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# Relationship between Drought Early Warning System Information, and Food and Nutrition Security in Arid and Semi-Arid Lands in Kenya

Foreign, Commonwealth & Development Office

Bill & Melinda Gates foundation

# Relationship between Drought Early Warning Information, and Food and Nutrition Security in Arid and Semi-Arid Lands in Kenya

## Water Sector

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## Abbreviations and Acronyms

| | |
|---|---|
| DEWs | Drought Early Warning Systems |
| MUAC | Mid Upper Arm Circumference |
| ALRMP | Arid Lands and Resource Management Project |
| CSG | County Steering Groups |
| FCS | Food Consumption Score |
| KFSSG | Kenya Food Security Steering Group |
| LRA | Long Rains Season |
| NDMA | National Drought Management Authority |
| RCSI | Reduced Coping Strategy |
| SPI | Standardized Precipitation Index |
| SRA | Short Rains Season |
| VCI | Vegetation Condition Index |

## Abstract

*Arid and semi-arid lands represent 88 per cent of the country's total land mass and are home to 38 per cent of the human population and 60 per cent of livestock and wildlife population. These areas bear the brunt of climate change as manifested through the effects of recurrent droughts. To manage drought effects, the country uses Drought Early Warning System (DEWS) information that is managed by the National Drought Management Authority (NDMA). This study set out to determine the effects of DEWS information on food and nutrition security for 23 ASAL counties for the period January 2016 to December2023. The findings indicate that an increase in standard precipitation index or rainfall is associated with a 6.555 units improvement in food consumption score. A unit increase in the vegetation condition index corresponded to 0.4069 units increase in food consumption score. The reduced coping strategies are effective drought coping mechanisms as they contribute to improved food consumption in ASALs. Further a unit increase in standard precipitation index was associated with an improvement in middle upper arm circumference by 0.1068 units, while a unit increase in the vegetation condition index was associated with nutrition improvement by 0.0076 units. The coping strategies index also significantly affected middle upper arm circumference with a unit increase in coping strategies index, resulting to the mid upper arm circumference increase by 0.0263 units. These findings indicate the critical role of drought early warning systems (DEWS) information in managing nutrition and food security outcomes amid drought episodes. It is therefore important for the government and other stakeholders to: (i) strengthen existing drought early warning systems information to ensure accuracy, and timely data with clear dissemination channels to facilitate early action; (ii) implement a multi-faceted approach to drought and adopt a multi-sectoral approach to address the complex interplay of factors influencing food and nutrition security in ASALs; (iii) invest in drought monitoring and early warning management systems and up to date geospatial technologies for early warning prompt action; (iv) coping strategies be strengthened and scaled up to enable communities better cope with drought emergencies.*

# 1 Introduction

Real-time monitoring of environmental phenomena has gained prominence due to technological advances and the adverse effects of environmental degradation on livelihoods. Detection of environmental changes and prediction of possible impacts is made possible by early warning systems (EWSs). An EWS is an integrated system for monitoring, collecting data, analyzing, interpreting, and communicating monitored data, which can then be used to make decisions early enough to protect public health and environmental effects and to minimize unnecessary concern and inconvenience to the public (USEPA, 2005). EWS entails gathering, analyzing, and disseminating information about drought vulnerability and risks (Powel, 2014). Early warning systems are designed for data collection that monitors people's vulnerability and risk to food insecurity, provide timely signals when a food crisis threatens, and therefore elicit appropriate action. The physical aspects of an EWS should be able to provide information on the spatial extent of drought; duration of drought, time of occurrence of drought in relation to the crop and livestock calendar, and severity of drought (Friel, 2014). Drought early warning systems are designed to provide information that helps communities better cope with food insecurity during times of scarcity by encouraging food storage, saving resources for food purchases, destocking, managing grazing zones, taking up crop insurance, and planting early maturing crops (ACTED, 2011; Wang et al., 2015).

The provision of early warning and prevention information is an important adaptive measure to vulnerability and risks of drought (Wilhite and Svoboda, 2000). A DEWS stimulates action by households to take early intervention to avoid the effects of drought through timely response to drought and food security. The ability of a household to undertake coping strategies determines its overall welfare in terms of food and nutritional status. Studies have shown that a household's timely response to drought is influenced by factors such as access to DEWS information, distance to water sources, ownership of arable land, and training on drought management (Wang et al., 2015; Akwango, 2016).

Seasonal monitoring by the famine early warning system network (FEWS NET) makes extensive use of satellite image products to achieve early detection of drought. Vegetation condition index images have been used since the mid-1980s to monitor the crop and rangelands of semi-arid Sub-Saharan Africa (Hutchinson, 1991). The normalized difference vegetation condition index (NDVI) exploits the contrast between red and near-infrared reflectance of plant canopies. It is proportional to the leaf area index, intercepted fraction of photosynthetically active radiation, and density of chlorophyll in plants (Tucker and Sellers, 1986). Maximum value composites for dekads (WMO, 1992), nominally 10-day periods, are used to overcome cloud cover problems. Images from several different sensors are used to make the NDVI composites used by FEWS NET.

Drought is regarded as the leading cause of food insecurity in Sub-Saharan Africa (SSA) since the region depends on rain-fed agricultural production (Agrhymet, 2014). This is in addition to other drivers of poverty and vulnerability. Drought undermines farm yields by reducing household and national food availability, and agricultural income that is derived from crop and livestock. Poor harvests in turn affect household nutritional security. Its effects on food security in turn diminish dietary diversity, leads to undernutrition, and protein-energy malnutrition and reduces overall food consumption leading to micronutrient deficiencies (Kumar et al., 2005; Menne and Bertonnini, 2000).

In Kenya, arid and semi-arid lands (ASALs) bear the brunt of climate change and variability. ASALs have experienced frequent drought cycles over approximately 10 years in the last century. In the past two decades, drought cycles have become more frequent and severe in ASALs in 1979/1981, 1984/1985, 1987/1988, 1991/1992, 1995/1996, 1998/ 2000, 2006/2007, 2012/2013, 2016/2017, 2021/2022 (NDMA, 2022). In 2022, ASALs suffered the worst drought in 61 years, an estimated 4.4 million people (27%) of the ASAL population faced high levels of acute food insecurity – Integrated phase classification (IPC), in which about 774,000 people were in food insecurity emergency (IPC, 2023). In 2018, ASALs experienced acute malnutrition where an estimated 482,882 children required treatment for acute malnutrition, including 104,614 who were suffering from severe acute malnutrition (UNICEF, 2018).

An understanding of the DEWS – food and nutrition security nexus is important in devising appropriate policy responses to ameliorate drought effects in ASALs. Against this background, this paper examines the relationship between drought early warning systems information on food and nutrition security in arid and semi-arid lands in Kenya. This study sought to: analyze trends and patterns of drought warning information; examine trends in food and nutrition security; and determine the nexus between drought early warning information, and food and nutrition security.

Based on the insights provided by this study, populations in ASALs could make informed decisions and implement appropriate strategies to mitigate the impact of drought proactively and prepare for drought conditions. Policy makers could also use the information to develop national disaster preparedness plans, while the private sector could prepare appropriate responses to regional food needs.

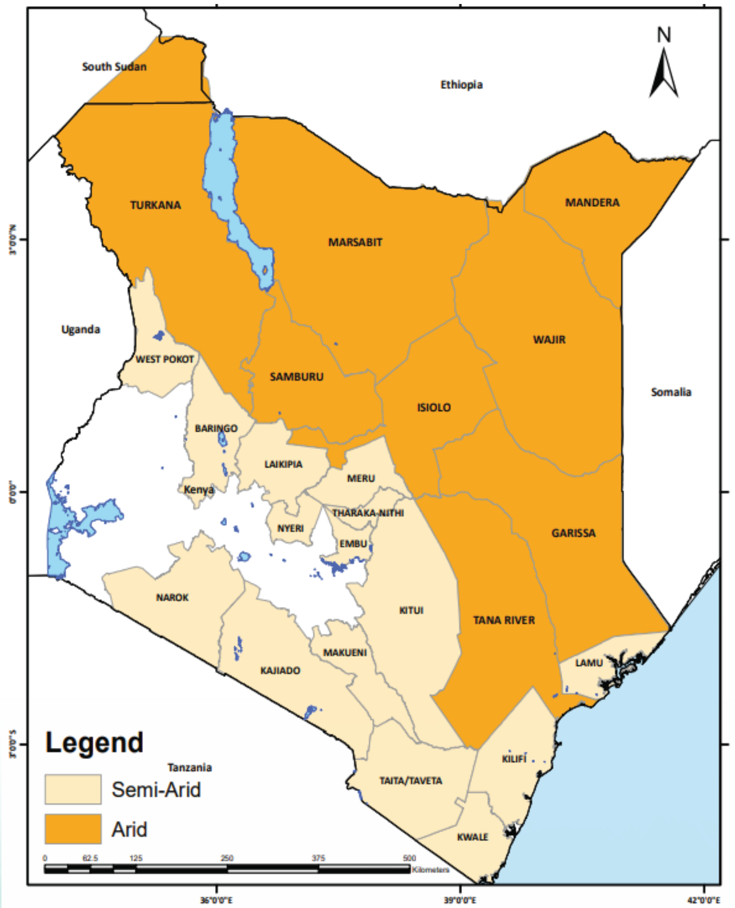
After the introduction section, the section that follows highlights drought conditions and management strategies in Kenya followed by the literature review. Section four describes the approach and methodology, while section five presents and discusses the findings. Conclusion and policy recommendations are presented in section six.

# 2 Drought Conditions and Management Strategies in Kenya

## 2.1 ASAL Counties in Kenya

This study focuses on arid and semi-arid lands from the southeast to the northwestern part of Kenya (Figure 2.1).

**Figure 2.1: ASAL counties in Kenya**



Administratively ASALs are divided into 23 counties out of which eight (8) are classified as arid counties due to their extreme level of aridity. They include Turkana, Samburu, Marsabit, Isiolo, Wajir, Garissa, Mandera, and Tana River. The 15 counties classified as semi-arid counties are West Pokot, Baringo, Laikipia, Kitui, Meru, Tharaka Nithi, Embu, Nyeri, Narok, Kajiado, Makueni, Kitui, Taita Taveta, Kwale, Kilifi, and Lamu. The country has a population of approximately 48 million people, with the ASALs hosting about 38 per cent of the population and close to 50 per cent of the country's livestock.

The area is characterized by unreliable, low, variable, and poorly distributed rainfall. Orindi et al. (2007) and FAO (2006) indicated that the mean annual rainfall in the semi-arid and arid areas of Kenya is between 300mm and 500 mm and that the soils in these areas are shallow and infertile, with Lake Turkana region receiving less than 250mm of rainfall per year. However, areas such as Marsabit with an altitude above 1,200m have fertile soil and receive rainfall up to 600mm per year (FAO, 2006). The eastern side of Turkana County receives an annual rainfall of 200mm and over 500mm in the western highlands (Omolo, 2010; Mureithi and Opiyo, 2010). The mean annual temperature in the ASALs of Kenya is between 22°C and 40°C. The temperature for Turkana County ranges between 26°C and 38°C (Jaetzold and Schmidt, 1983; Omolo, 2010; Mureithi and Opiyo, 2010). Arid and semi-arid lands receive bimodal rainfall patterns, a long rain season during March, April, and May; and a short rain season in October, November, and December.

The vegetation in ASALs is sparsely distributed and adapted to survive in arid conditions. The vegetation is composed of short drought-resistant shrubs, grasses, and trees that are adapted to withstand long periods of drought. It has a seasonal variation that is influenced by rainfall patterns, and seasons of growth during the rainy season and dormancy during dry periods.

ASALs have inadequate surface water flow due to low rainfall and high evaporation rates. Rivers and streams mainly flow seasonally after rainfall. However, due to the inadequacy of surface water, the local community members depend on groundwater that is often accessed through boreholes and shallow wells. Water scarcity is a major challenge experienced in ASALs, leading to competition for limited water resources among humans, livestock, and wildlife. Traditional water harvesting techniques such as building sand dams, rock catchments, and terracing are used to capture and store rainwater for domestic and agricultural use.

The economy of the arid areas is dominated by mobile pastoralism, while in the better-watered and better-serviced semi-arid areas, a more mixed economy prevails, including rain-fed and irrigated agriculture, agro-pastoralism, small-scale businesses based on dry land products, and conservation or tourism-related activities. The ecology of semi-arid areas allows for the intensification of production in a way that the ecology of arid areas does not allow other groups within the ASALs to depend on fishing, hunting, and gathering for their subsistence. Notably, towns across both arid and semi-arid areas are growing, creating an urbanized population with different needs and aspirations. This diversity within the ASALs requires a disaggregated policy response.

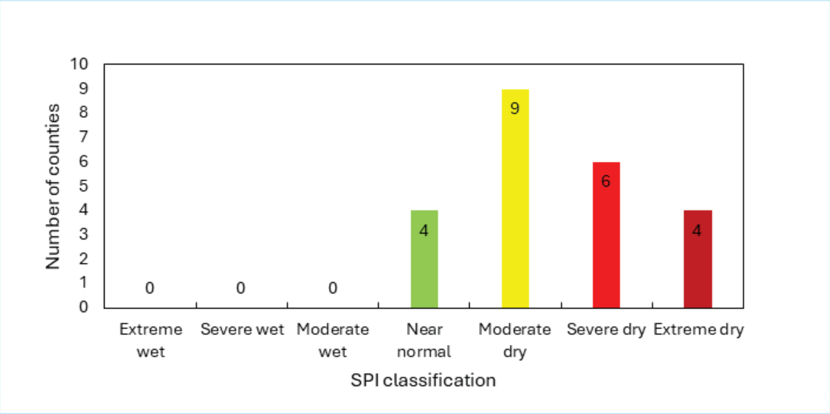
## 2.2 Early Warning Information on Drought

Drought Early Warning Systems monitor various indicators to provide information on the progress of impending drought – classifying the drought event as normal, alert, alarm, emergency, or recovery. These indicators advise on the biophysical, production, access, and utilization components. The biophysical indicators look at the environmental aspects such as rainfall statistics, the condition of vegetation, and the status of water (standardized precipitation index). Production indicators measure the productivity of crops and livestock in terms of livestock condition, milk produced, migration, and mortality statistics of livestock and crop productivity. Access indicators look at the human aspect of access to food, water, and markets; and terms of trade focus on the pricing levels for common food crops such as beans and maize, milk consumption, and distances from water sources. Utilization indicators look at the well-being aspects of human beings; the coping strategies adopted by locals, food consumption levels, and mid-upper arm circumference (MUAC) for children to detect malnutrition (Barrett et al., 2020; Welthungerhilfe, 2019).

The standardized precipitation index (SPI) is widely used as a drought indicator and, therefore, a key variable in DEWs. SPI characterizes departures from normal as a number of standard deviations above or below the mean, calculated for a range of accumulation periods, typically three (3), six (6), 12, and 24 months each. Its value measures the durations and intensities of drought across a predetermined range (McKee et al., 1993). It is a z-score deviation from the mean in units of the standard deviation using Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) precipitation values for each pixel location over a composite period.

The standard precipitation index characterizes the meteorological droughts based on precipitation data to quantify precipitation anomalies. To fit the gamma distribution, historical rainfall data is collected and transformed, allowing the SPI values to be calculated. SPI values indicate deviations from the mean over a period. Positive values are indicative of wetter-than-average conditions, while negative values imply drier-than-average conditions. In 2022, ASAL counties experienced different drought conditions; four (4) counties experienced near normal drought conditions (-1.00 < SPI < 1.00); nine (9) counties experienced moderate dry drought conditions (-1.50 < SPI < -1.00); six (6) counties experienced severe dry drought conditions (-2.00 < SPI < -1.50) while four (4) counties experienced extreme dry drought conditions (SPI < -2.00).

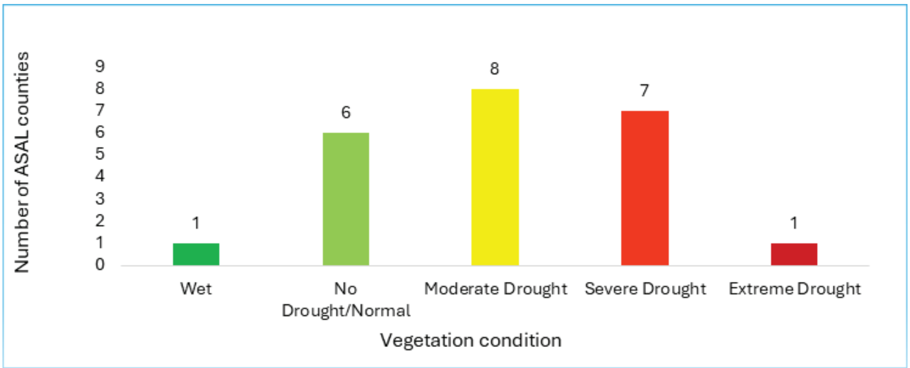
**Figure 2.2: Number of ASAL counties that experienced different drought conditions in 2022**




*Source: FEWNET (2022)*

The Vegetation Condition Index (VCI) measures vegetation health at a specific time, using the normalized difference vegetation index (NDVI). The NDVI values are normalized in a way as to highlight the vegetation response to weather changes, while minimizing ecosystem-specific impacts, by historic minimum and maximum VCIs of 0 per cent and 100 per cent, respectively. Due to the weather change, VCI is enhancing its detection of seasonal variation in vegetation. NDMA uses a vegetation cover index to develop thresholds for the classification of droughts, updated monthly. Figure 2.2 shows the classification and number of ASAL counties under different drought conditions.

**Figure 2.3: Vegetation Cover Index categories for ASAL counties (2022)**




*Source: NDMA EWS (2022*

The reduced Coping Strategies Index (rCSI) is an indicator used to assess the hardship faced by households due to food shortages. It measures the frequency and severity of food consumption behaviours over the past seven days when households lacked enough food or money to purchase food. This index is part of food security assessments and consists of five questions about food consumption strategies, resulting in a numeric score reflecting current food security status. Frequent data collection allows rCSI to indicate changes in food insecurity levels. A higher rCSI score indicates greater use of coping strategies to address the risks that affect livelihoods. The index assigns weights to different coping strategies based on their severity, and the household's rCSI score is calculated by combining these weighted frequencies (Table 2.1).

**Table 2.1: Drought categories**

| No. | Question severity | Weights of the question severity |
|---|---|---|
| 1 | Rely on less preferred and less expensive foods? | 1 |
| 2 | Borrow food, or rely on help from a friend or relative? | 2 |
| 3 | Limit portion size at mealtimes? | 1 |
| 4 | Restrict consumption by adults in order for small children to eat? | 3 |
| 5 | Reduce number of meals eaten in a day? | 1 |

At the household level, the rCSI is an indicator of food consumption and food security. To monitor the food security status of households, rCSI is normally collected as part of a food safety evaluation. To identify the most appropriate cuts for IPC purposes, the cut-off values are based on empirical research carried out by partners in the IPPC, which aims at assessing the distribution of rCSI compared with other food consumption indicators. Since it has not been possible to find an appropriate breakpoint for Phases four (4) and five (5) in the IPC Acute Reference Table, there are no breakpoints from these two phases. Table 2.2 classifies food consumption in accordance with Reduced Coping Strategies Index (rCSI) cut-off points in 2022. Phase one (1) encompasses households with rCSI scores ranging from zero (0) to three (3), totaling 6,272,000 households in ASAL counties. Phase two (2) includes households with rCSI scores from four (4) to 18, consisting of 15,049,000 households. Phase three (3) to five (5) comprises households with rCSI scores equal to or greater than 19, amounting to 3,486,000 households. This framework facilitates the assessment of coping mechanism interventions tailored to the specific needs of households that experienced acute food insecurity.

**Table 2.2: Acute food insecurity reference**

| Phase rCSI cut-off | Phase rCSI cut-off | Food consumption and food security at the household level |
|---|---|---|
| 1 | 0-3 | 6,272,000 |
| 2 | 4-18 | 15,049,000 |
| 3-5 | ≥19 | 3,486,000 |

*Source: ICP (2021)*

The Food Consumption Score (FCS) is a tool for measuring household food security. It serves as a proxy for caloric consumption by evaluating dietary diversity, food consumption frequency, and nutritional value of different food groups over the past week, using self-reported data. Households are categorized into three food consumption groups: poor, borderline, or acceptable – facilitating timely analysis

(WFP, 1996). Food security is also assessed using the Integrated Phase Classification (IPC), first used in Kenya in 2007. The IPC classifies food insecurity into five phases minimal/none, stressed, crisis, emergency, and catastrophe/famine – guiding intervention priorities based on severity. The households are then categorized into one of three food consumption groups – facilitating timely and interpretable analysis in various contexts (WFP, 2023).

**Table 2.3: Current acute food insecurity**

| | | |
|---|---|---|
| Phase 5 Catastrophe/ famine | Households with an extreme lack of food after full employment of coping mechanisms, exhibiting extreme starvation | Zero (0) people in catastrophe |
| Phase 4 Emergency | Households with large food consumption gaps reflected by acute malnutrition | 758,000 people in emergency |
| Phase 3 Crisis | Households that reflect a high above-usual malnutrition | 2,728,000 people in crisis |
| Phase 2 Stressed | Households with minimal adequate food consumption but can afford some essentials | 15,049,000 people stressed |
| Phase 1 Minimal/none, | Households able to meet essential needs without strain | 6,272,000 in food security |

*Source: ICP (2021)*

The phases describe the severity of drought and its impact on households, helping to quantify and describe the different levels of food insecurity and malnutrition affecting the population, in the context of food security. Phase five (5) (catastrophe/ famine) involves households experiencing an extreme lack of food after exhausting all coping mechanisms, resulting in severe starvation. Phase four (4) (emergency) relates to households with significant food consumption gaps that lead to acute malnutrition affecting 758,000 persons. Phase three (3) – (crisis) affects 2,728,000 people in ASAL counties and reflects households with higher-than-normal levels of malnutrition due to severe food shortages. Phase two (2) (stressed) indicates that, in ASAL counties, 15,049,000 people are affected, households with less than adequate food consumption who can still afford certain essential non-food items.

Mid-upper Arm Circumference (MUAC) is a measurement used to identify the nutritional status of children and pregnant women who have malnutrition and are at risk of dying (IFRC2023). There are different types of MUAC tape available. All are graduated in millimetres and some are colour-coded (red, yellow, and green) to indicate the nutritional status of a child or adult. The colour codes and gradations vary depending on the tape type. UNICEF (2009) issued a joint statement with WHO on child growth standards and the identification of severe acute malnutrition in children. The standard of MUAC tape (S0145620 MUAC, Child 11.5 Red/PAC-50) was made available as indicated in Table 2.4.

**Table 2.4: Standard of MUAC identification**

| **Cut-off points of SO145620 as per UNICEF** | | **Malnutrition identification** | **Number of ASAL counties at risk of malnutrition** |
|---|---|---|---|
| Red | 0-11.5 cm | | 13 |
| Yellow | 11.5 cm- 12.5 cm | | 4 |
| Green | From 12.5 cm | | 6 |

*Source: ICP (2021)*

## 2.3 Policy and Institutional Frameworks Governing ASALs

Existing legal, policy, and institutional frameworks in Kenya recognize that the ASALs are particularly vulnerable to climate change impacts especially in the absence of sufficient investments in mechanisms to build resilience. Sessional Paper No. 3 of 2016 on the National Climate Change Framework Policy was developed to guide the overall response to climate variability and change. This policy demonstrates the government's commitment to protecting the climate system for the benefit of the present and future generations by supporting the United Nations Framework Convention on Climate Change (UNFCCC) process, ratifying the Kyoto Protocol in 2005, and contributing to continental and regional climate change initiatives. The policy seeks to strengthen the linkages between sustainable national development and climate change. This is in recognition of the adverse impacts of climate change on key sectors that support economic development and livelihoods, which include environment, water, and forestry; agriculture, livestock, and fisheries; trade; extractive industries; energy; physical infrastructure; tourism; and health.

The NDMA Act of 2016 assigns the National Drought Management Authority the task of overseeing and coordinating all activities related to managing drought risks in Kenya. It is tasked with establishing mechanisms, either independently or in collaboration with stakeholders, to prevent drought emergencies and ensure they do not escalate into famines. Additionally, the Act mandates the NDMA to coordinate all matters relating to drought risk management that will end drought emergencies in Kenya. The primary responsibility of the Authority is to manage drought efficiently, effectively, and sustainably, thus eliminating a significant threat to the realization of Kenya Vision 2030. One of the key responsibilities outlined in the Act is the provision of reliable and precise Drought Early Warning information. This has prompted the NDMA to continuously seek innovative approaches to collecting and managing information generated by the Drought Early Warning System.

Disaster Risk Management Policy, 2017 seeks to build a safe and disaster-resilient nation through the establishment of a robust Disaster Risk Management System that contributes to and protects the achievements of Kenya's national development. This policy aims to substantially reduce natural and human-induced disaster risk and associated losses at the national and county levels through the establishment of an integrated multi-hazard DRM approach. The policy is intended to achieve a participatory, impartial, transparent, and useful DRM framework by providing for the enactment of an enabling comprehensive legislative framework, which lays down the legal foundation for collaborative partnership in institutional participatory management of disasters, including mobilization of the essential resources necessary for management of all disasters.

The thrust of the Kenya Vision 2030 development strategy for Northern Kenya and other arid lands, 2012 is to improve justice and equity and accelerate development in arid and semi-arid lands. The strategy recognizes the unique challenges facing Northern Kenya and the arid and semi-arid lands, which have persisted over the years and constrained their socio-economic transformation. To reduce the socio-economic challenges, the policy takes cognizant of pastoralism and has developed strategies to reinforce mobile pastoralism, coupled with complementary strategies to facilitate increasing urbanization. The policy further puts up interventions to establish the

National Drought Management Authority and the National Drought Contingency Fund. Moreover, the policy advocates for strengthening awareness of the impacts of climate variability and climate change to ensure better decision-making on coping strategies. This policy further proposes mainstreaming of variability, climate change, and adaptation into all policies, programmes, and investments – mobilizing resources necessary to manage climate variability and climate change effectively.

Various institutions, networks, and forums have been established to address the challenges and opportunities of the ASALs. The National Drought Management Authority, established in November 2011, leads drought management efforts, coordinates stakeholders, and ensures the implementation of the Ending Drought Emergencies (EDE) strategy. Previously, informal coordination structures such as the Kenya Food Security Meeting (KFSM) and the Kenya Food Security Steering Group (KFSSG) struggled due to their reliance on individual goodwill. The NDMA provides a statutory basis for these efforts, improving coordination and harmonization of multi-stakeholder responses to drought. Additionally, institutions such as the National Council on Nomadic Education in Kenya (NACONEK), the Livestock Marketing Board, and the ASAL Secretariat focus on ASAL-related challenges, ensuring their inclusion in national policies, programmes, and resource allocations.

National Food and Nutrition Security Policy, 2011 seeks to safeguard vulnerable populations and address food insecurity by enhancing capacity for early warning and emergency management through innovative and cost-effective safety nets and relief programmes linked to long-term development. Strengthening early warning systems is prioritized to provide essential information for emergency preparedness, response, mitigation, and long-term development planning.

Several institutions are responsible for drought early warning management, food, and nutrition security. The National Drought Management Authority (NDMA) is responsible for providing leadership in drought management, coordinating stakeholders involved in drought risk management activities, and ensuring the delivery of strategies to end drought emergencies. The Kenya Food Security Steering Group (KFSSG) is tasked with coordinating efforts to address food security challenges in the country, including early warning systems for food insecurity. The Ministry of Agriculture, Livestock, Fisheries, and Cooperatives plays a crucial role in ensuring food and nutrition security by implementing policies and programmes related to agriculture, livestock, and fisheries. The Kenya Meteorological Department is tasked with monitoring weather patterns and providing early warning information related to drought and other weather-related disasters. The Ministry of Health ensures access to nutrition services and implements programmes to address malnutrition, especially in drought-affected areas. The National Nutrition and Dietetics Unit is mandated with formulating nutrition policies and guidelines to address malnutrition and promote food and nutrition security. This study aims to assess the nexus between the drought early warning systems information and food and nutrition security in the ASALs.

# 3 Literature Review

## 3.1 Theoretical Literature

### 3.1.1 The Tipping Point Theory

The tipping point theory explains the usefulness of drought early warning systems in detecting early advancement of natural hazards before they become disasters while the affected agents adopt various coping mechanisms. The tipping point theory of climate change talks of a certain threshold that if surpassed may lead to a collapse of the system - the tipping point of the system. Such a scenario may occur when, for example, global temperatures increase by above two (2) degrees Celsius, causing global warming that in turn leads to the melting of glaciers, and a rise in sea levels that may in turn worsen the severity and magnitude of impending natural hazards. This theory recognizes the importance of climate change as an important ingredient in the occurrence of natural hazards such as drought events while noting the non-linear nature of the two aspects.

Krishnamurthy et al. (2020) note the possibility of determining drought events from climatic conditions visible through biophysical aspects such as rainfall variability and vegetation conditions. Hydraulic droughts that are a result of failure in rainfall during expected periods of rainfall – especially for areas that are highly dependent on rain-fed agriculture – can, therefore, be forecasted by drought early warning systems that use such indicators to advise on impending drought events. Using drought events as a tipping point in the climate system, drought effects can be measured quantitatively through drought early warning systems (Krishnamurthy et al., 2020). The ability to inform a proactive response to drought events thereby reduces vulnerability levels of communities living in drought-prone areas.

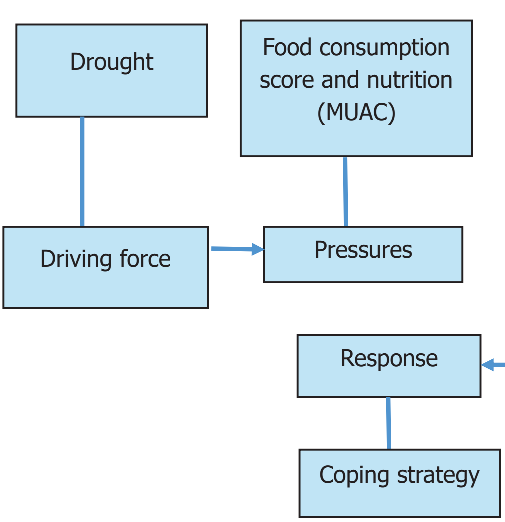
Drought is identified as a tipping point in the climatic system. This can occur from a variety of factors. For example, when the stock of livestock increases and livestock raring is uncontrolled leading to depletion of foliage, the natural environment suffers with the onset of shrubs and depleted vegetation and soil erosion. This would consequently set off an alarm of impending drought event given deteriorated vegetation conditions. Consequently, when rainfall fails leading to crop failure and depletion of available natural water sources, causing a strain on water availability and food security, this can be an impending risk signaling the likelihood of getting to the tipping point –a drought event. Drought early warning systems are, therefore, important in forecasting tipping points such as drought events. The impact or outcome approach to disaster management is another theory that explains the relationship between natural hazards and vulnerability levels of people living in disaster-prone areas. It looks at the relationship between stressors such as drought events and response to such stressors to reduce vulnerability levels to the stressors. The more severe the impact of the stressor, the more severe the drought. This theory helps in understanding the outcomes of drought severity on households and communities, which are put at a serious disadvantage in terms of coping with the consequences of significant disruptions it has on food security and nutrition.

### 3.1.2 Driver-Pressure-State-Impact-Response Theory

The driver-pressure-state-impact-response (DPSIR) model has evolved from the Pressure-State-Response (PSR) model developed by Canadian statistician, Anthony Friend, in the 1970s and later adopted by the Organization for Economic Co-operation and Development (OECD). The theory simplifies the understanding of human-environment interactions. It is applied to show the cause-effect relationships in past, present, and future phenomena and simplifies complex systems relations to one-to-one linkages (Burkhard, 2008). This model outlines how human demands (drivers) for goods create pressures on the environment, altering its state. These state changes impact ecosystem functioning and human well-being, prompting responses to mitigate adverse effects (Mueller, 2004). The drivers include economic, technological, social, and natural factors influencing human activities. These activities exert pressures such as pollution or resource extraction, which can be directly measured. State changes reflect the environmental conditions resulting from these pressures, such as increased droughts or floods. These state changes impact ecosystems and human welfare, leading to impacts such as food insecurity and health issues. Finally, the system triggers responses —strategies and measures by stakeholders to counteract the negative impacts and restore balance, such as implementing coping strategies for drought. Impacts often prompt responses from authorities or the private sector.

Integrating vulnerability assessments with climate change data into the DPSIR framework helps develop adaptation responses. Impact indicators are crucial for decision-making, describing environmental and social consequences. Responses aim to minimize drivers' and pressures' effects on ecosystems and improve human welfare through adaptation and mitigation. Responses include legislation, planning, market instruments, cooperation, and education, monitored by pressure and state indicators. For this study, the Driver-Pressure-State-Impact-Response (DPSIR) framework explains food and nutrition security within the ASALs as a result of drought that pushes the household and local community to adopt coping mechanisms. In this paper, the drivers are variability in the rainfall leading to prolonged droughts that put pressure on vegetation, affecting the food consumption score, dietary diversity, and quality, nutrition states (MUAC), impacts food insecurity and malnutrition that pushes the household to adopt coping strategies as the response as illustrated in Figure 3.1.

**Figure 3.1 Driver pressure state impact response**




*Source: Burkhard (2008)*

## 3.2 Empirical Literature

Droughts can be generally described as climatic conditions with characteristics such as unfavourable weather patterns, scarcity of water resources, generally high temperatures and wind strength, and degrading vegetation conditions. Droughts are a scientific phenomenon generally caused by climatic conditions. Their frequency and intensity are also aggravated by climate change, among other issues such as land-use changes and population pressure. Various scientists have seen the need for sufficient and timely information on the occurrence and severity of drought episodes to advise on the expected impact of these events (Moron, 1997; Mutai et al., 1998; Shanko and Camberlin, 1998).

Deltares and Future Waters (2017) worked on technical assistance on drought information and early warning systems aimed at providing technical and institutional advice following the severe drought in 2016 in Bolivia that affected the country. It became evident that the response to the drought event was different across the country as was shown by comparing La Paz/El Alto with Potosí water supply companies. Lack of communication and a proactive attitude caused a slow response in La Paz/El Alto and all stakeholders agreed that the impacts could have been considerably less severe if action had been taken in an earlier phase. The report emphasized that drought information availability should be strengthened at different levels of the administration and across different sectors. Considering future changes (population, climate change, land use change), this risk-based drought impact assessment should allow the drafting of drought-focused policies by identifying the most adequate indicators and developing better preparedness for future similar droughts.

Livelihoods and food security in the Southern African region are highly vulnerable to climate variability but climate predictions can play an important role in mitigating these impacts (Archer et al., 2007), by forecasting yields of major food crops, thereby enabling planners to better respond to production shocks and spikes in food prices (Iizumi et al., 2018). Timely provision of seasonal climate forecasts can enable farmers to make climate-smart farm decisions to avoid losses by choosing adaptive crops and optimal livestock numbers and composition to have in anticipation of dry-spell or reduced precipitation. This would guarantee some harvest and food security for households and enhance their food storage for consumption smoothing. Households can use early drought warnings to diversify their income sources to cushion themselves against production shocks. If seasonal forecasts predict a good season, farmers can diversify their production and, therefore, their diets and sell some of the stored surplus in anticipation of a good harvest later in the season. Sibhatu and Qaim (2018) find cash income generated through the sale of farm produce to have a more significant impact on dietary diversity than diverse subsistence production. Governments and aid agencies can use climate services and early warnings to plan, coordinate, and pre-position humanitarian interventions to meet food needs during severe droughts (Dilley, 2000).

In East Africa, the main economic activity in the arid and semi-arid lands (ASALs) is subsistence rain-fed agriculture, and livestock farming using pastures and grasslands as the main source of fodder. As a result, the pastoral and agro-pastoral communities who live in these drylands are particularly vulnerable to drought (Nyong et al., 2007; Orindi et al., 2007), especially since their existing coping strategies have been compromised by population growth and land use change in recent years (Galvin et al., 2001). Governments and donor agencies in the region have thus developed several tools and early warning systems (EWS) to mitigate the impact of droughts on pastoralists.

Early warning systems information is, therefore, important in monitoring current key biophysical and socio-economic factors to assess the possible exposure of vulnerable people to specific hazards. However, once the impacts are visible, it may be too late to mitigate the consequences (Kogan et al., 2013). Therefore, there is growing interest in moving towards a proactive humanitarian approach to disasters by developing preparedness actions based on climate forecasts (Coughlan de Perez et al., 2015; Lopez et al., 2018; Wilkinson et al., 2018). Additionally, it is estimated that being better prepared before a drought significantly reduces the costs and losses from these disasters (Venton et al., 2012). Therefore, EWS now increasingly includes expert knowledge and qualitative assessments of seasonal climate forecasts to assess the future development of food security and define actions to mitigate possible losses (Coughlan de Perez et al., 2015; Tozier de la Poterie and Baudoin, 2015). With changing climate, the frequency and severity of droughts are expected to increase in many parts with adverse effects on crop and livestock production, food security, and poverty and vulnerability.

Balint et al. (2013) developed a drought monitoring methodology for Kenya and the Horn of Africa that could measure the natural components of droughts by comparing the prevailing situation to the multi-year average situation in a year at a given place. A statistical approach that combines different parameters into an index, the components of drought index (CDI), was developed. According to the study, the index could trace the footprints of droughts in Kenya, had the potential to give short-term early warning up to the end of the season, had the potential for use in climate trends and climate change analysis, and the results were supported with drought reports in the country. The authors recommended that CDI be tested worldwide.

Tuitoek and Wausi (2016) looked at the effect of DEWS on drought mitigation and management in ASALs in Kenya. The study used a descriptive research design, using primary data collected through a survey of 23 ASALs in Kenya. Five (5) respondents per ASAL were interviewed, getting to a total of 115 respondents. The findings indicated that DEWS has enabled a timely and useful provision of drought-related information. The system's ease of use has enabled capacity building among stakeholders, especially communities living in ASALs. The system's ability to be responsive has ensured timely dissemination of drought early warning bulletins. The study recommended that NDMA should consider improving DEWS to enhance information dissemination and collaborate with stakeholders to create awareness in communities living in the ASALs.

Sandstorm et al (2020) studied the fluctuating rainfall and persistent food crisis — use of rainfall data in the Kenyan drought early warning systems (EWSs), which have been developed to trigger timely action to disasters, yet persistent humanitarian crises – we focused our research on ASAL counties in Kenya, where drought repeatedly results in humanitarian crises, especially regarding food and nutrition insecurity – resulting from hazards such as drought indicate that these systems need improvements. They used the biannual assessments, and the country bulletins used different sets of rainfall data and different methodologies for establishing the climate normality, leading to discrepancies in the output of the EWS. They recommended further steps to be taken towards standardization of methodologies and cooperation between various institutions to ensure streamlining of approaches.

Golicha and Wanyonyi (2018) investigated the influence of pastoralists' drought management practices on their livelihoods in Isiolo North sub-county, Kenya. The pastoralist communities mostly inhabiting the ASALs have been affected by drought, which is by far the most common disaster in the dry lands in Eastern and Northern Kenya. It affects more people more frequently than any other disaster in the arid and semi-arid areas in Kenya and the Horn of Africa. The research was designed as a cross-sectional descriptive study with a multivariate regression undertaken to test the relationship between the variables and enable the researcher to generalize results from the sample to the population. The study found that most of the areas in Isiolo North sub-county are frequently affected by drought and water scarcity, putting the pastoralists in a great drought disaster. The study deduces that the pastoralists are familiar with drought contingency planning. Drought relief strategy affects drought disaster risk reduction in Isiolo North. Pastoralists are knowledgeable about rehabilitation mechanisms as a mitigation strategy. The study recommends the need to enhance community communication and feedback mechanisms.

# 4 Methodology

## 4.1 Data and Data Sources

The computation of drought early warning systems information indicators was based on precipitation data obtained from Climate Hazard Group Precipitation with Station (CHIRPS) data from the University of California. The rainfall used in this analysis was in monthly timestep for the period January 2016–December 2023. Rainfall data was used for computation on the Standard Precipitation Index. Rainfall had a resolution of 0.05 degrees by 0.05 degrees.

Food security and nutrition data were obtained from the NDMA drought early warning system dataset, which contains food security-related data from representative counties across the study area. The data was collected from several sentinel sites spread across the counties monthly since 2016. The data collected in the drought early warning system targets specifically identified early warning indicators. It was, thus, determined jointly with the local communities in the counties that the most important indicators to monitor include changes in environmental resources (rainfall or standard precipitation index and vegetation cover index); production characteristics or availability (crop production, livestock production); access to food (food consumption score); nutrition status for children under five years old (mid-upper-arm circumference-MUAC); and reduced coping strategies index (rCSI). It is hypothesized that significant changes in these specific indicators would negatively affect the livelihood of the ASAL population and could lead to undernutrition and deaths when stretched to the extreme.

## 4.2 Computation of Study Variables

Five variables were used in the study, each of which is conceptually related to specific study objectives. These are the Standardized Precipitation Index (SPI), Vegetation Condition Index (VCI), Reduced Coping Strategy Index (rCSI), Food Consumption Score (FCS), and Mid-upper Arm Circumference (MUAC).

The standardized precipitation index (SPI) was used to detect drought in the ASALs. This followed the standard procure by first fitting the average rainfall into a probability distribution function as described by McKee et al. (1993). Three three-month average monthly precipitation data series were fed into a Gamma distribution function to transform it into SPI values and the drought severity was detected. The Mann-Kendall trend test, which is a non-parametric technique was applied to test for trends in the drought severity in the ASALs. This test can test for increasing, decreasing, or no trend (Mutua et al., 2015).

Food Consumption Score (FCS) was computed using past seven-day food consumption recall for the household and classified into three categories: poor consumption (FCS = 1.0 to 28); borderline (FCS = 28.1 to 42); and acceptable consumption (FCS = >42.0). The FCS is a weighted sum of food groups consumed by households in a county. The score for each food group was calculated by multiplying the number of days the commodity was consumed and its relative weight. Food Consumption Score thresholds were calculated for the 23 ASAL counties under long rains and short rains seasons. Food Consumption Score for each food group was computed using equation 4.1.

$$\text{FCS} = FCS = \sum_{n=1}^{i} (Wi \times Ci) \qquad 4.1$$

Where:

*FCS* = Food Consumption Score

*Wi* = Weight assigned to food group *i*

*Ci* = Quantity of food group *i* consumed

*n* = Total number of food groups included in the assessment

Once FCS was derived, the index was recoded to the variable food consumption score from a continuous variable to a categorical variable, to calculate the percentage of households of poor, borderline, and acceptable food consumption. According to the World Food Programme (WFP) standards, a score of 0-21 indicates poor food security, a score of 21.5-35 indicates borderline food security and a score greater than 35 is considered an acceptable food security level (Table 4.1). Poor and borderline groups were considered food insecure (Nie et al., 2011).

**Table 4.1: Thresholds for food security groups by calorie intake and FCS**

| | Food security group | FCS |
|---|---|---|
| Food insecurity | Poor | 0-21 |
| | Borderline | 21.5-35 |
| Food secure | Acceptable | >35 |

*Source: WFP (2005)*

Mid-upper arm circumference (MUAC) has been used for many decades to assess malnutrition in children aged above five (<5) years. The MUAC is a much simpler anthropometric measure than the BMI, as its use eliminates the need for expensive equipment, such as height charts and scales, and the need for calculations. It is also much easier to perform on an acutely unwell, bed-bound, or sedentary person. NDMA collects MUAC data at the county level through its county field monitor officers monthly. MUAC data in monthly timescale was accessed from the NDMA drought early warning system in daily timestep. Severe Acute Malnutrition (SAM) is less than or equal to 115mm, while for Moderate Acute Malnutrition (MAM), the MUAC value is between 115-125mm, which illustrates food insecurity. Above 125mm, the MUAC indicates no acute malnutrition hence food security.

Reduced coping strategy Index (CSI) was used as a proxy indicator of household food insecurity coping mechanisms into three categories: No or low coping (CSI= 0-3), medium (CSI = 4-9, high coping (CSI ≥10) (IPC 2021).

The non-parametric Mann-Kendall test was used to detect the temporal trends of the study variables. This analysis was adopted over the parametric test to avoid the problem arising from data skew (Smith, 2000). Mann-Kendall test was formulated by Mann (1945) as a non-parametric test for trend detection and the test statistic distribution was given by Kendall (1975) for testing non-linear trends and turning points. Studies show that trend detection in a series is largely affected by a positive or negative autocorrelation (Yue et al., 2003; Novotny and Stefan, 2007). A positive autocorrelation in the series points to a presence of a trend, but this is not always the case. Conversely, a negative autocorrelation shows the absence of a trend in the series. The coefficient of autocorrelation ρk of a discrete-time series for lag-*k* is given by:

$$\rho_k = \frac{\sum_{t=1}^{n-k}(x_t - \bar{x}_t)\,(x_{t+k} - x_{t+k})}{[\sum_{t=1}^{n-k}(x_t - \bar{x}_t)^2 * \sum_{t=1}^{n-k}(x_{t+k} - \bar{x}_{t=k})^2 *]]^{1/2}} \qquad 4.2$$

Where,

$x_t$ and Var ($x_t$) are considered as the sample mean and sample variance of the first ($n-k$) terms, respectively, and $x_t + k$ and Var ($x_t$+$k$) are the sample mean and sample variance of the last ($n-k$) terms, respectively. Further, the hypothesis of serial independence is tested by the lag-1 autocorrelation coefficient as $H_0$:$\rho1=0$ against $H_1$: $|\rho1| > 0$ using:

$$t = |\rho_1|\sqrt{\frac{n-2}{1-\rho_1^2}} \qquad 4.3$$

Where the t-test statistic has a Student's t-distribution with ($n-2$) degrees of freedom (Cunderlik and Burn, 2004). If $|t| \geq t\alpha/2$, then the null hypothesis about serial independence is rejected at the significance level α.

The Mann-Kendall statistic S is given as:

$$S = \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} sgn\,(x_j - x_i) \qquad 4.4$$

The trend test is applied to a time series $x_i$ that is ranked from i = 1,2,………n-1, and $x_j$, which is ranked from *j = i+1,2,……….n*. Each of the data points $x_i$ is taken as a reference point, which is compared with the rest of the data points $x_j$ so that:

$$Sgn(x_j - x_i) = \begin{cases} +1 > (x_j - x_i) \\ 0 = (x_j - x_i) \\ -1, < (x_j - x_i) \end{cases} \tag{4.5}$$

It has been documented that when *n ≥ 8*, the statistic *S* is approximately normally distributed with the mean.

*E(S) = 0*

The variance statistic is given as:

$$Var(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{m} t_i(i)(i-1)(2i+5)}{18} \tag{4.6}$$

Where $t_i$ is considered as the number of ties up to sample $_i$. The test statistics $Z_c$ is computed as follows:

$$Z_c = \begin{cases} \frac{S-1}{\sqrt{Var\ (S)}} \\ 0, S = 0 \\ \frac{S+1}{\sqrt{Var\ (s)}}, S < 0 \end{cases} \tag{4.7}$$

$Z_c$ here follows a standard normal distribution. A positive/negative value of *Z* signifies an upward/downward trend. A significance level α is also utilized for testing either an upward or downward monotone trend (a two-tailed test). If *Zc* appears greater than Zα/2 where α depicts the significance level, then the trend is considered as significant.

Modified Mann–Kendall test: Pre-whitening is used for detecting a trend in a time series in the presence of autocorrelation (Cunderlik and Burn, 2004). Nonetheless, pre-whitening is stated to reduce the rate of detection of significant trends in the MK test (Yue et al., 2003). Thus, the Modified MK test (Rao et al., 2003) has been used for trend detection of an autocorrelated series. In the present study, the autocorrelation between ranks of the observations ρk was estimated after subtracting an estimate of a non-parametric trend such as Sen's median slope from the data. Significant values of ρk were only used for calculating the variance correction factor n/n*S, as the variance of S is underestimated for the positively autocorrelated data:

$$\frac{n}{n_S^*} = 1 + \frac{2}{n(n-1)(n-2)} * \sum_{k=1}^{n-1} (n-k)(n-k-1)(n-k-2 \tag{4.8}$$

Where $n$ represents the actual number of observations, $n^*s$ is represented as an effective number of observations to account for the autocorrelation in the data, and $\rho k$ is considered as the autocorrelation function for the ranks of the observations. The corrected variance is then calculated as (Rao et al., 2003):

$$V^*(S) = V(S) * \frac{n}{n_s^*} \tag{4.9}$$

Where V (S) is from equation 4.6. The rest is the same as in the MK test.

Sen's Slope Estimator Test: The magnitude of the trend is predicted by Sen's estimator. Here, the slope ($T_i$) of all data pairs is computed as (Sen, 1968):

$$T_i = \frac{x_j - x_k}{j - k} \tag{4.10}$$

For I = 1,2…………………N

Where $x_j$ and $x_k$ are considered as data values at time $j$ and $k$ ($j>k$) correspondingly. The median of these N values of $T_i$ is represented as Sen's estimator of slope, which is given as:

$$Qi = \begin{cases} T_{\frac{N+1}{2}} & N \text{ is odd} \\ \frac{1}{2}\left(T_{\frac{N}{2}} + T_{\frac{N+2}{2}}\right) & N \text{ is even} \end{cases} \tag{4.11}$$

Sen's estimator is computed as $Q_{med}=T(N+1)/2)$ if $N$ appears odd, and it is considered as $Q_{med}=[TN/2+T(N+2)/2]/2$ if $N$ appears even. In the end, $Q_{med}$ is computed by a two-sided test at 100 (1-α)% confidence interval and then a true slope can be obtained by the non-parametric test.

A positive value of $Q_i$ indicates an upward or increasing trend and a negative value of $Q_i$ gives a downward or decreasing trend in the time series.

## 4.3 Descriptive Statistics

The descriptive statistics of the variables, namely MUAC, rCSI, SPI, VCI, and FSC based on monthly observations for the period 2016-2023 are presented in Table 4.2. MUAC mean of 0.5826 is slightly left-skewed with significant deviation from normality, as indicated by its Jarque-Bera p-value (0.0250). rCSI, mean (0.3245) is nearly symmetric and marginally normal p-value (0.078). SPI mean of 0.0241 is right-skewed with significant deviation from normality with a p-value = 0.0124. VCI mean is 0.4104 and shows right skewness and a near-normal distribution but with significant deviation p-value = 0.0182. FSC mean of 0.5410 is left-skewed and flatter than normal, with marginal normality p-value = 0.0962.

**Table 4.2: Descriptive statistics**

| | FCS | MUAC (mm) | RCSI | SPI | Vegetation Index |
|---|---|---|---|---|---|
| Mean | 67.5468 | 134.4723 | 32.6739 | 0.0241 | 47.2529 |
| Median | 77.3333 | 135.2892 | 31.5469 | -0.2167 | 44.0565 |
| Maximum | 84.7619 | 137.7244 | 46.7774 | 2.1704 | 92.2747 |
| Minimum | 2.0270 | 129.9312 | 19.1314 | -1.2830 | 15.3265 |
| Std. Dev. | 19.9102 | 1.9697 | 7.0171 | 0.8888 | 18.6322 |
| Skewness | -2.0262 | -0.4249 | 0.1570 | 0.6982 | 0.6634 |
| Kurtosis | 6.3347 | 1.8846 | 1.9389 | 2.3747 | 2.6253 |
| Jarque-Bera | 103.2849 | 7.3737 | 4.5914 | 8.7795 | 7.1292 |
| Probability | 0.0000 | 0.0250 | 0.1006 | 0.0124 | 0.0283 |
| Observations | 90 | 90 | 90 | 90 | 90 |

## 4.4 Regression Analysis Strategy

The relationship between the study variables was analyzed by first plotting the data and testing for stationarity using the Augmented Dickey-Fuller test. This test examines the null hypothesis of an autoregressive integrated moving average (ARIMA) against stationary and alternatively. The general and all-inclusive form of the conventional Dickey-Fuller test is provided as in Equations 4.12 and 4.13.

$$yt=a+\mathrm{bt}+uyt-1+et \qquad 4.12$$

It is estimated by OLS using Equation 2.

$$\triangle yt=u-1yt-1+a+\mathrm{bt}+et \qquad 4.13$$

The augmented Dickey-Fuller (ADF) tests the null hypothesis that *e = 1*. If the null cannot be rejected, then we cannot reject the existence of a unit root.

Volatility of food consumption score (FCS) and nutrition (MUAC) was given by:

$$Y_t = logP_t - logP_{t-1} \qquad 4.14$$

Where $Y_t$ = Food consumption score/nutrition at time *t*

$P_t$ = Food consumption score/nutrition at time *t-1*

The ARCH model was estimated as follows:

$$Y_t = C + \varepsilon_t^2 \qquad 4.15$$

The series is modelled by:

$$h_t = \alpha_0 + \sum_{t=1}^{q} \alpha_i \varepsilon_{t-1}^2 \qquad 4.16$$

Where $y_t$ is $P_t$ - $log\ P_{t-1}$, $C$ is the mean, $h_t$ is the conditional variance of $\varepsilon$ at time $t$ defined as the sum of residual lag weighted squares. $\sum_{t=1}^{q} \alpha_1 \varepsilon_{t-1}^2$ is the ARCH terms. If highly significant, the FCS and MUAC will show significant clustering and fluctuation will expand with $\alpha>1$, otherwise, the fluctuation will shrink.

The study employed an EGARCH and GARCH (1,1) model to evaluate the volatility in FCS and MUAC, respectively. The model is illustrated as follows:

$$Y_t = C + \varepsilon_t \qquad 4.17$$

$$r_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \pi r_{t-q}^2 + \beta_1 R_t^1 \qquad 4.18$$

Where $Y_t$ is $log\ P_t$ - $log\ P_{t-1}$, food score at time $t$,$R_t$ is dew variables at time $t$; $\varepsilon_{t-1}^2$ is the ARCH terms, squares of error term at time $t$; $\omega$ is the mean value; $\pi$ is the estimated coefficient of the GARCH terms at time.

The regression analysis used in this study explained the variability in the dependent variables – Food consumption score (FCS) and Mid-upper arm circumference (MUAC) – using the independent variables – drought early warning indicators (Standard Precipitation Index (SPI), Vegetation Condition Index (VCI), Reduced Coping Strategy Index (rCSI), and variability of the dependent variable (VMUAC). This study looked at the relationship between drought early warning information (standard precipitation index/rainfall, vegetation cover index, reduced coping strategies index -rCSI), and food and nutrition variability on food security (food consumption score-FCS; and nutrition (MUAC) to establish how much food and nutrition security varies with changes in drought early warning information. The relationship between drought early warning indicators on food and nutrition security was estimated using an ARCH regression model (Equation 4.19):

$$y = \beta_0 + \beta_1 x_2 + \beta_2 x_2 + \beta_3 x_3 + \omega + \varepsilon \qquad 4.19$$

Where γ represents the predicted value for the dependent variable food consumption score (FCS); and nutrition security (proxied by MUAC) and *x* represents the value for independent variable $x$ (drought early warning indicators: rainfall /SPI, VCI, rCSI); $\beta_0$ represents y-intercept and $\beta_1$ represents the rate of change/slope of the line of best fit; $\omega$ represents the variability of the dependent variable; and $\varepsilon$ represents the estimated error of the estimation.

Assumptions included:

i. The size of the prediction error (drought early warning indicators error) is homoscedastic; that is, the error does not differ significantly from the values of the independent variable.

ii. Independence of observations – the observations in the dataset were collected using statistically sound sampling techniques, and there is no hidden relationship between observations.

## 4.5 Unit Root Test

**Table 4.3: Summary results of the Unit Root Test results**

| Variable | Test statistic at level and p value | | Test statistics at first difference and p-value | | Order of integration |
|---|---|---|---|---|---|
| FSC | -3.1516 | 0.0510 | -5.0842 | 0.0001 | I (-1) |
| MUAC | -2.8889 | 0.1715 | -10.6536 | 0.0000 | I (-1) |
| RSCI | -2.2168 | 0.4742 | -7.6201 | 0.0000 | I (-1) |
| SPI | -3.0323 | 0.1295 | -10.0224 | 0.0000 | I (-1) |
| Vegetation Condition Index | -2.8368 | 0.1884 | -5.9723 | 0.0000 | I (-1) |

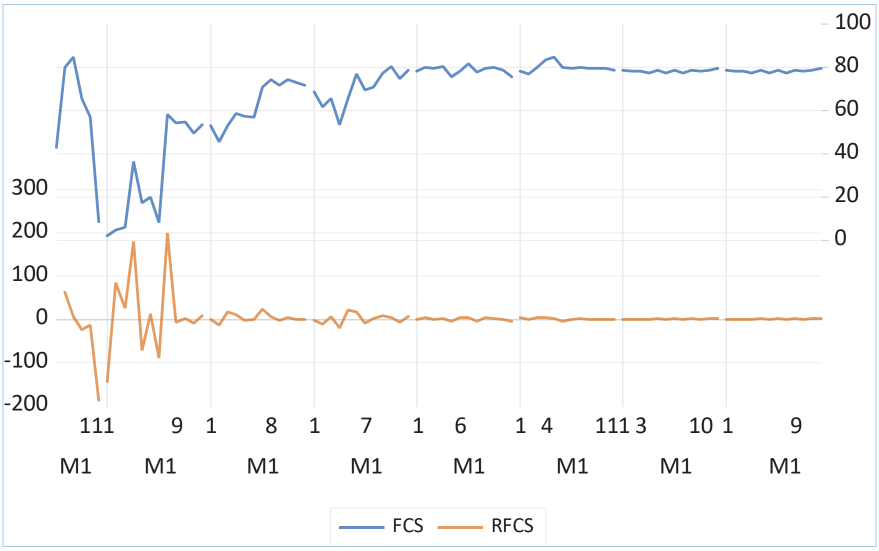
Table 4.3 indicates the ADF unit root test, which indicated that all variables were stationary at the first difference. FSC is non-stationary at the level (p-value = 0.0510) but becomes stationary at the first difference (p-value=0.0001). Therefore, it is integrated with order 1. MUAC (nutrition) is non-stationary at the level (p-value = 0.1715) but becomes stationary at the first difference (p-value = 0.0000), hence it is integrated with order 1 (I(1)). RSCI is non-stationary at the level (p-value = 0.4742) but becomes stationary at the first difference (p-value = 0.0000). It is integrated with order 1 (I(1)). SPI is non-stationary at the level (p-value = 0.1295) but becomes stationary at the first difference (p-value = 0.0000). It is integrated with order 1 (I(1)). The vegetation condition index is non-stationary at the level (p-value = 0.1884), but becomes stationary at the first difference (p-value = 0.0000). It is, therefore, integrated into order 1 (I(1)).

## 4.6 Volatility Test

Due to the fluctuation as exhibited in Figure 4.2 in food and nutrition patterns in ASALs, the study conducted a volatility diagnostic test in variables. This involved the tests for serial correlation (LM test) and heteroskedasticity (ARCH test) for each variable and presented the following:

## Figure 4.2: Volatility analysis

(a) Volatility of Food Consumption FCS




(b) Volatility of Nutrition MUAC

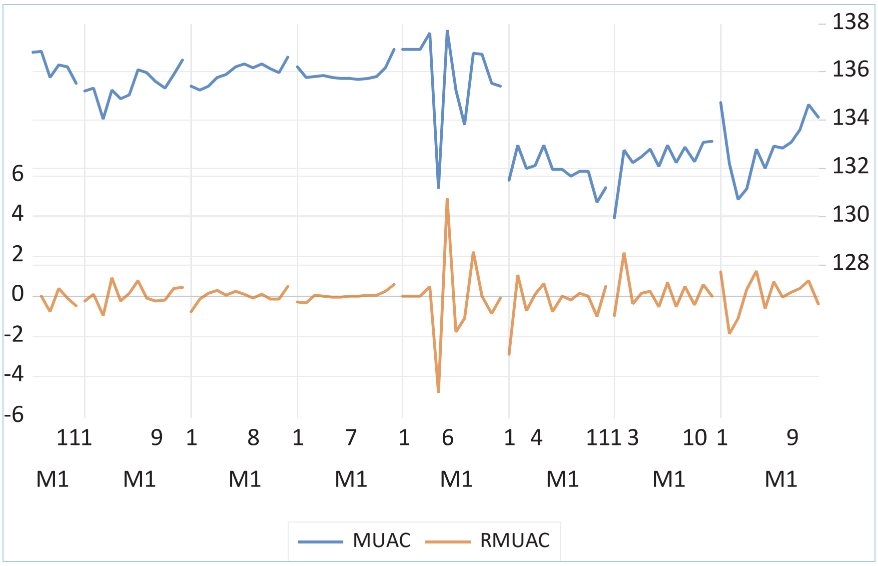



Figure 4.2 shows the FCS and MUAC at levels and their volatility forms RFCS and RMUAC, which indicates that there is evidence of volatility clustering and structural breaks.

**Table 4.4: Evidence of serial correlation and heteroskedasticity**

| Variable | Serial correlation (LM test) p value | Heteroskedasticity (ARCH) p value |
|---|---|---|
| RFSC | 0.5537 | 0.1429 |
| RMUAC | 0.1728 | 0.0318 |

The serial correlation test determined if the observations were correlated, while the heteroskedasticity test determined the changing variability of variables over time. The volatility analysis established the presence of time-varying conditional volatility. This study established the presence of heteroscedasticity and serial correlation in the return variables of FCS and MUAC identified by p-values, which were significant at a 0.05 significance level. Given the volatility results, the study determined that ARCH-GARCH analysis was best suited since it provided more accurate estimates that captured the time-varying volatility of the data. Liu et al. (2019) indicate that the ARCH-GARCH model is more useful in the accurate measurement of SPI drought index (DEWS).

# 5 Results and Discussion on the Relationship between DEWS and Food and Nutrition Security

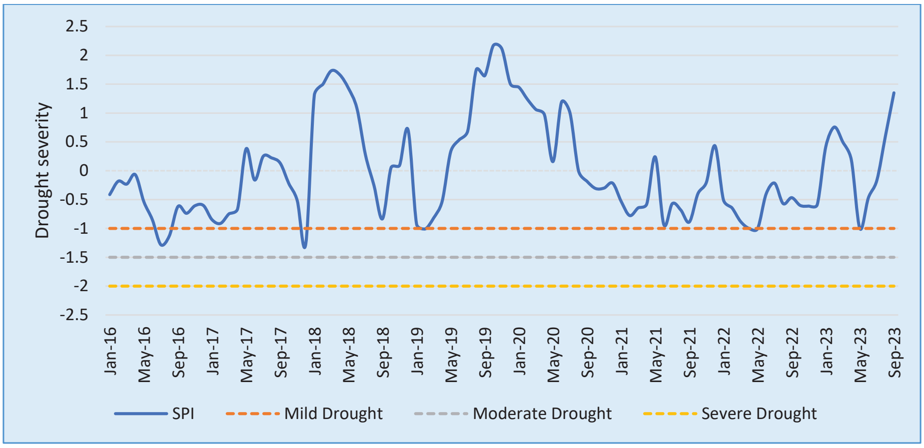
This section presents and discusses the study findings. The study conducted a Mann-Kendell test to determine the trends of the variables. It analyzed the relationship between drought early warning systems and variability of food consumption, and nutrition on food consumption score (FCS) and nutrition (MUAC), respectively. The study used the ARCH and GARCH models to capture the volatility of the variables.

## 5.1 Trends in Food and Nutrition Security

### 5.1.1 SPI trends

There are six drought episodes recorded in the study area during the period (93 months period since January 2016). These drought events were experienced in July 2016 (SPI=-1.283), August (SPI=-1.127), December 2017 (SPI=2019), February 2019 (SPI=-1.001), May 2022 (SPI=-1.005), and May 2023 (SPI=-1.000). The trend in average SPI for the ASAL counties is presented in Figure 5.1, which shows that all the ASAL counties did not experience a single case of moderate or severe drought category as the SPI values for the entire period remained above -1.5. However, given that drought is a highly localized phenomenon, it is possible that some counties wholly or partially experienced more severe drought.

**Figure 5.1: Trends in Standardized Precipitation Index, 2016-2023**

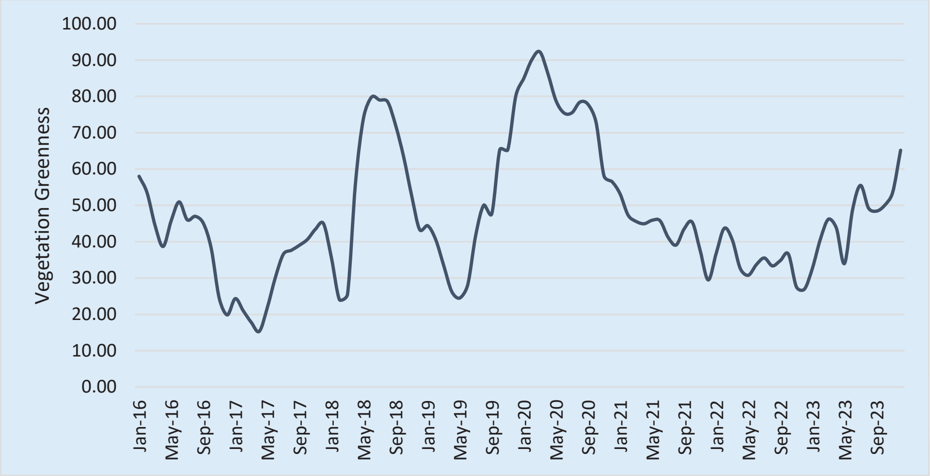



Further, drought was severe in the initial years compared with the later years. For example, in July 2016, the SPI3 value was 1.283, while that for December 2017 was SPI3 -1.269. The SPI3 values for the last two droughts were -1.00 in June 2022 and the same value in March 2023. Based on these findings, the area experienced a reduction in drought severity although the frequency almost doubled.

### 5.1.2 Vegetation condition trends

Over the period 2016-2023, the vegetation condition shows a high level of variability, with the majority of the months experiencing mild drought conditions. Five moderate droughts were experienced during November 2016-June 2017, February 2018-March 2018, April 2019-June 2019, December 2021, and November 2022-January 2023. One severe drought was experienced in April 2017.

**Figure 5.2: Trends in Mean Vegetation Condition Index, 2016-2023**

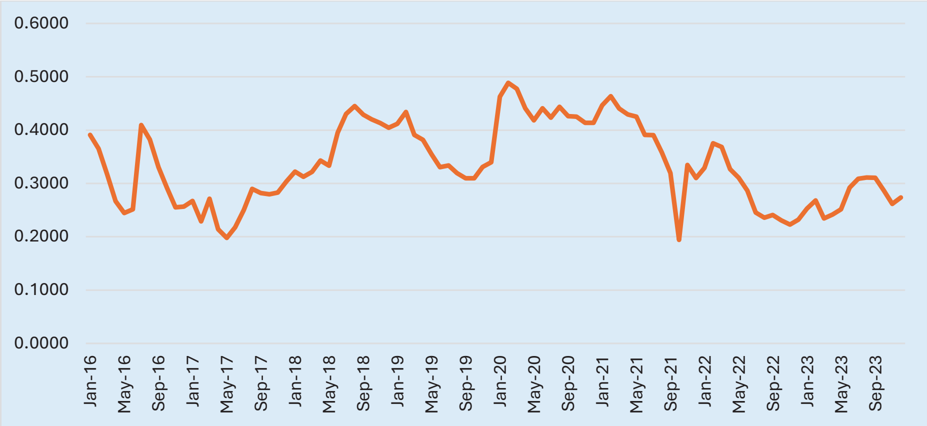



The results suggest that drought occurrence in the area is highly unpredictable as its occurrence is not confined to a particular month or season of the year.

### 5.1.3 Coping strategy trends

During the period of analysis, the value of the Reduced Coping Strategy Index (rCSI) fluctuated between 0.468 and 0.194 (Figure 5.3). This means that throughout the period, the proportion of food-secure households remained below 50 per cent. The majority of the population was either categorized as food stress or in food crisis and hence required food interventions.

**Figure 5.3: Trends in reduced Coping Strategy Index, 2016-2023**

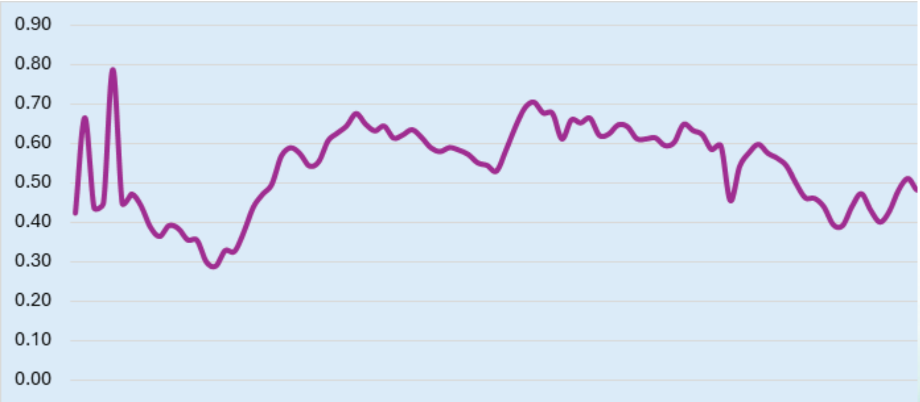



The sharp decline in October 2021 corresponds to the cumulative failure of the LRA and SRA rainfall season of 2021. This situation necessitated the government to declare the drought that was affecting part of the country a national disaster in September 2021 (OCHA, 2022).

### 5.1.4 Food consumption trends

The population of households having acceptable food consumption in the study area averaged 0.54 and oscillated between 0.79 in May 2016 and 0.29 in April 2017. This translated to a range of 0.5. However, in the final observed year, there was a drastic reduction in the range to 0.07 between June and October 2023.

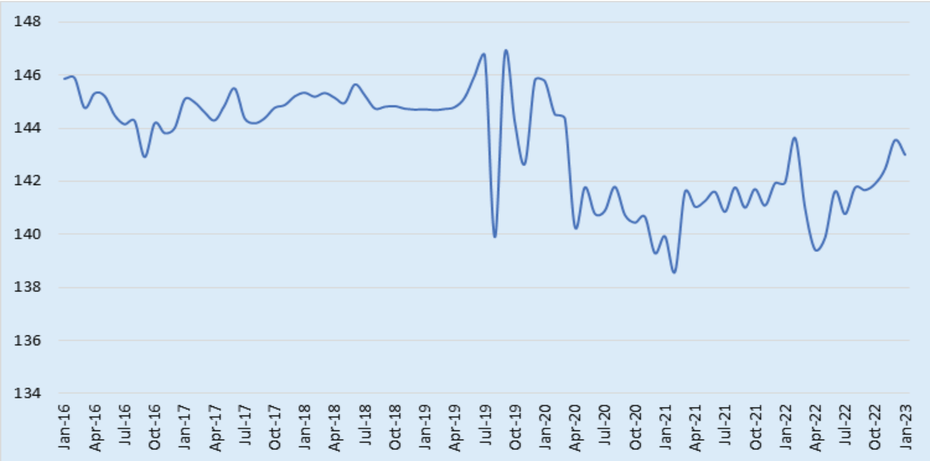
**Figure 5.4: Trends in Food Consumption Score (FCS), 2016-2023**



### 5.1.5 MUAC trends

Trends in MUAC are presented in Figure 5.5. According to the Figure, the period January 2016 to early 2019 show fluctuation in MUAC values, although the overall trend remained stable, averaging 144mm to 146mm. In Mid-2019, MUAC values increased sharply to approximately 147mm, followed by a rapid decline. From late 2019 onwards, MUAC values declined, reaching their lowest point in mid-2021 at around 139mm. This indicates a significant deterioration in nutritional status due to prolonged droughts. In mid-2021, there was a gradual recovery in MUAC values. The values of MUAC rose to 144mm in 2023, though they did not reach the high values recorded in 2019.

**Figure 5.5: Trends in Mid-Upper Arm Circumference (MUAC), 2016-2023**




Overall, all the observed MUAC values remained above the food security threshold of 125mm. This means that the nutritional status of the population is well-secured, perhaps due to the effectiveness of the interventions implemented by the government and other stakeholders in the ASALs.

### 5.1.6 Mann-Kendell trend analysis

The study determined the trend analysis using the Mann-Kendell test and presented the results in Table 5.1.

**Table 5.1: Mann-Kendell trend analysis**

| Item | Trend | P-value | Z-statistics | Tau | Slope | Intercept |
|---|---|---|---|---|---|---|
| SPI | ↑ | 0.638 | 0.471 | 0.034 | 0.001 | -0.273 |
| VCI | ↓ | 0.754 | -0.314 | -0.023 | 0.000 | 0.382 |
| rCSI | ↓ | 0.606 | -0.516 | -0.037 | 0.000 | 0.321 |
| FCS | ↑ | 0.000 | 6.536 | 0.467 | 0.003 | 0.642 |
| MUAC | ↓ | 0.000 | -5.103 | -0.366 | -0.006 | 0.934 |

The Mann-Kendall test results indicate that the Standardized Precipitation Index (SPI), and Food Consumption Score (FCS) had an increasing trend as indicated by Mann-Kendel z-statistics (z = 0.470 and z = 6.545), respectively; with FCS being significant at P-value 6.3e-11 while SPI being not significant at P-value 0.638. The magnitude of increasing trends illustrated by Sen's slope for SPI and FCS were 0.001 and 0.002, respectively. This showed that the rate of increase was higher in FCS than in SPI. The findings showed that rainfall over the ASAL counties has been increasing, hence the increase in SPI. An increase in FCS indicates a situation of improved food consumption in the ASAL counties during the period 2016-2023.

Vegetation Condition Index (VCI), Reduced Coping Strategy Index (rCSI) and Mid-Upper Arm Circumference (MUAC) showed a decreasing trend as indicated by Mann-Kendel z-statistics (z = -0.313, z = -0.515 and z = -5.103), respectively; with MUAC being significant at P - value 3.345e-7 while VCI and rCSI being not significant at P – values; 0.753 and 0.605, respectively. The magnitude of decreasing trends as illustrated by Sen's slope for VCI, rCSI, and MUAC were -0.0002, -0.0001, and -0.0055, respectively. This showed that the rate of decrease was higher in MUAC, followed by rCSI then VCI. These differences in the rate of change of the variables explain the lag time between the biophysical indicator of drought (VCI) and the outcome indicators of drought (rCSI and MUAC) over the study period. Decreasing trends in MUAC indicate a decline in nutritional status for children under five years, which has implications on wasting risk prevalence. The factors that could have led to decreasing trends in reduced coping strategies in the ASAL counties are strongly related to poor diet, whereby households consuming a diet high in processed foods, sugar, and unhealthy fats can lead to a decrease in the copying strategy index. These foods lack essential nutrients and can negatively impact cognitive function and overall brain health.

## 5.2 Relationship between Drought Early Warning System on Food Security

The study conducted an EGARCH analysis on the relationship between DEWS on FCS and presented the following results.

**Table 5.2: Relationship between drought early warning system and food security**

| Dependent variable: FCS | | | | |
|---|---|---|---|---|
| **Variable** | **Coefficient** | **Std. Error** | **z-Statistic** | **Prob.** |
| rCSI | 0.2119 | 0.0477 | 4.4418 | 0.0000 |
| SPI | -6.5548 | 1.5244 | -4.2995 | 0.0000 |
| VCI | 0.4069 | 0.0753 | 5.4046 | 0.0000 |
| C | 47.8629 | 4.4510 | 10.753 | 0.0000 |
| **Variance equation** | | | | |
| C(5) | 48.7663 | 46.5283 | 1.0481 | 0.2946 |
| C(6) | 0.9451 | 0.0392 | 24.072 | 0.0000 |
| C(7) | 0.1692 | 0.1046 | 1.6184 | 0.1056 |

| | | | | |
|---|---|---|---|---|
| C(8) | 0.1794 | 0.1695 | 1.0614 | 0.2885 |
| C(9) | 0.1054 | 0.1526 | 0.6909 | 0.4896 |
| C(10) | -0.8139 | 0.0359 | -22.6217 | 0.0000 |
| GED Parameter | 3.7872 | 1.6904 | 2.2403 | 0.0251 |

The analysis results presented in Table 5.2 show that SPI had a negative coefficient (-6.5548), suggesting that severe drought is associated with lower food consumption. A unit change in SPI value causes a 6.5548 decrease in the food consumption score. The magnitude of this change implies that drought has a huge influence on household food consumption.

As expected, the vegetation condition index coefficient was found to be positive (0.4069) relating to food consumption. This means that higher vegetation condition index values are linked with increased food consumption. For each unit change in VCI, FCS changed by 0.4069. Most ASAL counties are rural, with pastoralism as a dominant livelihood activity. The primary source of food for the majority of the households is livestock and livestock products, which depend on sensitive pasture. Therefore, changes in vegetation conditions are bound to influence the food consumption of pastoral communities.

The rCSI had a positive coefficient (0.2119), suggesting that a higher coping mechanism during drought increases food consumption. A unit change in rCSI is associated with a 0.2119 change in FCS. Based on these findings, the households with diverse drought coping strategies have higher food consumption scores. This is perhaps due to increased opportunities to access food. Variances (C(6)) and (C(10)) significantly impact current variance, indicating that high and low FCS are likely to persist, and fluctuation in FCS is expected while other terms do not contribute significantly, meaning that those variables cannot be used to explain the current variability in FCS. The significant GED parameter confirms that the error distribution and non-normality and that it provides a good fit for the data.

## 5.3 Relationship between Drought Early Warning Systems on Nutrition Security

The study conducted a regression analysis of the relationship between DEWS and volatility of MUAC on nutrition (MUAC) and presented the following results.

**Table 5.3: Relationship between drought early warning systems on nutrition security**

| Dependent variable: MUAC | | | | |
|---|---|---|---|---|
| **Variable** | **Coefficient** | **Std. Error** | **z-Statistic** | **Prob.** |
| rCSI | 0.0263 | 0.0036 | 7.7807 | 0.0000 |
| SPI | -0.1067 | 0.0243 | -4.3915 | 0.0000 |
| VCI | 0.0075 | 0.0019 | 3.9190 | 0.0001 |
| VMUAC | 0.6689 | 0.0244 | 27.3176 | 0.0000 |

| | | | | |
|---|---|---|---|---|
| C | 134.62 | 0.0461 | 2917.21 | 0.0000 |
| **Variance equation** | | | | |
| C | 0.0004 | 0.0018 | 0.2542 | 0.7993 |
| RESID(-1)^2 | 1.7630 | 0.4556 | 3.8696 | 0.0001 |
| GARCH(-1) | 0.1156 | 0.0870 | 1.3289 | 0.1839 |

The results show that rCSI has a positive and significant coefficient (0.0263), indicating an association with increased MUAC levels. A unit change in rCSI results in an increase in MUAC by 0.0263 units.

As expected, the SPI exhibits a negative coefficient (-0.1067), which is statistically significant at the 95 per cent confidence level (0.05). A unit change in SPI corresponds to a (-0.1067) change in MUAC. The change implies that severe drought is associated with global acute malnutrition (GAM) and severe acute malnutrition (SAM).

The VCI shows a significant positive association with MUAC (0.0075). This implies that a unit change in VCI corresponds to a 0.0075 change in MUAC. Increased vegetation cover leads to good forage conditions for livestock, which leads to improved livestock body conditions, associated with high milk production, hence milk is available for children under five years of age. As expected, the volatility of MUAC (VMUAC) demonstrates a highly significant positive coefficient, indicating a strong relationship with MUAC.

In the variance section, the ARCH and GARCH coefficients add up to more than one, and it is not statistically significant. This indicates that the current variance of MUAC cannot predict subsequent variance of MUAC. This is due to the spatial-temporal distribution patterns of drought.

# 6 Conclusion and Policy Recommendations

## 6.1 Conclusion

The study investigates the relationship between drought early warning systems, and food and nutrition security in ASALs in Kenya. The ADF test indicated that all variables were significant at the first difference, and the volatility analysis determined that the variables of concern (FCS and MUAC) had both heteroskedasticity and serial correlation. Therefore, the study adopted an ARCH-GARCH analysis model since it provided more insight into the relationship of the variables. The study determined the impact of DEWS (SPI, vegetation index, and coping mechanism (rCSI)) on FCS and demonstrated that all variables were significant and influenced food consumption scores. On nutrition (MUAC), the study determined that DEWS (SPI, vegetation index, and coping mechanism(rCSI) influenced nutrition. However, the variance section ARCH and GARCH terms were not significant, demonstrating that nutrition was not dependent on its volatility since drought is a temporary and fluctuating phenomenon.

The results of this study point to a close nexus between drought, and food and nutrition security in Kenya's ASALs. The analysis indicated that lower rainfall episodes were associated with reduced food consumption. An increase in standard precipitation index or rainfall is associated with a 6.555 unit improvement in food consumption score. A unit increase in the vegetation condition index corresponded to a 0.4069 unit increase in food consumption score. The reduced coping strategies are effective drought coping mechanisms as they contribute to improved food consumption in ASALs. For each unit increase in the reduced coping strategies index, the food consumption score increases by 0.2119 units. Further, a unit increase in the standard precipitation index was associated with an improvement in the mid-upper arm circumference by 0.1068 units while a unit increase in the vegetation condition index was associated with nutrition improvement as proxied by the mid-upper arm circumference by 0.0076 units. The reduced coping strategies index also significantly affected the mid-upper arm circumference, with a unit increase in the reduced coping strategies index resulting in the mid-upper arm circumference increase by 0.0263 units. These results show the critical role of rought early warning systems (DEWS) information in managing nutrition and food security outcomes amid drought episodes.

## 6.2 Policy Recommendations

(i) The national and county governments and other stakeholders need to revamp the existing drought early warning system to ensure accuracy, and timely data on drought with clear dissemination channels to facilitate early action. This will provide timely, actionable information to local communities in a changing climate.

(ii) The national government needs to invest in drought monitoring and early warning management systems and up-to-date geospatial technologies for early warning.

(iii) The government needs to have a multi-faceted approach to drought and adopt a multi-sectoral approach to address the complex interplay of factors influencing food and nutrition security in ASALs.

(iv) It is essential for the national and county governments to spearhead the identification of current viable coping strategies, to strengthen and scale them. This will help communities to better adapt to drought events.

(v) The relationship between drought, and food and nutrition security is a wakeup call for all actors engaged in ASAL development to adopt a holistic approach in addressing the challenges facing these areas.

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