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ORIGINAL PAPER

Projected future changes in food insecurity hotspots over the IGAD region of Eastern Africa

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Abstract

Food insecurity is a major issue in many parts of the world, driven by conflict, economic instability, environmental challenges, and poor governance processes. Understanding the impact of future rainfall extremes on areas already experiencing food insecurity is crucial. This study investigates how food insecurity hotspots (FIH), food crisis frequency, and duration will change in the near future (2021–2050) and far future (2071–2100) under Shared Socioeconomic Pathways scenarios (SSP1-2.6, SSP2-4.5, and SSP5-8.5). The study utilizes precipitation data from the Coupled Model Intercomparison Project Phase 6 (CMIP6) and FIH data from the NASA Socioeconomic Data and Applications Center (SEDAC). To calculate future exposure and vulnerability to FIH, as well as food crisis frequency and duration, weighted sum models were used. The results indicate that arid and semi-arid areas in northeastern Kenya, most of Somalia, zones in southeastern Ethiopia, most of Djibouti, and central and northern Sudan are highly vulnerable to future extreme rainfall events, an increase in FIH cases, and longer food crisis frequency and duration in the near future (2021–2050) and far future (2071–2100) under all scenarios. On the other hand, most districts in Uganda, southern and southwestern South Sudan, counties in western Kenya, and the majority of zones in western Ethiopia are projected to have very few FIH cases, low food crisis frequency, and duration in both the near and far future under all scenarios. These findings are crucial for early warning systems, humanitarian responses, and food security interventions. We recommend harnessing projected increases in rainfall for water harvesting in Kenya, as well as promoting cash and food crop production in central and western Ethiopia, central and northern Uganda, and most of South Sudan.

Keywords Food insecurity · Vulnerability · Hotspots · CMIP6 · IGAD region · East Africa

Introduction

The vulnerability to food insecurity varies globally and is influenced by climate change (Krishnamurthy et al. 2014; Ibok et al. 2019). African countries, in particular, have limited capacity to adapt to climate change and are at risk of acute food insecurity (Betts et al. 2018; Ibok et al. 2019). Food insecurity hotspots are regions where large populations face severe and persistent challenges in accessing sufficient, safe, and nutritious food (Walls et al. 2019). A food crisis normally occurs when a significant portion of a population faces acute food insecurity, leading to widespread hunger and malnutrition (Das 2021). These crises can have devastating effects on public health, economic stability, social structures, which results in recurrent food crisis frequency (Hardy et al. 2019). These food insecurity hotspots, frequency and duration are often characterized by a combination of factors including conflict, climate shocks, economic instability, and weak governance (Bedasa and Deksisa 2024).

Extreme rainfall events, such as droughts and floods, have become more frequent due to human activities and global warming (IPCC 2022). Understanding the factors that determine food security and assessing its impacts are crucial for informing mitigation and adaptation strategies,

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as well as policy development (Nef et al. 2022; Reynolds 2019; FAO 2016). The Intergovernmental Authority on Development (IGAD) region is particularly susceptible to changes in rainfall patterns due to both local and large-scale drivers (Omay et al. 2022; Nicholson 2017; Palmer et al. 2023). Evaluating past, present, and projected hotspots of food insecurity can help identify areas of high vulnerability and comprehend how communities cope with these challenges (Palmer et al. 2023). Changes in rainfall and temperature have significant implications for food production systems (Vervoort et al. 2014). Climate models are essential tools for studying climate-related hazards in sectors such as agriculture and food security (Betts et al. 2018), changes in ground water (Abdelkarim et al. 2024). Assessing the frequency and duration of future hotspots of food insecurity is essential for developing effective policies and initiatives to improve food security (Mathenge et al. 2023; Gebre and Rahut 2021; Sileshi et al. 2019).

Climate models are essential tools for understanding the climate system and informing actions to address climate change (Edwards 2011). The Climate Model Intercomparison Project Phase 6 (CMIP6) offers opportunities to enhance our understanding of climate change (Eyring et al. 2016). CMIP6 simulations and projections indicate an improvement in precipitation accuracy over East Africa compared to CMIP5 (Ayugi et al. 2021a; Ayugi et al. 2021b), instilling confidence in early warning information and projected hotspots based on climate change. Researchers in East Africa have utilized CMIP6 products to examine past and future changes in precipitation extremes (Ayugi et al. 2021b; Dike et al. 2022; Mbigi et al. 2022), wet days and dry spells (Omay et al. 2023b), drought patterns (Ayugi et al. 2022a), and population exposure (Ayugi et al. 2022b; Jiang et al. 2020).

Hunger and food insecurity are major challenges faced by East African countries (Omay et al. 2024). Both climatic and non-climatic factors contribute to food insecurity, affecting approximately 1 billion people worldwide (FAO 2018). Understanding the potential impact of extreme rainfall events on food security requires consideration of factors that influence food availability, access, and utilization, as well as how future climate changes could affect these aspects (Burke and Lobell 2010). Climatic determinants of food insecurity include changes in rainfall dates, length of rainy season (Omay et al. 2022), wet/dry days, wet/dry spells (Thoithi et al. 2021), total rainfall, rainfall intensity, frequency, and intensity of floods (Dike et al. 2022). These factors play a significant role in food and cash crop production (Stocks 2016), as well as food availability and accessibility through markets (John 2024). Studies conducted in Ethiopia, Kenya, and Tanzania show varying levels of food security due to climatic and non-climatic factors (Radeny et al. 2022).

Most of the published materials on food security in East Africa consist of review articles that focus on the current status of household food security. Research articles, on the other hand, delve into the different aspects of food security such as availability, accessibility, and utilization. However, these articles often fail to address how the situation will evolve in the near and distant future. Considering the nature of the issues and determinants of food security, hunger, and food insecurity in the IGAD region of eastern Africa (Omay et al. 2024), it is likely that the factors and circumstances contributing to current food insecurity will persist in the future, regardless of changes in climate. Surprisingly, there is a lack of evidence regarding the estimates of exposure under CMIP6 experiments and their potential impact on food security under common socioeconomic pathways like low (SSP1-2.6), medium (SSP2-4.5), and high emission (SSP5-8.5).

To the best of our knowledge, this study is the first to utilize CMIP6 models in order to assess the spatial patterns of future food insecurity hotspot frequencies and durations. By doing so, we aim to fill the existing gap in the literature. Therefore, this paper aims to address the following questions: (a) What might the spatial patterns of exposure look like in the future? How will past and present food insecurity hotspots be affected by projected exposure? How might the frequency and duration of food insecurity hotspots change in response to changes in total rainfall, rainfall intensity, wet days, wet spells, dry days, dry spells, RODs, RCDs, LRS, and the Standardized Precipitation Index (SPI) during the near future (2021–2050) and far future (2071–2100) under the shared socioeconomic pathways (SSP) scenarios? The rest of this paper is structured as follows: "Data sources and methodology" section provides an overview of the data and methods used. "Results and discussions" section presents the results and discusses the findings, and the last section, concludes the study.

Data sources and methodology

Data

Climate models simulations and projections

Climate model simulations and projection datasets from the Coupled Model Intercomparison Project phase 6 (CMIP6) were analyzed. These models were chosen based on their performance in the Intergovernmental Authority on Development (IGAD) region (Fig. 1), as validated by Omay et al. (2023a). Table 1 presents the list of climate model simulations and projections used. For more detailed information, including the area of study, list of 23 models, 10 best performers, institutions, model names, resolutions, and first

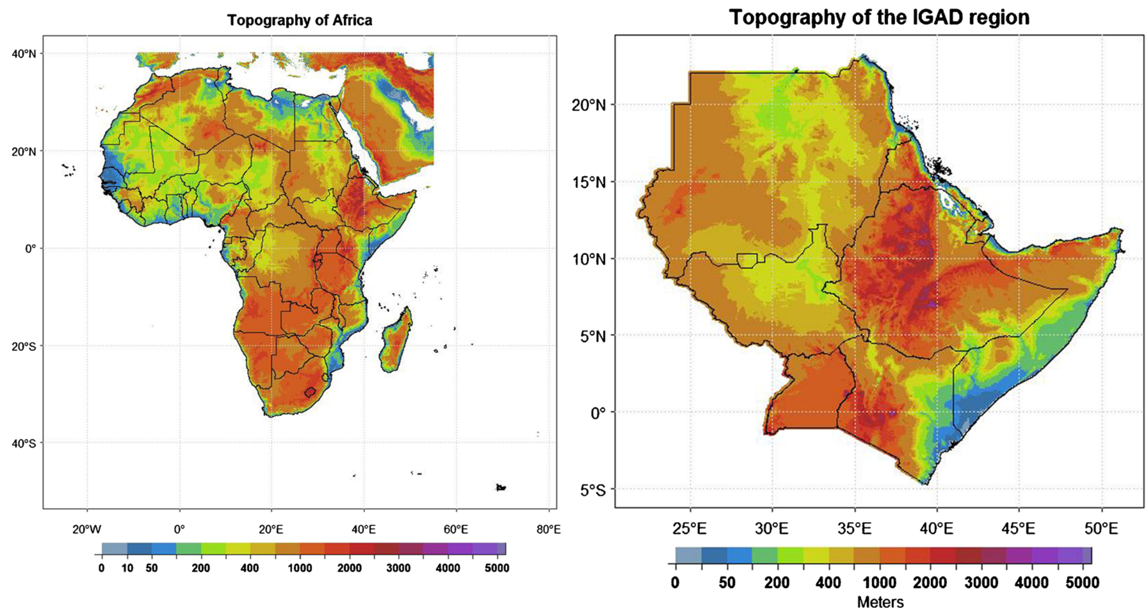


Fig. 1 The map of topography of the Intergovernmental Authority on Development (IGAD) region. The digital elevation model (DEM) datasets were retrieved from shuttle radar topography Mission (SRTM) 90 m spatial resolution http://dds.cr.usgs.gov/srtm/. Accessed on 11 January 2024

Table 1 List of the top ten CMIP6 performances over the IGAD region that were used to calculate the Multi-Model Ensemble (EnsMean), together with the names, institutions, and spatial resolutions of the models

	CMIP6 Model Name	Institution	Country	Coarse resolution
1	BCC-CSM2-MR	BBC	China	1.1° × 1.1°
2	CMCC-CM2-HR4	CMCC	Italy	0.942° × 1.25°
3	EC-Earth3	EC-Earth Consortium	Europe	0.7° × 0.7°
4	GFDL-ESM4	NOAA-GFDL	USA	1.3° × 1°
5	HadGEM3-GC31-MM	MOHC	UK	0.942° × 1.25°
6	INM-CM5-0	INM	Russia	2° × 1.5°
7	IPSL-CM6A-LR	IPSL	France	2.5° × 1.3°
8	MIROC6	JAMSTEC	Japan	1.4° × 1.4°
9	**NorESM2-MM**	NCC	Norway	0.94° × 1.25°
10	TaiESM1	CcliCS	Taiwan	1.25° × 0.94°

member realization outputs, as well as the mathematical formulas used in the validation, refer to the studies by Omay et al. (2023a) and Omay et al. (2023a), Omay et al. (2023b).

Food insecurity hotspots

To anticipate future changes in patterns of vulnerability to food insecurity, we utilized the Food Insecurity Hotspots (FIH) data from the NASA Socioeconomic Data and Applications Center (SEDAC). These datasets are based on food insecurity indicators from the Famine Early Warning Systems Network (FEWS NET), which have been re-processed by the Center for International Earth Science Information Network—CIESIN—Columbia University. The FIH datasets provide information on the intensity and frequency of food insecurity between 2009 and 2019(Center for International Earth Science Information Network—CIESIN—Columbia University 2020), as well as identify hotspot regions that have experienced recurrent food insecurity events. These FIH gridded datasets are derived from subnational food security analyses conducted by FEWS NET. In this study, we have adopted the five categories of food insecurity, as defined by the Famine Early Warning Systems Network (FNFIS) and integrated phase classifications (IPC): Minimal, Stressed, Crisis, Emergency, and Famine. However, for the purpose of this study, we have focused specifically on the food crisis category in order to examine how the FIH, food crisis frequency, and duration are projected to change in the near future (2021–2050) and the distant future (2071–2100)

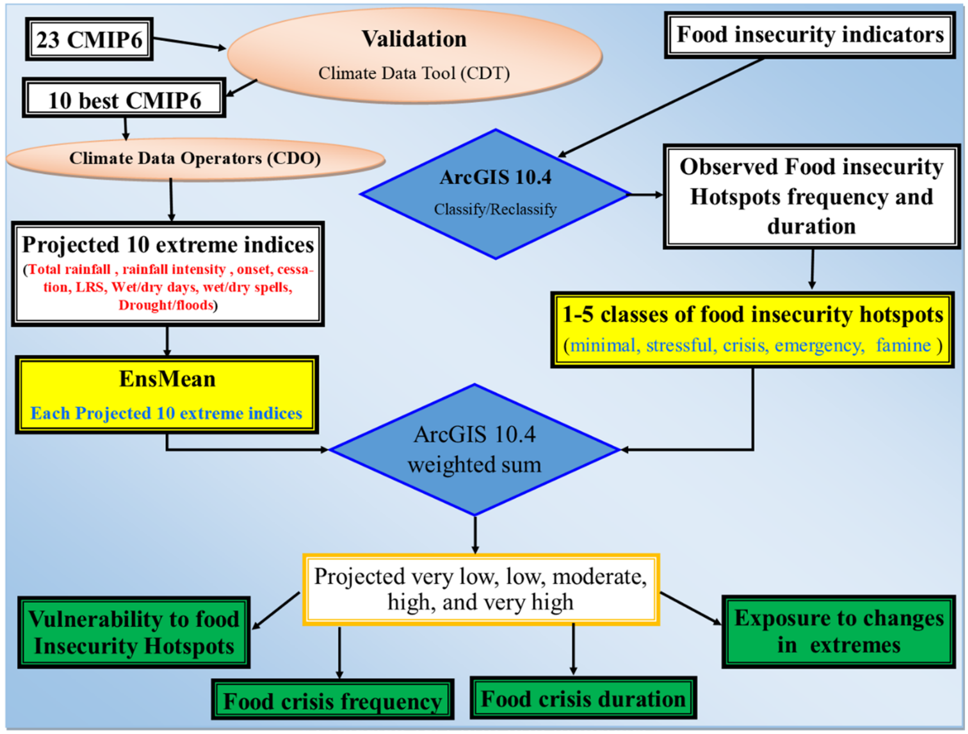


Fig. 2 Flipchart illustrating how projected food insecurity hotspots, food crisis frequency and duration computed

Table 2 Criteria for exposure to future extreme rainfall events

Exposure index	< 0.2	0.2–0.4	0.4–0.6	0.6–0.8	> 0.8
Severity of exposure	Very low	Low	Medium	High	Very high

under different Shared Socioeconomic Pathways (SSP1-2.6, SSP2-4.5, and SSP5-8.5).

Methods

Projected extreme rainfall events

The study examines changes in patterns of ten extreme rainfall events that impact food security, such as total rainfall, rainfall intensity, wet days, dry days, wet spells, dry spells, Standardized Precipitation Index (SPI), rainfall onset and cessation dates, and rainy season length. These changes are calculated for each of the ten selected models. Additionally, a Mult-Models Ensemble (MME) is computed for each extreme rainfall event during three time periods: the baseline period (1985–2014), near future (2021–2050), and far future (2071–2100) under three different scenarios (SSP1-2.6, SSP2-4.5, and SSP5-8.5). The study calculates the average or mean state, change, and rate of changes for each of the ten extreme rainfall events on annual and seasonal (DJF, MAM, JJAS, and OND) timescales. Wet/dry days and spells, as well as rainfall intensity, are defined based on specific criteria and a threshold of at least 1 mm for a rainy day. The threshold for onset is a total rainfall of 20 mm over 5 days, with at least 3 rainy days and a dry spell not exceeding 7 days in the next 21 days. The threshold for cessation is accumulated rainfall of less than 0.5 of the evapotranspiration over 10 days. The length of the season is determined by the number of days between the onset and cessation dates. To address resolution discrepancies among the ten CMIP6 models, all datasets were adjusted by scaling down their resolutions to a uniform scale of ten kilometers (0.1 degrees). This rescaling process utilized the bilinear interpolation technique as described by Song and Yan (2022). For more detailed mathematical information, formulas, expressions, and spatial patterns related to onset, cessation, and season length, refer to the study by Omay et al. (2023a), The evaluation of models, best performance

Table 3 Criteria for vulnerability to food insecurity

Vulnerability index	< 0.2	0.2–0.4	0.4–0.6	0.6–0.8	> 0.8
Severity of vulnerability	Very low vulnerability	Low vulnerability	Medium vulnerability	High vulnerability	Very high vulnerability

Table 4 Criteria for vulnerability to food crisis

Vulnerability index	< 0.2	0.2–0.4	0.4–0.6	0.6–0.8	> 0.8
Severity of frequency	Very low frequency	Low frequency	Medium frequency	High frequency	Very high frequency
Severity of duration	Very low duration	Low duration	Medium duration	High duration	Very high duration

selection, and formulas, expressions, and spatial patterns related to wet/dry days, wet/dry spells, and SPI can be found in the study by Omay et al. (2023b).

Baseline food insecurity hotspot, frequency and duration

The dataset described in "Food insecurity hotspots" section was used to plot the regional characteristics of Food Insecurity Hotspots (FIH) for each year from 2009 to 2019. These patterns show the prevalence and severity of food insecurity, as well as the locations of hotspots that experience multiple food insecurity incidents due to climatic and non-climatic factors. To facilitate comparison, the ArcGIS 10.4 classify function was used to arrange the spatial patterns of FIH, FIH frequency, and FIH duration values into 1–5 classes. The reclassify function was

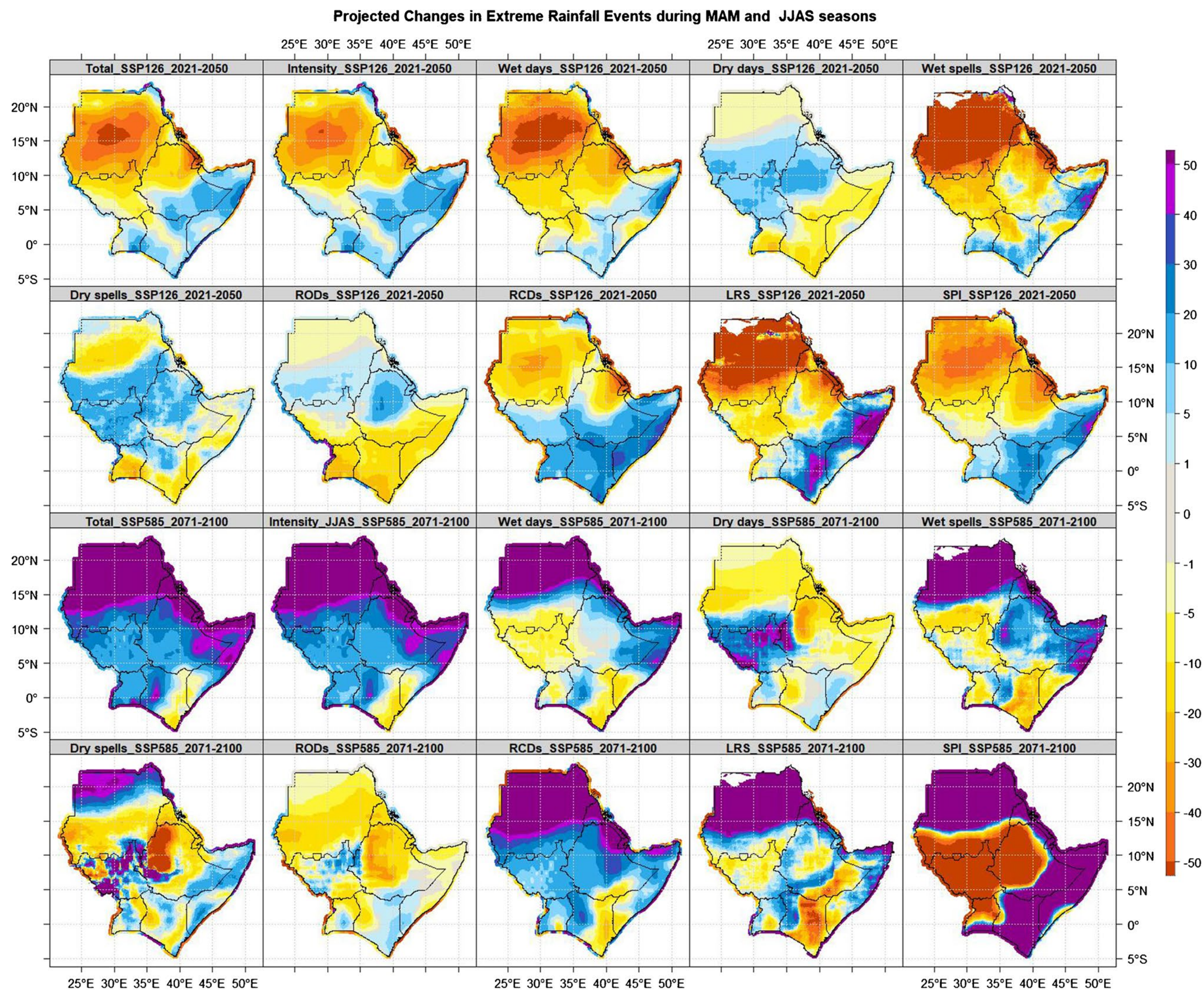


Fig. 3 Spatial patterns of projected changes in 10 extreme rainfall events (total rainfall, rainfall intensity, wet days, dry days, wet spells, dry spells, Rainfall Onset Date (RODs), Rainfall Cessation Dates (RCDs), Length of Rainy Season(LRS) and Standardized Precipitation Index (SPI). The analysis is conducted for the seasons of MAM under SSP1-2.6 (first and second row) and JJAS under SSP5-8.5 (third and fourth row)

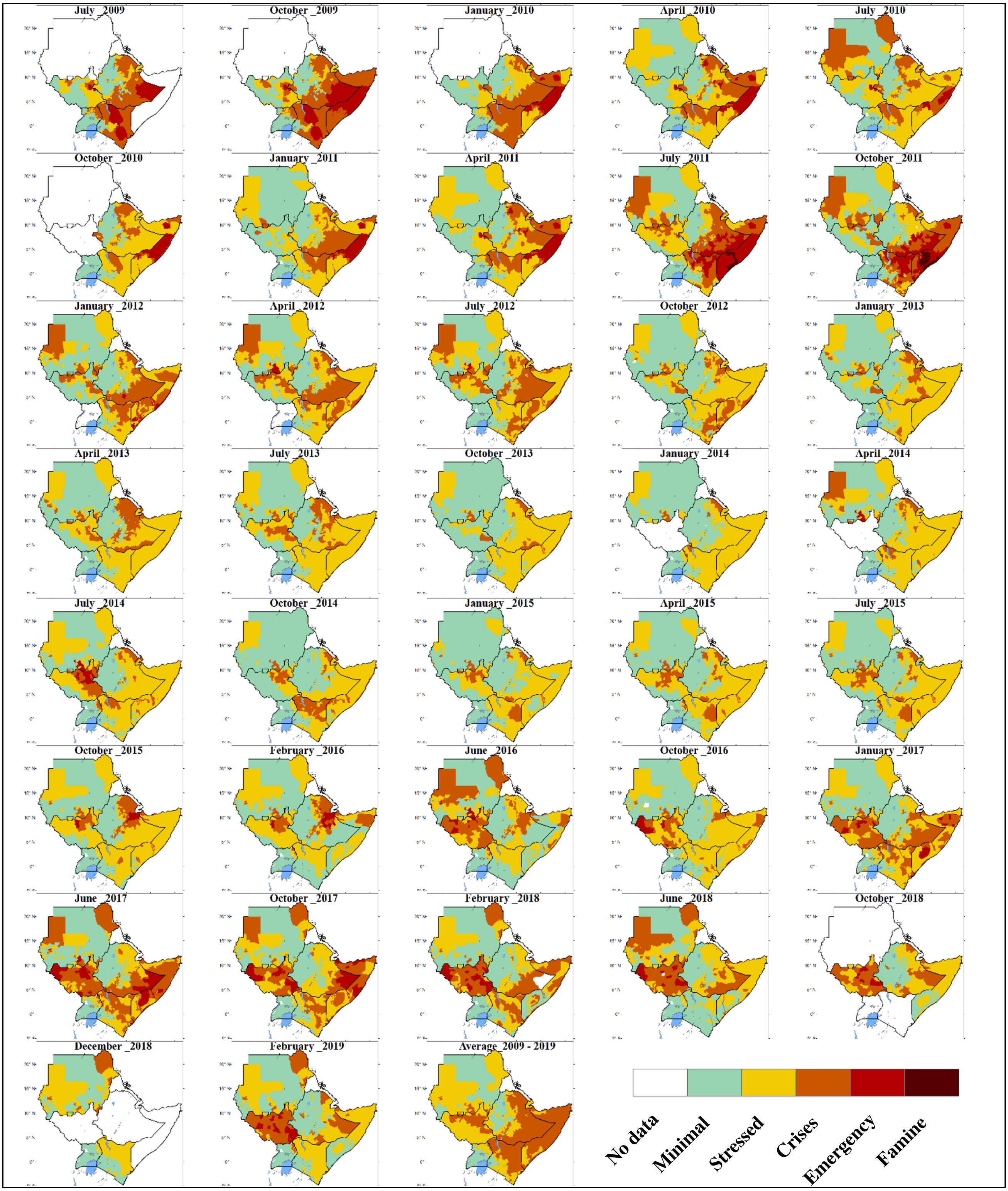


Fig. 4 Spatial patterns of Food Insecurity Hotspots (FIH) for each reporting period of January, June-July, and October between 2009–2019 over IGAD region. The last two maps in column five are mean average (**a**) and variability (**b**)

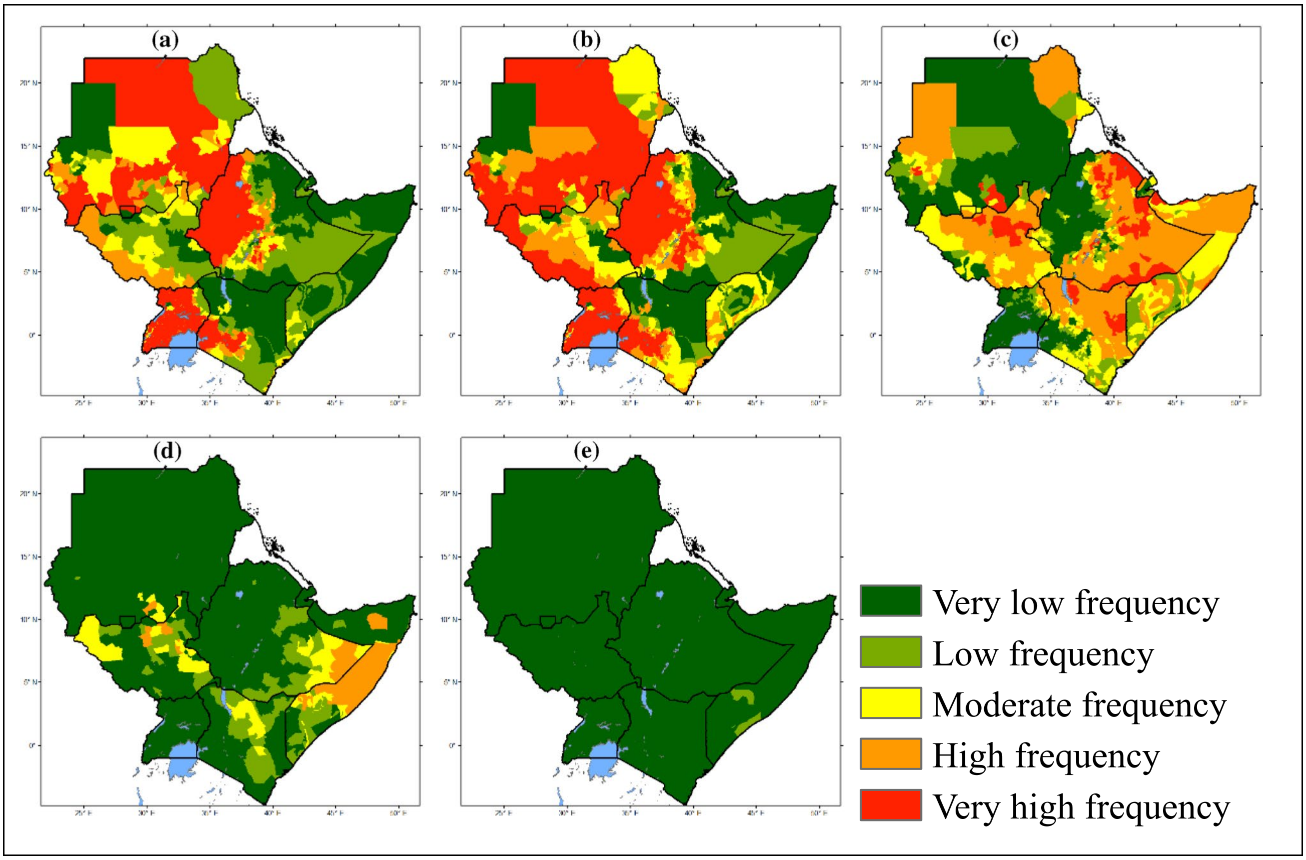


Fig. 5 Spatial patterns of Food insecurity frequency: (**a**) minimal, (**b**) stressed, (**c**) crises, (**d**) emergency and (**e**) famine over the 10 years between 2009 and 2019

then used to scale FIH values from 1–5, with 1, 2, 3, 4, and 5 representing minimal, stressful, crisis, emergency, or famine categories according to the Integrated Food Security Phase Classification (IPC). The FIH frequency and duration values were reclassified into very low, low, moderate, high, and very high frequency, while the FIH duration values were reclassified into very low, low, moderate, high, and very high duration. The variability in FIH is classified into three categories: low, moderate, and high variability.

Projected exposure to extremes

In order to calculate the projected exposure and vulnerability to food insecurity hotspots frequency and duration, as described in "Projected exposure to extremes" section and "Future vulnerability to food insecurity hotspots" sub-sections and "Future vulnerability to food crisis frequency and duration", this study utilized the concepts, criteria, and classification for vulnerability to climate risk developed by Krishnamurthy et al., (2014). These were employed as a tool to compute the Hunger and Climate Vulnerability Index. To assess the future changes in ten extreme rainfall events (discussed in "Projected extreme rainfall events" sub-section), we used them to determine the current and projected spatial patterns of exposure to extreme rainfall events. It was assumed that each index (ten extreme rainfall events) contributes 10% equally (layers with equal importance) to the food security hazard level. To facilitate comparison, the ArcGIS 10.4 classify function was utilized to arrange the ten extreme rainfall events related to food security values into five classes (1–5). The reclassify function was then employed to scale the values from 1–5, with 1, 2, 3, 4, and 5 representing very low, low, moderate, high, and very high exposure, respectively (Fig. 2). Finally, the ArcGIS 10.4 weighted sum function was used to calculate the percentage influence (%) of each of the ten extreme rainfall events in relation to food security. The final outputs are expressed as relative exposure and scaled into five categories (classes), with each class representing 20% of the values: < 0.2, 0.2–0.4, 0.4–0.6, 0.6–0.8, and > 0.8, which correspond to very low, low, medium, high, and very high exposure levels, as shown in Table 2.

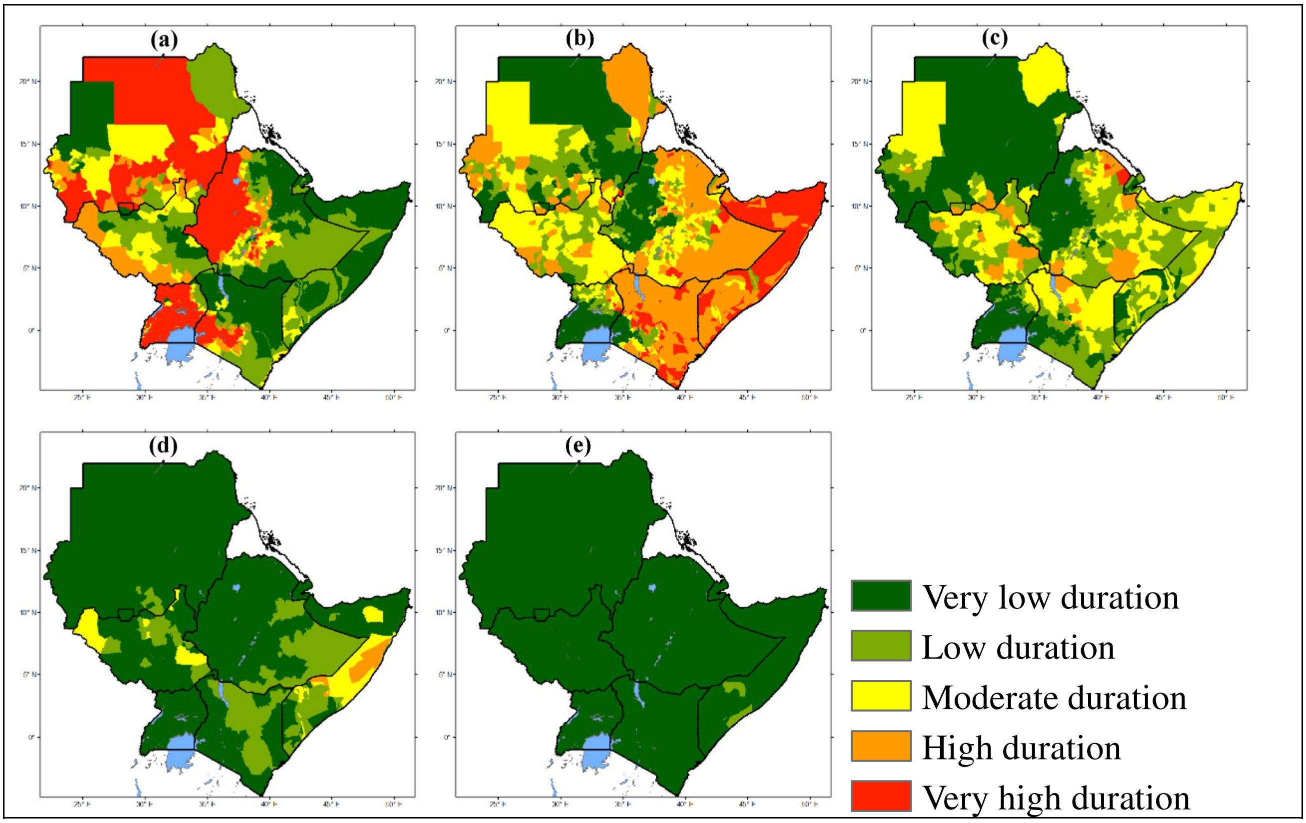


Fig. 6 Spatial patterns of Food insecurity duration: (**a**) minimal, (**b**) stressed, (**c**) crises, (**d**) emergency and (**e**) famine over the 10 years between 2009 and 2019

Future vulnerability to food insecurity hotspots

The mean, or arithmetic mean, is used to calculate the spatial average of 10 years of data for each Food Insecurity Hotspot (FIH), including baseline average and variability. The ArcGIS 10.4 classify function is then used to organize the spatial patterns of exposure to changes in rainfall from "Projected extreme rainfall events" subsection and the FIH baseline values from "Baseline food insecurity hotspot, frequency and duration" subsection into 1–5 classes for easy comparison (Fig. 2). The reclassify function is applied to scale the values from 1–5, with 1 representing very low vulnerability and 5 representing very high vulnerability. The ArcGIS 10.4 weighted sum function is used to calculate the percentage influence of each exposure and FIH baseline. It is important to note that there are various factors at the regional, national, and local levels that contribute to the current vulnerability to food insecurity, including demographic, social, environmental, biological, cultural, developmental challenges, and political aspects. For the future, it is assumed that these factors will either remain unchanged or experience a percentage change of 10%, 25%, and 50% under the SSP1-2.6, SSP2-4.5, and SSP5-8.5 emission scenarios, respectively. In order to assess the future pattern of vulnerability to FIH, the final outputs are ranked and scaled from 1–5, with 1 representing very low vulnerability and 5 representing very high vulnerability (Table 3).

Future vulnerability to food crisis frequency and duration

The mean, specifically the arithmetic mean, is used to calculate the spatial average of FIH frequency and duration over a period of 10 years. Among the five categories of FIH, we have chosen to focus on the food crisis category in order to analyze the spatial patterns of both frequency and duration. This category was selected because it represents the middle point between the minimal and stressed categories, which have lower rankings in terms of risk and emergency. These categories have less frequent and shorter duration occurrences. To facilitate comparison, the ArcGIS 10.4 classify function is employed to organize the spatial patterns of exposure, FIH food crisis frequency, and duration values into 1–5 classes. These classes are then further scaled using the reclassify function, with values ranging from 1–5(Fig. 2). These values represent very low, low, moderate, high, and very high frequency and duration, respectively. The ArcGIS 10.4 weighted sum function is used to calculate the percentage influence (%) of each exposure, FIH, food crisis frequency, and duration. This calculation is based on the assumption that the probability of the current observed FIH, food crisis frequency, and duration will not change (0%), or will change by 10%, 25%, and 50% in the future under SSP1-2.6, SSP2-4.5, and SSP5-8.5 emission scenarios. The final outputs were ranked from smallest to largest values and scaled from 1–5, with each number representing very low, low, moderate, high, and very high frequency and duration, respectively (Table 4).

The Climate Data Tool(CDT) developed by IRI through ENACTS project (Dinku et al. 2022), and ArcMap10.4 used to compute and visualized the spatial maps of exposure, vulnerability to FIH, food crisis frequency and duration.

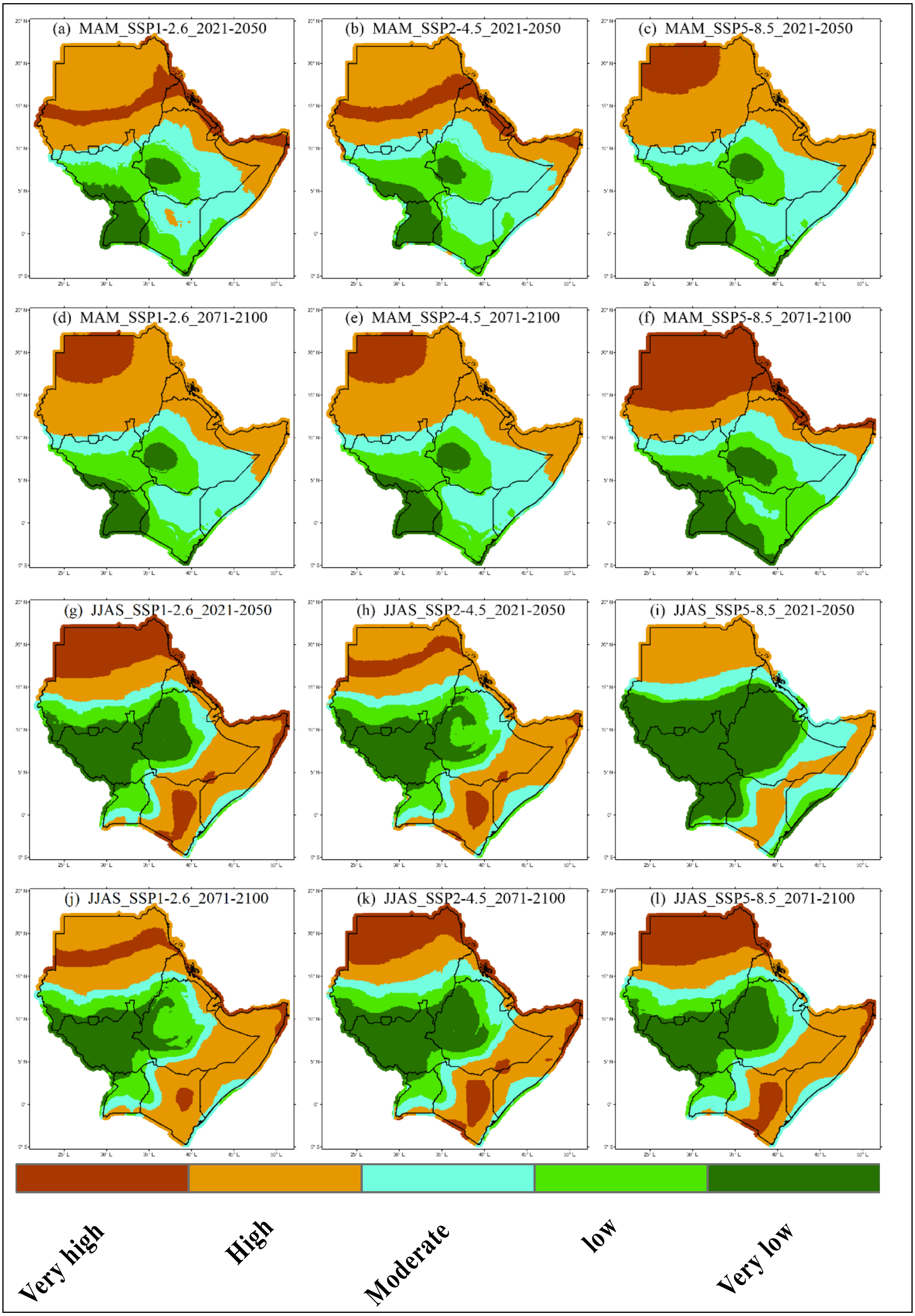
Results and discussions

Projected changes in extremes rainfall events

The percentage of change in various extreme indices, such as total rainfall, rainfall intensity, wet days, wet spells, dry days, dry spells, RODs, RCDs, LRS, and SPI, is presented in Fig. 3. These changes are assessed to understand the spatial patterns during the MAM and JJAS seasons under different scenarios: SSP1-2.6 for the near future (2021–2050) and SSP5-8.5 for the far future (2071–2100). The results indicate a 10–30% decrease in total rainfall, rainfall intensity, wet spells, RCDs, LRDs, and SPI over Sudan, the northern parts of South Sudan, and northern Ethiopia during MAM under SSP1-2.6 in the near future. The intensity of drought (SPI) is projected to increase by 10–20% over Sudan, South Sudan, central, and northern Ethiopia during MAM under SSP1-2.6 in the near future (2021–2050) due to decreased rainfall intensity, wet days, wet spells, rainfall, and an increase in dry days. For MAM under SSP1-2.6 in the near future, a 5–50% increase in total rainfall, rainfall intensity, wet days, and wet spells is projected over most parts of Kenya, southeastern Ethiopia, and Somalia. However, during JJAS under SSP5-8.5 in the far future, a 10–50% increase in total rainfall, rainfall intensity, early-onset RODs, and late RCDs is projected over Sudan, South Sudan, and Ethiopia. At the end of the century under SSP5-8.5 scenarios, more than a 50% increase in total rainfall is projected over semi-arid and desert areas in Sudan. This increase is due to higher rainfall intensity, an increase in wet days, and longer wet spells. Studies by Ayugi et al. (2021a) and Dike et al. (2022) suggest that there will be an increase in dry days (CDD) and a decrease in wet days during MAM and OND towards the latter part of the twenty-first century (2081–2100). The Turkana and Karamoja regions in Kenya and Uganda, which are highly vulnerable to climate change and variability, are projected to experience less rainfall during MAM due to decreased rainfall intensity, wet days, wet spells, an increase in dry days, and longer dry spells. This will contribute to an increase in aridity and semi-desert climate conditions, making the regions more vulnerable. These findings partly align with the study by Oscar et al. (2022), which projected an increase in total rainfall in March and a decrease in April and May over most parts of Uganda. The study also indicated an increase in rainfall variability across East Africa (Mbigi et al. 2022). The increase (or decrease) in the percentage of total rainfall and the change in intensity can be attributed to factors such as early RODs (or late), late RCDs (or early), prolonged LRS (or shorter), decreased (or increased) rainfall intensity, more wet days (or fewer dry days), and changes in dry days and dry spells. Additionally, the frequency of floods is projected to increase (or drought frequency and intensity to decrease) over most parts of the region during MAM and JJAS under low scenarios (SSP1-2.6) and high scenarios (SSP5-8.5) in the near and far future. However, contrary to Contrary to Ayugi et al. (2022a), who projected more frequent and intense droughts in the dry regions of East Africa in the far future. In general, there is strong evidence suggesting that climate change will lead to an increase in the intensity and frequency of extreme rainfall events in many areas. However, it is important to note that there is also considerable variation between regions and over time (Gebrechorkos et al. 2020). To effectively prepare for these changes, it is crucial to have access to accurate and timely information regarding current and projected changes in extreme events, as well as areas at higher risk, resilient food infrastructure, and adaptive management practices (Alkhalifah et al. 2023).

Baseline average and variability of food insecurity hotspots

To establish a baseline average of food insecurity in hotspots, it is necessary to analyze consistent and comparable data over time. Figure 4 illustrates the spatial patterns of Food Insecurity Hotspots (FIH) for each reporting period (January, June-July, and October) from 2009 to 2019 in the IGAD region. The results reveal an arid, semi-desert climate in northern, eastern, and northeastern Kenya, southeastern Ethiopia, most of Somalia, and Sudan. These regions consistently face food stress, crisis, and emergencies. The rainfall patterns starting from March to November in Uganda, most parts of South Sudan (April–October), and the highlands of western Ethiopia and Kenya, along with rain belts in southern Sudan, contribute to the persistence of minimal food insecurity hotspots. A study by Natamba et al. (2018), supports this, showing that fluctuating rainfall patterns in Eastern Africa are a major cause of food


(a) MAM_SSP1-2.6_2021-2050
(b) MAM_SSP2-4.5_2021-2050
(c) MAM_SSP5-8.5_2021-2050
(d) MAM_SSP1-2.6_2071-2100
(e) MAM_SSP2-4.5_2071-2100
(f) MAM_SSP5-8.5_2071-2100
(g) JJAS_SSP1-2.6_2021-2050
(h) JJAS_SSP2-4.5_2021-2050
(i) JJAS_SSP5-8.5_2021-2050
(j) JJAS_SSP1-2.6_2071-2100
(k) JJAS_SSP2-4.5_2071-2100
(l) JJAS_SSP5-8.5_2071-2100
Very high
High
Moderate
low
Very low

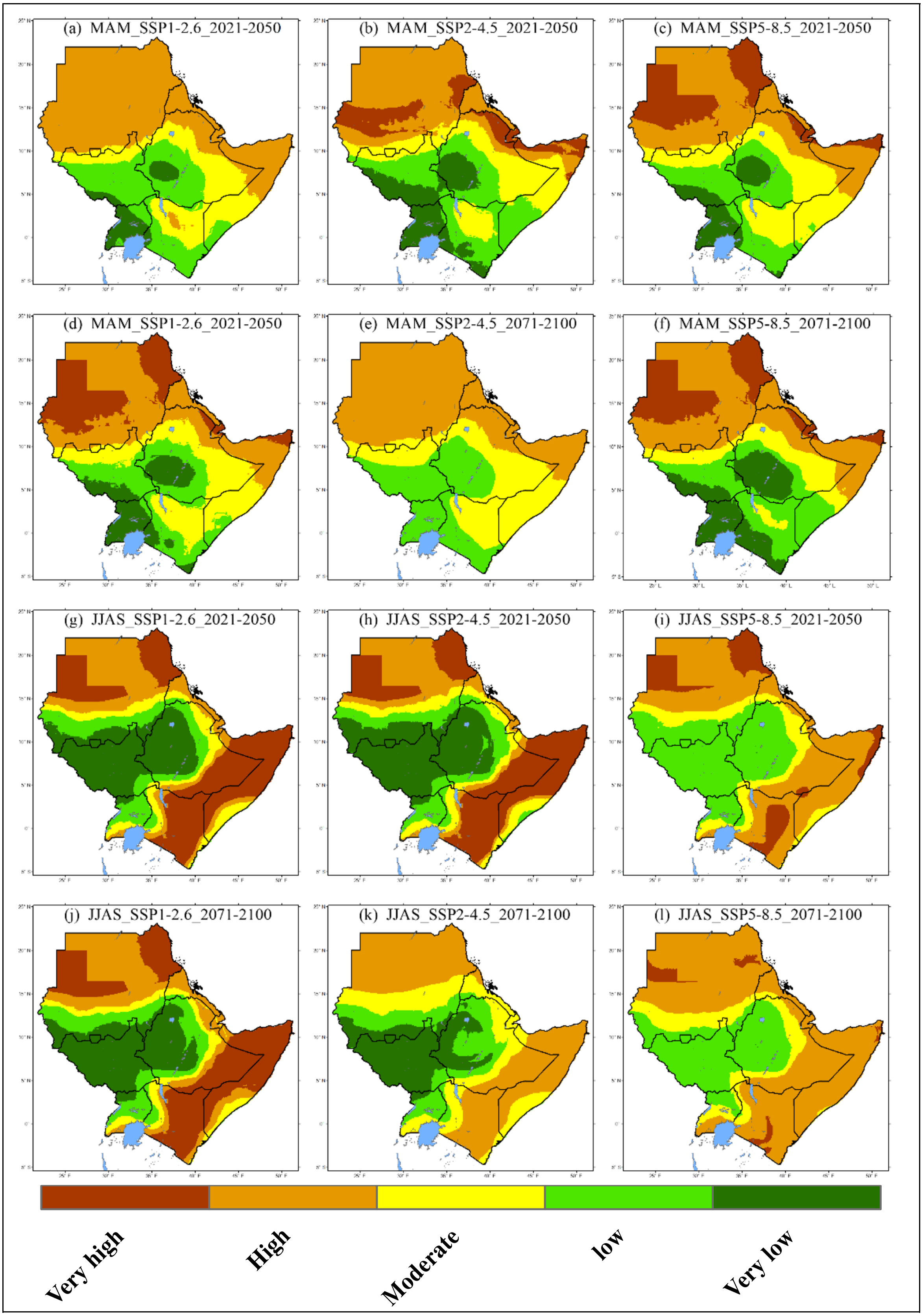
◀**Fig. 7** Projected changes in exposure to extreme rainfall events (changes in total rainfall, rainfall intensity, wet days, dry days, wet spells, dry spells, rainfall onset, cessation dates, and rainy season length and Standardized Precipitation Index (SPI)) during MAM (first and second row) and JJAS (third and fourth row). The analysis was conducted for near future 2021–2050 (first and third row), and far future 2071–2100 (second and fourth row) under the SSP1-2.6(first column), SSP2-4.5(second column) and SSP5-8.5 scenarios (third column)

insecurity. In South Sudan, there is a persistent food crisis in some parts of Upper Nile, Unity, and Jonglei states due to internal conflicts that occurred between 2009 and 2012 involving government and rebel forces led by George Athor and Johnson Olong (Krause 2019). However, the main driver of food insecurity in South Sudan from 2015 to 2019 is the devastating conflict that began in 2013 between President Kiir and his deputy, Reik Machar, which still has lingering consequences of insecurity and related poverty issues (Krause 2019). Minimal food insecurity hotspots were observed in the northern parts of Sudan, primarily due to the desert climate in these areas and the absence of assets at risk. During the first reporting period (January–February), the availability of food options in the red coastal parts of Sudan reduced food insecurity, stress, and crisis, thanks to rainfall patterns during the winter season (November-January). However, political instability and street protests in eastern cities such as Port Sudan and Kasala between 2018 and 2019 plunged the region into a food crisis and emergency category. The effects of the drought in 2011 over Somalia, northeastern Kenya, and southeastern Ethiopia had a clear and significant impact on food crises and emergencies for 10–12 consecutive reporting periods (2010–2012). Early onset, late cessation, longer rainy seasons, fewer dry days, more wet days, and consecutive spells were the main factors contributing to food security (no recorded incidents of food insecurity) in most parts of Uganda, western Kenya, and western Ethiopia throughout the four reporting periods examined over the 10-year study period, as a result of local food production. Despite the presence of fertile land and favorable rainfall patterns, South Sudan experienced food insecurity in July, October, and January, highlighting the significant impact of conflict and political instability on the country's food security systems. In other words, conflicts can push a region or country into social and political conflicts and food insecurity, even during the main agricultural season or crop harvest (Gemechu 2023).

Figures 5 and 6 present the average patterns of food insecurity hotspot frequency and duration over the 10-year period from 2009 to 2019. The areas with the lowest food insecurity hotspots, highest minimal category of FIH frequencies (Fig. 5a), and highest FIH minimal duration (Fig. 6a) were the Western Kenya and Ethiopian highlands, as well as southern and central Uganda. These areas had high food production due to prolonged rainy season, which typically started in March and continued until November (Omay et al. 2022). They also experienced prolonged wet days and consecutive wet spells (Omay et al. 2023b). The frequency and duration of food stress and crisis categories in ASALs in Eritrea, Djibouti, Kenya, Somalia, and southeast Ethiopia were very low. Similarly, the frequency and duration of famine category of food insecurity were very low in East Africa. Only certain districts in central Somalia experienced moderate to high frequency (Fig. 5d, e) and longer duration of famine (Fig. 6d, e) due to food emergencies and drought. The drought, which began in 2010 and was declared a national disaster by Somali authorities in 2011, resulted in between 244,000 and 273,000 deaths from hunger in southern and central Somalia, according to FAO and FEWS data (Checchi and Robinson 2013; Shukla et al. 2014). Due to less total rainfall, longer dry days, and longer consecutive dry spells on annual and seasonal scales, these areas cannot go for many reporting periods without reporting food stress and crisis. The frequency and duration of food insecurity confirmed the significant impact of extreme rainfall events on sustainable food security. The patterns of food insecurity hotspot frequency and duration between 2009 and 2019 highlighted the role of non-climatic factors in influencing food security in the future. The spatial patterns of food insecurity hotspots suggest that political instability is the main cause of the very high frequency and prolonged duration of food insecurity in East Africa. Additionally, conducive climatic conditions for crop failure, conflict, and poor governance contribute to hunger and food insecurity in all five Integrated Food Security Phase Classifications (IPC) categories in East Africa.

Projected future exposure to change in extreme rainfall

If the climate is changing in the present and we expect more significant changes in the future, how will the future patterns of exposure, as the main components of vulnerability, appear under different scenarios? To answer this question, we developed the ArcGIS weighted sum model. We assumed that each of the ten extreme rainfall events (total rainfall, rainfall intensity, wet days, dry days, wet spells, dry spells, Rainfall Onset Date (RODs), Rainfall Cessation Dates (RCDs), Length of Rainy Season (LRS), and Standardized Precipitation Index (SPI) computed in Fig. 3) has an equal weight influence of 10%. We computed the patterns for the MAM and JJAS seasons for the near and far future under SSP1-2.6, 2–4.5, and SSP5-8.5 scenarios. The results indicate that most parts of Uganda, southwestern South Sudan, and the highlands of southwestern Ethiopia and Kenya are projected to have a very low likelihood of susceptibility (exposure) to changes in extreme rainfall events under the SSP1-2.6,


(a) MAM_SSP1-2.6_2021-2050
(b) MAM_SSP2-4.5_2021-2050
(c) MAM_SSP5-8.5_2021-2050
(d) MAM_SSP1-2.6_2021-2050
(e) MAM_SSP2-4.5_2071-2100
(f) MAM_SSP5-8.5_2071-2100
(g) JJAS_SSP1-2.6_2021-2050
(h) JJAS_SSP2-4.5_2021-2050
(i) JJAS_SSP5-8.5_2021-2050
(j) JJAS_SSP1-2.6_2071-2100
(k) JJAS_SSP2-4.5_2071-2100
(l) JJAS_SSP5-8.5_2071-2100
Very high
High
Moderate
low
Very low

◂**Fig. 8** Projected changes in food insecurity hotspots (50% influence) under projected changes in exposure to extreme rainfall events during MAM (first and second row) and JJAS (third and fourth row). The analysis was conducted for near future 2021–2050 (first and third row), and far future 2071–2100 (second and fourth row) under the SSP1-2.6(first column), SSP2-4.5(second column) and SSP5-8.5 scenarios (third column)

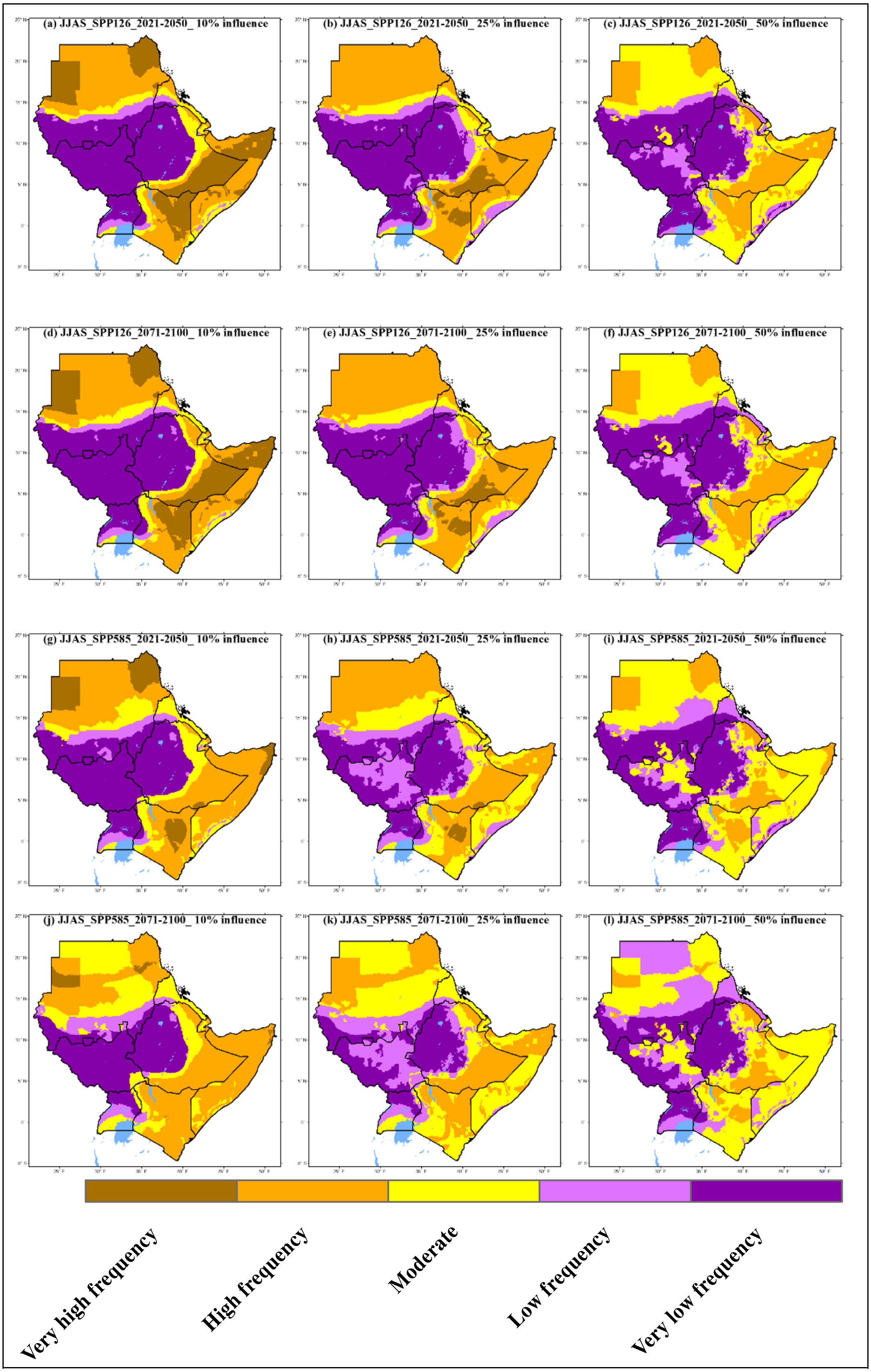
2–4.5, and SSP5-8.5 scenarios (Fig. 7). This is due to the projected increase in the number of wet days (Tegegne and Melesse 2021), consecutive wet spells, and rainfall intensity, as well as a decrease in dry days and dry spells (Omay et al. 2023b). Central and northern Sudan, Eritrea, Djibouti, northeastern Ethiopia, and northern Somalia, on the other hand, are projected to have a very high to high susceptibility to food insecurity. This is because of aridity, an increase in dry days, and prolonged dry spells during the MAM season. Moreover, the susceptibility increases or decreases proportionally with the primary rainy season (dry season). For instance, eastern and northeast Kenya have a very high exposure during JJAS compared to the MAM season under different scenarios. Under the SSP5-5.8 scenario, the category of very low exposure (susceptibility) is expected to expand/increase (low risks) over South Sudan and western Ethiopia due to the projected increase in total rainfall, rainfall intensity, and the number of wet days. In a similar study, Ayugi et al. (2022b) used CMIP6 models to assess the exposure of the East African population to precipitation extremes at 1.5 and 2.0 °C warming levels. The analysis reveals that population changes have a more significant impact on future exposure than climate or climate-population changes. If these increased rainfall patterns are utilized effectively for water harvesting in Kenya and for increased food and cash crops in South Sudan and Ethiopia, the level of food insecurity will significantly decrease. There may also be an increase in agricultural exports to other parts of the world, leading to an improvement in the countries' GDP and contributing to the achievement of the primary sustainable development goals such as No Poverty, Zero Hunger, Good Health, and Well-Being in Africa Union Agenda 63, as well as the IGAD development, peace, and security goals.

Projected changes in food insecurity hotspots

Figure 8 illustrates the projected changes in current hotspots of food insecurity due to future changes in exposure to extreme rainfall events. This is done using an ArcGIS weighted sum model, which combines the hotspots of food insecurity from Fig. 4 with the exposure to 10 extreme rainfall events from Fig. 7. The assumption is that the current root causes of food insecurity hotspots will change by 10%, 25%, or 50% in the future under projected changes in exposure under different scenarios (SSP1-2.6, SSP2-4.5, and SSP5-8.5). However, since there were insignificant changes in the spatial patterns of 10%, 25%, or 50% influence, we present outputs that reflect a 50% influence. The results indicate that the current prevalence of high to very high food insecurity hotspots in northern Darfour and the Red Sea in Sudan, Eritrea, Djibouti, and northern Somalia will continue in the near future (2021–2050) during the MAM and JJAS seasons under SSP5-8.5. However, by the end of the century (2071–2100), the hotspots will be reduced in both seasons due to projected increases in rainfall patterns and reduced exposure to extreme events under SSP5-8.5. Additionally, the results show that under SSP2-2.5 for the near future and SSP5-8.5 for the far future, the current zones of very low susceptibility in southwestern South Sudan, western Ethiopia, and southern and central Uganda will continue to expand, covering a wider area. On the other hand, under SSP1-2.6 and SSP2-4.5, the very low cases of food insecurity hotspots during the JJAS season will decrease in both the near (2021–2050) and far (2071–2100) future. This means that more people will fall into the low food insecurity hotspot category rather than the extremely low category in these places. Furthermore, the vulnerability category of very high vulnerability to food insecurity will change to high vulnerability over most of Kenya, northeastern Ethiopia, and Somalia. This is due to projected increases in rainfall in southeast Ethiopia, Kenya, and Somalia, and a decrease in rainfall extremes over South Sudan and western Ethiopia (Omay et al. 2023b). These findings align with the results of Ayugi et al. (2022a), who reported an increase in extreme precipitation and population exposure indices over East Africa at 1.5 °C and 2.0 °C of global warming under both SSP2-4.5 and SSP5-8.5 scenarios.

Projected changes in the patterns of food crisis frequency

Figure 9 illustrates the current and projected patterns of food crisis frequency in East Africa during the JJAS season. These patterns are based on the outputs of the ArcGIS weighted sum model, which combines hotspots of food insecurity frequency (shown in Fig. 5c) with exposure to 10 extreme rainfall events (computed in Fig. 7). We examine the potential impact of adaptation measures on the frequency of food insecurity hotspots in the future, considering three thresholds: 10%, 25%, and 50%. These thresholds indicate the extent to which adaptation can influence the underlying causes of food insecurity, in relation to the projected changes in extreme precipitation patterns. The projections are made under the SSP1-2.6 and SSP5-8.5 scenarios for the near future (2021–2050) and the far future (2071–2100). The current results reveal the highest frequency of food crises in Sudan's Blue Nile and South Kordofan, South Sudan's wider Upper Nile region (Unity, Upper Nile, and Jonglei), eastern and northeast Kenya,

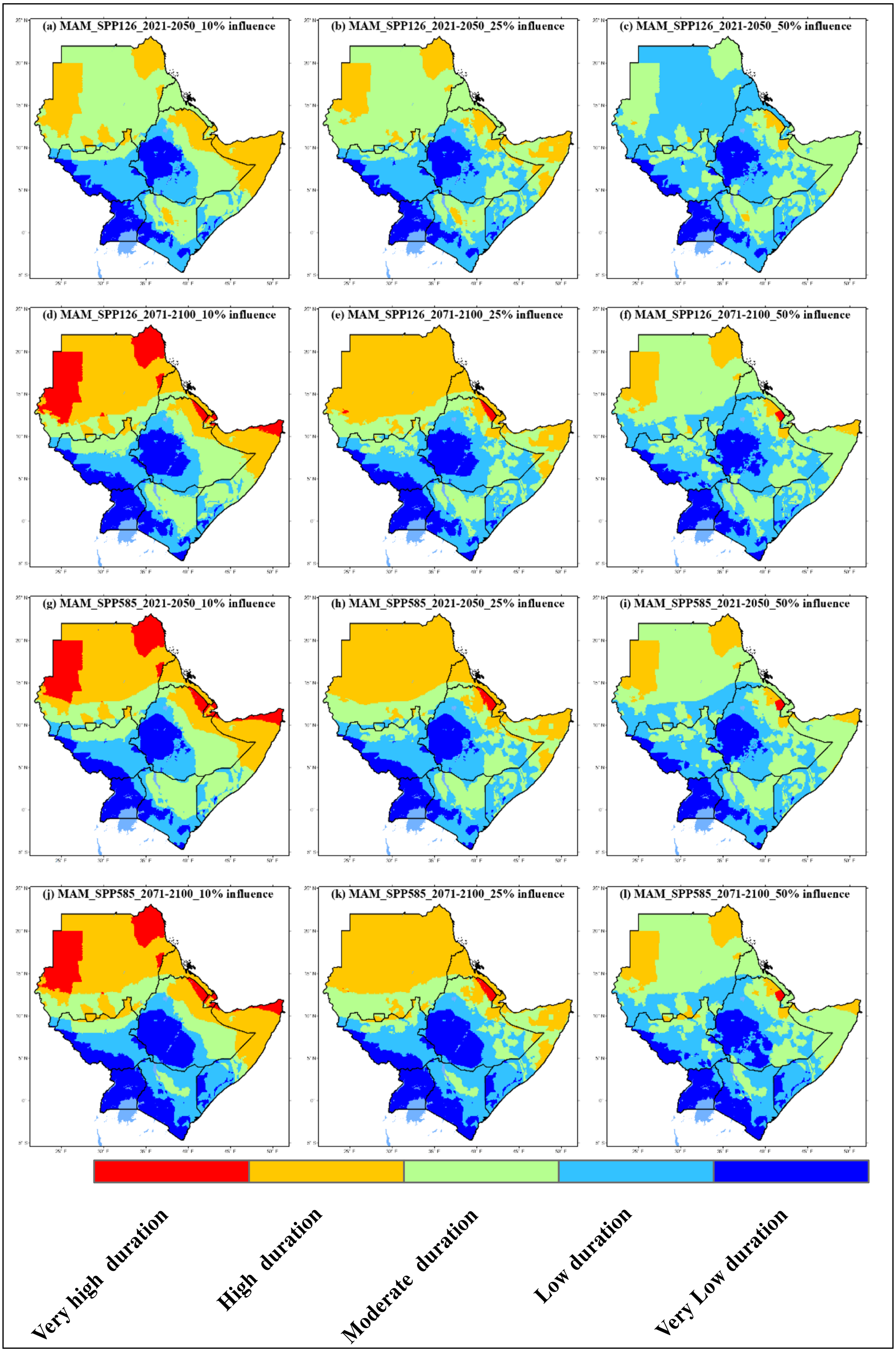

(a) JJAS_SPP126_2021-2050_ 10% influence
(b) JJAS_SPP126_2021-2050_ 25% influence
(c) JJAS_SPP126_2021-2050_ 50% influence
(d) JJAS_SPP126_2071-2100_ 10% influence
(e) JJAS_SPP126_2071-2100_ 25% influence
(f) JJAS_SPP126_2071-2100_ 50% influence
(g) JJAS_SPP585_2021-2050_ 10% influence
(h) JJAS_SPP585_2021-2050_ 25% influence
(i) JJAS_SPP585_2021-2050_ 50% influence
(j) JJAS_SPP585_2071-2100_ 10% influence
(k) JJAS_SPP585_2071-2100_ 25% influence
(l) JJAS_SPP585_2071-2100_ 50% influence
Very high frequency
High frequency
Moderate
Low frequency
Very low frequency

◂**Fig. 9** Projected changes in patterns of food crisis frequency under projected changes in exposure to extreme rainfall events associated with 10%, 25%, and 50% assumption of future changes in current root causes of food insecurity hotspots frequency. The patterns computed during JJAS under the SSP1-2.6(first and second tow) and SSP5-8.5 scenarios (third and fourth row)

southeast and northeast Ethiopia, and northern Somalia. These crises are caused by a combination of climatic and non-climatic factors. Political instability, such as fighting between the government and rebels, is the primary root cause in Unity, Upper Nile, Jonglei, the Blue Nile, and South Kordofan. Conflicts, crop failures, and poor governance are the main factors leading to food crises in eastern and northeast Kenya, southeast and northeast Ethiopia, and northern Somalia. Now, let's consider the impact of implementing adaptation measures to reduce the current non-climatic factors under the SSP1-2.6 and SSP5-8.5 scenarios. If we eliminate the root cause of political instability in the future in South Sudan, the food crisis will become a thing of the past. Similarly, if we invest 25% or more in addressing other underlying factors such as aridity, crop failures, and poor governance, the current very high food crisis category will shift to very low across most of the region. The key elements contributing to food insecurity in East Africa are violence, crop failures, and poor governance (Bedasa and Deksisa 2024). Therefore, if we allocate 50% of our resources to addressing these factors in eastern and northeast Kenya, southeast and northeast Ethiopia, and northern Somalia, the frequency of food crises will decrease from very high to moderate. Similarly, Somalia has been experiencing persistent droughts, conflicts, and economic challenges in recent years, which have led to repeated food crises affecting millions of people (Warsame et al. 2023). Likewise, Sudan is facing one of the world's worst humanitarian crises due to ongoing conflict, resulting in severe food insecurity and malnutrition. Additionally, South Sudan is grappling with civil war, economic collapse, and climatic shocks, leading to widespread hunger and displacement (Ensor 2022). Therefore, implementing adaptation measures to reduce or eliminate the root causes of food crises in Sudan, Somalia, and South Sudan will address the issues of food insecurity hotspots, frequency, and duration in the future.

Projected changes in the patterns of food crises duration

Figure 10 presents the projected duration of the food crisis during the MAM season for the near future (2021–2050) and far future (2072–2100) under SSP1-2.6 and SSP5-8.5. These projections are based on the ArcGIS weighted sum model outputs, which consider the hotspots of food insecurity duration shown in Fig. 6c, as well as the exposure to 10 extreme rainfall events presented in Fig. 7. The results show that most parts of Uganda, southwestern South Sudan, and western Ethiopia are expected to have a very low duration of food insecurity in both the near and far future, regardless of the SSP. Conversely, western Darfur and the Red Sea in Sudan are projected to have a very high duration of food insecurity. The projected duration of food crises varies significantly depending on the underlying causes, the region affected, and the response efforts (Bowen et al. 2021). This suggests that areas in East Africa with higher annual and seasonal rainfall, more wet days, fewer dry days, prolonged consecutive wet spells, and higher rainfall intensity per day are likely to experience a shorter duration of food insecurity, and vice versa. The impact of the 10%, 25%, and 50% assumptions on the duration of food crises becomes more significant as the influence percentage increases. The category of very high crisis duration is expected to decrease over ASALs in the region due to a slight projected increase in total rainfall and wet days. This implies that efforts to help people adapt to ASALs will have a more noticeable effect compared to a humid climate. Consequently, actions taken to address food crises will have a greater impact in Sudan, northeastern Ethiopia, and northern Somalia, regardless of the SSP scenario. However, if political instability, imbalanced development policies, and conflicts arising from electoral disputes continue in the IGAD region, the existing hotspots of food insecurity will persist. This could result in an increase in the frequency and duration of current food insecurity hotspots, or the emergence of new hotspots, even with an increase in rainfall. The key to shortening the duration lies in timely and effective intervention, addressing the root causes, and building resilience within affected


(a) MAM_SPP126_2021-2050_10% influence
(b) MAM_SPP126_2021-2050_25% influence
(c) MAM_SPP126_2021-2050_50% influence
(d) MAM_SPP126_2071-2100_10% influence
(e) MAM_SPP126_2071-2100_25% influence
(f) MAM_SPP126_2071-2100_50% influence
(g) MAM_SPP585_2021-2050_10% influence
(h) MAM_SPP585_2021-2050_25% influence
(i) MAM_SPP585_2021-2050_50% influence
(j) MAM_SPP585_2071-2100_10% influence
(k) MAM_SPP585_2071-2100_25% influence
(l) MAM_SPP585_2071-2100_50% influence
Very high duration
High duration
Moderate duration
Low duration
Very Low duration

◂**Fig. 10** Projected changes in patterns of food crisis duration under projected changes in exposure to extreme rainfall events associated with 10%, 25%, and 50% assumption of future changes in current root causes of food insecurity hotspots frequency. The patterns computed during MAM under the SSP1-2.6(first and second tow) and SSP5-8.5 scenarios (third and fourth row)

communities (Brough et al. 2022). These findings underscore the importance of addressing the underlying factors of food crises in order to create a brighter future for the next generation in the IGAD region of East Africa.

Conclusions

Total annual and seasonal rainfall patterns are projected to worsen in most of the IGAD region. This is due to an increase in heavy rain, wet days, and prolonged periods of rain, and a decrease in dry days and dry spells in the near (2021–2050) and far (2071–2100) futures, as indicated by the SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios. The observed instances of minimal food insecurity in Uganda, western Kenya, and Ethiopia were a result of high rainfall, more wet days, and higher rainfall intensity. In South Sudan, the areas classified as food insecurity hotspots under the stressful and crisis categories were primarily affected by conflicts rather than climate. The prevalence of food insecurity in the form of stressful, crisis, and emergency cases in ASALs in northern Sudan, Eritrea, Djibouti, Somalia, southeastern and northeastern Ethiopia, and Kenya can be attributed to the desert climate and arid and semi-arid conditions experienced throughout the years. The projected exposure to food insecurity is expected to be very high in ASALs in Sudan, Eritrea, Djibouti, Somalia, southeastern and northeastern Ethiopia, and Kenya under the SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios. Conversely, the projected vulnerability to food insecurity is anticipated to be very low in Uganda, South Sudan, western Kenya, and central and western Ethiopia under the same scenarios. Changes in total annual rainfall, rainfall intensity, prolonged wet days, and wet spells have a significant impact on the occurrence of low or high exposure and vulnerability to food insecurity, as well as the presence of food insecurity hotspots, and the frequency and duration of food insecurity in most regions of East Africa. These changes vary across different scenarios: SSP1-2.6, SSP2-4.5, and SSP5-8.5. The high exposure, vulnerability, frequency, and duration of food insecurity in the Arid and Semi-Arid Lands (ASALs) in the IGAD region underscore the urgent need for comprehensive food security interventions. It is crucial to implement appropriate adaptation strategies to protect the already vulnerable population and capitalize on the projected increase in rainfall and wet days in Uganda, South Sudan, western Kenya, and Ethiopia to boost food production in the region.

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Author contribution The authors collectively developed the idea and executed the study.Paulino Omoj was responsible for preparing the materials, collecting the data, analyzing, and the manuscript's initial draft. Josiah M. Kinama, Christopher Oludhe, and Nzioka J. Muthama supervised all stages of the manuscript. Zachary Atheru and Guleid Artan reviewed and secured funding for open access publication. Each author provided feedback on an earlier draft of the manuscript. The authors have reviewed and approved the final manuscript.

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Data availability You can request access to the secondary datasets that have been generated during the analysis. CMIP6 simulations and projections, Food Insecurity Hotspots datasets are freely available online.

Code availability We used ArcGIS10.4 and Climate Data Tool (CDT) based R-Packages.

Declarations

I affirm that the content presented in this article is all my own and has not been published elsewhere. In compliance with the standards set by the University of Nairobi, I have appropriately cited and recognized any instances where the work of others or myself has been utilized.

Consent to participate All authors consent to participate.

Consent for publication All authors consent to publish this work.

Conflict of interest All authors declare no competing interests.

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