Discussion Paper Series

The KENYA INSTITUTE for PUBLIC POLICY RESEARCH and ANALYSIS

# The Effect of Drought Early Warning Systems on Vulnerability of Kenyans Living in the ASALs: A Before and After Analysis Using Interrupted Time Series

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DP/272/2021

THE KENYA INSTITUTE FOR PUBLIC POLICY RESEARCH AND ANALYSIS (KIPPRA)

YOUNG PROFESSIONALS (YPs) TRAINING PROGRAMME

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Kenya Institute for Public Policy
Research and Analysis

*KIPPRA Discussion Paper No. 272*

*2021*

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Published 2021

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ISBN 978 9966 817 87 7

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## Abstract

*Kenya has about 80 per cent of its land mass falling within the Arid and Semi-Arid Lands (ASALs), therefore largely prone to drought events. Science, Technology and Innovation (ST&I) has been incorporated in Kenya's drought management through drought early warning systems (DEWS). This study sought to determine the effect of DEWS on vulnerability levels of people living in the ASALs, who are most affected by droughts through food insecurity. A comparison of the situation before and after introduction of DEWS, using multigroup Interrupted Time Series (ITS) analysis was undertaken. Data from the National Drought Management Authority (NDMA) database on the number of people facing food insecurity in the 23 ASAL counties of Kenya over the years was utilized. The study found that Turkana was the worst affected county in the ASALs with a 41 per cent increase in food insecure population before DEWS, and 20 per cent increase in food insecure population after DEWS. There was, however, a significant marginal reduction in number of people facing food insecurity in Turkana - a reduction of 20 per cent post-DEWS. However, DEWS effect was insignificant in the counties of Garissa, Marsabit, Isiolo, Narok, Samburu, Taita Taveta and Tana River. Two counties recorded a significant reduction in food insecure populations with the adoption of DEWS. Mandera recorded a 67 per cent reduction in food insecure populations over time after DEWS adoption, and Laikipia recorded a 45 per cent reduction in food insecure populations immediately DEWS were adopted. We conclude that DEWS are significant in reducing vulnerability levels of populations living in the ASALs, as illustrated from regression results. However, more effort is needed in increasing its effectiveness.*

## Abbreviations and Acronyms

| | |
|---|---|
| ASALs | Arid and Semi-Arid Lands |
| AU | African Union |
| CSI | Coping Strategy Index |
| DEWS | Drought Early Warning Systems |
| EDE | Ending Drought Emergencies |
| EM | Dat-Emergency Response Database |
| EWS | Early Warning Systems |
| FAO | Food and Agriculture Organization |
| FCS | Food Consumption Score |
| GDP | Gross Domestic Product |
| GoK | Government of Kenya |
| HSNP | Hunger Safety Net Programme |
| IGAD | Intergovernmental Authority on Development |
| IGAD DRSI | IGAD Drought Resilience and Sustainability Initiative |
| ITS | Interrupted Time Series |
| MUAC | Mid-Upper Arm Circumference |
| NDMA | National Drought Management Authority |
| NSP | National Spatial Plan |
| REC | Regional Economic Community |
| SDG | Sustainable Development Goals |
| ST&I | Science, Technology and Innovation |
| UN | United Nations |
| VCI | Vegetation Condition Index |

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**Annex**

# 1. Introduction

Drought is defined differently in different regions. It can be described as a prolonged and abnormally dry and hot period brought about by rainfall scarcity. It normally begins with less than average precipitation and may be worsened by evaporation of available surface water occasioned by extreme temperatures. When soil moisture is lost, the resultant effect is crop failure; this type of drought is referred to as agricultural drought. When drought leads to drying of upstream water sources, the drought is referred to as hydrological drought (He et al., 2019).

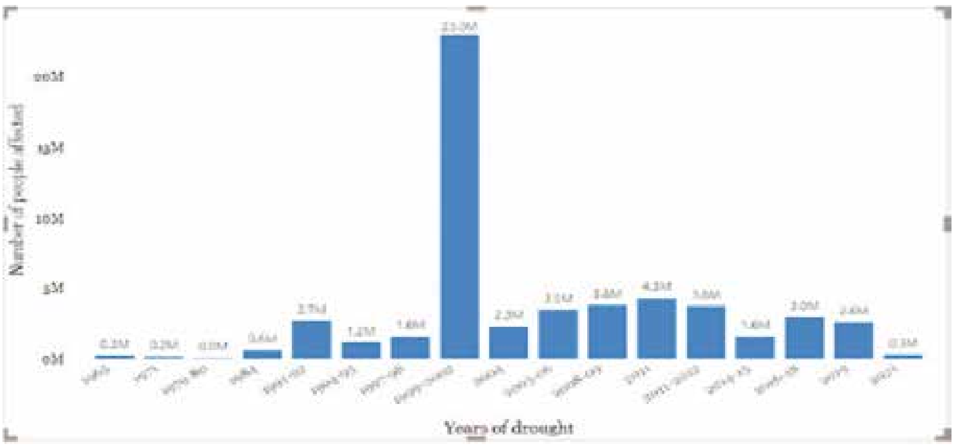
Drought, a naturally occurring hazard, may lead to a disaster if not well prepared for or mitigated against. Hazards occur all over the world and are on their own not harmful. However, when they interact with people, they are likely to cause damage of varying magnitude, resulting in a disaster. Disasters thus occur when hazards interact with vulnerable people, property, and livelihoods, thus causing varying damage depending on the level of vulnerability of the individual, group, property or livelihoods. Under the National Disaster Management Policy, drought is classified among the top disasters experienced in Kenya. Apart from droughts, other high impact disasters are identified as floods, fires, terrorism, accidents occurring in the transportation sector, and disease outbreaks (Government of Kenya, 2009).

According to the Food and Agriculture Organization (FAO) report of 2018, the cost of natural disasters to agriculture of developing world (2005-2015) is up to US$ 29 billion in losses caused by droughts. In Kenya, drought is the main form of disaster that significantly affects the economy. Given that 80 per cent of Kenya's land mass falls within the Arid and Semi-Arid Lands (ASALs), Kenya is largely prone to drought (Barrette et al., 2020). Drought occurrences lead to loss of 8 per cent of GDP every 5 years (Government of Kenya, 2018). These losses are attributed directly to the agricultural sector, which contributes about 33 per cent of Kenya's GDP. The areas that suffer the most are the ASALs of Kenya, which hold about 30 per cent of Kenya's population and 70 per cent of livestock available in Kenya. In Kenya, the livestock sector contributes to about 13 per cent in GDP and 43 per cent in the agricultural sector. The main economic activity in the ASALs is subsistence farming, which is heavily reliant on rain-fed agriculture alongside livestock raring reliant on naturally available pasture and green lands for feeding livestock. The residents in these areas are therefore predominantly pastoralist and agropastoral. Drought episodes heavily impact on these communities' well-being through food insecurity, including strained availability of water for human and animal consumption (Barrette et al., 2020; Government of Kenya, 2018; Odhiambo, 2013).

The impact of drought on food security can be through availability, access and stability. Availability speaks to the presence of food alternatives in terms of adequate crop and livestock production. Access determines the ability to acquire food that is enabled through existence of markets, available income for purchase of food items to enable trade to take place. Stability looks at sustainability of available food stock. Drought occurrences interfere with the three components of food security, leading to food crisis in vulnerable areas such as Sub-Saharan Africa that are largely dependent on rain-fed agriculture. Various food policies have been developed to help deal with food insecurity, including limiting food exports, subsidizing food prices and stockholding in marketing boards. However, these may have varied impact on food security (He et al., 2019).

The impact of drought depends on where and when they occur, and the methods taken to respond to them. The impact of drought events is further worsened by climate change, population growth and land use change (Galvin et al., 2001). Severe drought is estimated to affect 3-4 million people in a given drought cycle in Kenya, where even in 'good' years, many families in ASALs live with hunger or the fear of potential hunger (Government of Kenya, 2018).

**Figure 1.1: Trend in number of people affected by droughts in Kenya**




*Data source: Emergency Event Database (EM-Dat)*

Figure 1.1 shows the trend in number of people affected by droughts in Kenya in a given drought cycle. Kenya experienced its worst drought crisis in the period 1999 to 2002. During the 21st century, the worst drought crisis was experienced in 2011, after which the trend in vulnerability levels declined until 2016 to 2018, where it rose albeit not surpassing the 2011 figures.

Science, Technology and Innovation (ST&I) has been incorporated in Kenya's drought management through drought early warning systems, drought response and cash transfers. Some drought response approaches to drought management involve the use of satellite sensors, and machine learning technology. Satellite connected sensors have been used as a way of monitoring water supply in the ASALs of Kenya to inform water scarcity during periods of droughts. This data is used by NDMA and county governments to respond to emergency cases during drought events. With support from international organizations, including National Aeronautics and Space Administration (NASA), this data is to be linked with satellite-based earth observation centres to improve forecasting and consequently improve water security (Thomas et al., 2020).

The success of various insurance and cash transfer programmes in the ASALs is as a result of use of ST&I. A number of programmes have been developed since 2015 for communities living in ASALs of Kenya to protect them against losses occasioned by drought events. These include Index-based Livestock Insurance (IBLI) that insures against drought-related livestock mortality for Marsabit residents; IBLI that insures against asset losses in Northern Kenya; Kenyan Livestock Insurance Programme (KLIP), which is a subsidized insurance plan that covers against asset losses in droughts in Northern and Eastern Kenya; and Hunger Safety Net Programme (HSNP), which is a social protection programme to cushion residents in Northern Kenya from drought extremes - it has reached over 100,000 households. All these programmes are aided by satellite data from earth observations (Fava and Vrieling, 2021).

According to Maione (2020), HSNP has generally led to a reduction in poverty, hunger and food insecurity brought about by drought events in Kenya. Maione notes that the largest impact of HSNP was realized in phase I with the lifting of 10 per cent of target population above the absolute poverty line - reducing poverty severity by 7 per cent. 87 per cent of households under the programme reported a 16 per cent increase in food access. However, only 7 per cent reported having utilized the cash transfer for asset acquisition. The impact of phase II was, however, not as significant (Maione, 2020). Cash transfers are a significant coping mechanism for households in retaining their purchasing power during drought events; however, it may not be sustainable. Technological advancements to enable transparency and efficiency in transfer of cash to beneficiaries are advocated - these include use of biometric smart cards. However, caution to cash transfers is necessary to avoid increasing dependency rates, and a shift in policies to enhance resilience and adaptability to weather changes is preferred towards achieving both medium-term and long-term goals.

Drought Early Warning Systems (DEWS) is a significant application of ST&I in drought management. Machine learning in the form of earth observations is a technique applied to drought early warning systems in Kenya. Drought Early

Warning Systems (DEWS) are defined as a collection of capacities necessary to generate and disseminate timely and meaningful precautionary details that will assist actors threatened by a drought hazard to act accordingly to mitigate probability of losses or harm (UNISDR, 2009). Kenya's Drought Early Warning Systems monitor various indicators to enable advise 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, condition of vegetation and the status of water. Production indicators measure productivity of crop 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; terms of trade look at 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 circumference for children to detect malnutrition (Barrett et al., 2020; Welthungerhilfe, 2019).

Drought events is a problem given that it is the most prevalent natural disaster in Kenya, yet the least understood of naturally occurring disasters. Historically, less proactive measures have been relied on where drought events have been dealt with as emergencies. It is only recently that the approach to handling droughts was changed from reactive to proactive. In Kenya, 2011 marked the era of change in drought management where a resolution was made to end drought emergencies and to take proactive measures in dealing with droughts. DEWS is one such proactive approach that was adopted to end drought emergencies.

For DEWS to be effective, it has to satisfy some conditions. A drought early warning system is more than a forecast of expected onset of drought episodes. It is meant to deliver four objectives: to provide information on impending drought event; to monitor the prevailing situation and send warnings as necessary in an ongoing drought event; to disseminate in a timely manner, warnings to those directly affected by droughts; and to enable awareness of the public on the unfolding to allow preparatory actions for drought management and mitigations. If drought early warning systems fail to meet any of these objectives, then their success is curtailed. Drought early warning systems should be able to inform those affected by drought events to better prepare themselves for an eventuality, thereby reducing their vulnerability to drought events. Drought early warning systems should also be location-specific, and people-centred. Drought early warning systems should be able to detect food security concerns before famines occur and should be able to single out regions experiencing the advent of food distress. DEWS should be consistent, dependable, and timely (Pulwarty, 2014).

Our study seeks to determine the effect of DEWS on vulnerability levels of people living in the ASALs of Kenya. Currently, there are few studies that look at the effect of drought early warning systems in general. There are even fewer studies that look at drought early warning systems in Kenya, and its effect on vulnerability levels of people living in drought prone areas. A quantitative examination of the trends in food insecure populations in the ASALs over the years is undertaken. According to Perruzi et al (2009), drought casualties are not directly induced by physical drought but by food insecurity, and most of Africa is mainly affected by droughts through food insecurity.

The main objective of the study is to examine the effect of DEWS on vulnerability levels of people living in the ASALs of Kenya. The specific objectives are to determine DEWS adopted in Kenya, to draw lessons from DEWS adopted in other nations and to determine the direction and magnitude of the relationship between DEWS and vulnerability levels of Kenyans in the ASALs.

The rest of the paper is organized as follows: section two is the situational analysis, section three highlights the literature review, section four speaks to the data and methodology, section five speaks to results and discussions and the final section six presents the recommendations and conclusion.

# 2. Situational Analysis

## 2.1 Policy, Legal and Institutional Framework

In Kenya, the NDMA is the organization mandated to oversee the management of droughts. The NDMA Act of 2016 established the legal framework for operationalization of the institution. NDMA is under the State Department of ASALs within the Ministry of Devolution and ASALs. Some legislative frameworks guiding this sector include County Government Act, the Environment Management and Coordination Act, the Climate Change Act, the Community Land Act, and the Water Act (Government of Kenya, 2018a).

The main policy framework guiding drought management in Kenya is the Kenya Vision 2030, the Constitution of Kenya, and ASALs Policy. Socio-economic development of ASALs, given their unique circumstances and priorities, is guided by the Kenya Vision 2030. The third Medium-Term Plan (MTP III) outlines the key initiatives to be undertaken under the EDE programme. Flagship initiatives under this programme include nationally integrated Drought Early Warning Systems, National Drought Emergency Fund, Hunger Safety Net Programme, and the Integrated Knowledge Management System. Drought management contributes to the "Big Four" agenda through food security, with an aspiration of ensuring 100 per cent food security and nutrition for Kenyans. According to the Presidential Delivery Unit, this is to be achieved through an increase in average incomes of farmers by 34 per cent; decrease in malnutrition cases in children below 5 years old by 27 per cent; 50 per cent reduction in food insecure Kenyans; reduction in food costs as a percentage of income by 47 per cent; additional 1,000 Small and Medium Enterprises (SMEs) with additional 600,000 jobs; and an increase in agricultural sector contribution to GDP by 48 per cent.

The Constitution under Article 56 mandates the Government to incorporate affirmative actions to lift the most marginalized and vulnerable members of the community out of externalities such as poverty - most poor are within ASALs. Article 204 also establishes an Equalization Fund to provide basic services to such populations. To advance effective participation of communities in the ASALs in economic growth and productivity, the ASALs policy enables building resilience and adaptation of communities living in ASALs through economic empowerment, while ensuring investments are climate-proofed. The National Spatial Plan (NSP) 2015-2045 is a significant document that guides land use to ensure sustainable use of available land/the national space (Government of Kenya, 2018a).

Different collaboration and partnership platforms have been developed to deal with drought events in a collaborative manner. The Intergovernmental Authority on Development (IGAD) is the main Regional Economic Community (REC) that guides drought risk management in the region, given that droughts are a common area of concern for all members. IGAD members include Kenya, Uganda, Somalia, Sudan, Ethiopia, Eritrea, South Sudan and Djibouti. IGAD Drought Resilience and Sustainability Initiative (IDDRSI) was adopted in September 2011 by member States committing to end drought emergencies by 2027. Kenya leads the Ending Droughts Emergencies (EDE) initiative in IGAD (Government of Kenya, 2018a).

Global initiatives aimed at sustainable development include the African Union (AU) Agenda 2063; United Nations Sustainable Development Goals (SDGs); Sendai Framework for Disaster Risk Reduction 2015-2030 adopted in 2015; and the Paris Agreement on Climate Change adopted in 2015 (Government of Kenya, 2018a). The UN SDG No. 2 aims at reaching zero hunger levels by 2030 globally. The ambitious goal is to end malnutrition and get to the globally agreed stunting and waste targets for children below years and fulfil nutritional needs for all, including the most vulnerable in the society by 2030. Agenda 2063 seeks to eradicate hunger and food insecurity by 2063; increase intra-African trade in agricultural products by 50 per cent; advance use of modern technology in agricultural sector; and increase women participation in agriculture while ensuring at least 30 per cent financing is allocated to women. The Sendai framework monitors the measures put in place to prevent catastrophic disaster risks. Seven (7) global targets and 38 indicators are monitored for countries to determine progress towards disaster risk reduction. The Paris Agreement is a legally binding agreement between parties to limit climate change deterioration while committing to reduce global warming to below 2 degrees Celsius. Climate change has been shown to increase the frequency and severity of natural hazards such as droughts.

## 2.2 DEWS Adopted in Kenya

Strengthening Climate Information and Early Warning Systems for Climate Resilient Development and adaptation to climate change is a comprehensive programme operating across Africa, Asia and the Pacific. In Kenya, the NDMA has bulletins that are used to establish mechanisms that ensure that drought does not result in emergencies, and that the impact of climate change is sufficiently mitigated. Drought is the prime recurrent natural disaster in Kenya, having recurred in 1983/1984, 1991/1992, 1995/1996, 1998/2000, 2004/2005, and 2008/2011 according to the Kenya National Adaptation Plan 2015-2030.

The NDMA recommends localization and improvement of drought early warning systems through dissemination of DEWS. There is need for a manual to help inform mitigation strategies and guidelines for implementation. The NDMA works with academia for drought-related research, supporting inter-county multi-sector engagement and closely building communities capacity through participatory approaches to community empowerment, and harnessing technology in developing effective approaches to early warning response and preparedness.

To better prepare and mitigate the impact of drought, various indicators can be applied to monitor and forecast its onset, intensity, and severity. Although recent years have seen a strengthening of the institutional framework for drought management in Kenya, the existence of the NDMA means that drought issues are handled separately from general agricultural policies and programmes.

A total of 50 indicators are used in the biannual assessment process, divided into segments that describe factors that drive the food security situation and indicators of the impact on food security. However, the county drought bulletins from NDMA includes less indicators, only 14, grouped in four categories: biophysical, production, access, and utilization. The indicators are illustrated below.

**Table 1.1: Classification of indicators used by NDMA**

| Indicator classification | Indicators | Type of impact |
|---|---|---|
| Biophysical indicators | Rainfall data | Environmental |
| | Vegetation condition | |
| | State of water | |
| Production indicators | Livestock body condition | Livestock production |
| | Milk production | Crop production |
| | Livestock migration | |
| | Livestock mortality | |
| | Crop production | |
| Access indicators | Terms of trade (Maize/ Beans) | Markets access to food and water |
| | Milk consumption | |
| | Water distances | |
| | | |
| Utilization indicators | Mid Upper Arm Circumference - MUAC) | Nutrition |
| | Copying strategies | Copying strategies |
| | Food consumption score | |

*Source: NDMA (2021), National bulletin, June 2021*

The biophysical indicators look at the environmental and climatic aspects that indicate onset of drought events, such as rainfall statistics, condition of vegetation and the status of water available. Production indicators measure productivity of crop 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; terms of trade look at the pricing levels for common food crops such as beans and maize, access to milk for consumption and distances from water sources to gauge access. Utilization indicators look at the well-being aspects of human beings living in vulnerable areas; the copying strategies adopted by locals, food consumption levels, and mid-upper circumference for children to detect malnutrition. Kenya's Drought Early Warning Systems monitor various indicators to be able to advise on the progress of impending drought - classifying the drought event situation as normal, alert, alarm, emergency or recovery (Barrett et al., 2020; Welthungerhilfe, 2019).

Vegetative Condition Index (VCI) is one of the key indicators for early warning adopted in Kenya. It is used to identify drought situations and determine the onset, especially in areas where drought episodes are localized and ill-defined. It focuses on the impact of drought on vegetation and can provide information on the onset, duration and severity of drought by noting vegetation changes and comparing them with historical values.

According to Bowell et al.(2021), NDMA uses vegetation cover, livestock palatability and plant vigour using ground informants to assess the conditions. There is usually set out household surveys incorporating questions regarding food and water sources, health, and finances. The ground informants assess environmental 'conditions' such as pasture and browse, related selected sites that generally represent all livelihood zones within a given county. These datasets are published in monthly bulletins, which give an overview of each county's drought situation.

## 2.3 Lessons on DEWS from other Countries

As vulnerability to drought has increased globally, greater attention has been directed to reducing risks associated with its occurrence through introduction of proper planning to improved operational capabilities. In 2002, a network on Drought Management for the Near East, Mediterranean and Central Asia was formed to reduce risk, vulnerability and assess the impact of drought for proper planning mitigation strategies. This helped to improve planning and implementation of drought-mitigation programmes at national and regional levels.

In the United States of America (USA), the central government works hand in hand with academicians in drought early warning systems. National Integrated Drought

Information System (NIDIS) under the federal government partners with the National Drought Mitigation Centre (NDMC) from the University of Nebraska in undertaking drought impact studies, forecasting drought events, development of DEWS indicators and web-based information portals advising on available water sheds. NIDIS also works towards developing capacity of various actors in DEWS. A partnership formed between academicians and federal agencies known as the US drought monitor provides DEWS information to all actors within national and State governments using an interactive website that enables visualization of maps with summary of current drought situation and forecasts for the coming few weeks across the nation. Other innovative maps such as the World Atlas of Desertification by United Nations Environmental Programme (UNEP) provide information on global desertification (Pulwarty and Sivakumar, 2014).

In Syria, between 2004 and 2006, the FAO worked with the government to develop an effective early warning system for drought. This was done through processing of and monitoring data. The main challenges in Syria was outdated mitigation plans and monitoring early warning systems. The FAO project ensured training of the Syrian Ministry of Agriculture and Agrarian Reform, and strengthening institutional capacity in drought early warning systems. Progress has been made towards monthly drought bulletins that have been produced regularly since 2005 in both English and Arabic (DePauw, 2000).

Over many decades, Israel developed a centralized water management system to help deal with drought situations. Investment in technological innovations that include a scheme to supply water, digging extremely deep wells and seawater desalination plants has helped Israel in its water supply plans. Israel also reuses wastewater and requires its population to use water-saving technology. Israel has also invested in irrigation technology. Drought mitigation is simpler to implement with the options above in place (Andrew and Sukhmani, 2018).

Sahara and Sahel Observatory (OSS) put together a network of 25 observatories for long-term ecological monitoring in North Africa (Algeria, Egypt, Morocco, Tunisia and Mauritania). OSS also launched a project to help establish the drought early warning systems in Algeria, Morocco and Tunisia. Kenya, working with regional partners, could come together as part of the ongoing effort to mitigate the effects of drought. In the United States, the planning process has emphasis on attention to improve e-government response to drought emergencies through development of greater institutional capacity directed at creating an appropriate organizational structure, improving monitoring capability, defining a more explicit decision-making authority for implementing response measures, and improving information flow and coordination between and within levels of government (Wilhite and Svoboda, 2000).

In Nigeria, allocation of government funds goes to DEWS, more so than any other meteorological project (Nnoli et al., 2000). About 50 per cent of the total annual and 3-year rolling plan allocations to the department come under the EWS project. This funding has enabled the department to achieve 20-25 per cent of the optimal level of implementation of other related projects. Allocation to the EWS in Kenya is key, with the present awareness of the effects of ongoing climate change and global warming. Traditional forecasting plays a big role in providing early warning information, especially to communities in rural areas. In Uganda, communities covered under Rapid SMS Community Vulnerability Surveillance Project have been provided with mobile phones to enable rapid relay of early warning information to data monitoring centres. Currently, there is ongoing studies in Kenya to gain more knowledge on integration of traditional with modern forecasting methods (Pulwarty and Sivakumar, 2014).

Tackling drought varies from across regions and sovereign States. In most countries, there is a system to manage national drought and mitigation strategies and early warning systems. However, all these are work in progress. The two most widely used indicators are the Standardized Precipitation Index (SPI) and the Palmer Drought Severity Index (PDSI). There are many comparisons of different indicators and discussions about their advantages and disadvantages.

Borrowing from lessons learnt, Kenya has the biggest burden to set up a working regional network for knowledge sharing around drought mitigation and ensuring development of DEWS in consultation with stakeholders to provide a working efficient drought early warning system. Opportunity exists in empowering vulnerable communities in drought prone areas with early warning information and the ability to act proactively to mitigate drought impact. Community informed EWS are necessary to support community response and coping strategies to droughts. There is need for proper allocation and resource mobilization from partners to enable optimal implementation of the NDMA Strategic Plan 2018-2022, which comes to an end in one year. The need for coordination of drought response initiatives across all bodies involved cannot be over-emphasized, especially institutions and agencies in the hope of an integrated drought response and management of drought. Alignment of crisis calendar with response calendars for humanitarian action is also significant in reducing lead time necessary before action is taken, from 3 months to a few weeks. This would help reduce losses from drought events that lead to worsening vulnerability levels of those affected by droughts.

# 3. Literature Review

## 3.1 Theoretical Literature

The tipping point theory explains the usefulness of drought early warning systems in detecting early advancement of natural hazards before they become disasters. 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 2 degrees Celsius, causing global warming that in turn leads to melting of glaciers, 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 occurrence of natural hazards such as drought events, while noting the non-linear nature of the two aspects.

Krishnamurthy et al. (2020) notes the possibility of determining drought events from climatic conditions visible through biophysical aspects such as rainfall variability and vegetational conditions. Hydraulic droughts that are as 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 advice 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 proactive response to drought events thereby reducing vulnerability levels of communities living in drought prone areas is therefore consequently enhanced.

Drought is identified as a tipping point in the climatic system. This can occur from a variety of factors. For example, when 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 in water availability and food security, this can be an impending risk signalling likelihood of getting to the tipping point - a drought event. Drought early warning systems are therefore important in forecasting of 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 stessors. The more severe the impact of the stessor, the more severe the vulnerability levels of those affected by the stressor. This approach adopts the use of quantitative statistics of historical trends of the effect of the hazard as a proxy for vulnerability of the community (Peduzzi et al., 2009; Brooks et al., 2005).

According to Cardona (2005), the risk of losses is a function of the hazard, element of risk and vulnerability. For human losses, the element of risk is the exposed population; hazard occurrence is the frequency of the hazard; vulnerability is the degree of loss from a hazard occurring. Perruzi et al. (2009) notes the complexity in modelling droughts from the lack of clarity on its onset and dissimilarity in impact of precipitation on vegetation depending on soil fertility factors. DEWS come in handy in reducing vulnerability levels through proactive drought management.

## 3.2 Empirical Literature

Droughts can be generally described as climatic conditions with characteristics such as unfavourable weather patterns, scarcity in 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 Futurewaters (2017) worked on technical assistance on drought information and early warning systems aimed at providing technical and intuitional advice following the severe drought in 2016 in Bolivia that affected the country. It became evident that 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 of a proactive attitude caused a slow response in La Paz/El Alto and all stakeholders agree that the impacts could have been considerably less severe if action was 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. Taking into account future changes (population, climate change, land use change), this risk-based drought impact assessment should allow to draft drought-focused policies by identifying the most adequate indicators and developing better preparedness for future similar droughts.

Muthoni Masinde (2014) studied An Effective Drought Early Warning System for Sub- Saharan Africa: Integrating Modern and indigenous approaches. The paper describes an effective drought early warning system that integrates indigenous and scientific drought forecasting approaches. The research applied correlational structured research to identify the similarities and differences between modern science and indigenous ways. Indigenous knowledge ensures that the system is relevant, acceptable and resilient. The system is anchored on a novel integration framework called ITIKI (acronym for Information Technology and Indigenous Knowledge with Intelligence).

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 multiyear average situation in a year at a given place. A statistical approach that combines different parameters to an index, the CDI, was developed. According to the study, the index could clearly trace the footprints 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 recommend that CDI should be tested worldwide.

Tuitoek and Wausi (2016) looked at the effect of DEWS in drought mitigation and management in ASALs in Kenya. The study used descriptive research design, using primary data collected through a survey of 23 ASALs in Kenya. 5 respondents per ASAL area were interviewed, getting to a total of 115 respondents. The findings indicated that DEWS have enabled a timely and useful provision of drought-related information. The system 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 to communities living in the ASALs.

Sandstorm et al (2020) studied the Fluctuating Rainfall, 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 resulting from hazards such as drought indicate that these systems need improvements. We focus our research on Turkana County in Kenya, where drought repeatedly results in humanitarian crises, especially regarding food insecurity. They used the biannual assessments, and the country bulletins use different sets of rainfall data and different methodologies for establishing the climate normal, 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.

Shilenje and Ojwang (2015) studied the role of Kenya Meteorological Service in early warning in Kenya. The methodology employed literature review. The study argues that early warning and weather information communication are essential elements of effective governance of weather risks through a well-developed warning system. The study recommends strengthening of the existing structures with respect to weather monitoring.

Golicha and Wanyonyi (2018) investigated the influence of pastoralists' drought management practices on their livelihoods in Isiolo North Sub-County, Kenya. The pastoralists communities mostly inhabiting the ASALs regions have been affected by drought, which is by far the most common disaster in the dry lands in the Eastern and Northern Kenya. It affects more people more frequently than any other disaster in the arid and semi-arid areas in Kenya and in the Horn-of Africa region. 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 generalize results from the sample to the population. The study found that most of the areas in Isiolo North Sub-County are frequently struck by drought and water scarcity, putting the pastoralists at 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 mechanism.

## 3.3 Overview of Literature

According to the available literature regarding empirical literature reviewed, the results indicate, generally, that DEWS have enabled a timely and useful provision of drought-related information. The system ease of use has enabled capacity building among stakeholders, especially communities living in ASALs. In Kenya, Tuitoek and Wausi (2016) looked at the effect of DEWS in drought mitigation and management in ASALs in Kenya. The study recommended that NDMA should consider improving DEWS to enhance information dissemination. In both Muthoni Masinde (2014) and Golicha and Wanyonyi (2018), there is emphasis on community involvement in drought mitigation, and even suggestion of customised community indigenous knowledge and intelligence. The studies only came close to studying the effect but not the before and after effect with introduction of DEWS. This study seeks to fill this knowledge gap by studying the effect of drought early warning systems (DEWS) on drought vulnerability of Kenyans living in the ASALs, a before and after analysis using interrupted time series (ITS).

# 4. Methodology

## 4.1 Theoretical Framework

In accessing drought risks, our study adopts the outcome/impact approach. This approach is pegged on the relationship between stressors and response. The analysis looks at the vulnerability of the community affected - the more severe the impact is on community, the more vulnerable it is. The approach adopts the use of quantitative statistics of historical trends of the impact of the hazard as a proxy for vulnerability of the community (Peduzzi et al., 2009; Brooks et al., 2005).

This approach presents an alternative for estimating drought risk at different scales and levels of coordination. Given that impacts of droughts are context-specific and differ depending on locations, regression models are useful in providing guidance on preparedness plans and mitigation actions at both local and national levels (Vogt et al., 2018).

According to Cardona (2005), the risk of losses is a function of the hazard, element of risk and vulnerability. For human losses, the element of risk is the exposed population; hazard occurrence is the frequency of the hazard; vulnerability is the degree of loss from a hazard occurring. Peduzzi et al (2009) model the risk function as shown below:

$$R=Hfr\ Pop\ Vul \qquad (1)$$

Where:

R: number of expected human impact (killed/year)

Hfr: frequency of a given hazard (event/year)

Pop: population living in a given exposed area (exposed population/event)

Vul: vulnerability depending on socio-political economy

Equation 1 is transformed into a generalized multiplicative equation as follows:

$$K=C(PhExp)^{\alpha}V_1^{\alpha_1}V_2^{\alpha_2}\ldots V_p^{\alpha_p} \qquad (2)$$

Where

K: number of persons killed by a certain type of hazard.

C: multiplicative constant.

PhExp: physical exposure/population living in exposed areas multiplied by the frequency of occurrence of the hazard.

$V_i$: socio-economic variables.

Taking the natural logarithms of Equation 2 we get the transformed equation 3

$$Ln(K)=Ln(c)+\alpha Ln(PhExp)+\alpha 1Ln(V1)+\alpha 2Ln(V2)+\ldots+\alpha pLn(Vp)\ldots\ldots\ldots\ldots 3$$

In calibrating the risk model as per the hazard, equation 4 was developed as a risk model for a drought hazard.

$$Ln\ (K)= Ln\ (PhExpDd) + Ln(mALpc) + ln\ (GDPcap)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4$$

Where:

K: number of people affected

PhExpDd: physical exposure to drought (total exposed)

GDPcap: GDP purchasing power parity per capita

MAL.pc: modified percentage of arable land

$$MALpc=ALA/(TA-DA)\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 5$$

Where:

ALA: arable land area ($km^2$)

TA: total area (in $km^2$)

DA: desert area (in $km^2$)

Perruzi et al. (2009) notes the complexity in modelling droughts from the lack of clarity on its onset and dissimilarity in impact of precipitation on vegetation depending on soil fertility factors. They note that casualties are not directly induced by physical drought but by food insecurity. It would be erroneous to develop a global approach to human development without consideration of droughts, given that most of Africa is mainly affected by food insecurity.

For our analysis, we adopt a linear regression model with our outcome variable as the number of people that are food insecure in Kenya's 23 ASALs. We use interrupted time series analysis to analyze the effect of DEWS on vulnerability levels in Kenya's ASALs.

## 4.2 Interrupted Time Series Model Explained

The study adopts Interrupted Time Series (ITS) to analyze the effect of DEWS on the number of food insecure people in Kenya's ASALS. According to Lopez et al. (2018), ITS is used to analyze the impact of an intervention or exposure that occurs at a certain point in time. It is especially useful where an intervention affects a whole population as opposed to a certain group, as is the case for experimental or randomized control studies; it makes within group comparisons and not between group comparisons. This helps reduce cofounding factors and selection bias. Cofounding factors are occasions that are experienced during the time of intervention that can affect the outcome. Selection bias occurs during selection of control groups to be included in the regression - when non-similar groups are selected for inclusion/comparison in the analysis. ITS is also an effective method for evaluation of exposure to natural disasters and calamities such as drought events (Turner et al., 2021).

Our model adopts control groups in the regression. Lopez et al (2018) states that use of control series in ITS analysis is useful in controlling for cofounding factors. A control series is a series that is added in the regression for comparison with the intervention group. In Controlled Interrupted Time Series (CITS), comparisons are made within a single population, across time. This removes challenges associated with within group differences - selection bias and cofounding. Control series is a form of counterfactual introduced to improve the validity of the model. A control series should be as similar as possible to the focus group. It should be exposed to similar co-interventions as those of the focus group. Use of interrupted time series is vulnerable to trends and, therefore, adoption of control series is recommended to improve validity of estimates results (Mackenzie et al. 2016; Fowler et al., 2007).

According to Linden (2015), the models used to undertake ITS need to account for autocorrelation. The two most common methods used are the Autoregressive Integrated Moving Average Model (ARIMA) and the Ordinary Least Squares (OLS) model that account for autocorrelation such as the Newey-West model. OLS is preferred since it is broadly applicable and flexible. Our model, therefore, adopts Newey-West standard errors that account for autocorrelation and possible heteroskedasticity in the regression.

In its simplest form, an ITS model is as shown below:

$$Yt = \beta 0 + \beta 1 T_t + \beta 2 X_t + \beta 3 X_t T_t + \varepsilon t \qquad \text{......} 6$$

Where:

Yt: the aggregate outcome at each equally spaced t(time).

$T_t$: the time variable depicting the period of observation; 1, 2, ..., n

$X_t$: the variable representing the Intervention (usually captured as a dummy variable -0,1)

$X_t$ $T_t$: the interaction term that depicts the interaction between time and periods with/without DEWS intervention.

$\beta_o$: Initial intercept/level of the outcome.

$\beta_1$: Initial slope/trend of the outcome

$\beta_2$: change in level immediately after intervention

$\beta_3$: change in slope of outcome variable overtime

Equation 1 illustrates a simple ITS model with a single group of analysis. The parameters of significance here are $\beta_2$ and $\beta_3$ that illustrate the effect of the intervention experienced immediately after intervention and over time during the intervention, respectively.

Multigroup analysis is undertaken for this study. A multigroup analysis is performed when there is more than a single group available for analysis - where more observational groups are available for comparison - using multiple time series data. It is a more complex analysis with additional estimation parameters for the study. The multigroup analysis adopted for the study is as shown below.

$$Y_t = \beta_o + \beta_1 T_t + \beta_2 X_t + \beta_3 X_t T_t + \beta_4 Z + \beta_5 ZTt + \beta 6ZXt + \beta_7 ZX_t T_t + \varepsilon t \ldots\ldots\ldots\ldots\ldots\ldots\ldots 7$$

Where:

$Y_t$: The aggregate outcome at each equally spaced t(time)

$T_t$: The time variable depicting the period of observation; 1, 2, ..., n

$X_t$: The Intervention, usually captured as a dummy variable depicting period with/without the intervention (0,1)

$X_t$ $T_t$: The interaction term that depicts the interaction between time and periods with/without DEWS intervention

Z: A dummy variable that denotes cohort assignment depicting a series as either the focus group or a control group (0.1)

ZT, ZX and ZXT are interacting terms depicting interactions between Z and T(time), X (DEWS intervention), XT (DEWS intervention across time), respectively

Coefficients $\beta_o$ to $\beta_3$ are control group coefficients while $\beta_4$ to $\beta_7$ are focus group coefficients

$\beta_4$: Difference in level/intercept of outcome variable between control and focus group before intervention

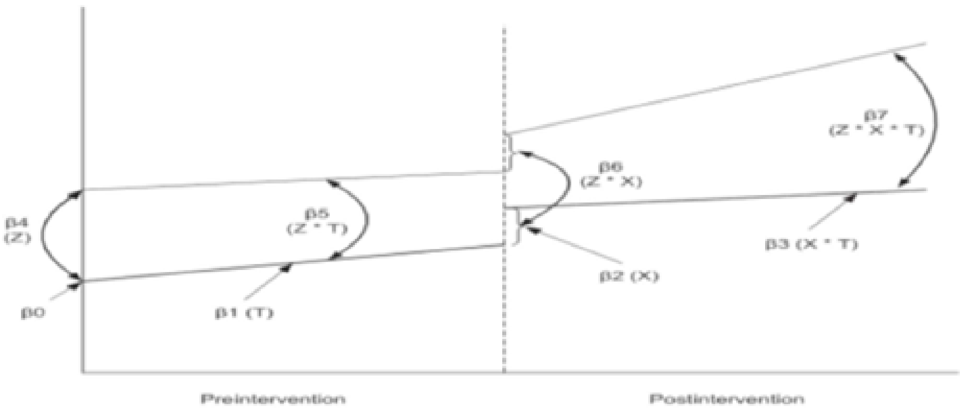
$\beta_5$: Difference in trend/slope of outcome variable between control and focus group before intervention

$\beta_6$: Difference in level of outcome variable between focus and control group immediately after intervention

$\beta_7$: Change in the outcome variable over time after the intervention (also difference between slopes of focus and control groups)

According to Linden (2015), a multiple group ITS is recommended where there is an adoption of an alien/external policy that affects the whole of a group. The change in trend/level in the outcome is assumed to be similar for both the control group and the focus group. The assumption is that omitted variables in the regression affect the focus and control variables in a similar way. To minimize the problem brought about by omitted variables, multiple group ITS uses randomized controls where the control groups are chosen according to a certain criterion - those with $\beta_4$ and $\beta_5$ whose P-values are greater than 0.05 (approaching P values of the focus group in similarity) are considered in the regression (Linden, 2015). An illustrative figure of ITS undertaken for both single group and multiple group analysis is presented in the figure below.

**Figure 2: Visual representation of single group and multiple group ITS**




*Source: Conducting interrupted time series analysis for single- and multiple-group comparisons by Linden (2015)*

The single group ITS is depicted by the lower curve, with parameters $\beta_0$ to $\beta_3$. $\beta_0$ and $\beta_1$ are the initial intercept and slope, respectively, while $\beta_2$ to $\beta_3$ are the changes in intercepts and slopes post-intervention, respectively. The multiple group ITS is depicted by the two curves (both lower and upper curves). The parameters $\beta_0$ to $\beta_3$ are control group parameters and the parameters $\beta_4$ to $\beta_7$ are focus group parameters. $\beta_0$ to $\beta_3$ are as defined earlier; $\beta_4$ and $\beta_5$ are the change in level and trend, respectively, between the cohort prior to intervention. $\beta_6$ to $\beta_7$ are the change in level immediately after intervention, and change in slope over time, respectively, within the cohort.

Linden (2017) notes the advantage of multigroup analysis over single group analysis. As opposed to single group analysis, where counterfactuals are derived only from focus group's pre-intervention trend, control groups in multiple group analysis act as counterfactual to focus group.

## 4.3 Definition of Study Variables

The variables employed in the study are explained in this section. The independent variable under the study is DEWS and the dependent variable or the outcome variable is number of people facing food insecurity (proxy for vulnerability levels). Other control variables employed in the study are the time variant variable (T), the cohort assignment variable (Z), and the interaction terms of the variables time, cohort and DEWS intervention. The table below further explains the list of variables.

**Table 2: Definition of variables**

| ITS symbol | Variable Definition | Symbol adopted in the study |
|---|---|---|
| $Y_t$ | Number of people facing food insecurity in Kenya's ASALs. This is used as a proxy for vulnerability levels | Food insec |
| $X_t$ | DEWS intervention measured as dummy variable (0,1); zero indicating periods without DEWS intervention and one indicating periods of DEWS intervention. DEWS adopted in September 2016. | DEWS |
| $T_t$ | Time variant variable. Measures the time period of equally spaced observations;1, 2,..,n | T |
| $X_t$ $T_t$ | Interaction term illustrating DEWS adoption across time. Zero for periods prior DEWS; 1,2,..,n for periods with DEWS intervention. | DEWST |
| Z | Cohort assignment with dummy variables (0,1); 1 indicates focus group and 0 control group | Cohort |
| $ZT_t$ | Interaction term illustrating focus group observed across time. Zeros for control group;1, 2, ..., n for focus group across time | CohortT |

| | | |
|---|---|---|
| $ZX_t$ | Interaction term illustrating initial interaction between focus group and DEWS adoption. Zero for control group interaction and one for focus group interaction. | Cohort_DEWS |
| $ZX_tT_t$ | Interaction term illustrating interaction between focus group and DEWS across time. Zeros for control group interaction and one for focus group interaction. | Cohort_DEWST$_t$ |

## 4.4 Model Specification

The study adopts the Ordinary Least Squares (OLS) method that accounts for autocorrelation and heteroskedasticity in the regression- Newey-West standard errors -to undertake ITS. Newey-West method is suitable for multiple time series (Bertrand et al., 2004).

Drought Early Warning Systems (DEWS) is the exogenous shock, whose effect on vulnerability levels is to be measured using a multigroup ITS. DEWS is the independent variable - intervention variable - while food insecure populations is the dependent/outcome variable. Perruzi et al. (2009) note that drought casualties are not directly induced by physical drought but by food insecurity. We therefore adopt number of people facing food insecurity in Kenya's ASALs as a proxy for measuring vulnerability levels . The generalized form of the ITS model is as follow:

$$y_t=\alpha+\beta x_t+\varepsilon_t \ldots\ldots(8)$$

Equation 8 shows a series of observations , n, where t=1,..., n ; made before and after adoption of an intervention. $x_t$ indicates presence of an intervention (x=0 or 1); α is expected response without intervention; $\varepsilon_t$ is error term independent of $x_t$ including other factors that affect the outcome $y_t$. The model would be mis-specified if some variables in the error term were correlated with $x_t$. To counter these issues of cofounding, a vector of cofounders is introduced in the model to get equation 9.

$$y_t=\alpha+\beta x_t+\sum_i \rho i(zit-zi0)+\varepsilon t \ldots\ldots(9)$$

*zit* is the *ith* cofounder and ρi the overall effect of the cofounders. If the confounders are known and statistically quantifiable, they are included in the regression model. But if they are unobserved as would be the case for other non-DEWS factors that affect vulnerability levels such as climate change, adoption of segmented regression models or control series can help deal with confounding challenges. Equation 9 can be transformed to equation 10 below:

$$y_t=\alpha +\beta x_t + \lambda_t + \varepsilon_t \text{..........} (10)$$

Here, $\lambda t$ is a vector of cofounders. Equation 9 represents a segmented regression model (Wanger et al., 2002). When the model is expanded to include time variant effects, that is, the interaction between time and intervention, equation 11 is adopted.

$$y_t=\alpha +\beta_1 x_t + \beta_2 x_t (t-T)+ \lambda_t + \varepsilon_t \text{..........} (11)$$

Equation 11 represents the single group ITS analysis as postulated in the study. When control series are adopted for the study, equation 11 is transformed to equation 12 as shown below.

$$y_{it}=\alpha_i +\beta_1 x_t + \beta_2 x_{it} (t-T)+ \lambda_{it} + \varepsilon_{it} \text{..........} (12)$$

Where $i=1,\ldots,k$ for focus series and $k-1$ for control series. $\alpha_i$ is modelled as a fixed effect and the common trend (shared by the control and focus group) is modelled through assumption of a linear functional form. Equation 12 can alternatively be broken down to disaggregate time variant and cohort assignment variables as shown in equation 13 below. This is the multigroup ITS model.

$$Y_t= \beta_0+ \beta_1 T_t+ \beta_2 X_t+ \beta_3 X_t T_t +\beta_4 Z + \beta_5 ZT_t + \beta_6 ZX_t + \beta_7 ZX_t T_t+ \varepsilon_t \text{..........} (13)$$

For this study, our ITS model is transformed to incorporate study variables that were defined in section 3.4. The natural log of the dependent variable is adopted for the regression to normalize it. The resultant model is represented by equation 14 below.

$$LnFood\_insec= \beta_0+ \beta_1 Tt+ \beta_2 DEWS+ \beta_3 DEWSTt +\beta_4 Cohort+ \beta_5 CohortT_t + \beta_6 Cohort\_DEWS + B_7 Cohort\_DEWS\, T_t + \varepsilon_t \text{..........} (14)$$

Where:

LnFood_insec is the number of people facing food insecurity in Kenya's ASAL areas

$T_t$: Is a time variant variable denoted by 1, 2, ..., t

DEWS: Denotes drought early warning system adoption with one for period of DEWS adoption and zero periods without DEWS intervention

$DEWST_t$: Is interaction between DEWS and time

Focus: is cohort assignment variable with one depicting the focus group and zero, control group.

$CohortT_t$: Is interaction of focus group across time

Cohort_DEWS: Is interaction between focus group and DEWS

Cohort_DEWST: Is the interaction between the focus group and DEWS across time

$\varepsilon t$: Is the error term

$\beta_0$: Initial intercept/level of the outcome

$\beta_1$: Initial slope/trend of the outcome

$\beta_2$: Change in level immediately after intervention

$\beta_3$: Change in slope of outcome variable overtime

$\beta_4$: Difference in level/intercept of outcome variable between control and focus group before intervention

$\beta_5$: Difference in trend/slope of outcome variable between control and focus group before intervention

$\beta_6$: Difference in level of outcome variable between focus and control group immediately after intervention

$\beta_7$: Change in the outcome variable over time after the intervention (also difference between slopes of focus and control groups)

Our focus group here is chosen as Turkana County, given that it is ranked historically as the worst affected county when it comes to droughts. According to Welthungerhilfe (2021), Turkana County was ranked as the most vulnerable of the 23 ASAL counties in Kenya, followed by Mandera and Wajir. The ranking of prioritizing the 23 ASAL counties was based on county-specific analysis of indicators of drought risk and humanitarian outcome-VCI, MUAC, FCS and CSI. These are the indicators used in monitoring drought progress through drought early warning systems.

We first run a simple uncontrolled ITS followed by a Controlled ITS (CITS). Lopez et al (2018) recommends starting ITS regression with the simple uncontrolled ITS followed by the Controlled ITS (CITS) regression. When the results of simple uncontrolled ITS are similar to that of CITS, then the relationship between the intervention and the effect is likely causal. However, when results from the uncontrolled and controlled ITS differ, care is needed in interpretation as this may point towards cofounding bias or historical bias.

To settle on control groups, individual counties are tested/regressed separately alongside Turkana County. Only those counties that have similar trend and level with Turkana are included in the regression. We run separate regression models for each control group checking for P-values of intercept (_z) and slope (z_t). From the analysis, eight counties are considered for inclusion as controls - Garissa, Isiolo, Laikipia, Marsabit, Narok, Samburu, Taita Taveta, Tana River. A single interruption model is postulated in the study, given that the adoption of DEWS is only done once in September 2016.

## 4.5 Descriptive Statistics

A descriptive analysis was undertaken for the variables under study before transformation. Due to data availability, the study conducted a descriptive statistic for both single group ITS - data at national level - and multiple group ITS. Results from the single ITS are shown in the Table below.

**Table 3: Descriptive statistics for national level data**

| Variables | Observations | Mean | Std. Deviation | Minimum value | Maximum Value |
|---|---|---|---|---|---|
| Food insecure population | 31 | 1, 638, 742 | 800, 878 | 616, 695 | 3, 356,088 |
| Time Variable | 31 | 16 | 9.092 | 1 | 31 |
| DEWS immediate effect | 31 | 0.225 | 0.425 | 0 | 1 |
| DEWS effect over time | 31 | 0.903 | 1.955 | 0 | 7 |

A descriptive statistic was undertaken for national level data from NDMA of 23 ASAL counties for the period September 2004 to February 2020. The total observations were 31. The average number of people who were food insecure in the period was about 1,639,000 with a standard deviation of about 800,900 people. The minimum number of people exposed to food insecurity was about 616,700 and the maximum of about 3,356,100 people. The time variable had 31 observations of minimum 1 and maximum 31. DEWS adoption was reflected as a dummy of ones and zeros, with 31 observations. Interaction between DEWS and time was depicted in numeric with 7 periods of DEWS adoption. A regression for the national level data was not undertaken due to the limited degrees of freedom.

**Table 4: Descriptive statistics for multiple group ITS**

| Variable | Observations | Mean | Std. Dev. | Minimum | Maximum |
|---|---|---|---|---|---|
| Food insecure population | 712 | 71, 200 | 71, 128 | 0 | 385, 822 |
| Time variable | 712 | 16.337 | 9.345 | 1 | 32 |
| DEWS immediate effect | 712 | 0.224 | 0.417 | 0 | 1 |
| DEWS effect overtime | 712 | 0.898 | 1.922 | 0 | 7 |
| Cohort | 712 | 0.043 | 0.204 | 0 | 1 |

A descriptive statistic was undertaken for county level data on the untransformed model for the period September 2004 to February 2020 - The multiple group data. The total observations were 712. The average number of people who were food insecure in the biannual period was 71,200 with a standard deviation of about 71,128 people. The minimum number of people exposed to food insecurity was zero and the maximum 385,822 people. The time variable had 712 observations of minimum 1 and maximum 32; there were 32 observations per county. DEWS adoption was reflected as a dummy of ones and zeros with 712 observations. Interaction between DEWS and time was depicted in numeric with 7 periods of DEWS adoption. Cohort assignment included 712 observations with dummy variables of zeros and ones to indicate assignment to control or focus group. The natural logarithm of food insecure populations was used for the regression, therefore doing away with data points with reported zero values.

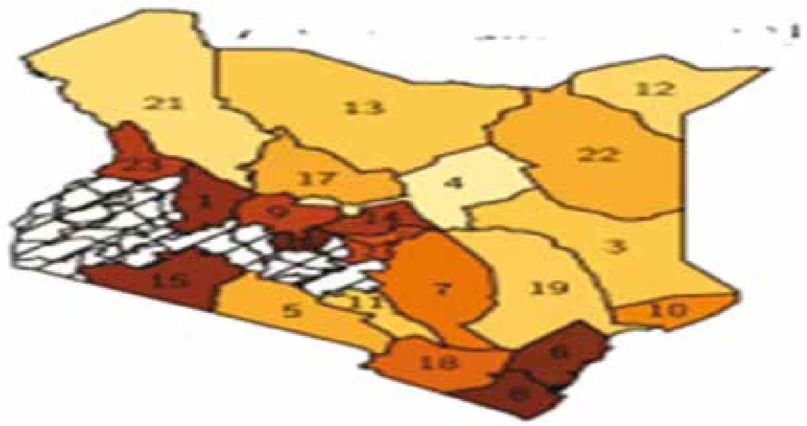
## 4.6 Data and Data Sources

The data used in the analysis was sourced from the National Drought Management Authority (NDMA) database. The data captured the total population in various areas in Kenya in need of food assistance. The data is collected biannually from September to February, and March to August. The data was collected in two batches: the period September 2004 to August 2014 and from September 2014 to February 2020. Data collected from September 2004 to August 2014 provided the total population in need of food assistance in the Districts of Turkana, Marsabit, Samburu, Moyale, Isiolo, Mandera, Wajir, Garissa, Ijara, West Pokot, Tana River, Baringo, East Pokot, Kajiado, Laikipia, Narok, Machakos, Makueni, Kitui, Mwingi, Mbeere, Tharaka, Kilifi, Kwale, Malindi, Taita Taveta, Lamu, Maragua, Meru North, Koibatek, and Nyeri North. The data is collected at the division level, then aggregated for each district. Additionally, a reference to 2009 population census is provided for the divisions and aggregated at district level.

Data collected from September 2014 to February 2020 provided the total population in need of food assistance in the counties of Turkana, Marsabit, Samburu, Isiolo, Mandera, Wajir, Garissa, Tana River, West Pokot, Baringo, Kajiado, Laikipia, Narok, Makueni, Kitui, Mbeere, Tharaka, Kilifi, Kwale, Taita Taveta, Lamu, Meru North, and Nyeri North. The data is collected at the sub-county level, then aggregated for county. The 2009 population census is provided as a reference point.

The data adopted for the study was limited to 23 ASAL counties of Kenya, namely: 1. Baringo; 2. Embu; 3 Garissa; 4. Isiolo; 5.Kajiado; 6. Kilifi; 7. Kitui; 8. Kwale; 9. Laikipia; 10. Lamu; 11. Makueni; 12. Mandera; 13. Marsabit; 14. Meru; 15. Narok; 16. Nyeri; 17. Samburu; 18.Taita Taveta; 19. Tana River; 20. Tharaka Nithi; 21. Turkana; 22. Wajir; 23. West Pokot.

**Figure 3: Map of ASAL counties of Kenya**




*Source: Bowell, A. et al (2021), "Validating commonly used drought indicators in Kenya". Environmental Research Letters.*

# 5. Results and Discussions

## 5.1 Discussion of Results

The simple uncontrolled ITS for Turkana is run and the results of the regression presented in Table 5. The model is significant at 1 per cent (%) significance level with Prob>F=0.007 <0.01. DEWS effect over time is significant at 1 per cent (%) significance level, showing a 20 per cent increase in number of people facing food insecurity in Turkana over time after DEWS adoption.

**Table 5: Results for simple uncontrolled ITS (Turkana)**

| Explanatory Variables | Simple uncontrolled ITS (Turkana) |
|---|---|
| Time | -0.012<br>(0.011) |
| DEWS_immediate effect | 0.247<br>(0.250) |
| DEWS_overtime effect | 0.202**<br>(0.079) |
| Constant | 12.214***<br>(0.132) |
| F-Statistics [p-value] | 5.06 [0.006] |
| Maximum lag | 1 |
| No. of observations | 31 |

*Note: *, **, and *** denote 10%, 5% and 1% significance levels, respectively; SE (standard errors) in parenthesis*

A post-trend for Turkana is significant at 1 per cent (%) significance level. This indicates that the food insecure population may increase by about 20 per cent if all else is held constant.

**Table 6: Post-trend results for Turkana uncontrolled ITS**

| Explanatory Variable | Diagnostics for uncontrolled ITS (Turkana) |
|---|---|
| Post-intervention linear trend | 0.191***<br>(.040) |

*Note: *, **, and *** denote 10%, 5% and 1% significance levels, respectively; SE (standard errors) in parenthesis*

When all the other 22 ASAL counties are introduced as controls, the results in table 7 are resultant. From the regression, the model is significant at 1 per cent (%) significance level (lag 3) as shown by prob>=F=0.00. The number of observations is 571. At the immediate point of intervention, there is a 118 per cent increase in food insecure populations in the control group compared to those in focus group (Turkana). There is also a significant change in number of people facing food insecurity in Turkana over time after DEWS - a 15 per cent increase in food insecure populations.

To improve our model, we employ only those comparable control groups in the study. Garissa, Isiolo, Laikipia, Marsabit, Narok, Samburu, Taita Taveta, Mandera and Tana River are regressed alongside Turkana as controls for the study. The result of this regression is also given in Table 7 below. From the regression, the model is significant at 1 per cent (%) significance level (lag 1) as shown by Prob>=F=0.00. The number of observations is 283. At the immediate point of intervention, there is a 120 per cent increase in food insecure populations in the control group compared to those in the focus group - Turkana. There is also a significant change in number of people facing food insecurity in Turkana over time after DEWS - a 20 per cent increase in food insecure populations in Turkana.

**Table 7: Results from Turkana's controlled ITS**

| Explanatory Variables | Turkana ITS (using all 22 counties as controls) | Turkana ITS (using comparable counties as controls) |
|---|---|---|
| Time Var (control group) | -0.002<br>(0.006) | -0.002<br>(0.006) |
| DEWS_immediate effect (control group) | 1.188***<br>(0.156) | 1.205***<br>(0.157) |
| DEWS_over time effect (control group) | -0.009<br>(0.0119) | -0.009<br>(0.012) |
| Initial intercept | 0.230*<br>(0.143) | 0.418**<br>(0.168) |
| Time Var (focus group) | 0.053<br>(0.068) | -0.004<br>(0.084) |
| | | |
| DEWS_immediate effect (focus group) | 0.0176<br>(0.244) | -0.170<br>(0.290) |
| DEWS_overtime effect (focus) group) | 0.149*<br>(0.082) | 0.207<br>(0.113) |
| Constant | 11.026***<br>(0.096) | 11.008<br>(0.094) |
| F-Statistics [p-value] | 55.96 [0.000] | 43.41 [0.000] |
| Maximum lag | 3 | 1 |
| No. of observations | 571 | 283 |

*Note: *, **, and *** denote 10%, 5% and 1% significance levels, respectively; SE (standard errors) in parenthesis*

**Table 8: Post-trend results for Turkana controlled ITS**

| Explanatory Variable | Diagnostics for uncontrolled ITS (Turkana) |
|---|---|
| Post-intervention linear trend (Focus group) | 0.191**<br>(0.074) |
| Post-intervention linear trend (Control group) | -0.007<br>(0.084) |
| Difference in post-intervention trend | 0.198*<br>(0.112) |

*Note: *, **, and *** denote 10%, 5% and 1% significance levels, respectively; SE (standard errors) in parenthesis*

A post-trend results for Turkana is significant at 5 per cent significance level. Food insecure populations in Turkana would increase by 19 per cent over time after DEWS adoption.

The results from the controlled (with comparable controls) and uncontrolled ITS are similar in magnitude and direction - 20 per cent increase in food insecure populations in Turkana over time post-DEWS. This improves the reliability of the results as postulated by Lopez et al. (2018). The significant increase in people facing food insecurity, immediately when DEWS were implemented in September 2016 is occasioned by the 2016-2017 droughts that begun between October and December 2016 when long rains failed. At the time, DEWS was still a new concept and was not timely enough to have informed the ongoing drought.

Other regression models are run for the other counties individually, where each individual county is taken as a focus group and the remaining as the control group. The result of these regressions is provided in the following tables. Table 9 shows results from regression of all other counties alternatively as focus groups.

The results for Garissa County as focus group indicates that the initial intercept of Garissa before DEWS is significant at 5 per cent level with a 42 per cent increase in food insecure populations in Garissa before DEWS adoption. The trend in food insecure populations post-DEWS adoption is not significant. Likewise, there is no post-trend results for Garissa.

The results for Isiolo County as focus group indicates that the initial intercept of Isiolo before DEWS is significant at 5 per cent level with a 45 per cent increase in food insecure populations in Isiolo before DEWS adoption. The trend in food insecure populations post-DEWS adoption is not significant. Likewise, there is no post-trend results for Isiolo.

**Table 9: Regression results from regressing other counties as focus group**

| Explanatory Variables | Regression results from regression of other counties (apart from Turkana) as focus groups | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Garissa | Isiolo | Mandera | Laikipia | Marsabit | Narok | Samburu | Taita Taveta | Tana River |
| Time Var (control group) | -0.003 (0.007) | -0.005 (0.007) | -0.003 (0.007) | 0.0002 (0.006) | -0.003 (0.012) | -0.004 (0.0109) | -0.003 (0.007) | -0.004 0.007 | -0.003 (0.007) |
| DEWS_immediate effect (control group) | 0.216 (0.181) | -0.621*** (0.216) | 0.726*** (0.135) | -0.285 (0.292) | 0.0107 (0.205) | -0.945*** (0.360) | -0.137 (0.161) | -0.424* (0.235) | -0.296 (0.205) |
| DEWS_overtime effect (control group) | 0.001 (0.011) | 0.018 (0.014) | 0.004 (0.008) | -0.034* (0.019) | 0.003 (0.013) | 0.008 (0.0208) | 0.002 (0.0108) | 0.005 (0.015) | 0.0003 (0.013) |
| Initial intercept (focus group) | 0.429** (0.213) | 0.454** (0.199) | 0.479** (0.203) | 0.259 (0.185) | 0.427* (0.221) | 0.396** (0.202) | 0.388* (0.212) | 0.430** (0.194) | 0.414** (0.210) |
| Time Var (focus group) | 0.014 (0.113) | 0.035 (0.106) | -0.003 (0.105) | 0.046 (0.104) | 0.028 (0.076) | 0.195 (0.066) | 0.032 (0.111) | 0.029 (0.099) | 0.012 (0.112) |
| DEWS_immediate effect (focus group) | -0.196 (0.266) | -0.361 (0.366) | -0.672** (0.279) | 1.955*** (0.376) | -0.154 (0.251) | 0.4709 (0.339) | 0.171 (0.319) | -0.224 (0.395) | -0.015 (0.346) |
| DEWS_overtime effect (focus) group) | 0.056 (0.130) | -0.113 (0.136) | 0.205 (0.146) | -0.457*** (0.105) | -0.056 (0.089) | omitted | -0.111 (0.135) | -0.136 (0.158) | 0.076 (0.162) |
| Constant | 11.115*** (0.115) | 11.206*** (0.110) | 11.060*** (0.108) | 11.159*** (0.105) | 11.137*** (0.188) | 11.188*** (0.170) | 11.153*** (0.116) | 11.185*** (0.112) | 11.171*** (0.114) |
| F-Statistics [p-value] | 5.69 [0.000] | 4.72 [0.000] | 17.54 [0.000] | 11702.60 [0.000] | 2.19 [0.035] | 7.15 [0.000] | 2.60 [0.013] | 4.43 [0.000] | 2.71 [0.009] |
| Maximum lag | 1 | 1 | 1 | 1 | 8 | 8 | 1 | 1 | 1 |
| No. of observations | 283 | 283 | 283 | 283 | 283 | 283 | 283 | 283 | 283 |

Note: *, **, and *** denote 10%, 5% and 1% significance levels respectively; SE (standard errors) in parenthesis.

The results for Mandera County as focus group indicates that the initial intercept of Mandera before DEWS is significant at 5 per cent level with a 47 per cent increase in food insecure populations in Mandera before DEWS adoption. However, immediately after DEWS adoption, there is a 67 per cent decrease in food insecure populations, at 5 per cent significance level.

The results for Laikipia County as focus group indicates that at the immediate point of adoption of DEWS, there was an increase in food insecure populations by 195 per cent at 1 per cent (%) significance level. However, over time during DEWS implementation, the percentage of food insecure population reduced by 45 per cent, at 1 per cent (%) significance level. The post-trend results are also significant at 5 per cent (%) significance level, showing a 44 per cent reduction in food insecure populations in Laikipia since DEWS adoption.

The results for Marsabit County as focus group indicate that there was a 42 per cent increase in food insecure populations in Marsabit before DEWS adoption. The trend in food insecure populations post-DEWS adoption is not significant. Likewise, there is no post-trend results for Marsabit.

The results for Narok County as a focus group indicate that there was a 39 per cent increase in food insecure populations in Narok before DEWS adoption. The trend in food insecure populations post-DEWS adoption is not significant. Likewise, there is no post-trend results for Narok.

The results for Samburu County as focus group indicate that there was a 38 per cent increase in food insecure populations in Samburu before DEWS adoption. The trend in food insecure populations post-DEWS adoption is not significant. Likewise, there is no post-trend results for Samburu.

The results for Taita Taveta County as focus group indicate that there was a 43 per cent increase in food insecure populations in Taita Taveta before DEWS adoption. The trend in food insecure populations post-DEWS adoption is not significant. Likewise, there is no post-trend results for Taita Taveta.

The results for Tana River County as focus group indicate that there was a 41 per cent increase in food insecure populations in Tana River before DEWS adoption. The trend in food insecure populations post-DEWS adoption is not significant. Likewise, there is no post trend results for Tana River.

The effect of DEWS on food insecure population has differed across counties. The majority of the ASAL counties report no significant effect of DEWS on vulnerability levels. These include Garissa, Marsabit, Isiolo, Narok, Samburu, Taita Taveta, and Tana River. Two counties have recorded a reduction in food insecure populations over time - Mandera at 67 per cent reduction in food insecure populations over time after DEWS adoption, and Laikipia at 45 per cent reduction in food insecure populations with immediate DEWS adoption. However, Turkana has recorded an increase in food insecure population over time after DEWS of 20 per cent. This increase is a marginal reduction of about 20 per cent compared to the pre-DEWS intervention results of 41 per cent increase in food insecure populations. From the results of the study, Turkana is the worst affected ASAL county in terms of vulnerability to drought.

### 4.6.1 Diagnostic tests

Post-estimation test was carried out on the regression models presented in the study. The Cumby-Huizinga test for autocorrelation was undertaken after model regression. The test found no serial correlation in the model at lag 3 - for the simple uncontrolled model as presented in Table 10 below.

**Table 10: Cumby_Huizinga test for uncontrolled regression (Turkana)**

| H0: q=0 (serially uncorrelated)<br>HA: s.c. present at range specified | | | | H0: q=specified lag-1<br>HA: s.c. present at lag specified | | | |
|---|---|---|---|---|---|---|---|
| lags | $Chi^2$ | df | p-value | lag | $Chi^2$ | df | p-value |
| 1 - 1 | 57.377 | 1 | 0.000 | 1 | 57.377 | 1 | 0.000 |
| 1 - 2 | 79.649 | 2 | 0.000 | 2 | 38.916 | 1 | 0.000 |
| 1 - 3 | 112.735 | 3 | 0.000 | 3 | 56.043 | 1 | 0.000 |

A similar post-trend analysis was carried out for the controlled ITS model to check for autocorrelation. The test indicated that there was no autocorrelation at the first lag for the controlled ITS regression.

**Table 11: Cumby_Huizinga test for controlled regression (Turkana)**

| H0: q=0 (serially uncorrelated)<br>HA: s.c. present at range specified | | | | H0: q=specified lag-1<br>HA: s.c. present at lag specified | | | |
|---|---|---|---|---|---|---|---|
| lags | $Chi^2$ | df | p-value | lag | $Chi^2$ | df | p-value |
| 1 - 1 | 19.106 | 1 | 0.000 | 1 | 19.106 | 1 | 0.000 |

# 6. Conclusion and Recommendations

## 6.1 Conclusion

This study sought to determine the effect of DEWS on vulnerability levels of Kenyans living in the ASALs. It set out to statistically investigate the results of adoption of the DEWS intervention that was meant to steer the country towards proactive response to droughts. Droughts, which have been identified as the worst naturally occurring disaster, lead to reduction to Kenya's GDP by 8 per cent every 5 years (Government of Kenya, 2018), directly affecting the agriculture sector and exacerbating food insecurity concerns.

From the findings, Turkana is the worst affected ASAL county. Turkana had a high percentage of people facing food insecurity before DEWS adoption; 41 per cent. However, after DEWS introduction over time, this margin has reduced to 20 per cent - a reduction by 20 per cent in food insecure populations post-DEWS. Most ASAL counties seem to be indifferent in terms of the effect of DEWS on vulnerability levels of the population. These counties include Garissa, Marsabit, Isiolo, Narok, Samburu, Taita Taveta and Tana River. Two counties have recorded a significant reduction in food insecure populations with the adoption of DEWS. Mandera recorded a 67 per cent reduction in food insecure populations over time after DEWS adoption, and Laikipia recorded a 45 per cent reduction in food insecure populations immediately DEWS were adopted.

We conclude that the effect of DEWS on vulnerability levels of populations living in the ASALS has varied depending on the area of residents. Although most counties recorded indifference in effect of DEWS on vulnerability levels, we have two counties recording significant effects of DEWS in reducing food insecure populations in Kenya. The marginal reduction in food insecure populations in Turkana by about 21 per cent after DEWS were introduced also points towards the ability of DEWS in reducing vulnerability levels of populations in Turkana, which is the worst affected county in ASALS when it comes to droughts.

The findings are consistent with Tuitoek and Wausi (2016) that DEWS were effective in drought management, and thus recommending that NDMA should consider improving DEWS to enhance information dissemination and collaborate with stakeholders to create awareness to communities living in the ASALS.

Droughts are naturally occurring events that are difficult to substantiate and complex in nature. They are expected to increase in severity and magnitude due to climate change. DEWS are useful in proactive drought management, but with the ever-increasing risk of more severe and prolonged droughts, the reinvention of DEWS to better inform on impending drought risks and the need for adoption by every actor within the ASALs cannot be over-emphasized. After all, the effectiveness of DEWS is in its ability to inform and nudge proactive behavioural change; DEWS is not an end, but a means to an end.

## 6.2 Recommendations

The study has demonstrated the effectiveness of DEWS in reducing vulnerability levels for some counties in the ASALs. There is, however, need to improve its effectiveness in reducing vulnerability levels.

The Government of Kenya, under leadership from State Department of ASALs, should put more effort into facilitating cooperation among regional countries in terms of data and technology sharing. The success of early warning systems relies on the free flow of information.

Leadership from the State Department of ASALs in standardization of methodologies, and cooperation between various institutions monitoring drought indicators will be essential in streamlining the approaches, given that humanitarian aid relies on analysis of early warning assessments.

County Governments in ASALs could consider putting more effort into innovative drought early warning systems that are region-specific and informed by the community to better capture community concerns. Integration of indigenous early warning systems with modern systems would be beneficial. Both traditional and modern dissemination techniques of early warning systems that consider attributes such as literacy levels, affordability and nomadic nature of the community should be considered to improve outreach and inform early community response to drought events before they become emergencies.

## 6.3 Study Limitations and Areas of Further Research

The study purposed to determine the direction and magnitude of the relationship between DEWS adoption and vulnerability levels of Kenyans living in the ASALs. Other factors that influence vulnerability of individuals in ASALs, such as conflicts, climate change, and population change could not be accounted for largely due to the technicality in deriving proxies for measurement and inclusion of some parameters into the linear model. Population change could not be accounted for given the limitation in data collection. Further research can be sort on inclusion of such parameters in the interrupted time series model to determine the effect of other factors other than DEWS adoption on vulnerability of people living in the ASALs.

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## Annexes

### Annex 1: Descriptive summary for national level data

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Food_insec~e | 31 | 1638742 | 800878.1 | 616695.5 | 3356088 |
| T | 31 | 16 | 9.092121 | 1 | 31 |
| X | 31 | .2258065 | .4250237 | 0 | 1 |
| TX | 31 | .9032258 | 1.955417 | 0 | 7 |

### Annex 2: Descriptive summary multiple group ITS (untransformed model)

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| ›le_foodi~e | 713 | 71200.79 | 71128.52 | 0 | 385822.2 |
| T | 712 | 16.33708 | 9.345915 | 1 | 32 |
| X | 712 | .2247191 | .4176906 | 0 | 1 |

### Annex 3: Results from uncontrolled ITS (Turkana)

Regression with Newey-West standard errors — Number of obs = 31
maximum lag: 1 — F( 3, 27) = 5.06
Prob > F = 0.0065

| lpple_food~e | Coef. | Newey-West Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| _t | -.0117833 | .0108402 | -1.09 | 0.287 | -.0340257 | .010459 |
| _x29 | .2477845 | .250196 | 0.99 | 0.331 | -.2655753 | .7611442 |
| _x_t29 | .2029362 | .0798496 | 2.54 | 0.017 | .0390984 | .366774 |
| _cons | 12.2144 | .1328275 | 91.96 | 0.000 | 11.94186 | 12.48694 |

Postintervention Linear Trend: 29

Treated: _b[_t]+_b[_x_t29]

| Linear Trend | Coef. | Std. Err. | t | | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| Treated | .1911529 | .0787172 | 2.43 | 0.022 | .0296385 | .3526673 |

## Annex 4: Controlled multigroup ITS (Turkana) with all 22 counties as controls

```
Regression with Newey-West standard errors          Number of obs     =
maximum lag: 3                                      F(  7,      563)  =
                                                    Prob > F          =     0.
```

| lpple_food~e | Coef. | Newey-West Std. Err. | t | P>\|t\| | [95% Conf. | Inte |
|---|---|---|---|---|---|---|
| _t | -.0022047 | .0066536 | -0.33 | 0.741 | -.0152735 | .01 |
| _z | 1.188278 | .1561583 | 7.61 | 0.000 | .881554 | 1.4 |
| _z_t | -.0095786 | .0119527 | -0.80 | 0.423 | -.0330559 | .01 |
| _x29 | .2301844 | .1433729 | 1.61 | 0.109 | -.0514266 | .51 |
| _x_t29 | .0535872 | .0688219 | 0.78 | 0.437 | -.0815918 | .18 |
| _z_x29 | .0176 | .2449705 | 0.07 | 0.943 | -.4635678 | .49 |
| _z_x_t29 | .149349 | .0824046 | 1.81 | 0.070 | -.012509 | .3 |
| _cons | 11.02613 | .0961121 | 114.72 | 0.000 | 10.83734 | 11. |

## Annex 5: Post-estimation test for autocorrelation (Turkana) controlled ITS of 22 counties

Cumby-Huizinga test for autocorrelation
H0: variable is MA process up to order q
HA: serial correlation present at specified lags >q

| H0: q=0 (serially uncorrelated)<br>HA: s.c. present at range specified | | | | H0: q=specified lag-1<br>HA: s.c. present at lag specified | | | |
|---|---|---|---|---|---|---|---|
| lags | chi2 | df | p-val | lag | chi2 | df | p-val |
| 1 - 1 | 57.377 | 1 | 0.0000 | 1 | 57.377 | 1 | 0.0000 |
| 1 - 2 | 79.649 | 2 | 0.0000 | 2 | 38.916 | 1 | 0.0000 |
| 1 - 3 | 112.735 | 3 | 0.0000 | 3 | 56.043 | 1 | 0.0000 |

Test allows predetermined regressors/instruments
Test requires conditional homoskedasticity

## Annex 6: Controlled multigroup ITS (Turkana) with comparable controls

```
Regression with Newey-West standard errors          Number of obs     =       283
maximum lag: 1                                      F(  7,       275) =     43.41
                                                    Prob > F          =    0.0000
```

| lpple_food~e | Coef. | Newey-West Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| _t | -.0025103 | .0065177 | -0.39 | 0.700 | -.0153413 | .0103207 |
| _z | 1.205903 | .1573678 | 7.66 | 0.000 | .8961046 | 1.515702 |
| _z_t | -.009273 | .0121576 | -0.76 | 0.446 | -.0332068 | .0146607 |
| _x29 | .4184395 | .1684175 | 2.48 | 0.014 | .0868881 | .749991 |
| _x_t29 | -.0049047 | .0847545 | -0.06 | 0.954 | -.1717547 | .1619454 |
| _z_x29 | -.1706551 | .2906396 | -0.59 | 0.558 | -.7428163 | .4015062 |
| _z_x_t29 | .2078408 | .1135699 | 1.83 | 0.068 | -.0157361 | .4314178 |
| _cons | 11.0085 | .0946097 | 116.36 | 0.000 | 10.82225 | 11.19475 |

## Annex 7: Post-estimation test for autocorrelation (Turkana) controlled ITS of comparable controls

```
Cumby-Huizinga test for autocorrelation
  H0: variable is MA process up to order q
  HA: serial correlation present at specified lags >q
```

| H0: q=0 (serially uncorrelated) HA: s.c. present at range specified | | | | H0: q=specified lag-1 HA: s.c. present at lag specified | | | |
|---|---|---|---|---|---|---|---|
| lags | chi2 | df | p-val | lag | chi2 | df | p-val |
| 1 - 1 | 21.944 | 1 | 0.0000 | 1 | 21.944 | 1 | 0.0000 |
| 1 - 2 | 37.155 | 2 | 0.0000 | 2 | 21.993 | 1 | 0.0000 |
| 1 - 3 | 53.257 | 3 | 0.0000 | 3 | 27.207 | 1 | 0.0000 |

```
  Test allows predetermined regressors/instruments
  Test requires conditional homoskedasticity
```

## Annex 8: Garissa as focus group

```
Regression with Newey-West standard errors          Number of obs     =        283
maximum lag: 1                                      F(  7,        275) =       5.69
                                                    Prob > F          =     0.0000

------------------------------------------------------------------------------
             |             Newey-West
lpple_food~e |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          _t |  -.0036557    .0077786    -0.47   0.639    -.0189689    .0116575
          _z |   .2166061    .1814125     1.19   0.234    -.1405277    .5737398
        _z_t |   .0011484    .0113964     0.10   0.920    -.0212867    .0235836
        _x29 |   .4299889    .2133866     2.02   0.045       .00991    .8500678
       _x_t29 |   .0142958    .1131332     0.13   0.900    -.2084214    .2370129
       _z_x29 |  -.1961416    .2663014    -0.74   0.462    -.7203899    .3281067
     _z_x_t29 |   .0563366    .1305198     0.43   0.666    -.2006083    .3132815
        _cons |   11.11562    .1157867    96.00   0.000     10.88768    11.34356
------------------------------------------------------------------------------

              Comparison of Linear Postintervention Trends: 29

Treated     : _b[_t] + _b[_z_t] + _b[_x_t29] + _b[_z_x_t29]
Controls    : _b[_t] + _b[_x_t29]
Difference  : _b[_z_t] +  _b[_z_x_t29]
------------------------------------------------------------------------------
Linear Trend |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     Treated |   .0681252    .0628234     1.08   0.279    -.0555507     .191801
    Controls |   .0106401     .112736     0.09   0.925    -.2112951    .2325753
-------------+----------------------------------------------------------------
  Difference |   .0574851    .1290588     0.45   0.656    -.1965837    .3115539
```

## Annex 9: Regression of Isiolo as focus group

```
       panel variable:  countyid (strongly balanced)
        time variable:  year, 2 to 32
                delta:  1 unit

Regression with Newey-West standard errors          Number of obs     =        283
maximum lag: 1                                      F(  7,        275) =       4.72
                                                    Prob > F          =     0.0001

------------------------------------------------------------------------------
             |             Newey-West
lpple_food~e |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          _t |  -.0055295     .007501    -0.74   0.462    -.0202962    .0092372
          _z |  -.6219713    .2163904    -2.87   0.004    -1.047964    -.195979
        _z_t |   .0183521    .0141493     1.30   0.196    -.0095025    .0462068
        _x29 |   .4545161    .1998158     2.27   0.024     .0611532    .8478789
       _x_t29 |    .035338    .1060528     0.33   0.739    -.1734405    .2441166
       _z_x29 |  -.3619505    .3667464    -0.99   0.325    -1.083938    .3600366
     _z_x_t29 |  -.1134921    .1363448    -0.83   0.406    -.3819043    .1549201
        _cons |   11.20641    .1104951   101.42   0.000     10.98889    11.42393
------------------------------------------------------------------------------
```

## Annex 10: Mandera as focus group

Regression with Newey-West standard errors — Number of obs = 283
maximum lag: 1 — F( 7, 275) = 17.54
Prob > F = 0.0000

| lpple_food~e | Coef. | Newey-West Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| _t | -.0039559 | .0072295 | -0.55 | 0.585 | -.018188 | .0102763 |
| _z | .7262128 | .1359852 | 5.34 | 0.000 | .4585086 | .9939171 |
| _z_t | .0040323 | .0085542 | 0.47 | 0.638 | -.0128077 | .0208723 |
| _x29 | .4796506 | .2032888 | 2.36 | 0.019 | .0794505 | .8798507 |
| _x_t29 | -.0039325 | .1053934 | -0.04 | 0.970 | -.211413 | .2035479 |
| _z_x29 | -.6728774 | .279459 | -2.41 | 0.017 | -1.223028 | -.1227267 |
| _z_x_t29 | .2058767 | .1462461 | 1.41 | 0.160 | -.0820275 | .493781 |
| _cons | 11.06044 | .1080467 | 102.37 | 0.000 | 10.84773 | 11.27314 |

Comparison of Linear Postintervention Trends: 29

Treated : _b[_t] + _b[_z_t] + _b[_x_t29] + _b[_z_x_t29]
Controls : _b[_t] + _b[_x_t29]
Difference : _b[_z_t] + _b[_z_x_t29]

| Linear Trend | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| Treated | .2020206 | .1013115 | 1.99 | 0.047 | .002576 | .4014653 |
| Controls | -.0078884 | .1050201 | -0.08 | 0.940 | -.2146339 | .1988572 |
| Difference | .209909 | .1459221 | 1.44 | 0.151 | -.0773572 | .4971753 |

## Annex 11: Laikipia focus group

Regression with Newey-West standard errors — Number of obs = 283
maximum lag: 1 — F( 6, 275) = 11702.60
Prob > F = 0.0000

| lpple_food~e | Coef. | Newey-West Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| _t | .0002227 | .0067056 | 0.03 | 0.974 | -.012978 | .0134234 |
| _z | -.2853711 | .2925794 | -0.98 | 0.330 | -.861351 | .2906089 |
| _z_t | -.0344263 | .0194627 | -1.77 | 0.078 | -.0727411 | .0038885 |
| _x29 | .2591592 | .185665 | 1.40 | 0.164 | -.1063461 | .6246645 |
| _x_t29 | .0466036 | .1041782 | 0.45 | 0.655 | -.1584846 | .2516917 |
| _z_x29 | 1.955749 | .3760632 | 5.20 | 0.000 | 1.215421 | 2.696078 |
| _z_x_t29 | -.4571603 | .1057683 | -4.32 | 0.000 | -.6653787 | -.2489419 |
| _cons | 11.15938 | .1056692 | 105.61 | 0.000 | 10.95135 | 11.3674 |

Comparison of Linear Postintervention Trends: 29

Treated : _b[_t] + _b[_z_t] + _b[_x_t29] + _b[_z_x_t29]
Controls : _b[_t] + _b[_x_t29]
Difference : _b[_z_t] + _b[_z_x_t29]

## Annex 12: Marsabit as focus group

Regression with Newey-West standard errors
maximum lag: 8

Number of obs = 283
F( 7, 275) = 2.19
Prob > F = 0.0351

| lpple_food~e | Coef. | Newey-West Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| _t | -.0039266 | .0120925 | -0.32 | 0.746 | -.0277322 | .0198791 |
| _z | .0107053 | .2055843 | 0.05 | 0.959 | -.3940137 | .4154244 |
| _z_t | .0036188 | .0131865 | 0.27 | 0.784 | -.0223405 | .0295781 |
| _x29 | .4270034 | .2214292 | 1.93 | 0.055 | -.0089084 | .8629152 |
| _x_t29 | .0280598 | .0760487 | 0.37 | 0.712 | -.1216517 | .1777714 |
| _z_x29 | -.154992 | .2518815 | -0.62 | 0.539 | -.6508529 | .3408688 |
| _z_x_t29 | -.0569275 | .0898652 | -0.63 | 0.527 | -.2338386 | .1199835 |
| _cons | 11.13791 | .1884657 | 59.10 | 0.000 | 10.76689 | 11.50893 |

## Annex 13: Narok as focus group

Regression with Newey-West standard errors
maximum lag: 8

Number of obs = 283
F( 6, 276) = 7.15
Prob > F = 0.0000

| lpple_food~e | Coef. | Newey-West Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| _t | -.0044763 | .0109784 | -0.41 | 0.684 | -.0260882 | .0171357 |
| _z | -.9451357 | .3606187 | -2.62 | 0.009 | -1.655048 | -.2352229 |
| _z_t | .0088487 | .0208673 | 0.42 | 0.672 | -.0322306 | .049928 |
| _x29 | .3965965 | .2020334 | 1.96 | 0.051 | -.0011256 | .7943186 |
| _x_t29 | .0195196 | .0668905 | 0.29 | 0.771 | -.1121609 | .1512 |
| _z_x29 | .4709743 | .3393419 | 1.39 | 0.166 | -.1970528 | 1.139001 |
| _z_x_t29 | 0 | (omitted) | | | | |
| _cons | 11.18818 | .1700654 | 65.79 | 0.000 | 10.85339 | 11.52297 |

## Annex 14: Samburu as focus group

Regression with Newey-West standard errors — Number of obs = 283
maximum lag: 1 — F( 7, 275) = 2.60
Prob > F = 0.0131

| lpple_food~e | Coef. | Newey-West Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| _t | -.0037787 | .00782 | -0.48 | 0.629 | -.0191733 | .0116159 |
| _z | -.1371817 | .1619631 | -0.85 | 0.398 | -.4560269 | .1816634 |
| _z_t | .002219 | .0108206 | 0.21 | 0.838 | -.0190828 | .0235208 |
| _x29 | .388864 | .2127042 | 1.83 | 0.069 | -.0298715 | .8075995 |
| _x_t29 | .0329647 | .1115788 | 0.30 | 0.768 | -.1866925 | .2526218 |
| _z_x29 | .1715483 | .3197786 | 0.54 | 0.592 | -.4579768 | .8010734 |
| _z_x_t29 | -.1117584 | .1353717 | -0.83 | 0.410 | -.3782549 | .1547381 |
| _cons | 11.15392 | .1165796 | 95.68 | 0.000 | 10.92442 | 11.38343 |

Comparison of Linear Postintervention Trends: 29

Treated : _b[_t] + _b[_z_t] + _b[_x_t29] + _b[_z_x_t29]
Controls : _b[_t] + _b[_x_t29]
Difference : _b[_z_t] + _b[_z_x_t29]

| Linear Trend | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| Treated | -.0803535 | .0774919 | -1.04 | 0.301 | -.2329062 | .0721992 |
| Controls | .0291859 | .1111468 | 0.26 | 0.793 | -.1896208 | .2479927 |
| Difference | -.1095394 | .1354939 | -0.81 | 0.420 | -.3762766 | .1571978 |

## Annex 15: Taita Taveta as focus group

Regression with Newey-West standard errors — Number of obs = 283
maximum lag: 1 — F( 7, 275) = 4.43
Prob > F = 0.0001

| lpple_food~e | Coef. | Newey-West Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| _t | -.0041403 | .007632 | -0.54 | 0.588 | -.0191648 | .0108842 |
| _z | -.4245653 | .2356207 | -1.80 | 0.073 | -.8884148 | .0392841 |
| _z_t | .0055138 | .0153149 | 0.36 | 0.719 | -.0246356 | .0356631 |
| _x29 | .4306166 | .1943534 | 2.22 | 0.028 | .0480072 | .8132261 |
| _x_t29 | .0290219 | .09906 | 0.29 | 0.770 | -.1659903 | .2240342 |
| _z_x29 | -.2248226 | .395373 | -0.57 | 0.570 | -1.003165 | .5535197 |
| _z_x_t29 | -.1368571 | .1584783 | -0.86 | 0.389 | -.4488419 | .1751276 |
| _cons | 11.18504 | .1128517 | 99.11 | 0.000 | 10.96288 | 11.4072 |

Comparison of Linear Postintervention Trends: 29

Treated : _b[_t] + _b[_z_t] + _b[_x_t29] + _b[_z_x_t29]
Controls : _b[_t] + _b[_x_t29]
Difference : _b[_z_t] + _b[_z_x_t29]

| Linear Trend | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| Treated | -.1064617 | .1232874 | -0.86 | 0.389 | -.3491687 | .1362452 |
| Controls | .0248816 | .0986289 | 0.25 | 0.801 | -.169282 | .2190452 |
| Difference | -.1313434 | .1578843 | -0.83 | 0.406 | -.4421587 | .179472 |

## Annex 16: Tana river as focus group

```
Regression with Newey-West standard errors      Number of obs     =        283
maximum lag: 1                                  F(  7,        275) =       2.71
                                                Prob > F          =     0.0099
```

| lpple_food~e | Coef. | Newey-West Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| _t | -.0035764 | .0076628 | -0.47 | 0.641 | -.0186616 | .0115088 |
| _z | -.2967561 | .2051387 | -1.45 | 0.149 | -.7005979 | .1070857 |
| _z_t | .0003117 | .013388 | 0.02 | 0.981 | -.0260444 | .0266678 |
| _x29 | .4145726 | .2106861 | 1.97 | 0.050 | -.0001898 | .8293351 |
| _x_t29 | .0124038 | .1120817 | 0.11 | 0.912 | -.2082434 | .2330511 |
| _z_x29 | -.0159595 | .3462793 | -0.05 | 0.963 | -.6976546 | .6657356 |
| _z_x_t29 | .0764496 | .162336 | 0.47 | 0.638 | -.2431296 | .3960288 |
| _cons | 11.1712 | .1140428 | 97.96 | 0.000 | 10.94669 | 11.39571 |

Comparison of Linear Postintervention Trends: 29

```
Treated    : _b[_t] + _b[_z_t] + _b[_x_t29] + _b[_z_x_t29]
Controls   : _b[_t] + _b[_x_t29]
Difference : _b[_z_t] +  _b[_z_x_t29]
```

| Linear Trend | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| Treated | .0855887 | .1145729 | 0.75 | 0.456 | -.1399627 | .3111402 |
| Controls | .0088274 | .1117763 | 0.08 | 0.937 | -.2112186 | .2288734 |
| Difference | .0767613 | .1600653 | 0.48 | 0.632 | -.2383477 | .3918703 |

ISBN 978 9966 817 87 7

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