC. (2018). *Global Warming of 1.5 °C*. World Meteorological Organization. <https://www.ipcc.ch/sr15/>
- IPCC. (2019a). *Special Report on the Ocean and Cryosphere in a Changing Climate—Summary for Policymakers*. https://www.ipcc.ch/site/assets/uploads/sites/3/2019/11/03_SROCC_SPM_FINAL.pdf
- IPCC. (2019b). *Special Report on Climate Change and Land*. <https://www.ipcc.ch/srccl/>
- James, R., Jones, R., Boyd, E., Young, H., Otto, F. E. L., Huggel, C., & Fuglestad, J. S. (2019). Attribution: How Is It Relevant for Loss and Damage Policy and Practice? In R. Mechler, L. M. Bouwer, T. Schinko, S. Surminski, & J. Linnerooth-Bayer (Eds.), *Loss and Damage from Climate Change: Concepts, Methods and Policy Options* (pp. 113–154). Springer International Publishing. https://doi.org/10.1007/978-3-319-72026-5_5

- James, R., Washington, R., Abiodun, B., Kay, G., Mutemi, J., Pokam, W., Hart, N., Artan, G., & Senior, C. (2018). Evaluating Climate Models with an African Lens. *Bulletin of the American Meteorological Society*, 99(2), 313–336. <https://doi.org/10.1175/BAMS-D-16-0090.1>
- Jayawardhan, S. (2017). *Vulnerability and Climate Change Induced Human Displacement*. 17(1), 103–142. <https://doi.org/10.7916/D8639VFH>
- Jézéquel, A., Dépoues, V., Guillemot, H., Trolliet, M., Vanderlinden, J.-P., & Yiou, P. (2018). Behind the veil of extreme event attribution. *Climatic Change*, 149(3), 367–383. <https://doi.org/10.1007/s10584-018-2252-9>
- Jones, C. D., Hughes, J. K., Bellouin, N., Hardiman, S. C., Jones, G. S., Knight, J., Liddicoat, S., O'Connor, F. M., Andres, R. J., Bell, C., Boo, K.-O., Bozzo, A., Butchart, N., Cadule, P., Corbin, K. D., Doutriaux-Boucher, M., Friedlingstein, P., Gornall, J., Gray, L., ... Zerroukat, M. (2011). The HadGEM2-ES implementation of CMIP5 centennial simulations. *Geoscientific Model Development*, 4(3), 543–570. <https://doi.org/10.5194/gmd-4-543-2011>
- Kassahun, A., Snyman, H. A., & Smit, G. N. (2008). Impact of rangeland degradation on the pastoral production systems, livelihoods and perceptions of the Somali pastoralists in Eastern Ethiopia. *Journal of Arid Environments*, 72(7), 1265–1281. <https://doi.org/10.1016/j.jaridenv.2008.01.002>
- Kaunda, C. S., Kimambo, C. Z., & Nielsen, T. K. (2012, August 28). *Potential of Small-Scale Hydropower for Electricity Generation in Sub-Saharan Africa* [Review Article]. ISRN Renewable Energy; Hindawi. <https://doi.org/10.5402/2012/132606>
- Kelley, C. P., Mohtadi, S., Cane, M. A., Seager, R., & Kushnir, Y. (2015). Climate change in the Fertile Crescent and implications of the recent Syrian drought.

- Proceedings of the National Academy of Sciences*, 112(11), 3241–3246.
<https://doi.org/10.1073/pnas.1421533112>
- Kew, S. F., Philip, S., Hauser, M., Hobbins, M., Wanders, N., van Oldenborgh, G. J., van der Wiel, K., Veldkamp, T. I. E., Kimutai, J., Funk, C., & Otto, F. E. L. (2021). Impact of precipitation and increasing temperatures on drought trends in eastern Africa. *Earth System Dynamics*, 12(1), 17–35.
<https://doi.org/10.5194/esd-12-17-2021>
- Kew, S. F., Philip, S., van Oldenborgh, G. J., van der Schrier, G., Otto, F. E. L., & Vautard, R. (2019). The Exceptional Summer Heat Wave in Southern Europe 2017. *Bulletin of the American Meteorological Society*, 100(1), S49–S53.
<https://doi.org/10.1175/BAMS-D-18-0109.1>
- Kew, S. F., Philip, S. Y., Hauser, M., Hobbins, M., Wanders, N., Oldenborgh, G. J. van, Wiel, K. van der, Veldkamp, T. I. E., Kimutai, J., Funk, C., & Otto, F. E. L. (2019). Impact of precipitation and increasing temperatures on drought in eastern Africa. *Earth System Dynamics Discussions*, 1–29.
<https://doi.org/10.5194/esd-2019-20>
- Khosla, R., Miranda, N. D., Trotter, P. A., Mazzone, A., Renaldi, R., McElroy, C., Cohen, F., Jani, A., Perera-Salazar, R., & McCulloch, M. (2020). Cooling for sustainable development. *Nature Sustainability*, 1–8.
<https://doi.org/10.1038/s41893-020-00627-w>
- Kilavi, M., MacLeod, D., Ambani, M., Robbins, J., Dankers, R., Graham, R., Titley, H., Salih, A. A. M., & Todd, M. C. (2018). Extreme Rainfall and Flooding over Central Kenya Including Nairobi City during the Long-Rains Season 2018: Causes, Predictability, and Potential for Early Warning and Actions. *Atmosphere*, 9(12), 472. <https://doi.org/10.3390/atmos9120472>

- King, A. D., Donat, M. G., Lewis, S. C., Henley, B. J., Mitchell, D. M., Stott, P. A., Fischer, E. M., & Karoly, D. J. (2018). Reduced heat exposure by limiting global warming to 1.5 °C. *Nature Climate Change*, 8(7), 549–551. <https://doi.org/10.1038/s41558-018-0191-0>
- King, J., Washington, R., & Engelstaedter, S. (2020). Representation of the Indian Ocean Walker circulation in climate models and links to Kenyan rainfall. *International Journal of Climatology*, n/a(n/a). <https://doi.org/10.1002/joc.6714>
- Klepp, S. (2017). Climate Change and Migration. *Oxford Research Encyclopedia of Climate Science*. <https://doi.org/10.1093/acrefore/9780190228620.013.42>
- Koutroulis, A. G. (2019). Dryland changes under different levels of global warming. *Science of The Total Environment*, 655, 482–511. <https://doi.org/10.1016/j.scitotenv.2018.11.215>
- Kruczkiewicz, A., Klopp, J., Fisher, J., Mason, S., McClain, S., Sheekh, N. M., Moss, R., Parks, R. M., & Braneon, C. (2021). Opinion: Compound risks and complex emergencies require new approaches to preparedness. *Proceedings of the National Academy of Sciences*, 118(19). <https://doi.org/10.1073/pnas.2106795118>
- Läderach, P., Martinez-Valle, A., Schroth, G., & Castro, N. (2013). Predicting the future climatic suitability for cocoa farming of the world's leading producer countries, Ghana and Côte d'Ivoire. *Climatic Change*, 119(3), 841–854. <https://doi.org/10.1007/s10584-013-0774-8>
- Lamb, W. F., Creutzig, F., Callaghan, M. W., & Minx, J. C. (2019). Learning about urban climate solutions from case studies. *Nature Climate Change*, 9(4), 279–287. <https://doi.org/10.1038/s41558-019-0440-x>

- Lawal, K. A., Abiodun, B. J., Stone, D. A., Olaniyan, E., & Wehner, M. F. (2019). Capability of CAM5.1 in simulating maximum air temperature patterns over West Africa during boreal spring. *Modeling Earth Systems and Environment*, 5(4), 1815–1838. <https://doi.org/10.1007/s40808-019-00639-2>
- Leal Filho, W., Taddese, H., Balehegn, M., Nzengya, D., Debela, N., Abayineh, A., Mworozzi, E., Osei, S., Ayal, D. Y., Nagy, G. J., Yannick, N., Kimu, S., Balogun, A.-L., Alemu, E. A., Li, C., Sidsaph, H., & Wolf, F. (2020). Introducing experiences from African pastoralist communities to cope with climate change risks, hazards and extremes: Fostering poverty reduction. *International Journal of Disaster Risk Reduction*, 50, 101738. <https://doi.org/10.1016/j.ijdr.2020.101738>
- Lott, F. C., Christidis, N., & Stott, P. A. (2013). Can the 2011 East African drought be attributed to human-induced climate change? *Geophysical Research Letters*, 40(6), 1177–1181. <https://doi.org/10.1002/grl.50235>
- Lugli, F., Cipriani, A., Capecchi, G., Ricci, S., Boschini, F., Boscato, P., Iacumin, P., Badino, F., Mannino, M. A., Talamo, S., Richards, M. P., Benazzi, S., & Ronchitelli, A. (2019). Strontium and stable isotope evidence of human mobility strategies across the Last Glacial Maximum in southern Italy. *Nature Ecology & Evolution*, 3(6), 905–911. <https://doi.org/10.1038/s41559-019-0900-8>
- Lyon, B. (2014a). Seasonal Drought in the Greater Horn of Africa and Its Recent Increase during the March–May Long Rains. *Journal of Climate*, 27(21), 7953–7975. <https://doi.org/10.1175/JCLI-D-13-00459.1>

- Lyon, B. (2014b). Seasonal Drought in the Greater Horn of Africa and Its Recent Increase during the March–May Long Rains. *Journal of Climate*, 27(21), 7953–7975. <https://doi.org/10.1175/JCLI-D-13-00459.1>
- Manning, C., Widmann, M., Bevacqua, E., Van Loon, A. F., Maraun, D., & Vrac, M. (2018). Soil Moisture Drought in Europe: A Compound Event of Precipitation and Potential Evapotranspiration on Multiple Time Scales. *Journal of Hydrometeorology*, 19(8), 1255–1271. <https://doi.org/10.1175/JHM-D-18-0017.1>
- Marthews, T. R., Jones, R. G., Dadson, S. J., Otto, F. E. L., Mitchell, D., Guillod, B. P., & Allen, M. R. (2019). The Impact of Human-Induced Climate Change on Regional Drought in the Horn of Africa. *Journal of Geophysical Research: Atmospheres*, 124(8), 4549–4566. <https://doi.org/10.1029/2018JD030085>
- Mastrorillo, M., Licker, R., Bohra-Mishra, P., Fagiolo, G., D. Estes, L., & Oppenheimer, M. (2016). The influence of climate variability on internal migration flows in South Africa. *Global Environmental Change*, 39, 155–169. <https://doi.org/10.1016/j.gloenvcha.2016.04.014>
- Maúre, G., Pinto, I., Ndebele-Murisa, M., Muthige, M., Lennard, C., Nikulin, G., Dosio, A., & Meque, A. (2018). The southern African climate under 1.5°C and 2°C of global warming as simulated by CORDEX regional climate models. *Environmental Research Letters*, 13(6), 065002. <https://doi.org/10.1088/1748-9326/aab190>
- Maystadt, J.-F., & Ecker, O. (2014). Extreme Weather and Civil War: Does Drought Fuel Conflict in Somalia through Livestock Price Shocks? *American Journal of Agricultural Economics*, 96(4), 1157–1182. <https://doi.org/10.1093/ajae/aau010>

- McMichael, C. (2020). Human mobility, climate change, and health: Unpacking the connections. *The Lancet Planetary Health*, 4(6), e217–e218. [https://doi.org/10.1016/S2542-5196\(20\)30125-X](https://doi.org/10.1016/S2542-5196(20)30125-X)
- Missirian, A., & Schlenker, W. (2017). Asylum applications respond to temperature fluctuations. *Science*, 358(6370), 1610–1614. <https://doi.org/10.1126/science.aao0432>
- Morrissey, J. W. (2013). Understanding the relationship between environmental change and migration: The development of an effects framework based on the case of northern Ethiopia. *Global Environmental Change*, 23(6), 1501–1510. <https://doi.org/10.1016/j.gloenvcha.2013.07.021>
- Motesharrei, S., Rivas, J., Kalnay, E., Asrar, G. R., Busalacchi, A. J., Cahalan, R. F., Cane, M. A., Colwell, R. R., Feng, K., Franklin, R. S., Hubacek, K., Miralles-Wilhelm, F., Miyoshi, T., Ruth, M., Sagdeev, R., Shirmohammadi, A., Shukla, J., Srebric, J., Yakovenko, V. M., & Zeng, N. (2016). Modeling sustainability: Population, inequality, consumption, and bidirectional coupling of the Earth and Human Systems. *National Science Review*, 3(4), 470–494. <https://doi.org/10.1093/nsr/nww081>
- Mueller, V., Sheriff, G., Dou, X., & Gray, C. (2020). Temporary migration and climate variation in eastern Africa. *World Development*, 126, 104704. <https://doi.org/10.1016/j.worlddev.2019.104704>
- Munday, C., Washington, R., & Hart, N. (2021). African Low-Level Jets and Their Importance for Water Vapor Transport and Rainfall. *Geophysical Research Letters*, 48(1), e2020GL090999. <https://doi.org/10.1029/2020GL090999>

- Myers, N. (2002). Environmental refugees: A growing phenomenon of the 21st century. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, 357(1420), 609–613. <https://doi.org/10.1098/rstb.2001.0953>
- Nangombe, S., Zhou, T., Zhang, L., & Zhang, W. (2020). Attribution Of The 2018 October–December Drought Over South Southern Africa. *Bulletin of the American Meteorological Society*, 101(1), S135–S140. <https://doi.org/10.1175/BAMS-D-19-0179.1>
- Naqvi, A. (2017). Deep Impact: Geo-Simulations as a Policy Toolkit for Natural Disasters. *World Development*, 99, 395–418. <https://doi.org/10.1016/j.worlddev.2017.05.015>
- National Academies of Sciences, Engineering, and Medicine, Division on Earth and Life Studies, Board on Atmospheric Sciences and Climate, & Committee on Extreme Weather Events and Climate Change Attribution. (2016). *Attribution of Extreme Weather Events in the Context of Climate Change*. National Academies Press.
- Nawrotzki, R. J., & Bakhtsiyarava, M. (2017). International Climate Migration: Evidence for the Climate Inhibitor Mechanism and the Agricultural Pathway. *Population, Space and Place*, 23(4), e2033. <https://doi.org/10.1002/psp.2033>
- Nawrotzki, R. J., & DeWaard, J. (2016). Climate shocks and the timing of migration from Mexico. *Population and Environment*, 38(1), 72–100. <https://doi.org/10.1007/s11111-016-0255-x>
- Nyaoro, D., Schade, J., & Schmidt, K. (2016). *Assessing the Evidence: Migration, Environment and Climate Change in Kenya* [Report]. International Organization for Migration. https://publications.iom.int/system/files/assessing_the_evidence_kenya.pdf

- Oakes, R., Banerjee, S., & Warner, K. (2019). *Human mobility and adaptation to environmental change*. 253–269. <https://doi.org/10.18356/2a8d511f-en>
- OCHA. (2020). *ReliefWeb*. ReliefWeb. <https://reliefweb.int/>
- Opondo, D. O. (2013). Erosive coping after the 2011 floods in Kenya. *International Journal of Global Warming*, 5(4), 452–466. <https://doi.org/10.1504/IJGW.2013.057285>
- Osaka, S., & Bellamy, R. (2020). Natural variability or climate change? Stakeholder and citizen perceptions of extreme event attribution. *Global Environmental Change*, 62, 102070. <https://doi.org/10.1016/j.gloenvcha.2020.102070>
- Otto, F. E. L. (2016). The art of attribution. *Nature Climate Change*, 6(4), 342–343. <https://doi.org/10.1038/nclimate2971>
- Otto, F. E. L., Boyd, E., Jones, R. G., Cornforth, R. J., James, R., Parker, H. R., & Allen, M. R. (2015). Attribution of extreme weather events in Africa: A preliminary exploration of the science and policy implications. *Climatic Change*, 132(4), 531–543. <https://doi.org/10.1007/s10584-015-1432-0>
- Otto, F. E. L., Harrington, L. J., Frame, D., Boyd, E., Laut, K. C., Wehner, M., Clarke, B., Raju, E., Boda, C., Hauser, M., James, R. A., & Jones, R. G. (2020). Towards an inventory of the impacts of human-induced climate change. *Bulletin of the American Meteorological Society*, 1–17. <https://doi.org/10.1175/BAMS-D-20-0027.1>
- Otto, F. E. L., Harrington, L. J., Schmitt, K., Philip, S., Kew, S. F., van Oldenborgh, G. J., Singh, R., Kimutai, J., & Wolski, P. (2020). Challenges to understanding extreme weather changes in lower income countries. *Bulletin of the American Meteorological Society*. <https://doi.org/10.1175/BAMS-D-19-0317.1>

- Otto, F. E. L., Philip, S., Kew, S., Li, S., King, A., & Cullen, H. (2018). Attributing high-impact extreme events across timescales—A case study of four different types of events. *Climatic Change*, *149*(3), 399–412. <https://doi.org/10.1007/s10584-018-2258-3>
- Otto, F. E. L., Wiel, K. van der, van Oldenborgh, G. J., Philip, S., Kew, S. F., Uhe, P., & Cullen, H. (2018). Climate change increases the probability of heavy rains in Northern England/Southern Scotland like those of storm Desmond—A real-time event attribution revisited. *Environmental Research Letters*, *13*(2), 024006. <https://doi.org/10.1088/1748-9326/aa9663>
- Owain, E. L., & Maslin, M. A. (2018). Assessing the relative contribution of economic, political and environmental factors on past conflict and the displacement of people in East Africa. *Palgrave Communications*, *4*(1), 1–9. <https://doi.org/10.1057/s41599-018-0096-6>
- Parker, H. R., Lott, F. C., Cornforth, R. J., Mitchell, D. M., Sparrow, S., & Wallom, D. (2017). A comparison of model ensembles for attributing 2012 West African rainfall. *Environmental Research Letters*, *12*(1), 014019. <https://doi.org/10.1088/1748-9326/aa5386>
- Perkins-Kirkpatrick, S. E., & Lewis, S. C. (2020). Increasing trends in regional heatwaves. *Nature Communications*, *11*(1), 3357. <https://doi.org/10.1038/s41467-020-16970-7>
- PERN. (2020). *Population Environment Research Network*. <https://populationenvironmentresearch.org/elibrary>
- Peterson, T. C., Hoerling, M. P., Stott, P. A., & Herring, S. C. (2013). Explaining Extreme Events of 2012 from a Climate Perspective. *Bulletin of the American*

- Meteorological Society*, 94(9), S1–S74. <https://doi.org/10.1175/BAMS-D-13-00085.1>
- Petrova, K. (2021). Natural hazards, internal migration and protests in Bangladesh. *Journal of Peace Research*, 58(1), 33–49. <https://doi.org/10.1177/0022343320973741>
- Philip, S., Kew, S. F., van Oldenborgh, G. J., Aalbers, E., Vautard, R., Otto, F. E. L., Haustein, K., Habets, F., & Singh, R. (2018). Validation of a Rapid Attribution of the May/June 2016 Flood-Inducing Precipitation in France to Climate Change. *Journal of Hydrometeorology*, 19(11), 1881–1898. <https://doi.org/10.1175/JHM-D-18-0074.1>
- Philip, S., Kew, S. F., van Oldenborgh, G. J., Otto, F. E. L., O’Keefe, S., Haustein, K., King, A., Zegeye, A., Eshetu, Z., Hailemariam, K., Singh, R., Jjemba, E., Funk, C., & Cullen, H. (2017). Attribution Analysis of the Ethiopian Drought of 2015. *Journal of Climate*, 31(6), 2465–2486. <https://doi.org/10.1175/JCLI-D-17-0274.1>
- Philip, S., Kew, S. F., van Oldenborgh, G. J., Otto, F. E. L., Vautard, R., van der Wiel, K., King, A., Lott, F., Arrighi, J., Singh, R., & van Aalst, M. (2020). A protocol for probabilistic extreme event attribution analyses. *Advances in Statistical Climatology, Meteorology and Oceanography*, 6(2), 177–203. <https://doi.org/10.5194/ascmo-6-177-2020>
- Philip, S., Sparrow, S., Kew, S. F., van der Wiel, K., Wanders, N., Singh, R., Hassan, A., Mohammed, K., Javid, H., Haustein, K., Otto, F. E. L., Hirpa, F., Rimi, R. H., Islam, A. K. M. S., Wallom, D. C. H., & van Oldenborgh, G. J. (2019). Attributing the 2017 Bangladesh floods from meteorological and hydrological

- perspectives. *Hydrology and Earth System Sciences*, 23(3), 1409–1429.
<https://doi.org/10.5194/hess-23-1409-2019>
- Philip, S., Sparrow, S., Kew, S. F., Wiel, K. van der, Wanders, N., Singh, R., Hassan, A., Mohammed, K., Javid, H., Haustein, K., Otto, F. E. L., Hirpa, F., Rimi, R. H., Islam, A. K. M. S., Wallom, D. C. H., & Oldenborgh, G. J. van. (2019). Attributing the 2017 Bangladesh floods from meteorological and hydrological perspectives. *Hydrology and Earth System Sciences*, 23(3), 1409–1429.
<https://doi.org/10.5194/hess-23-1409-2019>
- Piguet, E. (2010). Linking climate change, environmental degradation, and migration: A methodological overview. *Wiley Interdisciplinary Reviews: Climate Change*, 1(4), 517–524. <https://doi.org/10.1002/wcc.54>
- Piontek, F., Müller, C., Pugh, T. A. M., Clark, D. B., Deryng, D., Elliott, J., González, F. de J. C., Flörke, M., Folberth, C., Franssen, W., Frieler, K., Friend, A. D., Gosling, S. N., Hemming, D., Khabarov, N., Kim, H., Lomas, M. R., Masaki, Y., Mengel, M., ... Schellnhuber, H. J. (2014). Multisectoral climate impact hotspots in a warming world. *Proceedings of the National Academy of Sciences*, 111(9), 3233–3238. <https://doi.org/10.1073/pnas.1222471110>
- Pretis, F. (2021). Exogeneity in climate econometrics. *Energy Economics*, 96, 105122. <https://doi.org/10.1016/j.eneco.2021.105122>
- Pretis, F., Schwarz, M., Tang, K., Haustein, K., & Allen, M. R. (2018). Uncertain impacts on economic growth when stabilizing global temperatures at 1.5°C or 2°C warming. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 376(2119), 20160460. <https://doi.org/10.1098/rsta.2016.0460>

- Puma, M. J., Chon, S. Y., Kakinuma, K., Kummu, M., Muttarak, R., Seager, R., & Wada, Y. (2018). A developing food crisis and potential refugee movements. *Nature Sustainability*, 1(8), 380–382. <https://doi.org/10.1038/s41893-018-0123-z>
- Rademacher-Schulz, C., Schraven, B., & Mahama, E. S. (2014). Time matters: Shifting seasonal migration in Northern Ghana in response to rainfall variability and food insecurity. *Climate and Development*, 6(1), 46–52. <https://doi.org/10.1080/17565529.2013.830955>
- Raleigh, C., & Kishi, D. R. (2019). *SIMILARITIES AND DIFFERENCES ACROSS CONFLICT DATASETS*. 33.
- Raleigh, C., Linke, A., Hegre, H., & Karlsen, J. (2010). Introducing ACLED: An Armed Conflict Location and Event Dataset: Special Data Feature. *Journal of Peace Research*, 47(5), 651–660. <https://doi.org/10.1177/0022343310378914>
- Randall, A. (2015). Mobilizing action on climate change and migration. In *Organizational Perspectives on Environmental Migration* (p. 16).
- Ratter, B. M. W. (2013). Surprise and Uncertainty—Framing Regional Geohazards in the Theory of Complexity. *Humanities*, 2(1), 1–19. <https://doi.org/10.3390/h2010001>
- Raymond, C., Horton, R. M., Zscheischler, J., Martius, O., AghaKouchak, A., Balch, J., Bowen, S. G., Camargo, S. J., Hess, J., Kornhuber, K., Oppenheimer, M., Ruane, A. C., Wahl, T., & White, K. (2020). Understanding and managing connected extreme events. *Nature Climate Change*, 1–11. <https://doi.org/10.1038/s41558-020-0790-4>
- Řehůřek, R., & Sojka, P. (2011). *Gensim—Statistical Semantics in Python*.

- Rey, G., Jougl, E., Fouillet, A., Pavillon, G., Bessemoulin, P., Frayssinet, P., Clavel, J., & Hémon, D. (2007). The impact of major heat waves on all-cause and cause-specific mortality in France from 1971 to 2003. *International Archives of Occupational and Environmental Health*, 80(7), 615–626. <https://doi.org/10.1007/s00420-007-0173-4>
- Rigaud, K. K., De Sherbinin, A., Jones, B., Bergmann, J., Clement, V., Ober, K., Schewe, J., Adamo, S., McCusker, B., Heuser, S., & Midgley, A. (2018). *Groundswell: Preparing for Internal Climate Migration* (Washington, DC: World Bank).
- Rimi, R. H., Haustein, K., Allen, M. R., & Barbour, E. J. (2019). Risks of Pre-Monsoon Extreme Rainfall Events of Bangladesh: Is Anthropogenic Climate Change Playing a Role? *Bulletin of the American Meteorological Society*, 100(1), S61–S65. <https://doi.org/10.1175/BAMS-D-18-0152.1>
- Rohat, G., Flacke, J., Dosio, A., Dao, H., & Maarseveen, M. van. (2019). Projections of Human Exposure to Dangerous Heat in African Cities Under Multiple Socioeconomic and Climate Scenarios. *Earth's Future*, 7(5), 528–546. <https://doi.org/10.1029/2018EF001020>
- Rohde, R., Muller, R., Jacobsen, R., Perlmutter, S., & Mosher, S. (2013). Berkeley Earth Temperature Averaging Process. *Geoinformatics & Geostatistics: An Overview*, 01(02). <https://doi.org/10.4172/2327-4581.1000103>
- Romankiewicz, C., van der Land, V., & van der Geest, K. (2018). Environmental Change and Migration: A Review of West African Case Studies. In *The Routledge Handbook of Environmental Displacement and Migration*. <https://eref.uni-bayreuth.de/37443/>

- Salih, A. A. M., Baraibar, M., Mwangi, K. K., & Artan, G. (2020). Climate change and locust outbreak in East Africa. *Nature Climate Change*, 10(7), 584–585. <https://doi.org/10.1038/s41558-020-0835-8>
- Scheffran, J., Marmer, E., & Sow, P. (2012). Migration as a contribution to resilience and innovation in climate adaptation: Social networks and co-development in Northwest Africa. *Applied Geography*, 33, 119–127. <https://doi.org/10.1016/j.apgeog.2011.10.002>
- Schleussner, C.-F., Lissner, T. K., Fischer, E. M., Wohland, J., Perrette, M., Golly, A., Rogelj, J., Childers, K., Schewe, J., Frieler, K., Mengel, M., Hare, W., & Schaeffer, M. (2016). Differential climate impacts for policy-relevant limits to global warming: The case of 1.5 °C and 2 °C. *Earth System Dynamics*, 7(2), 327–351. <https://doi.org/10.5194/esd-7-327-2016>
- Schreiber, J. (2018). Pomegranate: Fast and flexible probabilistic modeling in python. *ArXiv:1711.00137 [Cs, Stat]*. <http://arxiv.org/abs/1711.00137>
- Schultz, K. A., & Mankin, J. S. (2019). Is Temperature Exogenous? The Impact of Civil Conflict on the Instrumental Climate Record in Sub-Saharan Africa. *American Journal of Political Science*, 63(4), 723–739. <https://doi.org/10.1111/ajps.12425>
- Schwerdtle, P., Bowen, K., & McMichael, C. (2018). The health impacts of climate-related migration. *BMC Medicine*, 16(1), 1. <https://doi.org/10.1186/s12916-017-0981-7>
- Schwerdtle, P., Bowen, K., McMichael, C., & Sauerborn, R. (2019). Human mobility and health in a warming world. *Journal of Travel Medicine*, 26(1). <https://doi.org/10.1093/jtm/tay160>

- Serdeczny, O., Adams, S., Baarsch, F., Coumou, D., Robinson, A., Hare, W., Schaeffer, M., Perrette, M., & Reinhardt, J. (2017). Climate change impacts in Sub-Saharan Africa: From physical changes to their social repercussions. *Regional Environmental Change*, 17(6), 1585–1600. <https://doi.org/10.1007/s10113-015-0910-2>
- Shepherd, T. G. (2016). A Common Framework for Approaches to Extreme Event Attribution. *Current Climate Change Reports*, 2(1), 28–38. <https://doi.org/10.1007/s40641-016-0033-y>
- Shongwe, M. E., van Oldenborgh, G. J., van den Hurk, B., & van Aalst, M. (2011). Projected Changes in Mean and Extreme Precipitation in Africa under Global Warming. Part II: East Africa. *Journal of Climate*, 24(14), 3718–3733. <https://doi.org/10.1175/2010JCLI2883.1>
- Shortland, A., Christopoulou, K., & Makatsoris, C. (2013). War and famine, peace and light? The economic dynamics of conflict in Somalia 1993–2009. *Journal of Peace Research*, 50(5), 545–561. <https://doi.org/10.1177/0022343313492991>
- Stal, M. (2011). Flooding and Relocation: The Zambezi River Valley in Mozambique. *International Migration*, 49(s1), e125–e145. <https://doi.org/10.1111/j.1468-2435.2010.00667.x>
- Stone, D. A., & Allen, M. R. (2005). The End-to-End Attribution Problem: From Emissions to Impacts. *Climatic Change*, 71(3), 303–318. <https://doi.org/10.1007/s10584-005-6778-2>
- Stott, P. A., Christidis, N., Otto, F. E. L., Sun, Y., Vanderlinden, J.-P., van Oldenborgh, G. J., Vautard, R., Storch, H. von, Walton, P., Yiou, P., & Zwiers, F. W. (2016). Attribution of extreme weather and climate-related events. *Wiley*

- Interdisciplinary Reviews: Climate Change*, 7(1), 23–41.
<https://doi.org/10.1002/wcc.380>
- Stuart-Smith, R. F., Roe, G. H., Li, S., & Allen, M. R. (2021). Increased outburst flood hazard from Lake Palcacocha due to human-induced glacier retreat. *Nature Geoscience*, 14(2), 85–90. <https://doi.org/10.1038/s41561-021-00686-4>
- Sultan, B., & Gaetani, M. (2016). Agriculture in West Africa in the Twenty-First Century: Climate Change and Impacts Scenarios, and Potential for Adaptation. *Frontiers in Plant Science*, 7. <https://doi.org/10.3389/fpls.2016.01262>
- Swain, D. L., Singh, D., Touma, D., & Diffenbaugh, N. S. (2020). Attributing Extreme Events to Climate Change: A New Frontier in a Warming World. *One Earth*, 2(6), 522–527. <https://doi.org/10.1016/j.oneear.2020.05.011>
- Tacoli, C. (2011). *Not Only Climate Change: Mobility, Vulnerability and Socio-economic Transformations in Environmentally Fragile Areas in Bolivia, Senegal and Tanzania*. IIED.
- Task Force on Displacement. (2018). *Report of the Task Force on Displacement*. https://environmentalmigration.iom.int/sites/default/files/2018_TFD_report_16_Sep_FINAL-unedited.pdf
- Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An Overview of CMIP5 and the Experiment Design. *Bulletin of the American Meteorological Society*, 93(4), 485–498. <https://doi.org/10.1175/BAMS-D-11-00094.1>
- Thalheimer, L., Ficko, A., Roque de Pinho, J., Hashimshony-Yaffe, N., Paschalidou, A., Savic, D., Stavi, I., Stojanov, R., Suska-Malawska, M., van der Geest, K., Webersik, C., & Williams, D. (2019). *Policy Brief: Food Security in Drylands Under a Changing Climate*. <https://collections.unu.edu/view/UNU:7469>

- Thalheimer, L., Simperingham, E., & Jjemba, E. (2020). *Forecast-based Financing and disaster displacement: Acting early to reduce the humanitarian impacts of displacement*. https://www.forecast-based-financing.org/wp-content/uploads/2020/10/RCRC_IFRC-FbF-and-Displacement-Issue-Brief.pdf
- Thalheimer, L., & Webersik, C. (2020). Climate Change, Conflicts and Migration. In *Environmental Conflicts, Migration and Governance* (pp. 59–82). Bristol University Press.
- Todaro, M. (1980). Internal Migration in Developing Countries: A Survey. In R. A. Easterlin (Ed.), *Population and economic change in developing countries*. Univ. of Chicago Pr.
- Tokarska, K. B., Schleussner, C.-F., Rogelj, J., Stolpe, M. B., Matthews, H. D., Pfleiderer, P., & Gillett, N. P. (2019). Recommended temperature metrics for carbon budget estimates, model evaluation and climate policy. *Nature Geoscience*, 12(12), 964–971. <https://doi.org/10.1038/s41561-019-0493-5>
- Tol, R. S. J. (2018). The Economic Impacts of Climate Change. *Review of Environmental Economics and Policy*, 12(1), 4–25. <https://doi.org/10.1093/reep/rex027>
- Uhe, P., Philip, S., Kew, S. F., Shah, K., Kimutai, J., Mwangi, E., van Oldenborgh, G. J., Singh, R., Arrighi, J., Jjemba, E., Cullen, H., & Otto, F. E. L. (2018). Attributing drivers of the 2016 Kenyan drought. *International Journal of Climatology*, 38(S1), e554–e568. <https://doi.org/10.1002/joc.5389>
- UNFCCC. (1992). *United Nations Framework Convention on Climate Change*. 33.
- UNFCCC. (2015). *Adoption of the Paris Agreement*. <https://unfccc.int/resource/docs/2015/cop21/eng/l09r01.pdf>

- UNHCR. (2020). *Situation Horn of Africa Somalia Situation*.
<https://data2.unhcr.org/en/situations/horn>
- UNHCR. (2021). *UNHCR Somalia—Interactive Internal Displacements Visualisation*.
 UNHCR Somalia Internal Displacement. <https://unhcr.github.io/dataviz-somalia-prmn/index.html>
- UNHCR Somalia. (2017). *Protection & Return Monitoring Network (PRMN)—Notes on methodology*. <https://data2.unhcr.org/en/documents/details/53888>
- UNHCR Somalia. (2020, December). *UNHCR Somalia PRMN Internal Displacements December 2020*. UNHCR Operational Data Portal (ODP).
<https://data2.unhcr.org/en/documents/details/84693>
- United Nations High Commissioner for Refugees. (2019). *Handbook on Procedures and Criteria for Determining Refugee Status under the 1951 Convention and the 1967 Protocol relating to the Status of Refugees*.
<https://www.unhcr.org/publications/legal/5ddfc47/handbook-procedures-criteria-determining-refugee-status-under-1951-convention.html>
- United Nations Office for Disaster Risk Reduction. (2015). *Sendai Framework for Disaster Risk Reduction 2015-2030*. <https://www.undrr.org/publication/sendai-framework-disaster-risk-reduction-2015-2030>
- Université de Neuchâtel. (2020). *CliMig—Bibliographic database*.
https://www.unine.ch/geographie/climig_database
- van Oldenborgh, G. J., Krikken, F., Lewis, S., Leach, N. J., Lehner, F., Saunders, K. R., van Weele, M., Haustein, K., Li, S., Wallom, D., Sparrow, S., Arrighi, J., Singh, R. K., van Aalst, M. K., Philip, S., Vautard, R., & Otto, F. E. L. (2021). Attribution of the Australian bushfire risk to anthropogenic climate change.

- Natural Hazards and Earth System Sciences*, 21(3), 941–960.
<https://doi.org/10.5194/nhess-21-941-2021>
- Vautard, R., Aalst, M. van, Boucher, O., Drouin, A., Haustein, K., Kreienkamp, F., van Oldenborgh, G. J., Otto, F. E. L., Ribes, A., Robin, Y., Schneider, M., Soubeyroux, J.-M., Stott, P., Seneviratne, S. I., Vogel, M. M., & Wehner, M. (2020). Human contribution to the record-breaking June and July 2019 heatwaves in Western Europe. *Environmental Research Letters*, 15(9), 094077.
<https://doi.org/10.1088/1748-9326/aba3d4>
- Wartenburger, R., Hirschi, M., Donat, M. G., Greve, P., Pitman, A. J., & Seneviratne, S. I. (2017). Changes in regional climate extremes as a function of global mean temperature: An interactive plotting framework. *Geoscientific Model Development*, 10(9), 3609–3634. <https://doi.org/10.5194/gmd-10-3609-2017>
- Watts, N., Adger, W. N., Ayeb-Karlsson, S., Bai, Y., Byass, P., Campbell-Lendrum, D., Colbourn, T., Cox, P., Davies, M., Depledge, M., Depoux, A., Dominguez-Salas, P., Drummond, P., Ekins, P., Flahault, A., Grace, D., Graham, H., Haines, A., Hamilton, I., ... Costello, A. (2017). The Lancet Countdown: Tracking progress on health and climate change. *The Lancet*, 389(10074), 1151–1164.
[https://doi.org/10.1016/S0140-6736\(16\)32124-9](https://doi.org/10.1016/S0140-6736(16)32124-9)
- Weber, T., Bowyer, P., Rechid, D., Pfeifer, S., Raffaele, F., Remedio, A. R., Teichmann, C., & Jacob, D. (2020). Analysis of Compound Climate Extremes and Exposed Population in Africa Under Two Different Emission Scenarios. *Earth's Future*, 8(9), e2019EF001473. <https://doi.org/10.1029/2019EF001473>
- White, A., Laoire, C. N., Tyrrell, N., & Carpena-Méndez, F. (2011). Children's Roles in Transnational Migration. *Journal of Ethnic and Migration Studies*, 37(8), 1159–1170. <https://doi.org/10.1080/1369183X.2011.590635>

- Wiederkehr, C., Beckmann, M., & Hermans, K. (2018). Environmental change, adaptation strategies and the relevance of migration in Sub-Saharan drylands. *Environmental Research Letters*, 13(11), 113003. <https://doi.org/10.1088/1748-9326/aae6de>
- Wilkinson, E. (2016). *Climate change, migration and the 2030 Agenda for Sustainable Development*.
- Williams, A. P., Abatzoglou, J. T., Gershunov, A., Guzman-Morales, J., Bishop, D. A., Balch, J. K., & Lettenmaier, D. P. (2019). Observed Impacts of Anthropogenic Climate Change on Wildfire in California. *Earth's Future*, 7(8), 892–910. <https://doi.org/10.1029/2019EF001210>
- Williams, D. S., Máñez Costa, M., Sutherland, C., Celliers, L., & Scheffran, J. (2019). Vulnerability of informal settlements in the context of rapid urbanization and climate change. *Environment and Urbanization*, 31(1), 157–176. <https://doi.org/10.1177/0956247818819694>
- World Bank. (2021a). *Population, total—Somalia* | Data. <https://data.worldbank.org/indicator/SP.POP.TOTL?locations=SO>
- World Bank. (2021b). *Somalia Urbanization Review* (world). <https://elibrary.worldbank.org/doi/pdf/10.1596/35059>
- World Bank Group. (2018). *Federal Republic of Somalia Systematic Country Diagnostic*. World Bank. <https://doi.org/10.1596/30416>
- World Weather Attribution. (2021). *Africa – World Weather Attribution*. <https://www.worldweatherattribution.org/location/africa/>
- Xu, C., Kohler, T. A., Lenton, T. M., Svenning, J.-C., & Scheffer, M. (2020). Future of the human climate niche. *Proceedings of the National Academy of Sciences*, 117(21), 11350–11355. <https://doi.org/10.1073/pnas.1910114117>

- Xu, J.-Z., & Zhu, D.-M. (2005). Application of Spatial Data Semantic Conversion Technique Based on FME. *Journal of Kunming University of Science and Technology*. https://en.cnki.com.cn/Article_en/CJFDTOTAL-KMLG200502003.htm
- Zickgraf, C. (2021). Climate change, slow onset events and human mobility: Reviewing the evidence. *Current Opinion in Environmental Sustainability*, 50, 21–30. <https://doi.org/10.1016/j.cosust.2020.11.007>
- Zommers, Z., van der Geest, K., De Sherbinin, A., Kienberger, S., Roberts, E., Harootunian, G., Sitati, A., & James, R. (2016). *Loss and Damage: The Role of Ecosystem Services*. United Nations Environment Programme. <https://collections.unu.edu/view/UNU:5614>