International Journal of Disaster Risk Reduction 119 (2025) 105309

Contents lists available at ScienceDirect

International Journal of Disaster Risk Reduction

journal homepage: www.elsevier.com/locate/ijdrr

# Drought impacts and community adaptation: Perspectives on the 2020–2023 drought in East Africa

Rhoda A. Odongo [a,*,1], Teun Schrieks [a,1], Ileen Streefkerk [a,1], Hans de Moel [a], Tim Busker [a], Toon Haer [a], David MacLeod [b], Katerina Michaelides [c], Michael Singer [b], Mohammed Assen [d], George Otieno [e], Anne F. Van Loon [a]

[a] Institute for Environmental Studies, the Netherlands
[b] Cardiff University, Cardiff, United Kingdom
[c] University of Bristol, Bristol, United Kingdom
[d] Addis Ababa University, Addis Ababa, Ethiopia
[e] IGAD Climate and Prediction Centre, Nairobi, Kenya

ARTICLE INFO

*Keywords:*
Drought
Impacts
Adaptation
Horn of Africa drylands
Agent-based modelling

ABSTRACT

The Horn of Africa drylands (HAD) encompassing Kenya, Somalia, and Ethiopia, recently endured an unprecedented multi-year drought from 2020 to 2023, causing devastating impacts. This study investigates these impacts and the dynamics of human adaptation in response to the drought, comparing it to earlier drought events (i.e., 2016–2018) to identify key lessons. First, drought impact data—covering milk production, trekking distances to water sources, and internally displaced persons (IDPs)—are analysed over time to provide a detailed overview of drought dynamics. Second, household survey data (n = 752) are used to examine community perceptions of the drought period and their adaptation strategies. Finally, agent-based modeling (ABM) simulations explore the interactions between mitigation, adaptation decisions, and drought impacts. The results reveal that, on average, the 2020–2023 drought had more severe impacts than the 2016–2018 drought, although the latter exhibited greater variability in impacts. Communities have adopted various adaptation measures to cope with drought effects; however, limited knowledge and financial resources remain significant barriers to scaling these efforts. ABM simulations indicate that enhancing extension services can boost the adoption of adaptation strategies, leading to increased crop and milk production. Additionally, the simulations suggest that water harvesting can mitigate drought impacts upstream, though it may reduce water availability downstream. These findings highlight the critical need for sustained investments in adaptation measures, timely and well-informed decision-making, and region-specific interventions while carefully considering the trade-offs associated with these strategies.

## 1. Introduction

The Horn of Africa drylands (HAD), encompassing Kenya, Somalia, and Ethiopia, are among the world's most drought-prone

* Corresponding author.
*E-mail address:* rhodaachieng.odongo@vu.nl (R.A. Odongo).
[1] first authors.

https://doi.org/10.1016/j.ijdrr.2025.105309
Received 5 December 2024; Received in revised form 12 February 2025; Accepted 12 February 2025
Available online 13 February 2025

regions, with climate projections indicating an increase in both the frequency and severity of droughts due to global warming [1–3]. The recent multi-year drought from 2020 to 2023, marked by five consecutive failed rainy seasons, stands out as the most severe in over four decades (WMO, 2022). This prolonged drought resulted in catastrophic impacts, including widespread crop failures, massive livestock losses, famine, acute malnutrition, and displacement. Over 20 million people experienced acute food insecurity, and more than 13 million livestock perished [4–6]. Compared to earlier severe droughts, such as those of 2010–2011 and 2016–2018, the 2020–2023 drought was not only more intense but also left deeper and longer-lasting socio-economic scars [7,8].

The unprecedented severity and duration of the 2020–2023 drought highlight the urgent need for a comprehensive understanding of human-drought dynamics and the implementation of proactive, impact-based strategies. Evidence from past studies highlight that drought impacts are not merely a function of meteorological conditions but are shaped by the interplay of hydrological, social, and economic systems [7,9,10]. For instance, limited adaptive capacity, exacerbated by resource constraints and governance challenges, has been shown to heighten the vulnerability of communities in drought-prone regions like the HAD [11–13]. Furthermore, projections of intensified droughts due to global warming reinforce the need to prioritize proactive strategies such as water management innovations, and livelihood diversification strategies to reduce risks and enhance resilience [14–16].

Studying the evolution of this recent drought, its impacts, and the interventions employed provides an opportunity to draw critical lessons for improving community resilience and preparedness. This study seeks to build on past knowledge to identify more effective responses to future climate shocks. The insights gained can inform targeted, context-specific adaptation strategies for regions like the HAD, where recurring droughts threaten livelihoods and exacerbate vulnerability [16]. This understanding is essential to mitigate the impacts of increasingly severe droughts and enhance the region's capacity to cope with the challenges posed by a changing climate.

Previous research on drought hazards in the HAD has predominantly focused on meteorological and agricultural aspects [17–20], with limited focus on the socio-economic impacts of droughts and the effectiveness of adaptation responses ([21,22]; Osamu et al., 2018). While some studies have examined drought propagation, the link between the drought hazard and impacts [23,24], and drought impacts and adaptation ([22,25]; Osamu et al., 2018; [26,27]), few have incorporated on-the-ground impact data and community survey insights as realistic inputs for modelling. Previous studies have explored the interactions between water systems and human adaptation using system-dynamics models and agent-based models (ABMs) (e.g. Ref. [28–32]). While system-dynamics models provide valuable insights, they often lack the ability to represent the heterogeneity of human behaviour—a key strength of ABMs [33].

The IPCC describes risk in the context of climate change impacts as the combination of hazard, exposure and vulnerability [34]. In

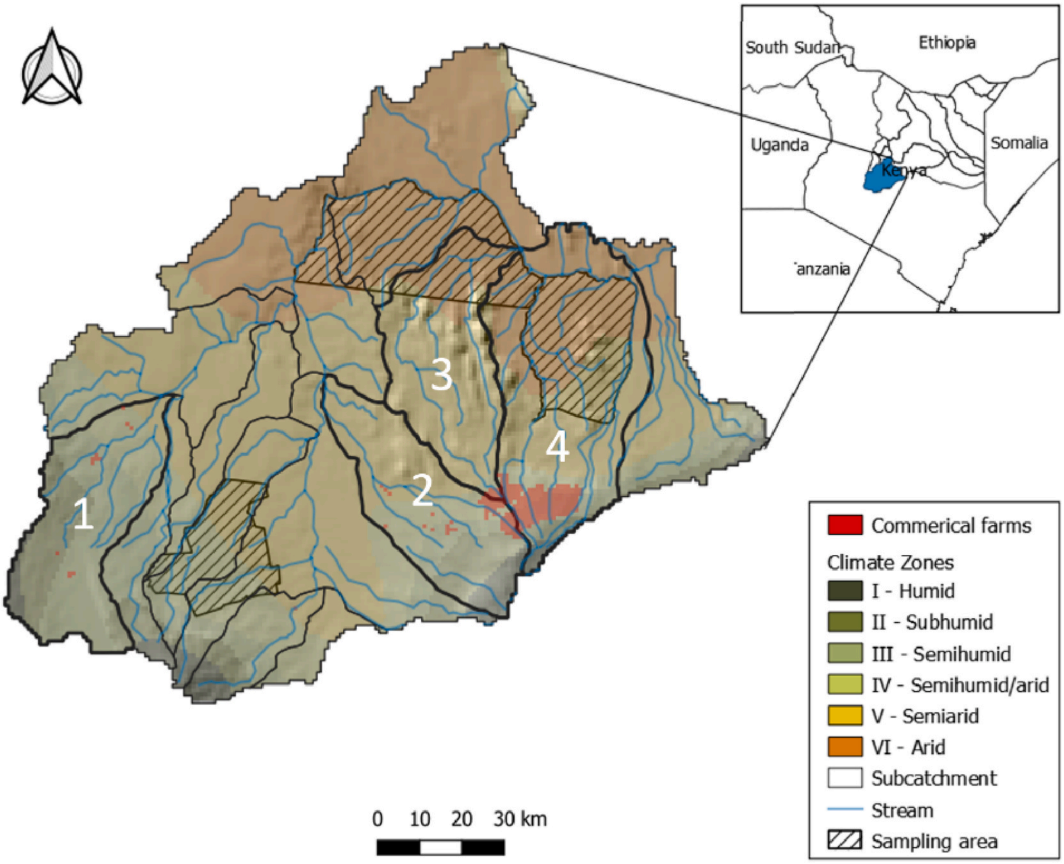


**Fig. 1.** The case study area (Upper Ewaso N'giro catchment, Kenya), including aridity zones [131], rivers, commercial export farms [46].

the IPCC Sixth assessment report, they added the concept of risk from climate change responses. These risks can result from responses not achieving the intended objectives or from trade-offs with other societal objectives [35]. In this paper we aim to provide a holistic view on the drought risk in the HAD by building on the IPCC risk concepts, considering both the risk of impacts, as a combination of hazard, exposure and vulnerability, and the risk from responses. Drought hazard is characterized using meteorological and hydrological data to capture the intensity and duration of droughts.

The 2020–2023 drought presents a critical opportunity to advance this understanding by analyzing multi-season drought impacts, which are expected to become more severe under climate change [36]. However, there remains a significant research gap in linking observed drought impacts to mitigation and adaptation actions in a comprehensive and spatially detailed manner. Addressing this gap between impacts and responses is essential for developing informed, actionable strategies for adaptive planning to enhance resilience in drought-prone regions. Therefore, in this paper we draw lessons from the 2020–2023 drought period by comparing it to past drought events, analysing community responses, and modelling various adaptation strategies in the HAD. Our goal is to get a better understanding of drought risks related to impacts and responses which can provide insights for future drought risk management in the region. We end this study with a discussion of lessons learned for mitigation of drought-related challenges in the future.

## 2. Case study area

The HAD, including Upper Ewaso Ng'iro catchment in Kenya, faces a challenging climate with bimodal rainfall patterns primarily in March–May (MAM) and October–December (OND), along with additional rains from June–September (JJAS) in northern Somalia and parts of Ethiopia [37,38]. This rainfall is low (100–600 mm), erratic, and paired with high temperatures and potential evapotranspiration, creating harsh agricultural conditions [39,40].

Despite this, 80 % of the HAD population depends on agricultural livelihoods, including rangeland farming, pastoralism, agro-pastoralism, and small-scale agriculture. Recent droughts (2020–2023, 2016–2018) exacerbated food insecurity and water scarcity in regions such as southern and southeastern Ethiopia, Somalia, and northeastern Kenya [41–44].

Focusing on Kenya's Upper Ewaso Ng'iro catchment for the ABM scenario analysis highlights these impacts. This area was selected for a case study utilizing an ABM, as this catchment corresponds to the survey locations, representing drought-prone communities in dryland regions. Furthermore, it was selected due to the availability of sufficient data for model calibration and validation. The model is validated with household survey data to assess scenario-based outcomes i.e., water harvesting, milk production, seasonal migration. Located in Laikipia, Isiolo, and Nyeri counties, on the leeward side of Mount Kenya and the Aberdares, the catchment supports a mix of pastoral, agricultural, and conservation livelihoods, and commercial farms [45], the catchment mirrors broader regional challenges. The commercial farms are primarily concentrated in sub-catchments 1, 2 and 3, with greenhouses spread throughout these areas and sub-catchment 4 having open farms, i.e. wheat (Fig. 1). The downstream region (household survey sampling area) is mostly arid, with

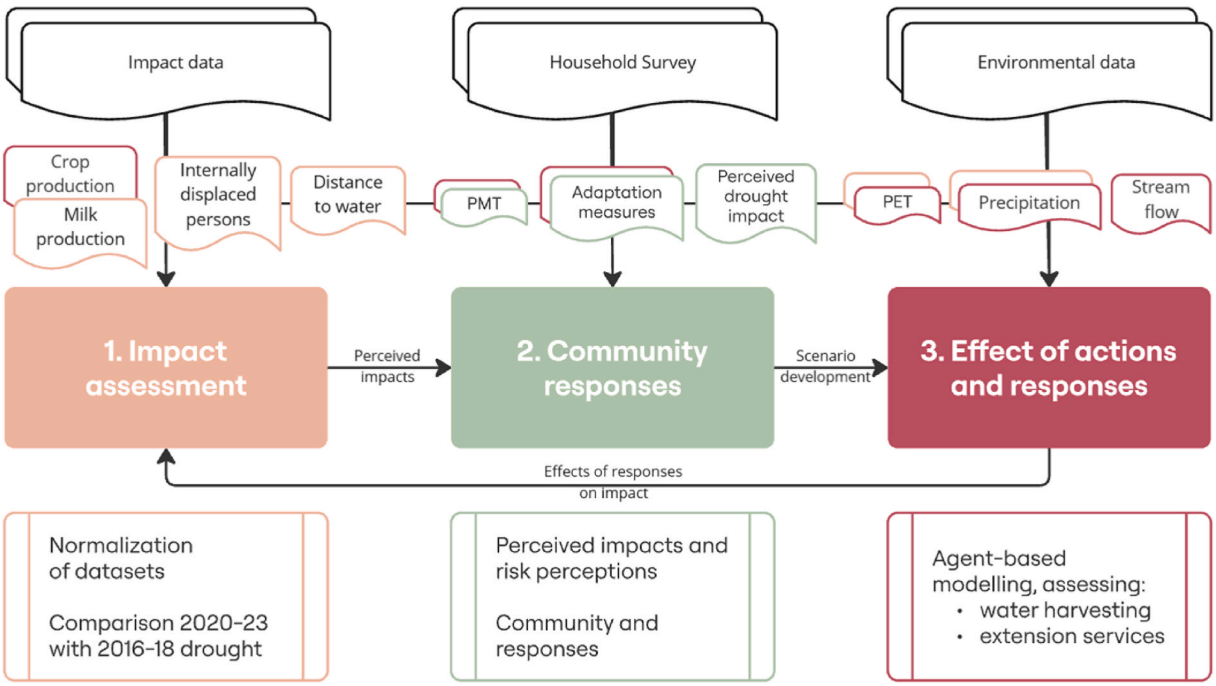


**Fig. 2.** Structure of the analysis.1. Impact assessment through a comparison of 2020-23 drought impact data with historical droughts. 2. Responses of communities on drought though a community survey and choice experiment. 3. Agent-based assessment through modelling adaptation and response scenarios.

the local livelihoods heavily dependent on livestock herding [27,46]. Increasing land use pressures and population growth have exacerbated water scarcity and conflicts [47]. The intensifying droughts in the catchment [45] and population growth, are likely to worsen water scarcity, land-use pressures, potentially contributing to conflicts and migration [48], indicating how local environmental stress reflects the larger HAD trends.

## 3. Data and methods

We apply a mixed-method approach to assess drought impacts, community responses, and agent-based model (ABM) scenario outcomes, providing a comprehensive framework for understanding human-drought dynamics (Fig. 2). In our analysis we make use of the IPCC definitions of climate change risk by looking both at risk of impacts and risk from responses [35]. First, we analyse impacts with data that are the results of the combination of hazard, exposure and vulnerability. The impact datasets at administrative level 1 (Kenya and Somalia) and level 2 (Ethiopia) are normalized to create a cohesive drought impact dataset, enabling a comparison of the 2020–2023 drought with the historical 2016–2018 drought at the country level (Section 3.1). This comparison focuses on the evolution of drought impacts over time, particularly severity and duration, which are critical for understanding vulnerability and recovery dynamics [49]. Second, we analyse household survey data from Kenya's Upper Ewaso Ng'iro catchment and Somaliland (Section 3.2). These surveys capture how agro-pastoral communities perceived the impacts of the 2020–2023 droughts, which provides valuable information on the exposure and vulnerability components. Furthermore, the survey data provides information on drought response in agro-pastoral communities by analyzing the actions that they took to mitigate impacts, and the barriers and enablers influencing their decision-making processes. This data feeds into an ABM framework that evaluates the effects of these community responses on drought impacts through scenario analysis (Section 3.3). The ABM approach integrates heterogeneous community behaviors and interactions between people, the environment, and potential interventions [32,50]. The ABM thus combines the risk as a result of hazard, exposure and vulnerability with the risk as a result of responses and the interaction between impacts and responses. Scenarios are developed based on community survey data to simulate human-environment interactions and evaluate how different actions could have mitigated drought impacts. By exploring what could have been done differently, this approach provides valuable insights into improving drought risk management strategies and enhancing resilience in future drought events.

### 3.1. Meteorological and evapotranspiration data

The daily Multi-Source Weighted-Ensemble Precipitation (MSWEP) version 2 dataset [51] provides global precipitation data from 1979 onward, with a spatial resolution of 0.1° (~11 km) and temporal resolutions of 3 h, daily, and monthly. MSWEP integrates gauge, satellite, and reanalysis data for robust coverage, making it effective in capturing the spatial and temporal variability of drought conditions [52]. The Global Land Evaporation Amsterdam Model (GLEAM) version 3.5a offers daily potential evapotranspiration (PET) estimates with a spatial resolution of 0.25°, derived from satellite and reanalysis data [53]. GLEAM incorporates MSWEP

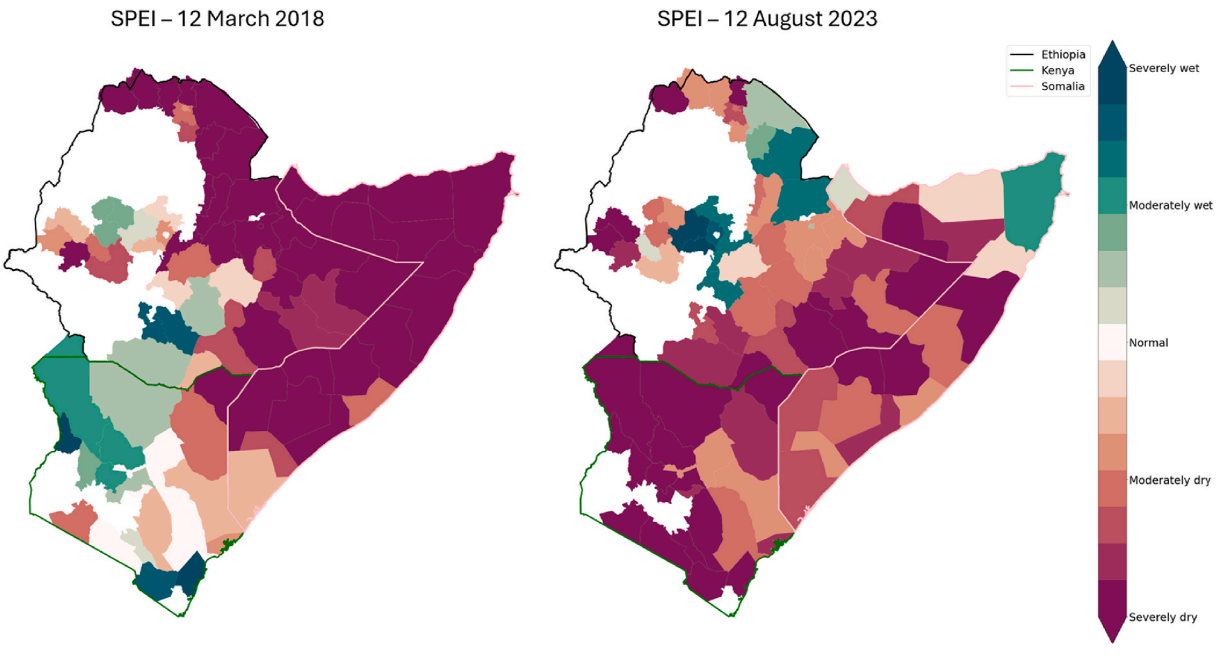


**Fig. 3.** A Map of the Horn of Africa (Kenya, Somalia and Ethiopia) showing the drought conditions (SPEI-12 March and SPEI-12 August) towards the end of the 2016–2018 and 2020–2023 drought for the arid/-semi-arid regions with −1 (Severely dry), −0.5 (Moderately dry), 0 (Normal), 0.5 (Moderately wet), and 1 (Severely wet).

precipitation, satellite-observed soil moisture, air temperature, radiation, and vegetation optical depth to estimate PET, using the Priestley-Taylor (PT) equation based on ECMWF ERA-Interim inputs [54]. GLEAM PET data for 2013–2023 were resampled to 0.1° to align with MSWEP precipitation data for drought index calculations.

### 3.2. Drought indices

To assess meteorological and agricultural drought conditions, we used the Standardized Precipitation Evapotranspiration Index (SPEI) to incorporate potential evapotranspiration, allowing for a more accurate reflection of water balance impacts on drought [55]. SPEI was calculated for 1–24 months accumulation periods following Odongo et al. [24], using monthly data from 2013 to 2023. This approach avoids zero-value issues typical of the Standardized Precipitation Index (SPI) by focusing on precipitation minus evapotranspiration [56]. Various distributions—Normal, Generalized Extreme, Generalized Logistic, and Pearson3—were fitted to ensure standardized results within each administrative unit, emphasizing the interaction between drought indices and local impacts rather than cross-unit comparisons. SPEI-6 and SPEI-12 (Fig. 3) were selected for analysis based on their strong correlations with trekking distances to water sources and milk production, respectively, capturing the lagged effects of drought on these variables [57].

Similarly, we selected SPEI-12 to characterize drought effects on IDP due to its ability to capture long-term drought conditions that often lead to socio-economic impacts like displacement [58]. This extended period captures the gradual intensification of drought impacts, which compels affected populations to migrate as access to essential resources becomes increasingly scarce [58]. Moreover, the 12-month scale accounts for lagged responses to drought, providing insights into how sustained drought influences migration and displacement patterns over time.

### 3.3. Drought impact data

Drought impacts are multi-sectoral, arising from complex interactions across hydrological, agricultural, and socio-economic systems [59] and frequently linked to both hydrological and agricultural droughts [60]. Given this complexity, we incorporated diverse data sources to comprehensively characterize drought impacts (Table 1). Specifically, we obtained data on agro-pastoral impacts, such as livestock trekking distances to water sources and milk production levels, from Kenya's National Drought Management Authority (NDMA), as these indicators provide insight into the strain on rural livelihoods and food security. NDMA operates drought early warning systems and develops preparedness strategies and contingency plans in Kenya. The organization publishes monthly drought impact information as early warning bulletins for each of the 23 arid and semi-arid administrative units in Kenya. The impact reports provide the input for the impact categories (Table 1) considered in this study (see Odongo et al. [57] for more information). The impact datasets contain continuous monthly timeseries data. Only some gaps exist when impacts were not recorded within the reports or specific reports were not published (see Ref. [57] for more information on impact data cleaning).

Additionally, since displacement is a significant drought-related impact in the HAD because most communities move in search of natural resources and better living conditions [61], we included data on drought-induced internal displacement in Somalia and Ethiopia to capture socio-economic effects on vulnerable populations [5,62–66]. By focusing on drought-specific drivers of displacement, this study aims to highlight both immediate and long-term repercussions on communities dependent on natural resources and agriculture for their livelihoods. While we acknowledge that displacement is influenced by multiple structural and contextual factors, such as governance and socio-economic conditions ([67]; Adger et al., 2014; [66,68]), our focus remains on the role of drought to provide a clearer understanding of its impacts during the 2020–2023 drought compared to the 2016–2018 drought.

The IDP data due to drought for Somalia is collected by the PRMN project which acts as a platform for identifying displacements (including returns) of populations as well as protection incidents underlying such displacements. Protection incidents include various

**Table 1**
Impact data types used in this study.

| Country | Impact type | Unit | Temporal and spatial resolution | Impact description | Source |
|---|---|---|---|---|---|
| Kenya | Milk Production (MPR) | Litres (l/day/hh) | 2014–2023 \| administrative level 1 scale | Average daily milk production per household (hh) provided in monthly. | NDMA Early Warning Bulletins |
| | Return Distance to Water Sources<br>• Livestock (LDW)<br>• Household (HDW) | Kilometres (Km) | 2014–2023 \| administrative level 1 scale | Average return trekking distance to water sources for household and return distances from livestock grazing areas to watering points for livestock. | NDMA Early Warning Bulletins |
| Somalia | Internally Displaced Persons (IDP) due to drought | Number of people | 2016–2023 \| administrative level 1 scale | The impact data on IDP due to drought was monitored by the United Nations High Commissioner for Refugees PRMN. | United Nations High Commissioner for Refugees website |
| Ethiopia | Internally Displaced Persons (IDP) due to drought | Number of people | 2017–2023 \| administrative level 2 scale | The impact data is for the newly displaced people within the administrative level 2. The number of IDPs are based on refugee camp assessments via different rounds throughout the year aggregated annually by the Internally Displaced Monitoring Centre. | Internal displacement monitoring centre (IDMC) through the Global Internal Displacement Database |

forms of harm, abuse or threats that the IDP may encounter during displacement or in the areas of refuge. They employ a systematic approach through interviews to monitor population displacements and movements, focusing on strategic locations like transit sites, established IDP settlements, border crossings, and other relevant sites. The collected reports are uploaded onto a web-based platform for quality control by Norwegian Refugee Council (NRC) and undergo verification by NRC field staff before approval, either through in-person validation or third-party verification [69]. The IDP datasets were filtered on drought displacement cases for this study.

The IDP data due to drought for Ethiopia is collected by the IDMC. IDMC's approach begins with event-based monitoring, capturing displacement incidents by date, location, trigger, and duration, allowing for a more granular understanding of displacement events and trends. This event-based data is stored in IDMC's Global Internal Displacement Database (GIDD). To ensure data accuracy, IDMC applies rigorous triangulation which involves cross-referencing data from multiple reliable sources to validate accuracy and prioritizing conservative objective estimates. Data quality is further enhanced through an internal and external peer review process. After quality control, IDMC publishes validated datasets annually in the Global Report on Internal Displacement (GRID).

#### 3.3.1. Normalization of impact datasets

To effectively analyse and compare drought impacts relative to drought hazard indicators (see Refs. [24,57] for the calculation of SPEI-12) across Somalia, Ethiopia, and Kenya, a min-max normalization method was applied, drawing from Wang et al. [70] and Below et al. [71]. This approach allowed for comparability across different time periods while preserving the unique characteristics of each administrative unit. The process included data collection, hybrid standardization, and visualization to ensure consistency and accuracy in the analysis.

The normalization approach scales the impact data within a range of 0–1. We first did a temporal normalization within each administrative unit, followed by a global aggregation across the units. The impacts were normalized using the following formula:

$$SD_{impact} = \frac{x_i - \min x_i}{\max x_i - \min x_i} \quad \text{eq. 1}$$

where $SD_{impact}$ is the normalized drought impact for each administrative unit and impact type; $x_i$ are monthly impact value for the unit and time period, $\min x_i$ and $\max x_i$ are the minimum and maximum values of drought impacts for the time period for a given impact type for the administrative unit.

The normalization was applied to each administrative unit separately to account for local conditions (e.g., varying geographies and population densities), making it possible to compare how much each unit's drought impacts deviate from its own historical average. Afterward, global aggregation was performed by averaging the normalized values across units within each country, creating a single normalized drought impact timeline per impact type for each country. The two-step normalization allows for both local comparability by capturing relative changes within each administrative unit and cross unit comparability. This aggregation made it possible to visualize and compare the drought impacts across different time periods. The impact timelines were then plotted alongside the corresponding SPEI indicator (SPEI-6 for trekking distances to water sources, SPEI-12 for milk production and IDP [57]) to visually analyse the drought impacts during 2020–2023 and 2016–2018. Additionally, we calculated the percentage change of impacts (HDW, LDW, MPR, IDP) between the two periods, with the 2016–2018 drought treated as the baseline when looking at the deviation of impacts of 2020–2023 for HDW, LDW and MPR impacts using equation (2), while the percentage change for IDP impacts was based on a baseline of zero as shown in equation (3):

$$Percentage\ change_{HDW,LDW,MPR} = \frac{\mathrm{Mean}_{2020-2023} - \mathrm{Mean}_{2016-2018}}{\mathrm{Mean}_{2016-2018}} \times 100 \quad \text{eq. 2}$$

$$Percentage\ change_{IDP} = \mathrm{Mean}_{2020-2023} - \mathrm{Mean}_{2016-2018} \times 100 \quad \text{eq. 3}$$

In this study, each country (Kenya, Ethiopia, and Somalia) was analysed independently to address challenges associated with differing drought impact types and data sources. Min-max normalization was applied per country to aggregate data across administrative units, ensuring comparability within each country. No direct comparisons were made between countries; instead, analyses focused on identifying trends and patterns within each country's administrative units. This approach allowed us to maintain methodological consistency while recognizing the distinct contexts of each country.

### 3.4. Household survey on community perceptions and responses

The impact of the 2020-23 drought on rural communities to a large extent depends on how well they were prepared for the drought. We therefore used household survey data to analyse perceptions and behaviour in communities. First, we analysed how communities perceived the 2020–2023 drought, and second, we evaluated their drought adaptation decisions. In May 2022, we conducted 502 household survey interviews in Isiolo County (Kenya) and 250 household survey interviews in Odweyne district (Somaliland, Somalia). In both countries we used a stratified sampling method for which we divided the population into six subgroups, based on gender and age categories (18–29, 30–49, and 50+), based on the Kenya Population and Housing Census [72] and The Somaliland Health and Demographic Survey 2020 [73].

Firstly, we used this survey data to assess community perceptions towards and experience with drought impacts. Both surveys were conducted in May 2022, therefore we could not ask about people's drought experiences during 2022 and 2023. We did ask in which years respondents remembered experiencing a drought in the period from 2001 until 2021. First, we asked the respondents to mark each year in which they experienced a drought and second, we asked them to state which drought year they experienced to be most severe. Subsequently, we asked crop farmers about their crop yields in the year that they marked as most extreme and about the average crop yield in a year with normal rains. We used this data to show the impact of drought on crop yield in the interviewed communities for the respectively the 2020/2021 drought in Isiolo County and the 2017 drought in Odweyne district. Furthermore, the survey contained several questions on drought risk perceptions. For the year that people marked as most severe drought, we asked about the perceived impact of the drought on a Likert scale from 1 *(very small)* to 5 *(very large)*. To assess people expectation about future droughts, we asked respondents how likely they think it is that they will experience livestock deaths, crop failure and food insecurity due to drought in the coming five years, on a Likert scale from 1 (*very unlikely*) to 5 (*very likely*).

Besides data on drought risk perceptions and experiences, the surveys contained information on, among others, adaptation decisions and drivers and barriers of adaptation. Schrieks et al. [27] have analysed the drivers and barriers of adaptation from the survey data from Kenya. We combine insights from Schrieks et al. [27] with the survey data from Odweyne district to provide a community perspective on adaptation. Whether people implement adaptation measures is influenced by a combination of several perceptions, social and cultural norms, and economic factors [27,74–78]. An often-used theory to describe adaptation decisions is the protection motivation theory (PMT, [79–83]). According to this theory, a person's intention to adapt depends on risk appraisal and coping appraisal [81,84]. In the context of drought adaptation, risk appraisal consists of the perceived severity and perceived frequency of a drought, and coping appraisal consists of the perceived efficacy of an adaptation measure, the perceived self-efficacy (a person's belief in their own ability to implement the adaptation measures) and the perceived costs of an adaptation measure [85]. We included survey questions on all these PMT constructs in our survey.

### 3.5. *Effects of actions and responses*

We analysed how responses of different agencies and community adaptation options would have modified the drought impact felt by agropastoral communities in the upper Ewaso N'giro catchment in Kenya (Fig. 1) during the 2020-23 drought. We used the agent-based model developed by Streefkerk et al. [46], aiming to explore the interactions between drought hazard and human responses.

The model consists of three modules which are dynamically coupled: hydrology [86], socio-hydrological interactions, and human-decision making [83]. This coupled model allows for assessing how agropastoral communities ('agents') respond to drought. The agropastoralists grow crops and tend livestock to sustain their livelihood, and use water and land in the process. We identified the six most-common adaptation measures these agents can make in the model to cope with droughts to meet their water demand and optimize grass/crop yields [27]. The six measures include i) agroforestry (planting trees in agricultural field), ii) seasonal migration with livestock (changing location of livestock), iii) irrigation (abstraction water from river or groundwater to land), iv) water harvesting (capturing rain and runoff for later use), v) changing livestock types (change from cows to more drought resistant and less water-intensive goats), vi) and changing crop types (changing to drought-tolerant crops). Implementing adaptation measures have influence on the (socio-)hydrology, by changing land properties, (location of) water abstraction, storage and demands. Adaptation decisions are made on yearly basis following the protection motivation theory (PMT, see Section 3.2). In times of insufficient water to meet the water demand, the assumes that domestic purposes are prioritised, following livestock demands, and lastly crop (irrigation) demands. Household's actual water abstraction is limited by the water available in the nearest (non-dry) water source (either river or groundwater well). The choice of migration location is based on the maximum grass availability in the neighbourhood of the agent. Agents influence each other's grass availability by consumption of grass by livestock. Grass is consumed in a random order – the agent who is first has most grass available. The model includes ~15000 agents with a heterogeneous set of characteristics (e.g. income, age, etc.). The spatial resolution is 1 by 1 km and the temporal resolution is 1 day. Each grid cell has one agropastoral agent making decisions at different moments in time. Since there is one agent for every grid cell, an agent can represent multiple households, depending on the population density. In addition, commercial export farms present in the upstream areas of the Upper Ewaso Ng'iro catchment are represented through water management rules defining the required storage and abstraction of water, as elaborated on in Streefkerk et al. [46].

The modelling framework used data for the hydrological, socio-hydrological and human-behaviour components. The hydrological component has precipitation [51], potential evapotranspiration [87], Soil Adjusted Vegetation Index (SAVI) (Copernicus Global Land Service) as drivers of the model. The socio-hydrological component included information on domestic water demand [88–90], crops water demand and properties [91], and livestock water and grass demand [92–94]. The human-behaviour component of the agent-based model is informed by the household survey (Section 3.2) and Tegemeo Institute [95]. The model was calibrated on streamflow at the outlet of the Ewaso N'giro catchment (CETRAD), crop production (Ministry of Agriculture), and milk production [96]. The way the model was set up and calibrated is described in Streefkerk et al. [46], which we refer to as the 'baseline model'. We compared the observed and calibrated values for the drought impact variables (crop/milk production and distance to household water). A sensitivity analysis of the modelling framework has been performed in Streefkerk et al. [31]. The results of this analysis showed that irrigation (demand) is the most influential on drought adaptation and hazard. See for more details about the model setup Streefkerk et al. [31,46].

Based on the results of the community responses (Section 4.2) we simulated two interventions in the ABM. In the first, the uptake of the water harvesting adaptation measure is *halved* and *doubled* compared to the baseline. In the second intervention, the access to extension services is *halved* and *doubled*. Extension services promote and give training on adaptation measures. To explore potential interventions to drought, two types of intervention were simulated with two scenarios each.

1) **Increased or decreased water harvesting by communities**: communities have *halved* or *doubled* access to water harvesting infrastructure at home, compared to the base scenario. Water is harvested from both rain and runoff and stored in a tank, pond or similar, with a capacity of 5000 L/household. It is assumed that water from roofs can used for household water, and that people use water in the following order i) households purposes, ii) livestock purposes, and iii) irrigation purposes.
2) **Expansion or reduction of extension services:** communities have halved or doubled access to extension services. Extension services promote and give training on drought adaptation measures by extension officers from government, NGO's or farmers groups. The extension services are implemented in the model by increasing the adaptation efficacy. The household survey by Schrieks et al. [27] informs how much the adaptation efficacy is increased for every adaptation measure when households receive extension services. If agents do not have access to extension services they rely on neighbours for information about the adaptation efficacy by comparing crop and livestock production with neighbours who have adapted.

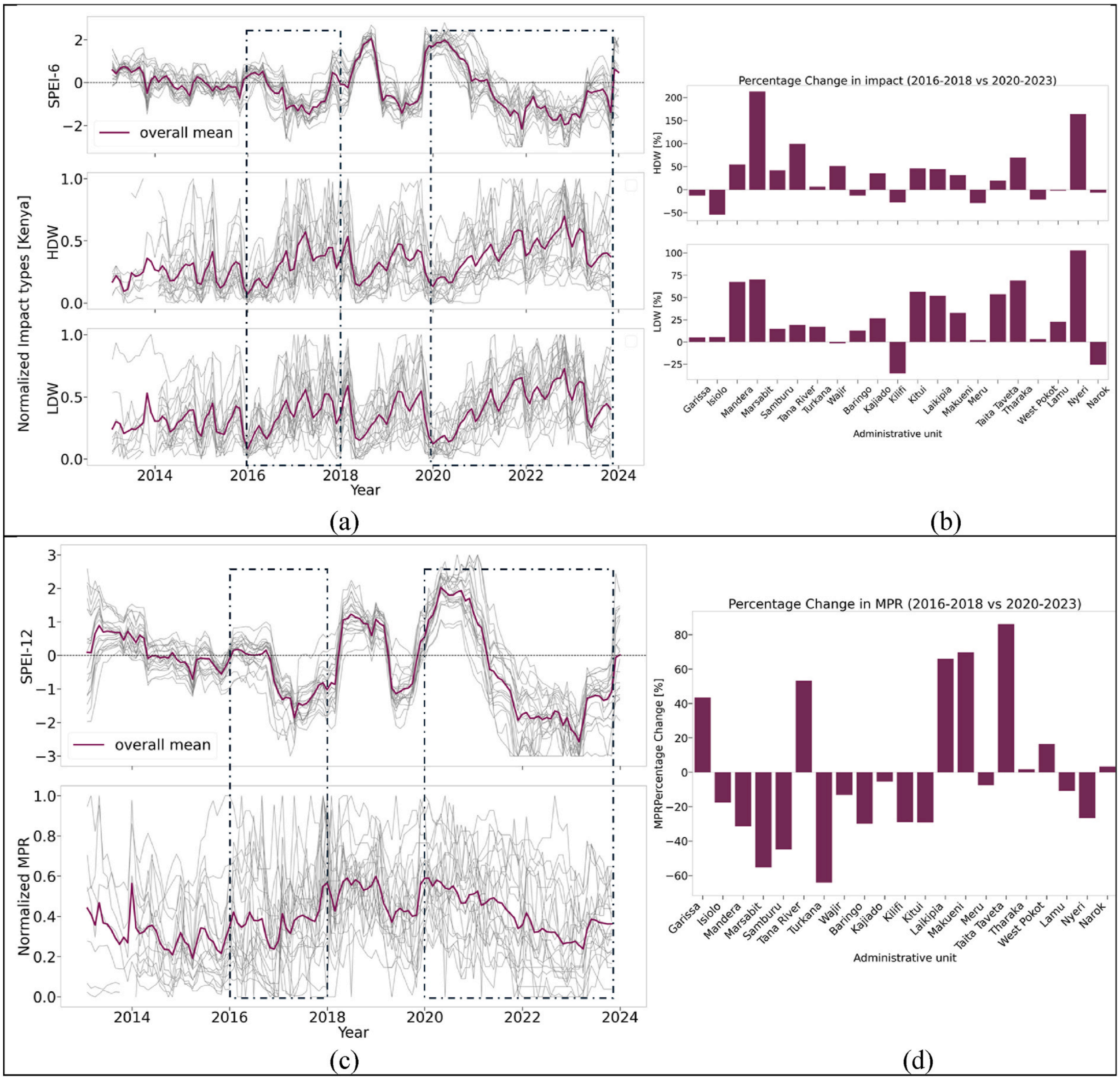


**Fig. 4.** a and c) The SPEI-6 (HDW and LDW) and SPEI-12 (MPR) over the study period (2013–2023) for all the administrative units (grey lines) and overall mean (red line). Timelines of the individual administrative unit impacts: Household distance to water sources(HDW), Livestock distance to water sources (LDW), and Milk production (MPR) for Kenya's ASAL administrative units for all administrative units separately (grey lines), and the average over all ASALs (red lines). The two drought periods (2016–2018 and 2020–2023) are indicated within the black boxes, dash-dotted line. b and d) The percentage change of impacts during 2020–2023 drought compared to 2016–2018 drought periods of each of the administrative units per impact type.

We compare the two interventions above with the baseline scenario and analyse the resulting drought impacts over the 2020-23 drought (as counterfactuals), measured by model outputs including crop production, milk production and household distance to water. Additionally, we compared the 2020–2023 drought in terms of hydrological variables for the first scenario, looking into upstream-downstream interaction. For the second intervention, the uptake of adaptation measures is compared to the baseline.

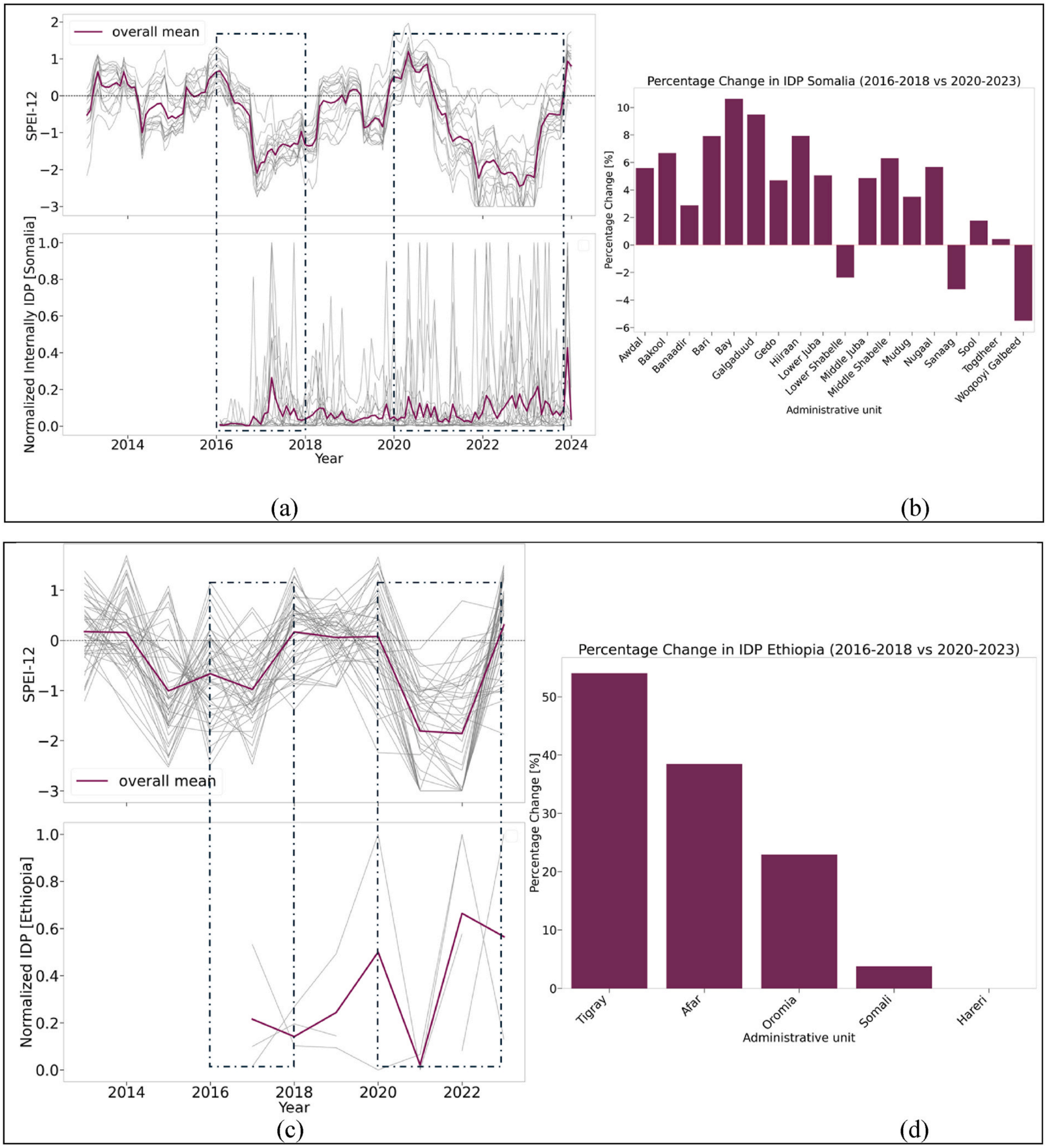


**Fig. 5.** a and c) The SPEI-12 over the study period (2013–2023) period for all the administrative units (grey lines) and overall mean (red line). Normalized Internally displaced Persons in Somalia and Ethiopia with the grey lines indicating the displacements in the various administrative units. The two drought periods (2016–2018 and 2020–2023) are indicated within the black boxes). b and d) Percentage change in IDP as compared to normal (overall mean) for the two drought periods for each of the administrative units for Somali and Ethiopia.

# 4. Results

## 4.1. 2020–2023 drought in perspective

### 4.1.1. Kenya

When comparing the SPEI-6 values for the 2020–2023 drought with those of the 2016–2018 drought, the 2020–2023 period exhibited greater overall severity, with SPEI values dropping below −2 (Fig. 4a). This heightened severity is likely attributed to elevated potential evapotranspiration rates compounded by the extended duration of the 2020–2023 drought, which spanned three years compared to the 1.5-year duration of the 2016–2018 drought. Seasonal comparisons reveal that the 2016–2018 drought was characterized by two failed rainy seasons (2016 OND and 2017 MAM), whereas the 2020–2023 drought experienced five consecutive failed seasons (2021 MAM and OND, 2022 MAM and OND, and 2023 MAM). The most severe failures occurred during the 2021 OND and 2022 OND seasons. Similarly, analysis of SPEI-12 (Fig. 4c) indicates that the 2020–2023 drought had more severe seasonal failures, with values consistently around −2 during the 2021 OND, and 2022 MAM and OND seasons, compared to the 2016–2018 drought.

The percentage changes in trekking distances to water and milk production between the two drought periods, using the 2016–2018 drought as a baseline, demonstrate that the 2020–2023 drought had more pronounced impacts in most administrative units (Fig. 4b and d). Trekking distances to water (HDW and LDW) saw substantial increases, with many administrative units reporting increases above 50 %. Marsabit (212 %), Tana River (163 %), and Nyeri (100 %) had the largest increases, while Isiolo (−54 %) experienced the greatest reduction in HDW. Similarly, for LDW, Nyeri (102 %) recorded the largest increase, while Kilifi (−36 %) showed the greatest decrease. Milk production (MPR) experienced significant declines, with reductions exceeding 20 % in most administrative units. Notably, Taita Taveta and Turkana recorded the highest increase and decrease in MPR, respectively. The progressive intensification of impacts during the 2020–2023 drought is evident, with peak deviations from the mean occurring around the 2022 OND season (Fig. 4a and c).

The magnitude of impacts also varied significantly across administrative units. The total average normalized impacts were higher during the 2020–2023 drought than in the 2016–2018 drought for HDW (8.67 vs. 6.47) and LDW (9.31 vs. 7.22), but slightly lower for MPR (8.61 vs. 9.11). However, the spread of impacts across administrative units, as indicated by variance, was smaller during the 2020–2023 drought. For example, the variance in HDW during 2016–2018 was 0.046 compared to 0.036 during 2020–2023, indicating more consistent impacts across administrative units in the latter period. Similarly, the variance in MPR declined from 0.053 to 0.023 between the two periods. In contrast, the variance in LDW impacts remained relatively constant (∼0.045) across both droughts. The 2016–2018 drought also exhibited lower severity towards the end of the period across most administrative units compared to the 2020–2023 drought (Fig. 3).

Variations in impact magnitude across administrative units during the 2020–2023 drought may reflect the influence of interventions such as improved access to credit and the installation of small water infrastructure, as well as changes in socio-economic and demographic factors. These variations are evident in the percentage differences relative to the 2016–2018 drought for individual administrative units (Fig. 4b and d). Most administrative units experienced larger percentage differences during the 2020–2023 drought, although exceptions were observed. For instance, Isiolo, Garissa, Kilifi, and Meru recorded decreases in HDW, while Kilifi and Narok had decreases in LDW. For MPR, units such as Taita Taveta, Makueni, Laikipia, Tana River, Garissa, and West Pokot demonstrated increases during the 2020–2023 drought. Notably, Meru exhibited a decline in HDW and an increase in MPR during the same period.

Overall, the extent of increases in trekking distances to water (HDW, LDW) and reductions in milk production (MPR) varied significantly across administrative units during the 2020–2023 drought. Certain regions experienced percentage changes exceeding 100 %, particularly for HDW and LDW (Fig. 4b and d), highlighting the spatial variability of drought impacts across the study area.

### 4.1.2. Somalia and Ethiopia

The 2020–2023 drought had a marked and significant impact on human displacement in both Somalia and Ethiopia, with all regions in both countries experiencing higher numbers of internally displaced persons (IDPs) compared to the 2016–2018 drought period (Fig. 5a and c). Average normalized displacement values were higher across most administrative units during the 2020–2023 drought than in the 2016–2018 drought, reflecting the more severe and prolonged nature of the later event. The sum of average normalized displacements further underscores this contrast, with values significantly higher during the 2020–2023 drought (Somalia: 1.798 vs. 0.606; Ethiopia: 1.654 vs. 1.024). The stark increase in displacement during the 2020–2023 drought is likely attributable to its extended duration and greater intensity, particularly in Somalia, where SPEI-12 values (red line) declined to as low as −2 by the end of 2023 (Fig. 3).

In Ethiopia, most administrative units experienced displacement increases exceeding 50 % compared to the 2016–2018 drought, with Tigray recording the highest percentage increase (54 %) (Fig. 5d). While drought-related factors undoubtedly played a role, this period also coincided with a civil war in Tigray. The conflict, compounded by accusations of famine being used as a weapon, significantly exacerbated displacement trends [97–99]. This overlap between conflict and climatic stressors highlights the difficulty of isolating drought impacts from other socio-political drivers, particularly in regions experiencing prolonged crises. In Somalia, displacement increases were generally less pronounced, ranging between 5 % and 10 %, with some regions, such as Sanaag, Lower Shebelle, and Woqooyi Galbeed, reporting decreases of 3 %, 2 %, and 6 %, respectively, relative to the 2016–2018 drought (Fig. 5b).

Furthermore, the normalized IDP data and SPEI-12 values exhibited a wider spread across administrative units during the 2020–2023 drought compared to the 2016–2018 period, reflecting greater variability in displacement impacts (Fig. 5; grey lines). In

Somalia, the variance in normalized IDP data increased from 0.043 during the 2016–2018 drought to 0.321 during the 2020–2023 drought. Similarly, in Ethiopia, variance rose from 0.013 to 0.031 between the two periods. This heightened variability may result from the interplay between the increased hazard intensity of the 2020–2023 drought and changes in socio-economic and demographic factors across regions, in contrast to the relatively uniform hazard magnitude of the 2016–2018 drought.

#### 4.1.3. Perceived impacts and risk perceptions in agropastoral communities

The section above discussed country-scale impact data, but to get a clear picture of drought impacts it is also important to study the impact on households in dryland communities. Therefore, we include data from our household survey in pastoral and agropastoral communities in two regions: Isiolo county, Kenya and Odweyne district, Somali Somaliland. The results show that in both regions, 2021 was experienced as a drought by many respondents (74 % and 52 %). In Isiolo, 2021 was also experienced as the most severe drought by 60 % of the respondents, while in Odweyne, almost everyone (92 %) experienced 2017 as the most severe drought.

Fig. 6 shows boxplots of the stated crop production for the two most common crop types in Isiolo (Maize and beans) and Odweyne (Maize and Sorghum). The first four boxplots give the stated average crop production for a year with normal rainfall, and in the lower four boxplots we compare this with the crop production in the year that people marked as most extreme drought year. For Isiolo, we compare the crop production in a normal year with that in 2020 and 2021, and for Odweyne, we compare a normal year with 2017, because these are the most severe drought years for these regions as selected in the survey. Fig. 6 shows that the droughts in respectively 2020/2021 and 2017 had a severe impact on crop production, with the majority of respondents having zero crop production in these severe drought years.

It is likely that 2022 and 2023 would have been experienced as severe droughts by even more people, because it was a consecutive, multi-season drought. It is also evident from the questions that we asked about drought risk perceptions and drought impacts that people experienced severe drought conditions in 2021 and the first half of 2022. Since the questions were asked in the middle of the drought (May 2022), it is highly likely that answers were influenced by the drought that people were experiencing. Especially in Isiolo, the risk perceptions were extremely high, with more than 80 % stating that it is *very likely* that they will experience livestock deaths and food insecurity in the coming five years and more than 70 % for crop failure. In Odweyne, the perceptions were less extreme, but still around 50 % of respondents stated that both crop failure and livestock deaths are *very likely* and around 30 % state that it is *likely*. For food insecurity almost 40 % said it is *very likely* and a bit more than 30 % said it is *likely*. For the households in Isiolo who selected 2020 or 2021 as the most severe drought year, more than 80 % experienced a very large impact on their household income and 90 % experienced a very large impact on livestock productivity. For Odweyne, we do not have these data for the year 2021 and 2022 since 92 % of the respondents selected 2017 as the year of the most severe drought.

### 4.2. Community and responses

To decrease the vulnerability to the above-described drought impacts, communities and households can implement several types of adaptation measures. In our household surveys, we have identified which types of adaptation measures people already had taken in May 2022. Fig. 7 gives an overview of the percentage of respondents that implemented the adaptation measures that were included in

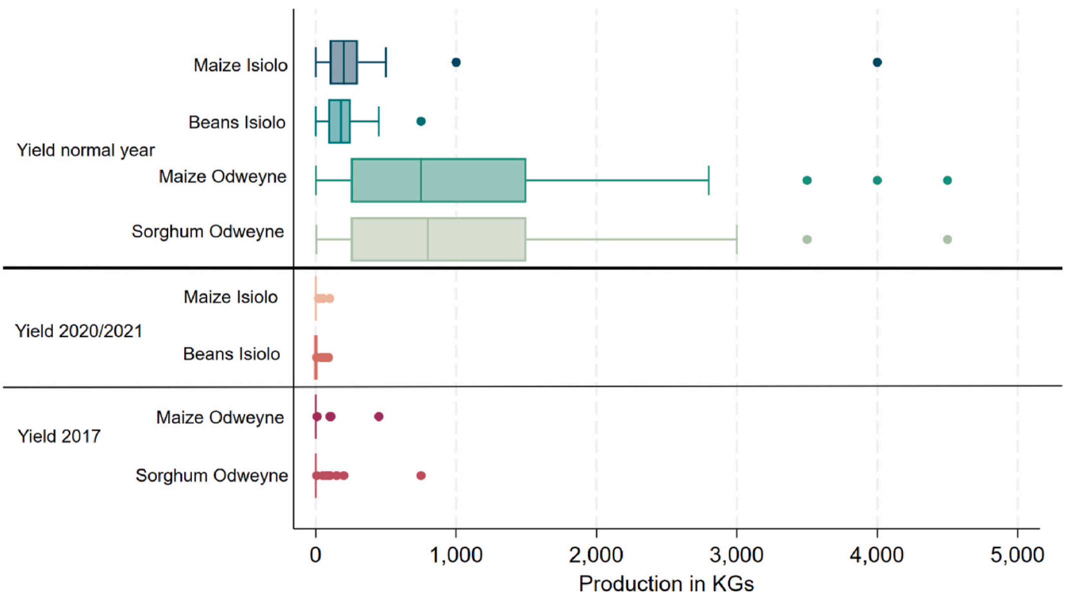


**Fig. 6.** *Maize and beans production in a normal year and in 2020/2021 for crop farmers in Isiolo county (Kenya) who selected 2020 or 2021 as the most severe drought year and Maize and sorghum production in normal year and in 2017 for crop farmers in Odweyne district (Somaliland) who selected 2017 as the most severe drought year.* The spread in the boxplots illustrate variation between respondents.

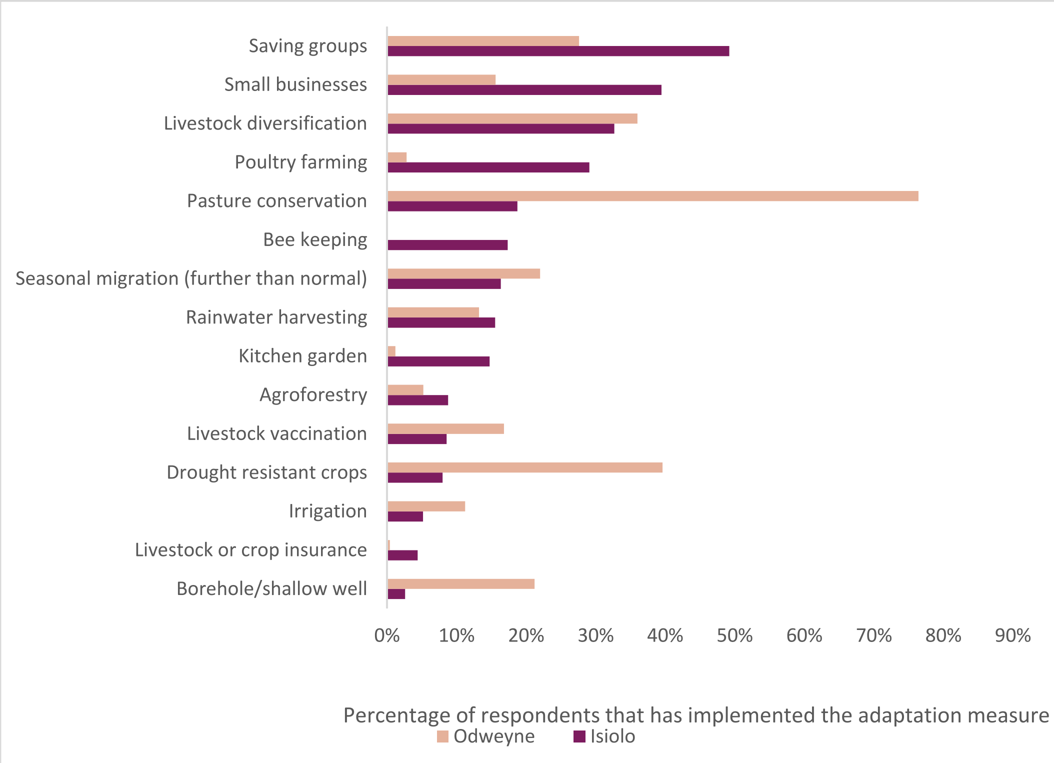


**Fig. 7.** Percentage of respondents that has implemented the adaptation measures in Odweyne district and in Isiolo county.

our survey. The most popular adaptation measure for pastoralists is changing and diversifying livestock species from grazers to browsers [27]. Traditionally, most people in this region keep cattle, but people are switching to camels and goats, because they are more drought-resistant [25]. In 2022, 33 % of our respondents in Isiolo and 36 % of our respondents in Odweyne had already implemented livestock diversification. Other common adaptation measures for pastoralists are migrating with livestock, starting poultry farming, beekeeping and pasture conservation. Examples of adaptation measures for crop farmers are planting drought-resistant crop types, irrigation, and agroforestry. Although some people in our sample engage in both livestock keeping and crop farming, we observe that most people are more likely to either implement livestock-related measures or crop-related measures. Besides the livestock- and crop-related measures, other adaptation measures were identified, not necessarily related to one of these livelihood activities. People can, for example, take measures to diversify and secure their income sources. Popular strategies are participating in savings groups and starting a small business. Furthermore, people can increase water availability through investments in rainwater harvesting or the construction of a borehole or shallow well. The above mentioned measures are based on the two case study areas, but the adaptation strategies are similar to other regions in the HAD [25,100,101].

In the analyses of the factors that influence adaptation decisions, following the protection motivation theory (PMT), we find that especially the coping appraisal variables are important in explaining the adaptation decision of the agropastoral communities in Isiolo County [27]. People are more likely to implement adaptation measures if the perceived efficacy and self-efficacy of the measure are high and the perceived costs are low. We use these results to simulate adaptation behaviour in the ABM, for which we discuss the results in the next section (Section 4.3). A person's perceptions of the PMT factors are influenced by personal characteristics and external factors such as social network, past experiences, and interventions by governments and NGOs [81]. Important barriers for adaptation are lack of knowledge and lack of financial resources [32]. An increase in knowledge and information can increase adaptation efficacy and self-efficacy, and better access to financial resources can increase self-efficacy and reduce perceived costs. Governments and NGO can thus improve uptake of adaptation measures by providing training and extension services and improving access to financial resources. During the 2020–2023 drought, the Isiolo county government implemented several interventions to reduce drought impacts. The main adaptation interventions from county government were cash transfers for vulnerable households, livestock destocking, vaccination of livestock, drilling of boreholes and provision of vegetables seeds [96]. During the most extreme periods of the drought, the county government also provided emergency support, such as water trucking, emergency drilling of boreholes and sand dams, emergency livestock feeds, relief foods and emergency cash transfers [96]. In Somaliland, the emergency support consisted of, among other things, water trucking, food vouchers, cash transfers and cash for work programs, and measle vaccination campaigns [102].

A lot of the emergency support is related to water supply. Investments are being made in groundwater abstraction points, which does increase water supply, but there is also a risk of groundwater depletion in the long term [103]. Another adaptation measure that can help to increase water availability is investments in rainwater harvesting. This cannot be done as emergency support when the drought has already started. Communities can only benefit from rainwater harvesting if investments are made before a drought period, so that rainwater can be harvest when it is raining. Our survey data shows that only 16 % of the people in Isiolo and 13 % of the people in Odweyne had implemented rainwater harvesting in May 2022. The people in the interviewed communities consider rainwater harvesting to be highly effective to reduce drought impacts, but it is also considered to be a costly measure. Investments in rainwater harvesting could be an effective way to help communities become more drought resilient. To get a better picture of the effectiveness of rainwater harvesting, the next section simulates the effect of a change in the uptake of water harvesting on crop production, milk production and distance to water sources.

### 4.3. Effects of actions and responses

The drought impacts simulated by the model are shown in Fig. 8, and compared to the observed values for the upper Ewaso Ng'iro catchment. This validation is described in more detailed in Streefkerk et al. [46]. The bias ratio for crop production is 0.62, for milk production 0.51, and for distance to household water 0.11. The distance to water is continuously overestimated by a factor of around 2. Note that the model is not calibrated on distance to water, but is on crop and milk production (and streamflow). These simulated values are the considered the 'baseline scenario'; the other scenarios will be analysed relative to the baseline scenario.

#### 4.3.1. Uptake of water harvesting

Fig. 9 shows the effect of the uptake of water harvesting as an adaptation measure (*halved* or *doubled* compared to the baseline) on the crop production, milk production and distance to household water. These drought impact variables are shown relative to the baseline scenario. The simulations show that the effect of water harvesting on crop production varies over time, with both positive and negative effects of *doubling* the uptake of water harvesting. During the 2020-23 drought we observe an increase in average crop production after the OND 2020 season (around 0.1 %), but the effect is negative in the next two OND seasons. On the contrary, the crop production is increased when the uptake of water harvesting is *halved*. For the OND 2016 growing season, the same effect can be seen for doubling the water harvesting; it has a negative effect on crop production. This could be explained by the increased water harvested for household and livestock purposes, leaving less water available for irrigation.

Milk production is higher when more people adopt water harvesting. Especially in the *doubled* scenario we see a peak in milk production during the 2020-23 drought, probably caused by prevented livestock deaths due to the increased access to water in a certain area. A decrease in milk production is simulated in the scenario where water harvesting is *halved*. Both effects gradually decrease during the drought periods of 2016-17 and 2020-23. Possibly because of the initial effects of water harvesting, which decreases as the drought continues and the water harvested has run out. The household distance to water is decreased with around 50 % (equivalent to around 3 km) compared to the base scenario, when the uptake of water harvesting is increased. Conversely, we see that the distance to household water is increased when water harvesting uptake is *halved*. We see more variability among the agents in the *doubled* scenario, compared to the *halved* scenario.

Fig. 10 shows the drought hazard results for the two scenarios of the uptake of water harvesting spatially during the 2020-23 drought, compared to the baseline. The left and middle panel of Fig. 10 show that soil moisture and discharge are decreased upstream in the *halved* scenario, but are increased downstream. The results are the opposite for the *doubled* scenario; upstream soil moisture is increased, but decreased downstream. On average, soil moisture is decreased over the entire period when increasing the uptake of water harvesting. The simulations show that streamflow is decreased when increasing the uptake of water harvesting. The

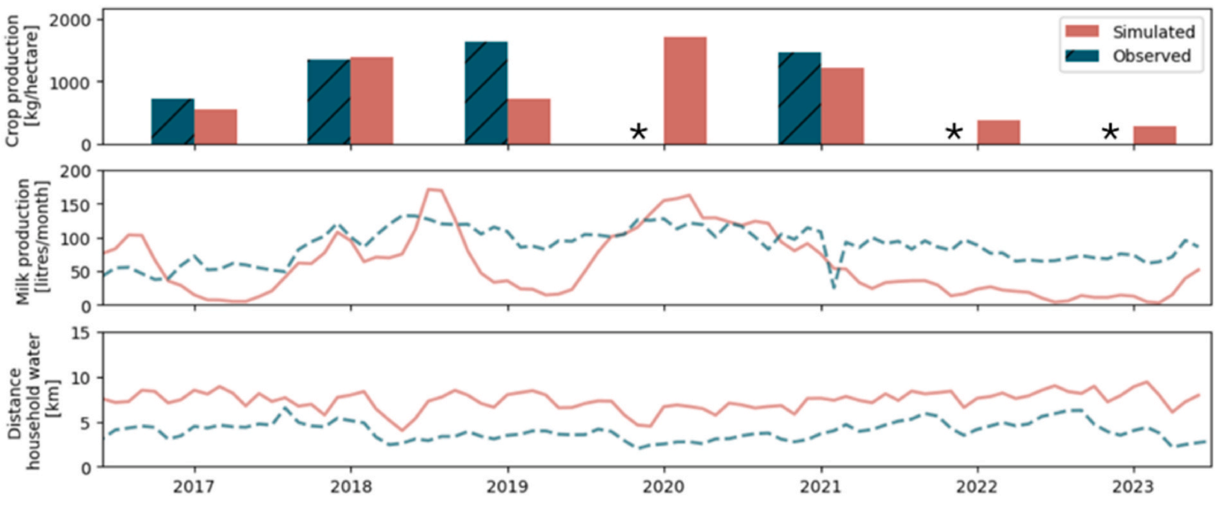


**Fig. 8.** Simulated and observed time series of crop production [kg/hectare], milk production [litres/month], and distance to household water [km] for the upper Ewaso Ng'iro catchment. The * in the upper plot indicates there is no observed data for those years.

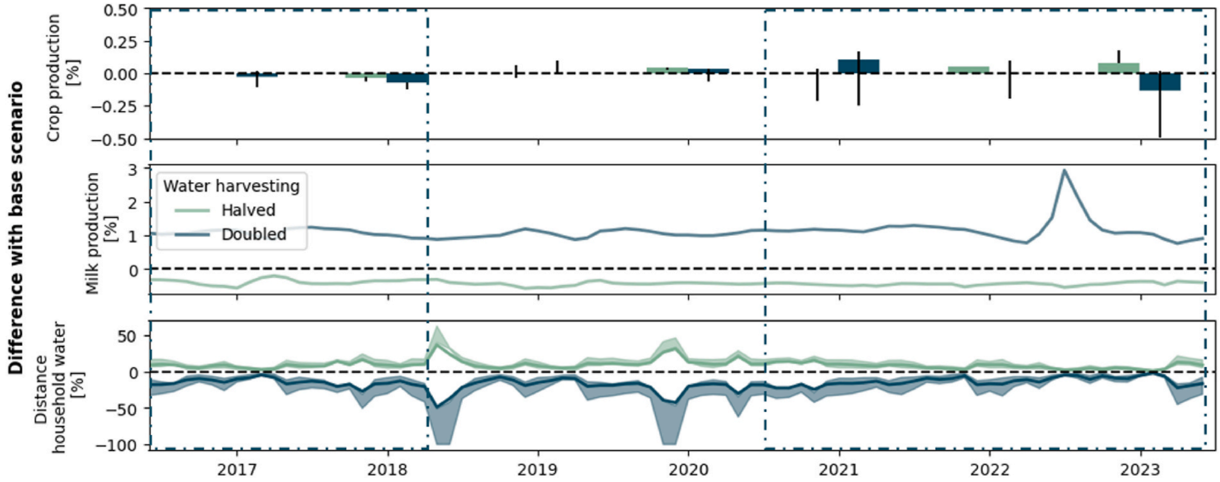


**Fig. 9.** Difference between baseline scenario and increased uptake of water harvesting on drought impact indicators: crop production (%), milk production (%) and distance to household water (%). The spread indicates the 25th and 75th percentile of the impacts over the agent population.

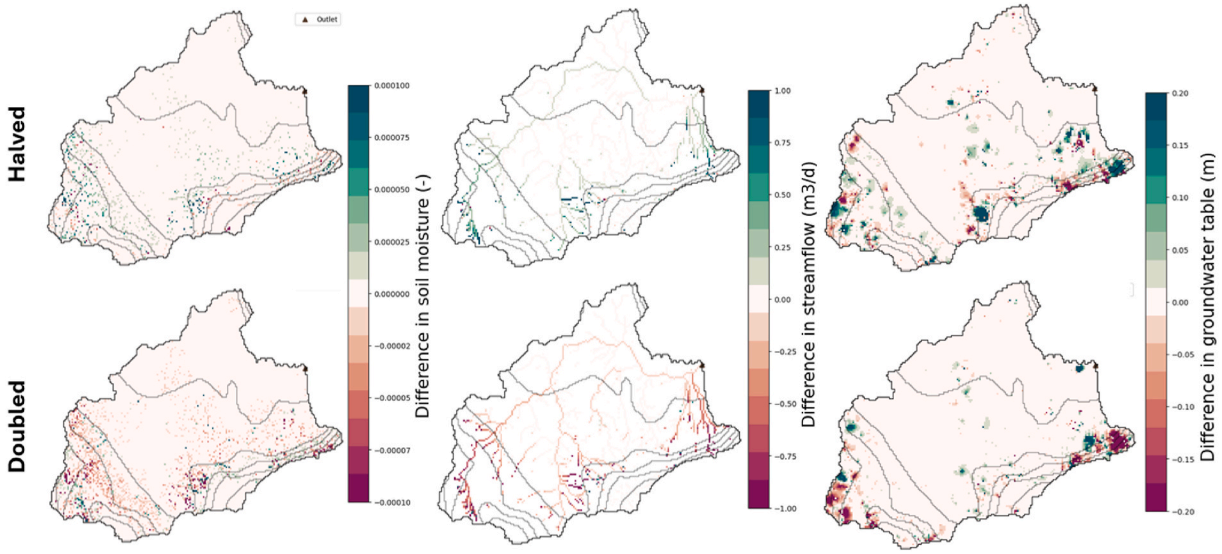


**Fig. 10.** Difference between baseline scenario and halved/doubled uptake of water harvesting on drought hazard indicators during the 2020/23 drought. Soil moisture (–), streamflow at outlet ($m^3/s$) and groundwater table (m).

overall decrease in discharge when doubling water harvesting could be explained by the fact that water consumption is increased due to the harvesting of water, and thus not contributing to discharge. On average, the groundwater table is lowered when *halving* the uptake of water harvesting and increased in the *doubled* scenario. However, when looking at the model results of the groundwater level spatially (right panel of Fig. 10), we see some 'hotspots' of marked raising and lowering of groundwater levels for both scenarios. In the *doubled* scenario, groundwater is mostly lowered upstream, and increased downstream. This might be explained by the increased water use for livestock and domestic purposes, which do not have a return flow (contrary to irrigation). In the *halved* scenario the hotspots are more randomly distributed.

### *4.3.2. Access to extension services*

We analysed the effect of increasing and decreasing access to extension services, which in turn affects the perceived adaptation efficacy of drought adaptation measures, and compared this with the base scenario (Section 3.3). For the measures agroforestry, irrigation and water harvesting, increasing the adaptation efficacy does not result in a significant increase of the uptake of those measures (Fig. 11). This can imply that other factors are of greater importance. For example, the perceived cost may play an important role, as these measures are (considered) most costly. There is a positive increase in the uptake of diversifying crop types and migration in the *doubling* of access to extension services scenario (up to 0.5 % of all households), compared to a negative effect in the *halved*

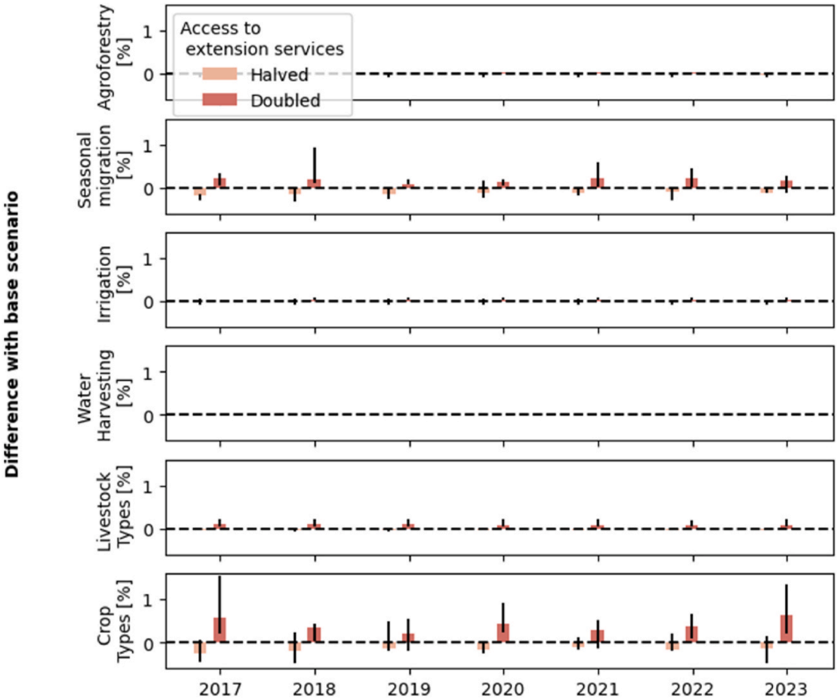


**Fig. 11.** Uptake of drought adaptation measures (% of households) in the scenarios of increased adaptation efficacy for crop and livestock measures scenario, compared to baseline. The spread indicates the 25th and 75th percentile of the results over the agent population.

scenario. Diversifying livestock types is slightly increased when *doubling* access to extension services, while *halving* the access to extension served has no notable effect.

When *doubling* the access to extension serves, crop production is increased with up to 1 % (around 10 kg/ha) compared to the baseline. This can be explained by the increased uptake of drought-resistant crop types (Fig. 12), compared to the baseline, resulting in higher crop production during drought. The spread among the agents is however large, indicating that agents are affected differently. In the *halved* scenario, however, there is a decrease in crop production for all seasons. Milk production is increased with up to 1 % when *doubling* the access to extension services during the 2020-23 drought, while it remains around the baseline during the rest of the period. The difference in the uptake of adaptation measures could be an underlying factor for explaining these differences between the scenarios. The household's distance to water is both increased and decreased compared to the baseline for both scenarios, with a

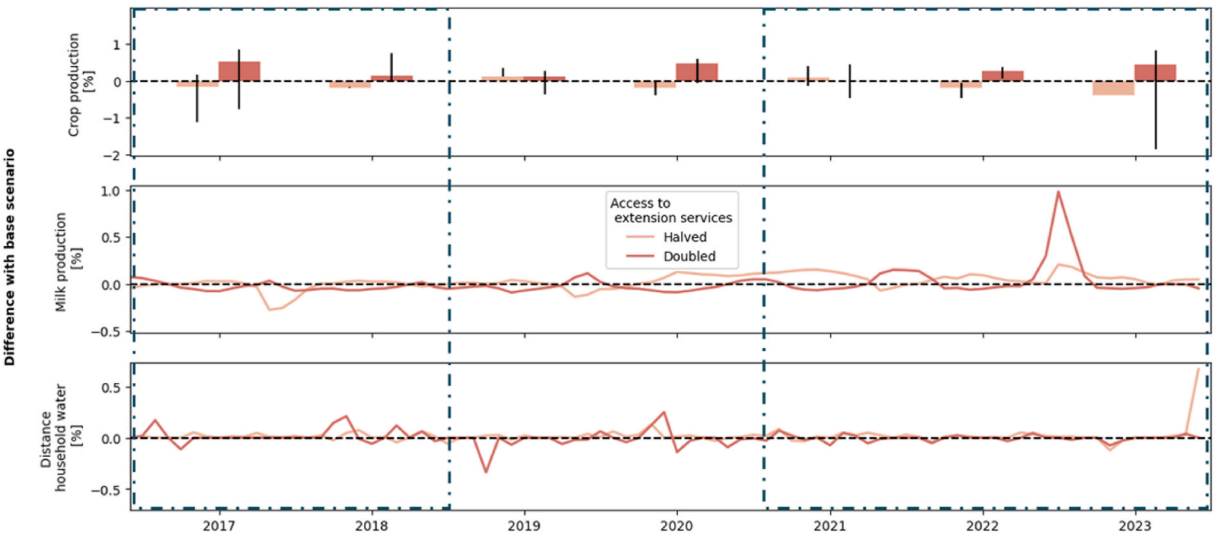


**Fig. 12.** Drought impacts compared to baseline in the halved and doubled scenario of access to extension services. Crop production [%]. Milk production [%]. Distance to household water [%]. The spread indicates the 25th and 75th percentile of the results over the agent population.

maximum variation of 0.25 % on average. Note that these changes are all relatively small, indicating that changing the access to extension services have a limited effect on drought impacts.

## 5. Discussion

### 5.1. Lessons learned

#### 5.1.1. From hazard to impact

The comparative analysis of drought impacts between 2020-2023 and 2016–2018 provides valuable insights for enhancing future drought mitigation strategies. Notably, key indicators in Kenya, such as trekking distances to water sources and milk production, experienced greater average impacts during the 2020–2023 drought. However, an unexpected finding was that impact variance was higher during the 2016–2018 drought, with more uniform hazard intensity across administrative units. The lower variance observed in 2020–2023 suggests that impacts were more evenly distributed, which could be attributed to several factors: (a) changes in the hazard itself, such as more widespread or equally severe drought conditions, resulting in historically extreme impacts areas experiencing less variability; (b) shifts in exposure due to socio-economic and demographic changes, including population distribution; and (c) reduced vulnerability stemming from improved drought mitigation measures, such as infrastructure improvements that may have minimized disparities. Determining whether the reduced variance is primarily driven by improved interventions or changes in hazard and exposure requires further investigation, including an analysis of specific administrative units and related datasets.

The 2020–2023 drought was further exacerbated by a confluence of geopolitical factors, including food commodity trade bans, elevated fuel and transportation costs, the global COVID-19 pandemic, hyperinflation, and a desert locust invasion [4,6]. These factors collectively worsened food insecurity across the region. In contrast, the impacts of the 2016–2018 drought appeared to be compounded by mostly local/regional socio-economic and demographic differences i.e., the crop pest manifestation and the post-election violence [7]. Interestingly, some administrative units, such as Meru, Kilifi, Taita Taveta experienced fewer drought impacts in 2020–2023 than in 2016–2018. This may suggest that in these counties measures to reduce in vulnerability were implemented, such as changing crop calendar, improved seed varieties, drought-tolerant crops and water harvesting [104,105]. Increased access to credit from commercial banks and service providers, as well as improvements in water infrastructure and water-use efficiency, may have also contributed to this resilience. Support for this comes from Agent-Based Modelling (ABM) scenario results, which demonstrate that doubling the uptake of water harvesting had positive effects on milk production during the 2020–2023 drought and a slight reduction in water collection distances. However, the effect of more water harvesting on crop production was mixed, and only the first OND 2020 season was positively influenced by doubling the uptake of water harvesting.

In Somalia and Ethiopia, the 2020–2023 drought further underscored the complex relationship between hazard magnitude and vulnerability across administrative units. The significant rise in internally displaced persons (IDPs) during this period reflected both the severity of the drought and pre-existing vulnerabilities. Displacement rates were notably higher during this period compared to 2016–2018 with the exception of some administrative units such as Lower Shebelle, Saanag and Woqooyi Galbeed. The discrepancy may be partially explained by the limited availability of data during the earlier drought, which could have masked the full extent of displacement at the time. Environmental degradation has further hindered the region's capacity to withstand extreme drought events. In Somalia, for example, approximately 49 % of land is moderately degraded, while 30 % suffers from severe degradation [6]. In Ethiopia, regions such as Oromia, Tigray, and Afar—already affected by conflict—experienced the highest rates of displacement, compounding the challenges faced by these communities.

The displacement trends observed in Tigray during the 2020–2023 drought illustrate the complex interplay between climate and non-climate drivers. While our study primarily focused on drought-induced displacement, we acknowledge that the civil war in Tigray during this period likely contributed significantly to the observed increase in displacement, particularly given reports of famine being used as a weapon [97–99]. This highlights the importance of considering both climatic and socio-political factors when analyzing displacement trends, as conflict can exacerbate the vulnerabilities created by drought and vice versa.

This study focused on drought as a key driver of displacement in East Africa. While we acknowledge that displacement is influenced by a range of structural and contextual factors—including ethno-political exclusion, poor governance, socio-economic inequalities, and state capacity ([67]; Adger et al., 2014; [66,68])—our analysis specifically isolated the impacts of drought to understand its direct and indirect socio-economic repercussions. This approach allows us to evaluate the unique role of drought in shaping displacement patterns. Future research could build on this work by integrating broader drivers of displacement and exploring methods for disentangling the overlapping effects of these drivers, enabling a more comprehensive understanding of the interplay between climatic and non-climatic factors on the dynamics of displacement in crisis-prone areas.

#### 5.1.2. Community adaptation

To reduce drought vulnerability people can implement several types of adaptation measures. But important barriers to adaptation are a lack of financial resources and a lack of knowledge. Schrieks et al. [27] show that perceived adaptation efficacy, perceived self-efficacy and perceived costs are important factors in the adaptation decision. Other research from various developing countries has shown that factors such as education, access to financial services, and participation in farmer organizations positively impact smallholder farmers' welfare, although these effects vary by region [106–108]. An increase in knowledge and information can increase adaptation efficacy and self-efficacy, and better access to financial resources can increase self-efficacy and reduce perceived costs. Governments and NGO can thus improve uptake of adaptation measures by providing training and information about these measures and improving access to financial resources. Mwongera et al. [109] and Ngigi & Muange [110] both indicate that strengthening existing institutions and implementing coherent local policies can improve adaptation uptake in Kenya along the value chain, which is consistent with our findings.

The experience from Somalia and Ethiopia, where there was a significant increase in internally displaced persons (IDPs) during the 2020–2023 drought compared to 2016–2018, underscores the need for improving political and economic stability, education and reducing youth unemployment to minimize vulnerability, hence displacements during drought events [111]. Enhancing access to financial resources, and expanding training/education facilities or workshops can significantly contribute to reducing displacement during drought periods [111–113].

The ABM scenarios further emphasize the need for diversification of livelihoods, concluding that increased access to extension services significantly boosts crop production and milk output, particularly through the adoption of drought-resistant crops and diversified farming practices. Additionally, while improving access to extension services enhanced crop diversification, migration, and livestock and crop production, its influence on other adaptation measures remained limited. It should be noted that extension services are not always well established or effective in Kenya, because of constraints of bureaucracy or inadequate funds [114]. Therefore, the relationship between adaptation efficacy and receiving extension services is also depended on the quality of the services, not necessarily the potential of receiving training and information. Financial barriers continue to impede the uptake of costly adaptation measures like agroforestry, rainwater harvesting and irrigation. An increase in adaptation efficacy through extension services and training is therefore not likely to increase the update of these adaptation measures if it is not also combined with financial support. King-Okumu et al. [115] also show that the challenges that affect uptake of different interventions in Kenya include financial issues and the need for better use of information to trigger adaptations. One of the adaptation measures that is especially expensive is rainwater harvesting. Schrieks et al. [116] shows that people are indeed more likely to implement rainwater harvesting if they receive a subsidy.

*Unintended consequences of water infrastructure interventions*

In the aftermath of the severe 2010–2011 droughts in Kenya and Ethiopia, governments and international aid agencies have increasingly shifted from reactive to proactive drought management approaches [117,118]. This transition involves developing national drought management policies, improving early warning systems and enhancing collaboration across sectors and policy levels. The drought management efforts have focused on addressing the root causes of drought vulnerability through strategic investments, including enhancing small-scale water supply infrastructures such as deep wells, boreholes, and piped water systems to ensure reliable access to water during scarcity [16,103,119,120]. Scaling up these infrastructures remains a priority to improve communities' adaptive capacities ahead of future droughts [113,121]. While infrastructure improvements are crucial, they must be balanced with sustainable resource management to prevent long-term negative impacts, such as groundwater depletion [103,122,123]. Moreover, Gebresenbet & Kefale [124] and Jónsson [125] both argue that increased mobility and traditional coping mechanisms may sometimes be more effective than fixed infrastructure improvements especially in addressing environmentally-induced migration in Africa.

Contributing to studies that have examined the effects of water infrastructure, this study simulated how drought impact and hazard would be modified under varying implementation of water harvesting as adaptation measure. The simulations show that an increase in the uptake of water harvesting decreases drought impact for milk production and distance to water, but in some seasons increases the drought impact on crop production. This might be explained by the way the model is set up; water is prioritised for domestic and livestock purposes. Drought hazard is increased by a reduction in soil moisture, streamflow and groundwater recharge in downstream areas, confirming earlier research [126]. These findings illustrate that trade-offs of water harvesting exist; one may alleviate certain drought impacts, but increase drought hazard due to increased water consumption upstream [127]. This phenomenon is not new; it combines the supply-demand cycles and reservoir effect, where an increase in water supply enables higher water demand and where there may be an over-reliance on water storage, increasing vulnerability to drought [122]. The findings illustrate the importance considering water-human feedbacks in analysing drought impacts and the effectiveness of adaptation measures. Unintended consequences of adaptation should therefore be taken into account when designing drought-related interventions [50,128]. These interventions should create synergies within the human-water feedbacks, rather than trade-offs [129].

### *5.3. Future research and limitations*

The varying impacts of drought across different regions and administrative units highlight the need for targeted interventions. Resource allocation should be based on specific county needs, ensuring that areas with higher vulnerability receive more attention. For example, counties with consistently dire conditions, as identified from the standardized impact data [57], should be prioritised for immediate interventions, such as emergency water supply and food security programs [130]. Moreover, long-term investments in infrastructure, education, and economic development should be tailored to address the unique challenges faced by each county.

Linking these targeted interventions to scenario analysis can help policymakers identify the most effective strategies for reducing drought impacts. By simulating different adaptation measures and their potential outcomes, decision-makers can prioritize actions that offer the greatest benefits in terms of resilience and sustainability [32]. This approach ensures that resources are used efficiently and that communities are better prepared to withstand future droughts.

This study acknowledges several limitations that should be considered when interpreting the findings, including the availability of impact datasets, uncertainties associated with the Agent-Based Model (ABM), and potential biases in the household surveys. There is an urgent need for more comprehensive drought impact datasets with high spatial and temporal resolution to enhance drought risk assessments and adaptation strategies. High-resolution data facilitate a more nuanced understanding of localized drought impacts, which can vary considerably across different regions and communities. However, existing datasets often lack the granularity required to capture these variations, particularly in remote or underrepresented areas, thereby constraining the capacity to model drought dynamics and design targeted interventions.

For instance, the National Drought Management Authority (NDMA) of Kenya provides valuable high-resolution impact data on a monthly basis at the administrative level 1 scale, which is publicly accessible. This dataset could be further enhanced through consistent reporting, integration of vulnerability factors, and dissemination via interactive dashboards rather than static reports. Extending this model of monthly impact data publication to Ethiopia and Somalia would represent a significant advancement in drought monitoring and response in the region. Furthermore, the availability of detailed datasets would enable researchers and policymakers to better comprehend the temporal progression of drought impacts, facilitating the development of more effective mitigation and adaptation strategies. Addressing these data limitations is essential for advancing our understanding of drought dynamics and improving resilience in vulnerable regions.

The independent treatment of each country in our analysis was essential to address potential data comparability issues arising from differences in drought impact types and data sources. By focusing on comparisons within administrative units for each country, we avoided introducing biases that might arise from directly comparing data across countries. This approach highlights the unique socio-economic and environmental contexts of Kenya, Ethiopia, and Somalia while recognizing their shared vulnerabilities to drought. The inclusion of Ethiopia and Somalia, despite data limitations, underscores the importance of integrating underrepresented contexts into regional drought studies. We acknowledge that future studies could benefit from standardized data collection across countries to facilitate more robust cross-country comparisons.

Additionally, when employing the ABM to analyse the drought impacts and perform scenario analysis, uncertainties can arise due to the complexity and heterogeneity of human-environment interactions. To accurately capture the behaviour of agents is challenging especially due to the limited data on human decision-making processes, which can be influenced by socio-cultural norms that may be hard to quantify. Furthermore, assumptions made in defining the rules that govern agent behaviour introduce additional uncertainty, especially when data on historical responses to drought are sparse. As for the household surveys used, there is also uncertainty that may be introduced due to respondents' answers being influenced by recall bias and social desirability bias, where individuals may not accurately remember events or misreport the severity of drought impacts and provide answers they deem more acceptable to the researcher rather than reflecting on their true experiences, respectively. Furthermore, the survey only measures preferences and behaviour at one point in time, which means that answers are influenced by the situation at that moment. Longitudinal data is needed to better capture developments in preferences and causal relationships in adaptation decisions. We tried to overcome these biases by using carefully designed questions from behavioural theories that have been extensively tested in previous research, but biased can never be fully eliminated which adds to the uncertainties in modelling human-drought dynamics.

## 6. Conclusion

This study combines drought impact data, household survey data and agent-based model simulations to learn lessons from past droughts in the HAD, which can inform more effective responses in the future. The impacts of the 2020–2023 drought in Kenya, including trekking distances to water sources and milk production, were found to be bigger than the 2016–2018 period. Because this difference could not be seen in the drought hazard, it suggests that exposure and vulnerability play a crucial role in determining drought impacts. The analysis of adaptation in rural communities shows that the uptake of adaptation measure can be increased by providing extension services and improving access to financial resources. The ABM simulations confirm that an increased access to extension services increases crop and milk production, particularly through the adoption of diversified farming practices. However, for more costly adaptation measures, extension-services are only effective when combined with financial support. The model simulations also show that an increased uptake of water harvesting can reduce drought impacts, but there is also a risk that increasing water harvesting upstream can increase drought hazard downstream.

In conclusion, the lessons learned from the 2020–2023 drought period emphasize the importance of continuous investment in adaptive measures, timely and informed decision-making, and targeted interventions based on specific regional needs, taking into account potential trade-off resulting from these interventions. Structural investments (e.g. education, infrastructure, access to credit) are needed to reduce vulnerability of the communities. Improved understanding of socio-economic impacts is critical in designing effective drought early warning systems and development of impact triggers and thresholds for anticipatory action. By implementing these strategies, communities, governments, and organizations can work together to reduce the impacts of future droughts and build more resilient societies.

## CRediT authorship contribution statement

**Rhoda A. Odongo:** Writing – original draft, Visualization, Formal analysis, Conceptualization. **Teun Schrieks:** Writing – original draft, Visualization, Formal analysis, Conceptualization. **Ileen Streefkerk:** Writing – original draft, Visualization, Formal analysis, Conceptualization. **Hans de Moel:** Writing – review & editing, Supervision, Conceptualization. **Tim Busker:** Writing – review & editing, Conceptualization. **Toon Haer:** Writing – review & editing. **David MacLeod:** Writing – review & editing. **Katerina Michaelides:** Writing – review & editing. **Michael Singer:** Writing – review & editing. **Mohammed Assen:** Writing – review & editing. **George Otieno:** Writing – review & editing. **Anne F. Van Loon:** Writing – review & editing, Supervision, Conceptualization.

## Data availability

The python scripts are available on request. Impact datasets for Kenya: National drought management authority (NDMA - KnowledgeWeb), Internally displaced persons datasets obtained from Internally displacement monitoring centre (IDMC; Global Internal Displacement Database | IDMC - Internal Displacement Monitoring Centre)- Ethiopia and the United Nations High Commissioner for Refugees PRMN -Somalia. Household survey data is not available because of privacy reasons. Calibration data for the ABM: CETRAD for streamflow, and Kenya's National Information Dashboard on Food Security and Nutrition for crop production.

## Funding sources

This study was funded by the European Union Horizon 2020 Programme (DOWN2EARTH Project No. 869550).

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgements

We thank the BAZIS cluster use for computation resources. In addition we thank our fellow partners of DOWN2EARTH who thought along with and worked with us. And finally we would like to thank the communities whom we interviewed for their time and participation, and ActionAid for the data collection efforts.

## Data availability

Data will be made available on request.

## References

[1] A.A. Alasow, M.M. Hamed, S. Shahid, Spatiotemporal variability of drought and affected croplands in the horn of Africa, Stoch. Environ. Res. Risk Assess. 38 (1) (2024) 281–296, https://doi.org/10.1007/s00477-023-02575-1.

[2] IPCC, in: H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (Eds.), Climate Change 2022: Impacts, Adaptation and Vulnerability (Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, 2022, p. 3056, https://doi.org/10.1017/9781009325844.

[3] C. Funk, A.H. Fink, L. Harrison, Z. Segele, H.S. Endris, G. Galu, S. Nicholson, Frequent but predictable droughts in East Africa driven by a Walker circulation intensification, Earths Future 11 (11) (2023) e2022EF003454.

[4] C. Funk, Ethiopia, Somalia and Kenya face devastating drought, Nature 586 (7831) (2020) 645, https://doi.org/10.1038/d41586-020-02698-3, 645.

[5] ReliefWeb, Kenya: Drought - 2014-2024, ReliefWeb, 2023. https://reliefweb.int/disaster/dr-2014-000131-ken.

[6] UNDRR, Horn of Africa floods and drought, 2020-2023—forensic analysis | UNDRR. https://www.undrr.org/resource/horn-africa-floods-and-drought-2020-2023-forensic-analysis, 2024, September 17.

[7] A. Matanó, M.C. de Ruiter, J. Koehler, P.J. Ward, A.F. Van Loon, Caught between extremes: understanding human-water interactions during drought-to-flood events in the horn of Africa, Earths Future 10 (9) (2022) e2022EF002747, https://doi.org/10.1029/2022EF002747.

[8] ReliefWeb, Kenya 2022 drought response in review—Kenya | ReliefWeb. https://reliefweb.int/report/kenya/kenya-2022-drought-response-review, 2023.

[9] M. Hagenlocher, G. Naumann, I. Meza, V. Blauhut, D. Cotti, P. Döll, K. Ehlert, F. Gaupp, A.F. Van Loon, J.A. Marengo, L. Rossi, A.S. Sabino Siemons, S. Siebert, A.T. Tsehayu, A. Toreti, D. Tsegai, C. Vera, J. Vogt, M. Wens, Tackling growing drought risks—the need for a systemic perspective, Earths Future 11 (9) (2023) e2023EF003857, https://doi.org/10.1029/2023EF003857.

[10] A.F. Van Loon, T. Gleeson, J. Clark, A.I.J.M. Van Dijk, K. Stahl, J. Hannaford, G. Di Baldassarre, A.J. Teuling, L.M. Tallaksen, R. Uijlenhoet, D.M. Hannah, J. Sheffield, M. Svoboda, B. Verbeiren, T. Wagener, S. Rangecroft, N. Wanders, H.A.J. Van Lanen, Drought in the anthropocene, Nat. Geosci. 9 (2) (2016) 89–91, https://doi.org/10.1038/ngeo2646.

[11] A. Hoell, B.-A. Parker, M. Downey, N. Umphlett, K. Jencso, F.A. Akyuz, D. Peck, T. Hadwen, B. Fuchs, D. Kluck, L. Edwards, J. Perlwitz, J. Eischeid, V. Deheza, R. Pulwarty, K. Bevington, Lessons learned from the 2017 flash drought across the U.S. Northern great plains and Canadian prairies. https://doi.org/10.1175/BAMS-D-19-0272.1, 2020.

[12] M. Mortimore, Adapting to drought in the Sahel: lessons for climate change, WIREs Climate Change 1 (1) (2010) 134–143, https://doi.org/10.1002/wcc.25.

[13] C. Vogel, D. Olivier, Re-imagining the potential of effective drought responses in South Africa, Reg. Environ. Change 19 (6) (2019) 1561–1570, https://doi.org/10.1007/s10113-018-1389-4.

[14] A.J. Baxter, D. Verschuren, F. Peterse, D.G. Miralles, C.M. Martin-Jones, A. Maitituerdi, T. Van der Meeren, M. Van Daele, C.S. Lane, G.H. Haug, D.O. Olago, J. S. Sinninghe Damsté, Reversed holocene temperature–moisture relationship in the horn of Africa, Nature 620 (7973) (2023), https://doi.org/10.1038/s41586-023-06272-5. Article 7973.

[15] J. Kimutai, C. Barnes, M. Zachariah, S. Philip, S. Kew, I. Pinto, P. Wolski, G. Koren, G. Vecchi, W. Yang, S. Li, M. Vahlberg, R. Singh, D. Heinrich, C. Pereira, J. Arrighi, L. Thalheimer, C. Kane, F. Otto, Human-induced Climate Change Increased Drought Severity in Horn of Africa, Imperial College London, 2023, https://doi.org/10.25561/103482.

[16] E. Thomas, E. Jordan, K. Linden, B. Mogesse, T. Hailu, H. Jirma, P. Thomson, J. Koehler, G. Collins, Reducing drought emergencies in the horn of Africa, Sci. Total Environ. 727 (2020) 138772, https://doi.org/10.1016/j.scitotenv.2020.138772.

[17] N.O. Agutu, J.L. Awange, C. Ndehedehe, M. Mwaniki, Consistency of agricultural drought characterization over Upper Greater Horn of Africa (1982–2013): topographical, gauge density, and model forcing influence, Sci. Total Environ. 709 (2020) 135149, https://doi.org/10.1016/j.scitotenv.2019.135149.

[18] W.B. Anderson, B.F. Zaitchik, C.R. Hain, M.C. Anderson, M.T. Yilmaz, J. Mecikalski, L. Schultz, Towards an integrated soil moisture drought monitor for East Africa, Hydrol. Earth Syst. Sci. 16 (8) (2012) 2893–2913, https://doi.org/10.5194/hess-16-2893-2012.

[19] J.L. Awange, Khandu, M. Schumacher, E. Forootan, B. Heck, Exploring hydro-meteorological drought patterns over the Greater Horn of Africa (1979-2014) using remote sensing and reanalysis products, Adv. Water Resour. 94 (2016) 45–59, https://doi.org/10.1016/j.advwatres.2016.04.005.

[20] S.E. Nicholson, A detailed look at the recent drought situation in the Greater Horn of Africa, J. Arid Environ. 103 (2014) 71–79, https://doi.org/10.1016/j.jaridenv.2013.12.003.

[21] H.M. Berman, A.K.C. Brackel, M.A. Caretta, C. Dowler, V. Fanghella, S.L. Gomes, B.J. Gray, G. Hegde, J. Lautze, Y. Yashoda, Effectiveness of Water Adaptation Responses in Reducing Climate Related Risks: A Meta-Review, ACIAR, Australia, 2021. No. FR2021- 011).
[22] D.B. Ombogoh, J. Tanui, S. McMullin, J. Muriuki, J. Mowo, Enhancing adaptation to climate variability in the East African highlands: a case for fostering collective action among smallholder farmers in Kenya and Uganda, Clim. Dev. 10 (1) (2018) 61–72, https://doi.org/10.1080/17565529.2016.1174665.
[23] M.R. Lam, A. Matanó, A.F. Van Loon, R.A. Odongo, A.D. Teklesadik, C.N. Wamucii, M.J.C. van den Homberg, S. Waruru, A.J. Teuling, Linking reported drought impacts with drought indices, water scarcity and aridity: the case of Kenya, Nat. Hazards Earth Syst. Sci. 23 (9) (2023) 2915–2936, https://doi.org/10.5194/nhess-23-2915-2023.
[24] R.A. Odongo, H. De Moel, A.F. Van Loon, Propagation from meteorological to hydrological drought in the Horn of Africa using both standardized and threshold-based indices, Nat. Hazards Earth Syst. Sci. 23 (6) (2023) 2365–2386, https://doi.org/10.5194/nhess-23-2365-2023.
[25] F. Opiyo, O. Wasonga, M. Nyangito, J. Schilling, R. Munang, Drought adaptation and coping strategies among the Turkana pastoralists of northern Kenya, International Journal of Disaster Risk Science 6 (3) (2015) 295–309, https://doi.org/10.1007/s13753-015-0063-4.
[26] B. Shiferaw, K. Tesfaye, M. Kassie, T. Abate, B.M. Prasanna, A. Menkir, Managing vulnerability to drought and enhancing livelihood resilience in sub-Saharan Africa: technological, institutional and policy options, Weather Clim. Extrem. 3 (2014) 67–79, https://doi.org/10.1016/j.wace.2014.04.004.
[27] T. Schrieks, W.J.W. Botzen, T. Haer, O.V. Wasonga, J.C.J.H. Aerts, Assessing key behavioural theories of drought risk adaptation: evidence from rural Kenya, Risk Anal. 44 (7) (2024) 1681–1699.
[28] J.A. De Bruijn, M. Smilovic, P. Burek, L. Guillaumot, Y. Wada, J.C. Aerts, GEB v0. 1: a large-scale agent-based socio-hydrological model–simulating 10 million individual farming households in a fully distributed hydrological model, Geosci. Model Dev. (GMD) 16 (9) (2023) 2437–2454.
[29] J. Sušnik, L.S. Vamvakeridou-Lyroudia, D.A. Savić, Z. Kapelan, Integrated system dynamics modelling for water scarcity assessment: case study of the kairouan region, Science of the total environment 440 (2012) 290–306.
[30] A.N. Lindqvist, R. Fornell, T. Prade, L. Tufvesson, S. Khalil, B. Kopainsky, Human-water dynamics and their role for seasonal water scarcity–a case study, Water Resour. Manag. 35 (2021) 3043–3061.
[31] I.N. Streefkerk, J. de Bruijn, T. Haer, A.F. Van Loon, E.A. Quichimbo, M. Wens, J.C. Aerts, A coupled agent-based model to analyse human-drought feedbacks for agropastoralists in dryland regions, Frontiers in Water 4 (2023) 1037971.
[32] M.L.K. Wens, A.F. van Loon, T.I.E. Veldkamp, J.C.J.H. Aerts, Education, financial aid, and awareness can reduce smallholder farmers' vulnerability to drought under climate change, Nat. Hazards Earth Syst. Sci. 22 (4) (2022) 1201–1232, https://doi.org/10.5194/nhess-22-1201-2022.
[33] G. Di Baldassarre, A. Viglione, G. Carr, L. Kuil, K. Yan, L. Brandimarte, G. Blöschl, Debates—perspectives on socio-hydrology: capturing feedbacks between physical and social processes, Water Resour. Res. 51 (6) (2015) 4770–4781.
[34] IPCC, in: C.B. Field, V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, P.M. Midgley (Eds.), Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, UK, and New York, NY, USA, 2012, p. 582.
[35] A. Reisinger, & M. Howden, C. Vera, The Concept of Risk in the IPCC Sixth Assessment Report: A Summary of Cross-Working Group Discussions, vol. 15, Intergovernmental Panel on Climate Change, 2020, p. 130.
[36] K.E. Trenberth, A. Dai, G. Van Der Schrier, P.D. Jones, J. Barichivich, K.R. Briffa, J. Sheffield, Global warming and changes in drought, Nat. Clim. Change 4 (1) (2014) 17–22, https://doi.org/10.1038/nclimate2067.
[37] W. Kalisa, J. Zhang, T. Igbawua, F. Ujoh, O.J. Ebohon, J.N. Namugize, F. Yao, Spatio-temporal analysis of drought and return periods over the East African region using Standardized Precipitation Index from 1920 to 2016, Agric. Water Manag. 237 (2020) 106195, https://doi.org/10.1016/j.agwat.2020.106195.
[38] L.S. Seregina, A.H. Fink, R. van der Linden, N.A. Elagib, J.G. Pinto, A new and flexible rainy season definition: validation for the Greater Horn of Africa and application to rainfall trends, Int. J. Climatol. 39 (2) (2019) 989–1012, https://doi.org/10.1002/joc.5856.
[39] M.G. Ghebrezgabher, T. Yang, X. Yang, Long-term trend of climate change and drought assessment in the horn of Africa, Adv. Meteorol. 2016 (1) (2016) 8057641, https://doi.org/10.1155/2016/8057641.
[40] X. Han, Y. Li, W. Yu, L. Feng, Attribution of the extreme drought in the horn of Africa during short-rains of 2016 and long-rains of 2017, Water 14 (3) (2022) 3, https://doi.org/10.3390/w14030409.
[41] C. Funk, M.D. Dettinger, J.C. Michaelsen, J.P. Verdin, M.E. Brown, M. Barlow, A. Hoell, Warming of the Indian Ocean threatens eastern and southern African food security but could be mitigated by agricultural development, Proc. Natl. Acad. Sci. USA 105 (32) (2008) 11081–11086, https://doi.org/10.1073/pnas.0708196105.
[42] J.M. Kourouma, E. Eze, G. Kelem, E. Negash, D. Phiri, R. Vinya, A. Girma, A. Zenebe, Spatiotemporal climate variability and meteorological drought characterization in Ethiopia, Geomatics Nat. Hazards Risk 13 (1) (2022) 2049–2085, https://doi.org/10.1080/19475705.2022.2106159.
[43] J. Lind, R. Sabates-Wheeler, M. Caravani, L.B.D. Kuol, D.M. Nightingale, Newly evolving pastoral and post-pastoral rangelands of Eastern Africa, Pastoralism 10 (1) (2020) 24, https://doi.org/10.1186/s13570-020-00179-w.
[44] I. Masih, S. Maskey, F.E.F. Mussá, P. Trambauer, A review of droughts on the African continent: a geospatial and long-term perspective, Hydrol. Earth Syst. Sci. 18 (9) (2014) 3635–3649, https://doi.org/10.5194/hess-18-3635-2014.
[45] J.J. Kimaiyo, B.M. Mati, J.K. Sang, E.K. Kanda, Assessment of drought trends in the upper Ewaso Ng'iro river basin using the SPI and SPEI, Water Pract. Technol. 18 (8) (2023) 1863–1879, https://doi.org/10.2166/wpt.2023.122.
[46] I.N. Streefkerk, J.C. Aerts, J. de Bruijn, K. Hassaballah, R. Odongo, T. Schrieks, A.F. Van Loon, The effects of upstream water abstraction for commercial export farming on drought risk and impact of agropastoral communities in the drylands of Kenya, EGUsphere 2024 (2024) 1–25.
[47] J.K. Mutiga, S.T. Mavengano, S. Zhongbo, T. Woldai, R. Becht, Water allocation as a planning tool to minimise water use conflicts in the upper Ewaso Ng'iro north basin, Kenya, Water Resour. Manag. 24 (14) (2010) 3939–3959, https://doi.org/10.1007/s11269-010-9641-9.
[48] E. Nkiaka, R.G. Bryant, Z. Kom, Understanding links between water scarcity and violent conflicts in the sahel and lake Chad basin using the water footprint concept, Earths Future 12 (2) (2024) e2023EF004013, https://doi.org/10.1029/2023EF004013.
[49] D. Wilhite, National Drought Policies: Addressing Impacts and Societal Vulnerability, 2011.
[50] J.C. Castilla-Rho, G. Mariethoz, R. Rojas, M.S. Andersen, B.F. Kelly, An agent-based platform for simulating complex human–aquifer interactions in managed groundwater systems, Environ. Model. Software 73 (2015) 305–323.
[51] H.E. Beck, E.F. Wood, M. Pan, C.K. Fisher, D.G. Miralles, A.I. Van Dijk, R.F. Adler, MSWEP V2 global 3-hourly 0.1 precipitation: methodology and quantitative assessment, Bull. Am. Meteorol. Soc. 100 (3) (2019) 473–500.
[52] Z. Xu, Z. Wu, H. He, X. Wu, J. Zhou, Y. Zhang, X. Guo, Evaluating the accuracy of MSWEP V2.1 and its performance for drought monitoring over mainland China, Atmos. Res. 226 (2019) 17–31, https://doi.org/10.1016/j.atmosres.2019.04.008.
[53] B. Martens, D.G. Miralles, H. Lievens, R. van der Schalie, R.A.M. de Jeu, D. Fernández-Prieto, H.E. Beck, W.A. Dorigo, N.E.C. Verhoest, GLEAM v3: satellite-based land evaporation and root-zone soil moisture, Geosci. Model Dev. (GMD) 10 (2017) 19031925, https://doi.org/10.5194/gmd-10-1903-2017.
[54] D.P. Dee, S.M. Uppala, A.J. Simmons, P. Berrisford, P. Poli, S. Kobayashi, U. Andrae, M.A. Balmaseda, G. Balsamo, P. Bauer, P. Bechtold, A.C.M. Beljaars, L. van de Berg, J. Bidlot, N. Bormann, C. Delsol, R. Dragani, M. Fuentes, A.J. Geer, L. Haimberger, S.B. Healy, H. Hersbach, E.V. Hólm, L. Isaksen, P. Kållberg, M. Köhler, M. Matricardi, A.P. McNally, B.M. Monge-Sanz, J.-J. Morcrette, B.-K. Park, C. Peubey, P. de Rosnay, C. Tavolato, J.-N. Thépaut, F. Vitart, The ERA-Interim reanalysis: configuration and performance of the data assimilation system, Q. J. Roy. Meteor. Soc. 137 (2011) 553–597, https://doi.org/10.1002/qj.828.
[55] S.M. Vicente-Serrano, S. Beguería, J. Lorenzo-Lacruz, J.J. Camarero, J.I. López-Moreno, C. Azorin-Molina, J. Revuelto, E. Morán-Tejeda, A. Sanchez-Lorenzo, Performance of drought indices for ecological, agricultural, and hydrological applications, Earth Interact. 16 (2012) 1–27, https://doi.org/10.1175/2012EI000434.1.
[56] V. Blauhut, K. Stahl, J.H. Stagge, L.M. Tallaksen, L.D. Stefano, J. Vogt, Estimating drought risk across Europe from reported drought impacts, drought indices, and vulnerability factors, Hydrol. Earth Syst. Sci. 20 (2016) 2779–2800, https://doi.org/10.5194/hess-20-2779-2016.

[57] R.A. Odongo, H. de Moel, M. Wens, D. Coumou, N. Limones, V. Otieno, A.F. Van Loon, From indices to impacts: understanding the dynamics of drought impacts through environmental and socio-economic clustering (SSRN scholarly paper 4770432), Social Science Research Network (2024), https://doi.org/10.2139/ssrn.4770432.

[58] R. Hoffmann, G. Abel, M. Malpede, R. Muttarak, M. Percoco, Drought and aridity influence internal migration worldwide, Nat. Clim. Change (2024) 1–9, https://doi.org/10.1038/s41558-024-02165-1.

[59] M.M. De Brito, J. Sodoge, A. Fekete, M. Hagenlocher, E. Koks, C. Kuhlicke, G. Messori, M. de Ruiter, P.-J. Schweizer, P.J. Ward, Uncovering the dynamics of multi-sector impacts of hydrological extremes: a methods overview, Earths Future 12 (1) (2024) e2023EF003906, https://doi.org/10.1029/2023EF003906.

[60] A.F. Van Loon, Hydrological drought explained, WIREs Water 2 (4) (2015) 359–392, https://doi.org/10.1002/wat2.1085.

[61] ReliefWeb, Amid Record Drought and Food Insecurity, East Africa's Protracted Humanitarian Crisis Worsens—Ethiopia, ReliefWeb, 2023. https://reliefweb.int/report/ethiopia/amid-record-drought-and-food-insecurity-east-africas-protracted-humanitarian-crisis-worsens.

[62] M. Achour, N. Lacan, DROUGHT IN SOMALIA: A MIGRATION CRISIS, IDDRI, 2012. http://labos.ulg.ac.be/hugo/wp-content/uploads/sites/38/2017/11/The-State-of-Environmental-Migration-2011-75-90.pdf.

[63] P. Bonneau, DROUGHT and INTERNAL DISPLACEMENTS of PASTORALISTS IN NORTHERN KENYA IN 2012: an ASSESSMENT (The State of Environmental Migration 2013), IDDRI, 2013. http://labos.ulg.ac.be/hugo/wp-content/uploads/sites/38/2017/11/The-State-of-Environmental-Migration-2013-101-116.pdf.

[64] R. Chetto, M. Mdemu, J. Kihila, Climate change-related drivers of migration in East Africa: an integrative review of the literature, Environmental Science & Sustainable Development 9 (1) (2024) 42–56, https://doi.org/10.21625/essd.v9i1.1005.

[65] C. Hillbruner, G. Moloney, When early warning is not enough-Lessons learned from the 2011 Somalia Famine, Global Food Secur. 1 (1) (2012) 20–28, https://doi.org/10.1016/j.gfs.2012.08.001.

[66] E.L. Owain, M.A. Maslin, 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) (2018) 1–9, https://doi.org/10.1057/s41599-018-0096-6.

[67] C.-A. Achberger, Climate change and droughts: effects on migration within Africa [the university of graz]. https://doi.org/10.13140/RG.2.2.30559.89764/1, 2020.

[68] H. Buhaug, Climate–conflict research: some reflections on the way forward, WIREs Climate Change 6 (3) (2015) 269–275, https://doi.org/10.1002/wcc.336.

[69] PRMN, Protection & Return Monitoring Network (PRMN)—Notes on Methodology—UNHCR Somalia, 2017.

[70] Y. Wang, J. Lv, J. Hannaford, Y. Wang, H. Sun, L. Barker, M. Ma, Z. Su, M. Eastman, Linking drought indices to impacts to support drought risk assessment in Liaoning province, China, Nat. Hazards Earth Syst. Sci. 20 (2020) 889–906, https://doi.org/10.5194/NHESS-20-889-2020.

[71] R. Below, E. Grover-Kopec, M. Dilley, Documenting drought-related disasters: a global reassessment, J. Environ. Dev. 16 (2007) 328–344.

[72] Kenya National Bureau of Statistics, Kenya population and housing Census 2019. https://ghdx.healthdata.org/record/kenya-population-and-housing-census-2019, 2019.

[73] Central Statistics Department, The Somaliland Health and Demographic Survey 2020, Ministry of Planning and National Development, Somaliland Government, 2020.

[74] N. Arunrat, C. Wang, N. Pumijumnong, S. Sereenonchai, W. Cai, Farmers' intention and decision to adapt to climate change: a case study in the Yom and Nan basins, Phichit province of Thailand, J. Clean. Prod. 143 (2017) 672–685, https://doi.org/10.1016/j.jclepro.2016.12.058.

[75] F. Delfiyan, M. Yazdanpanah, M. Forouzani, J. Yaghoubi, Farmers' adaptation to drought risk through farm–level decisions: the case of farmers in Dehloran county, Southwest of Iran, Clim. Dev. 13 (2) (2021) 152–163, https://doi.org/10.1080/17565529.2020.1737797.

[76] T. Gebrehiwot, A. van der Veen, Farmers' drought experience, risk perceptions, and behavioural intentions for adaptation: evidence from Ethiopia, Clim. Dev. 13 (6) (2021) 493–502.

[77] M. Keshavarz, E. Karami, Farmers' pro-environmental behavior under drought: application of protection motivation theory, J. Arid Environ. 127 (2016) 128–136, https://doi.org/10.1016/j.jaridenv.2015.11.010.

[78] M.L. Wens, M.N. Mwangi, A.F. van Loon, J.C. Aerts, Complexities of drought adaptive behaviour: linking theory to data on smallholder farmer adaptation decisions, Int. J. Disaster Risk Reduct. 63 (2021) 102435.

[79] T. Gebrehiwot, A. Van Der Veen, Farmers prone to drought risk: why some farmers undertake farm-level risk-reduction measures while others not? Environ. Manag. 55 (2015) 588–602.

[80] T. Grothmann, A. Patt, Adaptive capacity and human cognition: the process of individual adaptation to climate change, Glob. Environ. Change 15 (3) (2005) 199–213, https://doi.org/10.1016/j.gloenvcha.2005.01.002.

[81] R.W. Rogers, Cognitive and physiological processes in fear appeals and attitude change: a revised theory of protection motivation, Social psychology: A source book (1983) 153–176.

[82] R. Van Duinen, T. Filatova, P. Geurts, Empirical analysis of farmers' drought risk perception: objective factors, personal circumstances, and social influence, Risk Anal. 35 (2015) 741–755, https://doi.org/10.1111/risa.12299.

[83] M. Wens, T.I. Veldkamp, M. Mwangi, J.M. Johnson, R. Lasage, T. Haer, J.C. Aerts, Simulating small-scale agricultural adaptation decisions in response to drought risk: an empirical agent-based model for semi-arid Kenya, Frontiers in water 2 (2020) 15.

[84] J.E. Maddux, R.W. Rogers, Protection motivation and self-efficacy: a revised theory of fear appeals and attitude change, J. Exp. Social Psychol. 19 (1983) 469–479, https://doi.org/10.1016/0022-1031(83)90023-9.

[85] T. Schrieks, W.J.W. Botzen, M. Wens, T. Haer, J.C.J.H. Aerts, Integrating behavioral theories in agent-based models for agricultural drought risk assessments, Frontiers in water 3 (2021) 686329.

[86] E.A. Quichimbo, M.B. Singer, K. Michaelides, D.E. Hobley, R. Rosolem, M.O. Cuthbert, Dryp 1.0: a parsimonious hydrological model of DRYland Partitioning of the water balance, Geosci. Model Dev. (GMD) 14 (11) (2021) 6893–6917.

[87] M.B. Singer, D.T. Asfaw, R. Rosolem, M.O. Cuthbert, D.G. Miralles, D. MacLeod, K. Michaelides, Hourly potential evapotranspiration at 0.1 resolution for the global land surface from 1981-present, Sci. Data 8 (1) (2021) 224.

[88] M. Mattijssen, Linking Drought Severity Indices to Drought Impacts: Experiences of Kenyan Agro-Pastroralists. [unpublished Master Thesis], Vrije Universiteit Amsterdam, 2022.

[89] I. Oageng, G.P. Mmopelwa, Water consumption patterns in a rural setting in Ngamiland district, Botswana: the case of Boro village, J. Water, Sanit. Hyg. Dev. 4 (4) (2014) 720–726.

[90] M.J. Otte, P. Chilonda, Cattle and small ruminant production systems in sub-Saharan Africa, A systematic review (2002) pp. 105.

[91] S. Siebert, P. Döll, Quantifying blue and green virtual water contents in global crop production as well as potential production losses without irrigation, J. Hydrol. 384 (3–4) (2010) 198–217.

[92] S. Lopez, Non-linear functions in animal nutrition, in: Mathematical Modelling in Animal Nutrition, CABI, Wallingford UK, 2008, pp. 47–88.

[93] S. Pande, H.H. Savenije, A sociohydrological model for smallholder farmers in Maharashtra, India, Water Resour. Res. 52 (3) (2016) 1923–1947.

[94] J.M. King, Livestock Water Needs in Pastoral Africa in Relation to Climate and Forage, International Livestock Centre for Africa, 1983.

[95] Tegemeo Institute, Tegemeo Agricultural Policy Research Analysis (TAPRA) Project–Household Survey 2010, Tegemeo Institute, Nairobi, 2010.

[96] NDMA, County Drought Early Warning Bulletins 2020-2024, Isiolo County. Government of Kenya, 2024. Available at: https://knowledgeweb.ndma.go.ke/Public/Resources/CountyBulletins.aspx?ID=11&_gl=1*uduzgg*_ga*MTE3MjE1NTUzNy4xNzI3MjY3Njg2*_ga_RVYWZRJTGS*MTcyOTUwNzcxMy40LjEuMTcyOTUwNzc0Ni4wLjAuMA.

[97] F.A. Afriyie, S. Ayangbah, K.O. Effah, Diagnosing Ethiopia's Tigray war: reverberations in the horn of Africa, Insight Afr. 15 (2) (2023) 139–151, https://doi.org/10.1177/09750878231170177.

[98] A.O. Jima, Ethiopian political crisis after reform: causes of Tigray conflict, Cogent Social Sciences 9 (1) (2023) 2209991, https://doi.org/10.1080/23311886.2023.2209991.

[99] P. Pellet, Understanding the 2020-2021 Tigray conflict in Ethiopia: background, root causes, and consequences (KKI elemzések) [KKI elemzések]. Külügyi És Külgazdasági Intézet, 2021, https://doi.org/10.47683/KKIElemzesek.KE-2021.39.
[100] T. Ackerl, L.F. Weldemariam, M. Nyasimi, A. Ayanlade, Climate change risk, resilience, and adaptation among rural farmers in East Africa: a literature review, Regional Sustainability 4 (2) (2023) 185–193, https://doi.org/10.1016/j.regsus.2023.05.004.
[101] S.W. Ndiritu, Drought responses and adaptation strategies to climate change by pastoralists in the semi-arid area, Laikipia County, Kenya, Mitig. Adapt. Strategies Glob. Change 26 (3) (2021) 10, https://doi.org/10.1007/s11027-021-09949-2.
[102] OCHA Somalia, Drought response plan Somalia 2022. https://reliefweb.int/report/somalia/somalia-2022-drought-response-plan, 2021.
[103] L. Piemontese, S. Terzi, G. Di Baldassarre, D.A. Menestrey Schwieger, G. Castelli, E. Bresci, Over-reliance on water infrastructure can hinder climate resilience in pastoral drylands, Nat. Clim. Change 14 (3) (2024) 267–274, https://doi.org/10.1038/s41558-024-01929-z.
[104] MoALF, Climate Risk Profile Nyeri (Kenya County Climate Risk Profile Series), The Kenya Ministry of Agriculture, Livestock and Fisheries (MoALF), 2016. https://hdl.handle.net/10568/80459.
[105] MoALF. Climate Risk Profile Meru (Kenya County Climate Risk Profile Series), The International Center for Tropical Agriculture (CIAT) and the Kenya Ministry of Agriculture, Livestock and Fisheries (MoALF), 2016, p. 21. https://hdl.handle.net/10568/80454.
[106] A. Adams, E.T. Jumpah, Agricultural technologies adoption and smallholder farmers' welfare: evidence from Northern Ghana, Cogent Economics & Finance 9 (1) (2021) 2006905, https://doi.org/10.1080/23322039.2021.2006905.
[107] H. Ahmed, M. Ahmed, Influencing factors on adoption of modern agricultural technology in developing economy countries, Dev. Ctry. Stud. 13 (2) (2023) 1.
[108] S. Ruzzante, R. Labarta, A. Bilton, Adoption of agricultural technology in the developing world: a meta-analysis of the empirical literature, World Dev. 146 (2021) 105599, https://doi.org/10.1016/j.worlddev.2021.105599.
[109] C. Mwongera, A. Nowak, A.M.O. Notenbaert, S. Grey, J. Osiemo, I. Kinyua, M. Lizarazo, E. Girvetz, Climate-Smart agricultural value chains: risks and perspectives, in: T.S. Rosenstock, A. Nowak, E. Girvetz (Eds.), The Climate-Smart Agriculture Papers: Investigating the Business of a Productive, Resilient and Low Emission Future, Springer International Publishing, 2019, pp. 235–245, https://doi.org/10.1007/978-3-319-92798-5_20.
[110] M.W. Ngigi, E.N. Muange, Access to climate information services and climate-smart agriculture in Kenya: a gender-based analysis, Clim. Change 174 (3) (2022) 21, https://doi.org/10.1007/s10584-022-03445-5.
[111] IDMC, Briefing paper: recommendations for addressing drought displacement, in: Somalia. Internal Displacement Monitoring Centre (IDMC), 2021. https://api.internal-displacement.org/sites/default/files/publications/documents/21_1903_Somalia_BriefingPaper.pdf.
[112] B. Riché, E. Hachileka, C.B. Awuor, A. Hammill, Climate-related Vulnerability and Adaptive-capacity in Ethiopia's Borana and Somali Communities, International Institute for Sustainable Development, 2009 (IISD), https://www.iisd.org/system/files/publications/climate_ethiopia_communities.pdf?q=sites/default/files/publications/climate_ethiopia_communities.pdf.
[113] J. Rockström, M. Falkenmark, Agriculture: increase water harvesting in Africa, Nature 519 (7543) (2015) 283–285, https://doi.org/10.1038/519283a.
[114] M. Muyanga, T.S. Jayne, Private agricultural extension system in Kenya: practice and policy lessons, J. Agric. Educ. Ext. 14 (2) (2008) 111–124.
[115] C. King-Okumu, V.A. Orindi, L. Lekalkuli, Chapter 19 - drought management in the drylands of Kenya: what have we learned?, in: E. Mapedza, D. Tsegai, M. Bruntrup, R. Mcleman (Eds.), Current Directions in Water Scarcity Research, vol. 2 Elsevier, 2019, pp. 277–294, https://doi.org/10.1016/B978-0-12-814820-4.00019-5.
[116] T. Schrieks, W.J.W. Botzen, T. Haer, O.V. Wasonga, J.C.J.H. Aerts, Preferences for drought risk adaptation support in Kenya: evidence from a discrete choice experiment and three decision-making theories, Ecol. Econ. 227 (2025) 108425, https://doi.org/10.1016/j.ecolecon.2024.108425.
[117] M. Brüntrup, Chapter 20—achieving policy coherence for drought-resilient food security in SSA—lessons from Ethiopia and Kenya, in: E. Mapedza, D. Tsegai, M. Bruntrup, R. Mcleman (Eds.), Current Directions in Water Scarcity Research, vol. 2, Elsevier, 2019, pp. 295–310, https://doi.org/10.1016/B978-0-12-814820-4.00020-1.
[118] F. Pischke, R. Stefanski, Drought management policies – from global collaboration to national action, Water Policy 18 (S2) (2016) 228–244, https://doi.org/10.2166/wp.2016.022.
[119] NDMA, Ending drought emergencies common programme framework. Government of Kenya, national drought management authority. National drought management authority of Kenya. https://reliefweb.int/report/kenya/ending-drought-emergencies-common-programme-framework-drought-risk-management, 2014.
[120] N.J. Wilson, J. Inkster, Respecting water: indigenous water governance, ontologies, and the politics of kinship on the ground, Environ. Plann.: Nature and Space 1 (4) (2018) 516–538.
[121] F. Mugagga, B.B. Nabaasa, The centrality of water resources to the realization of Sustainable Development Goals (SDG). A review of potentials and constraints on the African continent, International Soil and Water Conservation Research 4 (3) (2016) 215–223, https://doi.org/10.1016/j.iswcr.2016.05.004.
[122] G. Di Baldassarre, N. Wanders, A. AghaKouchak, L. Kuil, S. Rangecroft, T.I.E. Veldkamp, M. Garcia, P.R. van Oel, K. Breinl, A.F. Van Loon, Water shortages worsened by reservoir effects, Nat. Sustain. 1 (11) (2018) 617–622, https://doi.org/10.1038/s41893-018-0159-0.
[123] J. Vinke-De Kruijf, M.E. Heim LaFrombois, B. Warbroek, J.C. Morris, S.M.M. Kuks, Climate-resilient water infrastructure: a call to action, Journal of Critical Infrastructure Policy 5 (1) (2024) 17–29, https://doi.org/10.1002/jci3.12017.
[124] F. Gebresenbet, A. Kefale, Traditional coping mechanisms for climate change of pastoralists in South Omo, Ethiopia, IJTK 11 (4) (2012) [October 2012], http://nopr.niscpr.res.in/handle/123456789/14945.
[125] G. Jónsson, The environmental factor in migration dynamics: a review of African case studies, IMI Working Paper Series 21 (2010). https://www.migrationinstitute.org/publications/wp-21-10.
[126] K.K. Garg, L. Karlberg, J. Barron, S.P. Wani, J. Rockstrom, Assessing impacts of agricultural water interventions in the Kothapally watershed, Southern India, Hydrol. Process. 26 (3) (2012) 387–404.
[127] S.N. Ngigi, H.H. Savenije, F.N. Gichuki, Land use changes and hydrological impacts related to up-scaling of rainwater harvesting and management in upper Ewaso Ng'iro river basin, Kenya, Land Use Policy 24 (1) (2007) 129–140.
[128] M.F. Alam, M. McClain, A. Sikka, S. Pande, Understanding human–water feedbacks of interventions in agricultural systems with agent based models: a review, Environ. Res. Lett. 17 (10) (2022) 103003.
[129] S. Torhan, C.A. Grady, I. Ajibade, E.K. Galappaththi, R.R. Hernandez, J.I. Musah-Surugu, Global Adaptation Mapping Team, Tradeoffs and synergies across global climate change adaptations in the food-energy-water nexus, Earths Future 10 (4) (2022) e2021EF002201.
[130] S. Eriksen, J. Lind, Adaptation as a political process: adjusting to drought and conflict in Kenya's drylands, Environ. Manag. 43 (5) (2009) 817–835, https://doi.org/10.1007/s00267-008-9189-0.
[131] F.N. Gichuki, Water scarcity and conflicts: a case study of the upper Ewaso Ng'iro north basin, in: The Changing Face of Irrigation in Kenya: Opportunities for Anticipating Change in Eastern and Southern Africa, 2002, pp. 113–134.