September 2021

Nawiri Desk Study: Climatic variability and disasters in Kenya's arid and semi-arid lands

Anastasia Marshak and Aishwarya Venkat
Feinstein International Center, Tufts University

USAID FROM THE AMERICAN PEOPLE

CRS CATHOLIC RELIEF SERVICES

This publication was produced under the Nawiri project supported by the United States Agency for International Development (USAID) Bureau for Humanitarian Assistance (BHA). The project's goal is to sustainably reduce levels of acute malnutrition among vulnerable populations in Kenya's arid and semi-arid lands (ASALs). The project is being implemented in Isiolo and Marsabit Counties by a consortium led by Catholic Relief Services, and in Samburu and Turkana Counties by a consortium led by Mercy Corps.

This publication was possible thanks to the generous support of the people of the United States of America, through the United States Agency for International Development (USAID). The contents are the responsibility of Catholic Relief Services (CRS) and do not necessarily reflect the views of USAID or the United States Government.

Table of Contents

Acknowledgment

We would like to thank the county governments of Isiolo and Marsabit Counties. Special thanks to the Nawiri consortium and staff for their immense support and contribution to the report. We would also like to thank team members from Kenyatta University for supporting accessing the appropriate nutrition data, as well as the EM-DAT team for sharing the disaster data. Nawiri would also like to thank the United States Agency for International Development (USAID) Bureau of Humanitarian Assistance for providing funding for this activity.

Executive Summary

This desk study provides an overview of the patterns and variability in climate (temperature, precipitation, and vegetation), conflict, reported disasters, and nutrition outcomes using available secondary data. The emphasis is on Marsabit and Isiolo Counties, with even more detailed data on the three sentinel sites of interest—Garbatulla and NgareMara Wards in Isiolo and Laisamis Ward in Marsabit. However, the value of secondary data is in its sheer amount, and thus findings are also presented across Marsabit, Isiolo, and neighboring arid and semi-arid lands (ASAL) counties in Kenya with similar climatic conditions. While this desk study only focuses on the secondary data analysis of climate, conflict, and disasters—or more basic causes of child malnutrition—it is part of a larger review under the Nutrition in the ASALs within Integrated Resilient Institutions (Nawiri) program that includes additional desk studies that aim to capture the role of more immediate and underlying drivers of child malnutrition (Marshak 2021c). We also include a short section reviewing available literature from Kenya's ASAL counties to identify how seasonality is understood and analyzed in this context. Below we summarize the key findings and how they can better inform the Nawiri program.

Findings of the climate data underscore the incredible diversity[1] found between, but also within, the counties. While we are able to draw on learning and techniques from previous secondary climate and nutrition analysis in unimodal dryland contexts, the Kenyan ASALs, with their multiple different climatic regimes over a relatively small geographic area, present a new challenge. The climate data show that not all of the selected counties have two identifiable rainfall peaks, with Baringo and Turkan indicating a more unimodal rainfall pattern. More so, within the counties, different levels of elevation create significant within-county variability in the monthly means of precipitation, temperature, and vegetation. The latter is in line with other dryland contexts, where rapid changes in elevation, as well as high diversity in geology and soil types, result in extreme variability in climatic variables over short distances (Saverio, Eldirani et al. 2013, Kratli 2015). For example, the sentinel site chosen in Marsabit—Laisamis—does not mimic the seasonal pattern found in Marsabit as a whole, with two uneven—as opposed to even—sized peaks in precipitation. Similarly, Garbatulla and NgareMara—both in Isiolo—have different levels of Normalized Difference Vegetation Index (NDVI) and rainfall, resulting in a different emphasis on livelihood specializations. This combined diversity in geography with climatic variability has important implications for Nawiri, particularly in relation to the level of aggregation that can be done with secondary data (county vs. ward vs. community) and the extrapolation of findings from both our own research and existing work done in the Kenya ASALs.

While the analysis of climatic factors indicates an extremely variable context, a review of how seasonality is understood in the literature paints a much more simplistic picture. According to the general literature, there is a dry and rainy season, which can further be broken up into a short rainy season between October and December, followed by a short dry season in January and February, and a long rainy season between March and May, followed a by a long dry season from June through September. More so, some of the literature

1 US When we use the term "diversity" we are specifically referring to more fixed attributes such as topography, soil type, and geology across space, while the term "variability" refers to the dispersion of temperature, rainfall, and vegetation across both time and space.

ignores this seasonality all together, providing little information on the timing of data collection and associated seasonal context. The general consensus in the literature is that malnutrition peaks in the dry season. Given the timing of the Standardized Monitoring and Assessment of Relief and Transitions (SMART) data collection, the assumption is that the primary peak is during the short dry season.

Our own secondary data analysis of Nutrition Drought Monitoring Association (NDMA) data shows that there is seasonal variability in nutrition outcomes. When using mid-upper arm circumference (MUAC) data, seasonality is only apparent for children 6–11 months of age. For this group, peak timing in wasting falls slightly earlier than what is assumed by SMART: around November/December, thus corresponding to the peak or end of the short rainy season. By March, children 6–11 months already exhibit their lowest prevalence of wasting. Review of the secondary SMART data does not allow us to say much about seasonality, but it does indicate—in line with the literature—that drought years, or lower NDVI, are associated with significantly lower MUAC, weight-for-height z-scores (WHZ), and higher prevalence of wasting. However, there is not total agreement between the MUAC and WHZ data. MUAC identifies children 6–11 months and girls as the most vulnerable population, while WHZ identifies children 24–59 months and boys as the most vulnerable population. While this distinction most likely is due to the fact that we are not using age- or sex-standardized MUAC, it requires greater unpacking and exploration as part of the Nawiri primary data collection.

Thus, all together the secondary data analysis indicates extreme levels of seasonality and variability across the Kenya ASALs and within Marsabit and Isiolo Counties. The findings around nutrition outcomes further underscore that seasonality is present, but for whom and who is most vulnerable is far more difficult to unpack in the secondary data alone. Primary research under Nawiri will be designed to address some of these gaps and remaining queries and identify programmatic recommendations to address acute malnutrition in Isiolo and Marsabit Counties.

Introduction

Nawiri program: objective and goal, and the role of desk studies (DS)

This desk study on "Climatic variability and disasters in Kenya's arid and semi-arid lands (ASALs)" is part of the Nutrition in the ASALs within Integrated Resilient Institutions (Nawiri) project funded by United States Agency for International Development (USAID)/Bureau of Humanitarian Assistance (BHA) and implemented by a consortium led by Catholic Relief Services (CRS). The Nawiri project is being implemented in Isiolo and Marsabit Counties in northern Kenya. The goal of Nawiri is to sustainably reduce persistent acute malnutrition by designing and implementing an approach for supporting, strengthening, and protecting systems and institutions. Nawiri is designed to allow for research and learning to directly inform program implementation. Thus, Nawiri has commissioned multiple desk studies to better understand the state of the evidence in the Kenyan ASALs and make sure primary research and program implantation build on the existing evidence while addressing any identified gaps. This desk study focuses on the environmental variability and disaster history in Marsabit and Isiolo Counties, as well as neighboring ASAL counties in Kenya with a similar climatic context.

Conceptual framework for drivers of malnutrition in drylands

Nawiri has adapted a recent reframing of the nutrition causal framework specifically for dryland contexts (Figure 1) (Young 2020). The framework lays out the immediate and underlying drivers of acute malnutrition, unchanged from the original UNICEF framework (UNICEF 1990). However, and most relevant for this desk study, the amended framework expands on the basic drivers, with a particular focus on seasonality and environment. In addition, the framework builds in the role of idiosyncratic and covariate shocks in shaping the basic causes and their impact on the underlying and immediate drivers. For this desk study, we review the seasonality of secondary data on precipitation, temperature, vegetation, conflict, and disasters in Isiolo and Marsabit Counties, as well as Garissa, Isiolo, Mandera, Samburu, Tana River, Turkana, Baringo, and Wajir Counties. While we present data for the ASALs as a whole, we also extracted these climatic variables for the three key sentinel wards for the primary research. We summarize the limited but existing evidence base on the role of covariate shocks, both climatic and human-made, on nutrition outcomes as well as the literature around the seasonality of child malnutrition in the Kenya ASALS. This desk study is part of a Nawiri desk study series that addresses each level of the conceptual framework for drivers of malnutrition in drylands, including:

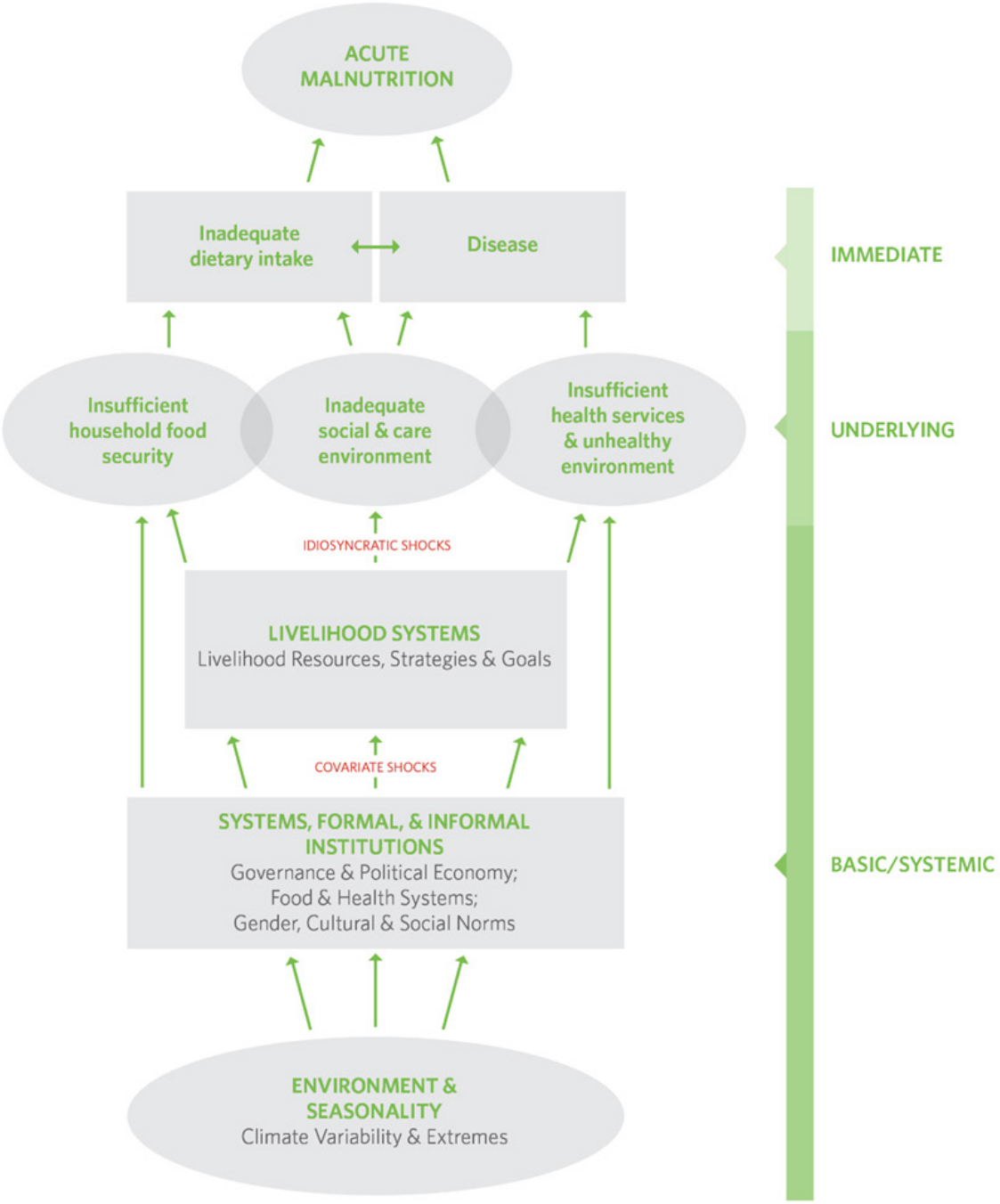
- Acute malnutrition hotspot analysis in Marsabit and Isiolo (Ocholo 2021a; Ocholo 2021b);
- Immediate and underlying drivers: the immediate and underlying drivers of child malnutrition in the Kenyan ASALs (Marshak 2021c);
- Basic causes:
  - Livelihoods and nutrition (Stites 2020);
  - Gender gap analysis (Stites and Dykstra-McCarthy 2020);
  - Natural resource management and nutrition (Birch 2020);
  - Climatic variability, disasters, conflict, and nutrition in the Kenya ASALs (this study).

Layout

In the next section we discuss the methodology for the climate, disaster, and conflict data, as well as the approach to the literature review. Next, we describe the temporal and spatial trends

across the different climate and environment measures: precipitation, temperature, and vegetation. Next, we discuss the history of disasters across the Kenyan ASALs and any observed seasonal variability in those disasters, followed by a presentation of the conflict data. We then report on the analysis of the seasonality of nutrition outcomes across two secondary datasets, independently and in combination with the climatic, conflict, and disaster data. We then present a summary of the reviewed literature, with a focus on seasonality of nutrition outcomes as well as the role of climatic and human-made shocks on those outcomes. Next, we provide additional secondary data that are available for future analysis, followed by a summary of the findings so far. We end this desk study with a set of recommendations for future analysis of secondary data, as well as Nawiri's planned primary data collection.

Figure 1. Nutrition causal framework for drylands.



Methodology

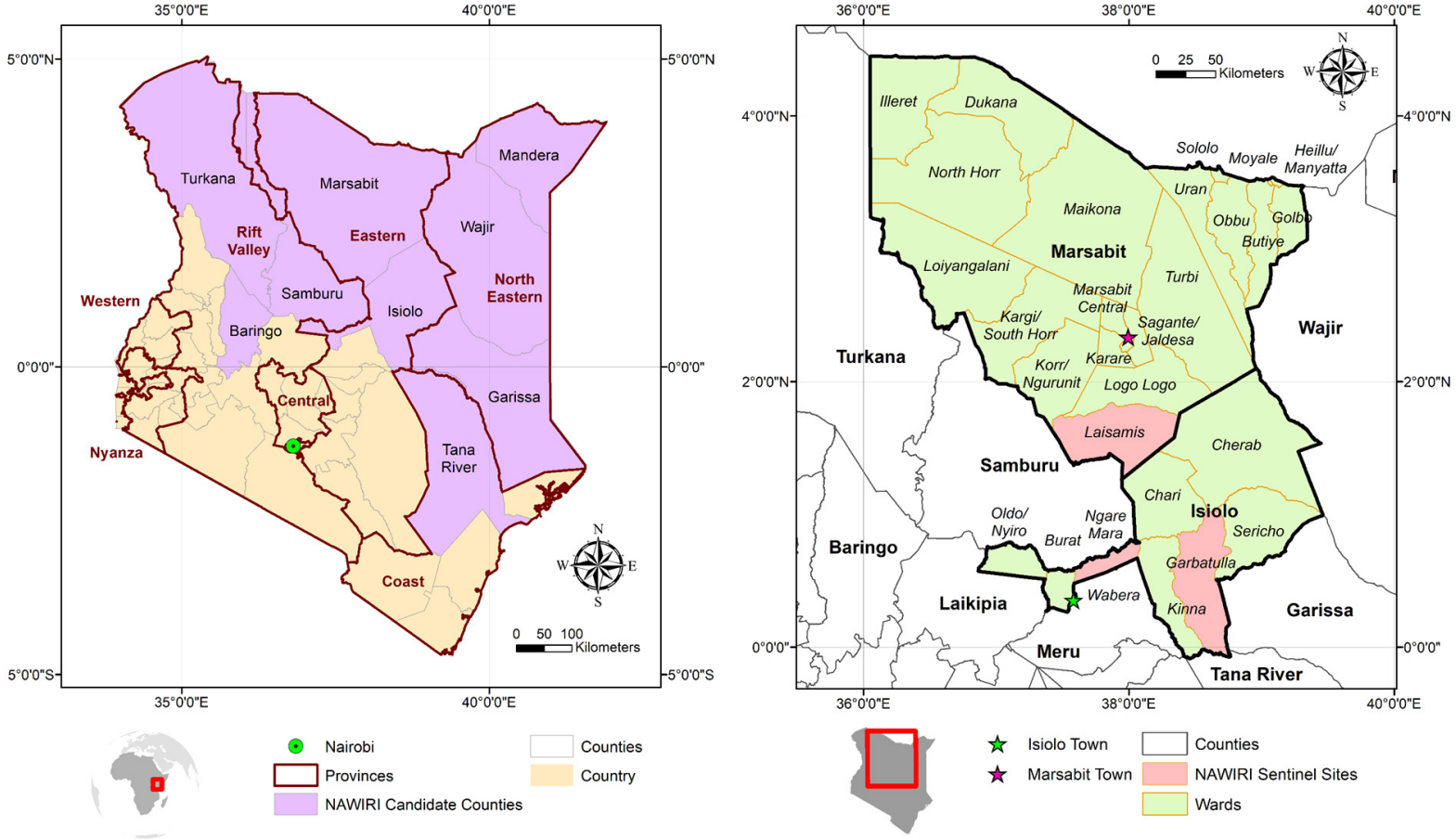
Study area

The geographic focus of the study is Marsabit and Isiolo Counties in northern Kenya given the Nawiri programmatic focus on those counties, and more specifically Laisamis Ward in Marsabit County and Garbatulla and NgareMara Wards in Isiolo County (Figure 2: left). However, given that the value of secondary data comes from the large sample sizes, we also provide information on counties that fall under the category of Kenyan arid and semi-arid lands (ASALs) and have similar climatic seasonal patterns. Specifically, the additional counties include Turkana, Baringo, Samburu, Moyale, Mandera, Wajir, Garrissa, Tana River, and Ijara (Figure 2: right). It is important to note that since 2010, Ijara is part of Garissa and Moyale is part of Marsabit County. The latest mapping is used through the report.

Literature review

Only studies that utilized a measure of child malnutrition, either self-reported or anthropometrically defined,[2] across the ASAL counties in Kenya were included in the literature review for the purpose of comparability. While Marsabit and Isiolo Counties were the priority

Figure 2. Map of desk study area (left) and map of programmatic area (right).



2 Weight for height z-score (WHZ), mid-upper arm circumference (MUAC), wasting (WHZ < −2 or MUAC < 135), height for age z-score (HAZ), stunting (HAZ < −2), weight-for-age z-score (WAZ), underweight (WAZ < −2), and upper-arm fat area (UAFA).

for this desk study, given the low availability of literature we expanded our search to include additional Kenya ASALs counties that show similar rainfall, temperature, and vegetation patterns as Isiolo and Marsabit, including Garissa, Mandera, Samburu, Tana River, Ijara,[3] Turkana, and Wajir. In addition, Machakos and Mukueni County studies were selectively included given that the two counties do have semi-arid ecological zones. We also included any literature on Kenya as a whole. All literature is based on either primary or secondary data analysis, with no inclusion of literature reviews or availability of meta-analyses. We did not set a start date and explored all electronically available literature, with our earliest paper coming from 1982.

Secondary data and analysis

Administrative and climate data

Level one and level two administrative boundaries (counties and wards respectively) were extracted from the Database of Global Administrative Areas (GADM) (GADM 2012) and subset to the study area of Baringo, Garissa, Isiolo, Mandera, Marsabit, Samburu, Tana River, Turkana, and Wajir Counties. These spatial boundaries were used to extract mean monthly temperature, precipitation, and NDVI covariates from gridded data sources. Temperature was extracted from TerraClimate (Abatzoglou, Dobrowski et al. 2018), precipitation from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) dataset (Funk, Peterson et al. 2015), and NDVI from the National Aeronautics and Space Administration's Vegetation Index and Phenology (VIP) dataset (Didan and Barreto 2016) (Table 1). These datasets were chosen for their high spatial resolution, greater accuracy in Africa, and coverage for the study period of 2000–2017. Extracted data were visualized as gridded monthly maps and boxplots of monthly means.

Disaster data

For information on the experience of disasters in our region of interest, we relied on the publicly available International Disaster Database (EM-DAT), which is maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the Catholic University of Louvain (CRED 2020) (http://www.emdat.be/). Information on the

Table 1. Data source, reference, variable, spatial resolution, temporal resolution for secondary data

Data Source	Reference	Variables	Spatial Resolution	Temporal Resolution
CHIRPS 2.0	(Funk, Peterson et al. 2015)	Infrared Precipitation	0.05 x 0.05	Monthly
TerraClimate	(Abatzoglou, Dobrowski et al. 2018)	Land Surface Temperature	0.05 x 0.05	Monthly
NASA MEa-SUREs VIP-30	(Didan and Barreto 2016)	NDVI	0.05 x 0.05	Monthly
ACLED	(Raleigh, Linke et al. 2010)	Conflict Events	Latitude/ Longitude	Daily
EM-DAT		Disaster Events	County	Monthly

3 Ijara was formerly a district and is now a sub-county within Garissa County.

type of disaster and its timing is compiled from various sources, such as United Nations (UN) agencies, non-governmental organizations (NGOs), insurance companies, research institutions, and press agencies. According to EM-DAT, a disaster is a natural situation or event that overwhelms local capacity and/or necessitates a request for external assistance. Specifically, to be included in the database, an event must meet at least one of the following criteria:

- Ten or more people are reported killed.
- One hundred or more people are reported affected.
- A state of emergency is declared.
- A call for international assistance is issued.

Conflict data

Conflict data for Kenya was sourced from the Armed Conflict Location & Event Data Project (ACLED) database (Raleigh, Linke et al. 2010). The following terms were utilized to identify farmer-herder conflicts: cattle; camel; goat; cow; animal; livestock; farm; farmer; raid; herd; herder; graze; grazing; rustle; rustling; pasture; pastoral; and pastoralist. The total number of conflict events and fatalities by month were aggregated and visualized by county using boxplots and Loess smoothers. The seasonal pattern of conflict for each county was then analyzed using both Poisson and Negative Binomial harmonic regression with first and second harmonics as shown below. In this equation, t represents the series month and ω represents a cycle of 1/12 months.

$$\text{Count of Conflict Events} = \beta_0 + \beta_1 t + \beta_2 \sin(2\pi\omega t) + \beta_3 \cos(2\pi\omega t) + \beta_4 \sin(4\pi\omega t) + \beta_5 \cos(4\pi\omega t)$$

Supporting spatial data were extracted to contextualize the study area. Livelihood zones were extracted for Kenya from FEWS NET (FEWS NET 2018). GPS points of market locations were sourced from financial access survey data collected by FSD Kenya in 2017 (FSD Kenya 2019). Land use and land cover information were extracted from the 2016 Sentinel2 Land Use Land Cover dataset published by the Kenyan Regional Centre For Mapping Of Resources For Development (RCMRD) in partnership with NASA and USAID (RCMRD Kenya 2017). Shuttle Radar Topography Mission (SRTM) elevation at 30-meter resolution was also sourced from RCMRD (RCMRD Kenya 2015). Population density gridded data were extracted from the Global High Resolution Population Denominators Project (Lloyd, Chamberlain et al. 2019). Vector data for roads were sourced from the Intergovernmental Authority on Development (IGAD) Climate Prediction & Applications Centre (ICPAC) (ICPAC 2017). Data on physical features including water bodies and rivers derive from the Digital Chart of the World via the World Resources Institute (WRI 2007, ESRI 2010).

Nutrition data

For the secondary data analysis of seasonal nutrition trends, we use two different datasets. The first dataset is composed of Standardized Monitoring and Assessment of Relief and Transitions (SMART) surveys from Isiolo and Marsabit Counties. SMART datasets use a standardized 30 clusters by 30 household nutrition anthropometry survey design as standard per SMART methodology (UNICEF and USAID 2006). The second dataset—National Drought Management Authority (NDMA)—comes from sentinel site monitoring in Marsabit and Isiolo. See Table 2 for sample sizes.

The data set included the following variables: weight, height, mid-upper arm circumference (MUAC), age (in months), height-for-age z-score (HAZ), weight-for-age z-score (WAZ), weight-for-

Table 2. Sample size for nutrition data analysis

Survey	County	Individual Observations	Year Range
SMART	Isiolo	7,257	2010-2020
	Marsabit	16,076	2010-2019
NDMA	Isiolo	116,902	2010-2020
	Marsabit	113,380	2010-2019

height z-score (WHZ), MUAC gender, administrative region, and country. Outliers (z-score greater than 5 or less than −5) were removed. We present information on the seasonality wasting using both WHZ < −2 standard deviations and MUAC < 115 cm, as well as WHZ and MUAC separately. To help triangulate findings, we present findings separately for the MUAC data available in the SMART and NDMA surveys. Finally, all data analysis is stratified by county.

Several regression formulations were tested to assess the sequential effect of environmental, conflict, and disasters on nutrition outcomes. The outcomes of interest in this analysis include the weight-for-height z-score (WHZ), the mid-upper arm circumference (MUAC), and global acute malnutrition (GAM) as measured by both WHZ and MUAC cutoffs. MUAC less than or equal to 125 mm and WHZ less than or equal to −2 were considered the threshold for defining GAM.

In addition to child-level characteristics including age and sex, temporal characteristics including categorical month and seasonal harmonics were tested in later models. First, a time series of all months from 2010 to 2020 was created. This month series t was used to create half-year harmonic terms using *sine*(2π(1/12)t) and *cosine*(2π(1/12)t), and quarter-year harmonics using *sine*(4π(1/12)t) and *cosine*(4π(1/12)t). These terms are collectively referred to as *Harmonics* and are critical for capturing cyclical seasonal cycles of acute malnutrition. All temporal variables were matched to the appropriate month of NDMA and SMART survey implementation.

Two regression techniques were used in the analysis. Ordinary Least Squares (OLS) regression was used to measure continuous outcomes of WHZ and MUAC, and logistic regression was used to analyze binarized outcomes based on aforementioned cutoffs. For child *i* in location *j* at month *m* and month series *t*, the regression formulations presented in Table 3 were tested for each of the continuous and binarized outcomes of WHZ and MUAC.

Table 3. Regression model details

Indicator	Regression Equation
Baseline	$\text{Outcome}_i = \text{Age Group}_i + \text{Sex}_i$
Baseline + Month	$\text{Outcome}_i = \text{Age Group}_i + \text{Sex}_i + \text{Survey Month Category}$
Baseline + Month Series + Harmonics	$\text{Outcome}_i = \text{Age Group}_i + \text{Sex}_i + t + \text{Harmonics}_t$
Baseline + Month Series + Harmonics + Environment	$\text{Outcome}_i = \text{Age Group}_i + \text{Sex}_i + t + \text{Harmonics}_t + \text{Temperature}_{jm} + \text{Precipitation}_{jm} + \text{NDVI}_{jm} + \text{I(Precipitation * Temperature)}_{jm}$
Baseline + Month Series + Harmonics + Environment + Conflict Events	$\text{Outcome}_i = \text{Age Group}_i + \text{Sex}_i + t + \text{Harmonics}_t + \text{Temperature}_{jm} + \text{Precipitation}_{jm} + \text{NDVI}_{jm} + \text{I(Precipitation * Temperature)}_{jm} + \text{Conflict}_{jm}$
Baseline + Month Series + Harmonics + Environment + Disasters	$\text{Outcome}_i = \text{Age Group}_i + \text{Sex}_i + t + \text{Harmonics}_t + \text{Temperature}_{jm} + \text{Precipitation}_{jm} + \text{NDVI}_{jm} + \text{I(Precipitation * Temperature)}_{jm} + \text{Disasters}_{jm}$
Baseline + Month Series + Harmonics + Environment + Conflict + Disasters	$\text{Outcome}_i = \text{Age Group}_i + \text{Sex}_i + t + \text{Harmonics}_t + \text{Temperature}_{jm} + \text{Precipitation}_{jm} + \text{NDVI}_{jm} + \text{I(Precipitation * Temperature)}_{jm} + \text{Conflict}_{jm} + \text{Disasters}_{jm}$

Findings

Environment and variability

Climatic variability—both spatial and temporal—is a defining trait of dryland environments (Hutchinson and Hermann 2008, Kratli 2015). However, the spatial variability is even more pronounced in eastern Africa compared to the rest of the African continent (Figure 3) (Herrmann and Mohr 2011). Kenya alone encompasses seven seasonal classifications, with areas that can be defined as arid, humid, one unimodal wet season, one bimodal wet season, one multimodal wet season, two unimodal wet seasons, two wet seasons with one being unimodal and the other being bimodal, as well as areas defined as having more than two wet seasons.

Even when isolating our data just to the counties in Kenya that fall under the classification of ASALs, we still see an incredible level of variability across our three main climate indicators: precipitation, temperature, and vegetation (measured via NDVI) (Figure 4). There are clear outlier counties in terms of both variability and amplitude across the climatic measures. Marsabit has the lowest vegetation and some of the hottest temperatures, while Samburu is one of the coolest climates. Baringo is clearly much wetter, greener, and cooler compared to the rest of the counties, with a less defined dual seasonal peak in precipitation. Turkana also only has one precipitation peak with a small shoulder. These distinctions are extremely important both for understanding the value and consequences of aggregation across counties as well as for a temporal understanding for program planning. We discuss all three climatic and environmental variables by county in detail below, looking at yearly means and seasonal patterns.

Figure 3. Seasonality classes according to Herrmann and Mohr, 2011 (copied image).

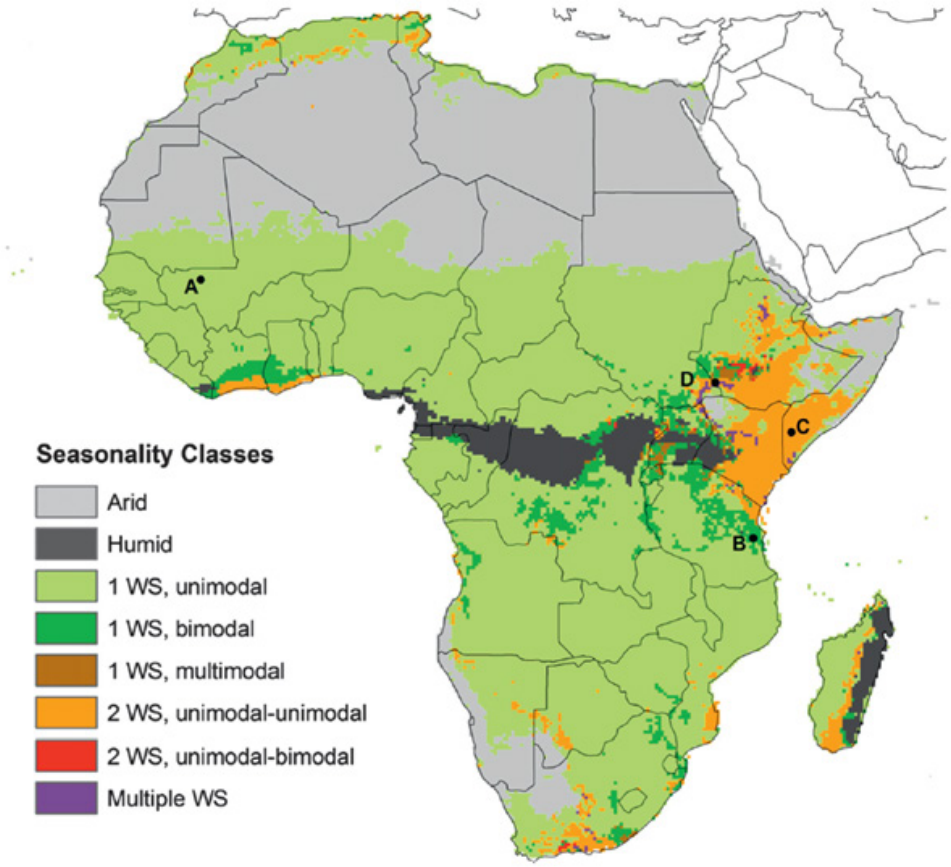
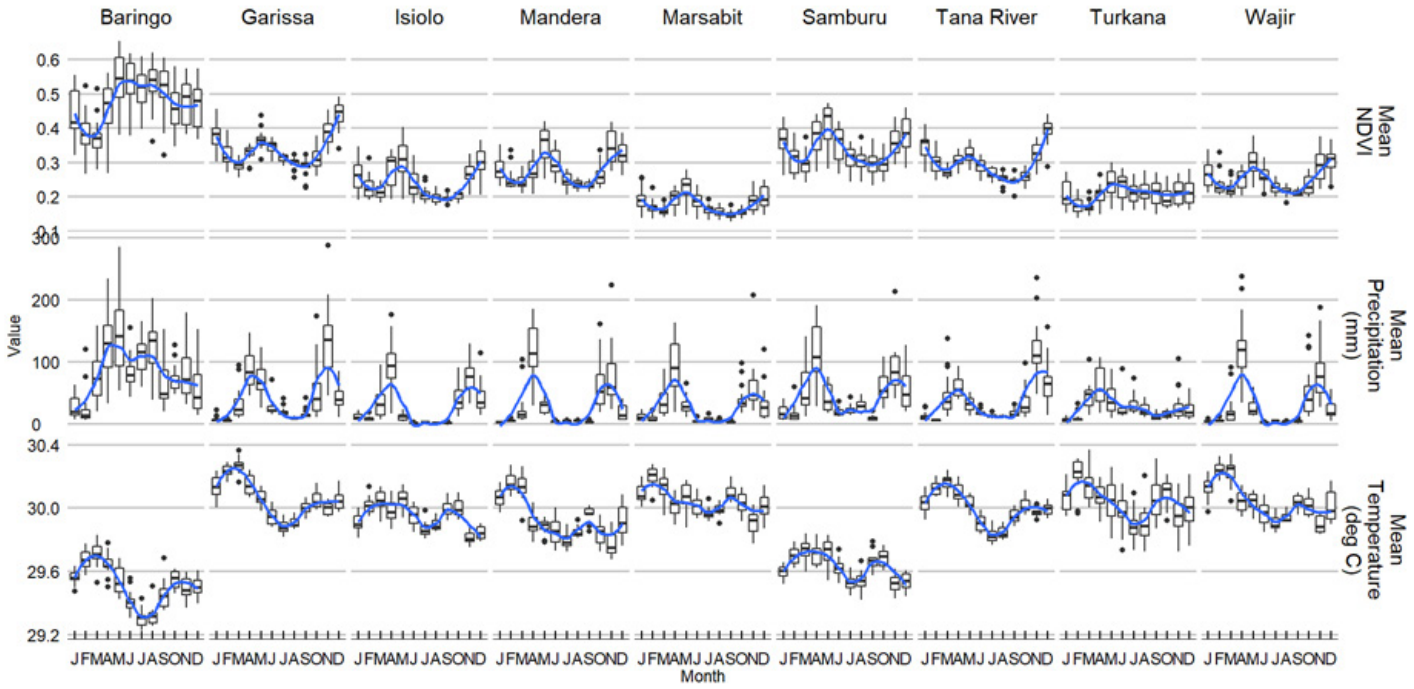


Figure 4. Inter-year variability in NDVI, precipitation, and temperature in the Kenyan ASALs by county.



Precipitation

When looking at annual precipitation in mm (Figure 5, panel a), there is some evidence of a bit of a north-to-south gradient, with southern parts of Garissa and Tana River clearly experiencing much greater rainfall (> 800 mm/year) while the northern areas of Turkana and Marsabit experience less rainfall (< 500 mm/year). However, there are spots with comparably high rainfall in Samburu in Marsabit, which correspond to areas of higher elevation (Figure 4, panel b). Parts of Turkana, Marsabit, Isiolo, and Wajir experience the lowest mean annual rainfall. For example, even in the wettest months, parts of Turkana, Marsabit, Isiolo, and Wajir still receive less than 50 mm/month (Figure 6).

Across the nine counties, we find that, with the exception of Baringo and Turkana, the rest of the counties have two clear seasonal rainfall peaks (Baringo has more of a shoulder than a peak). The first peak of rainfall happens around April and the second peak occurs around November, with a distinct dry period in between. With the exception of Garissa and Tana River, the remaining counties have much greater variability when it comes to the first rainy season (look at the box plots for each month) (Figure 7). The April and November rainfall peaks are clearly apparent in Figure 6, with slightly later (May) first rains in southern Garissa and Tana River.

There is also variability related to the start time for the rains, which happens around February or March for the first rainy season and September or October for the second rainy season.

When looking at a much smaller geographic area, focused on the three wards of interest: Garbatulla and NgareMara Wards in Isiolo County and Laisamis Ward in Marsabit County, we find a fairly similar rainfall pattern and precipitation means for the two wards in Isiolo (with some distinctions in terms of the first rainy season/peak) but very different monthly means in Laisamis. See Figure 8. While the second rainy season in Garbatulla and NgareMara is similar to the first rainy season, in Laisamis the seasonal peak in the second rainy season is much smaller. The smaller second rainy season is not representative of Marsabit more broadly, likely because the aggregated Marsabit data include some of the higher elevation areas that receive significantly more rainfall than the rest

Figure 5. Mean annual precipitation (mm) (panel a) and elevation (panel b).

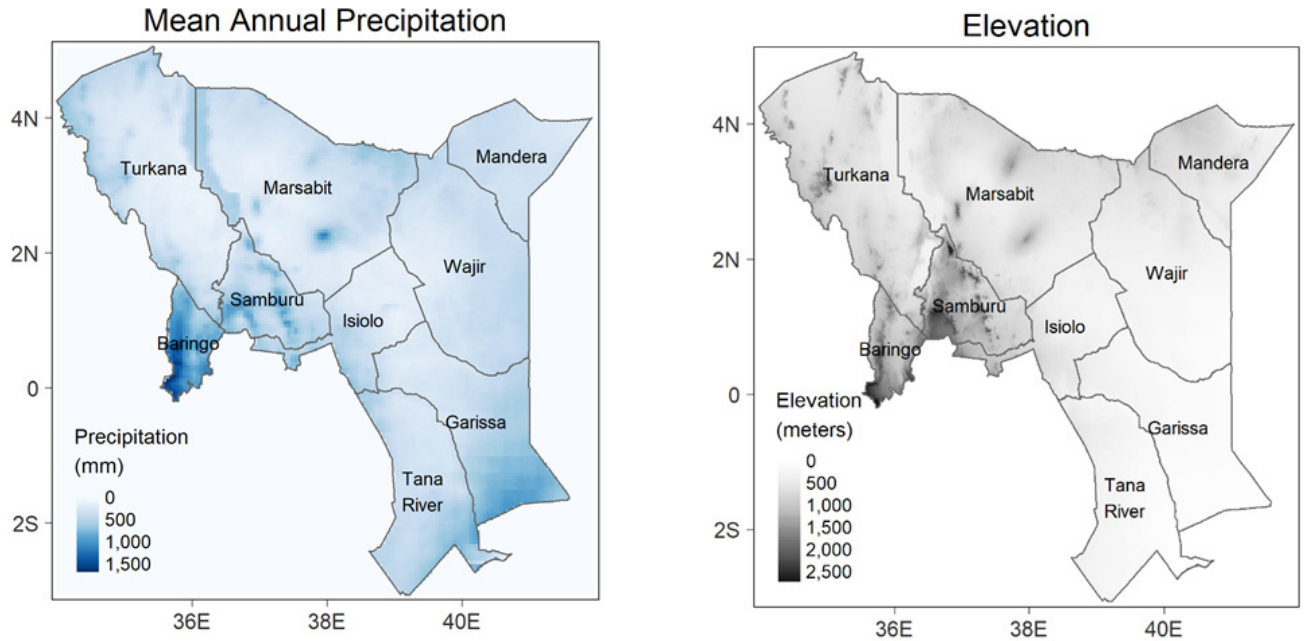


Figure 6. Spatial distribution of monthly precipitation (mm) in the Kenyan ASALs.

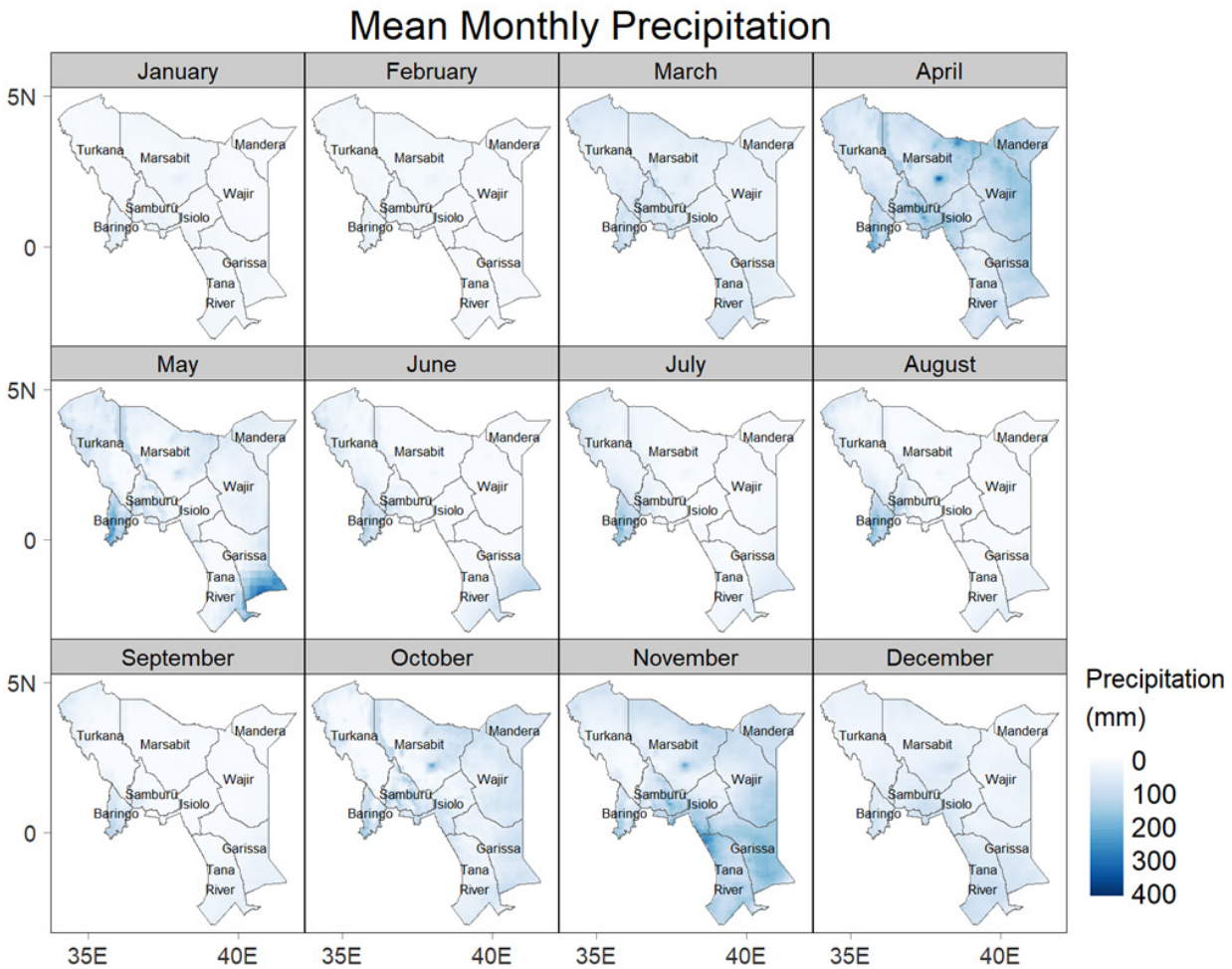


Figure 7. Variability across 20 years of precipitation data by month and county.

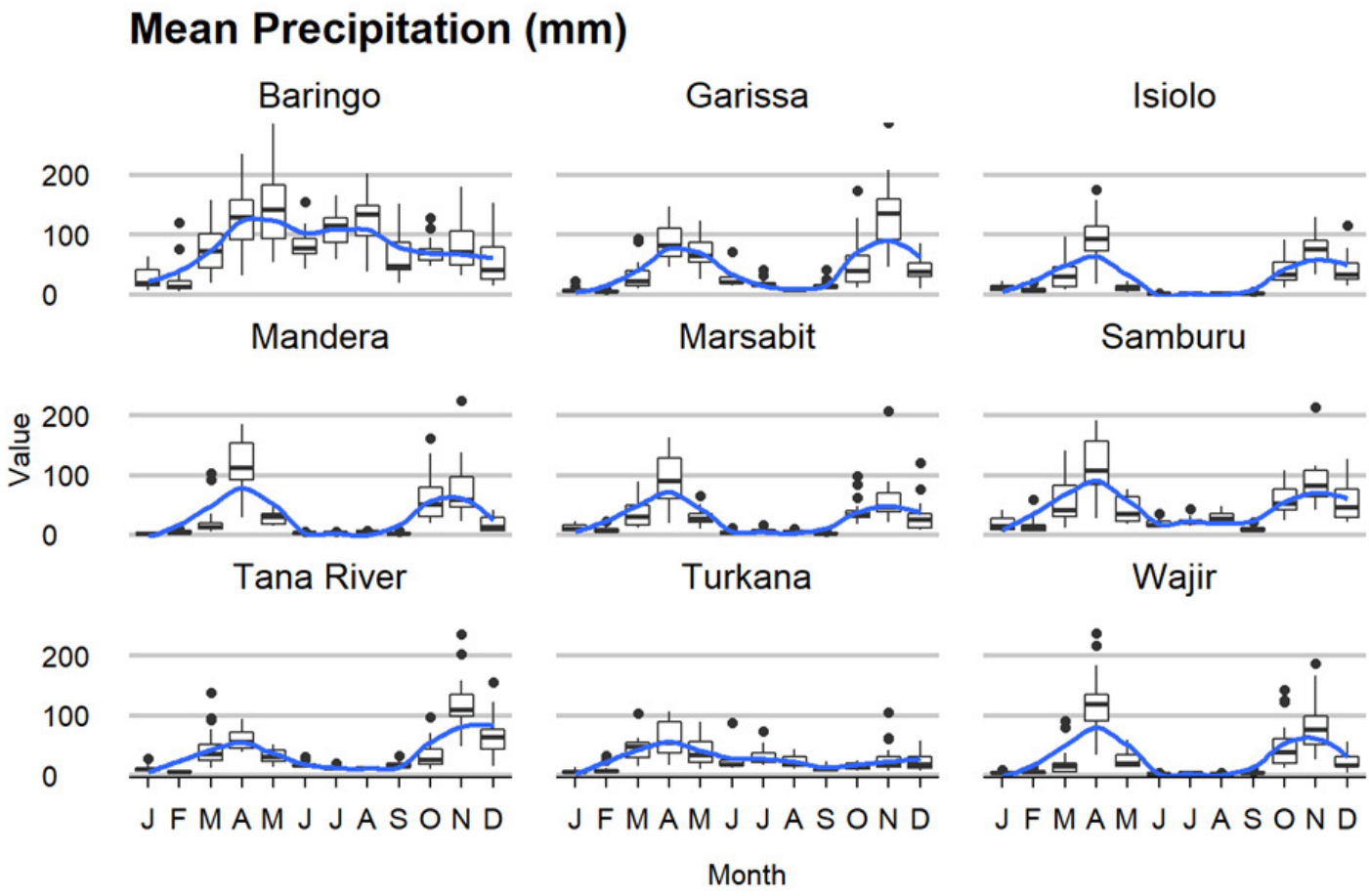
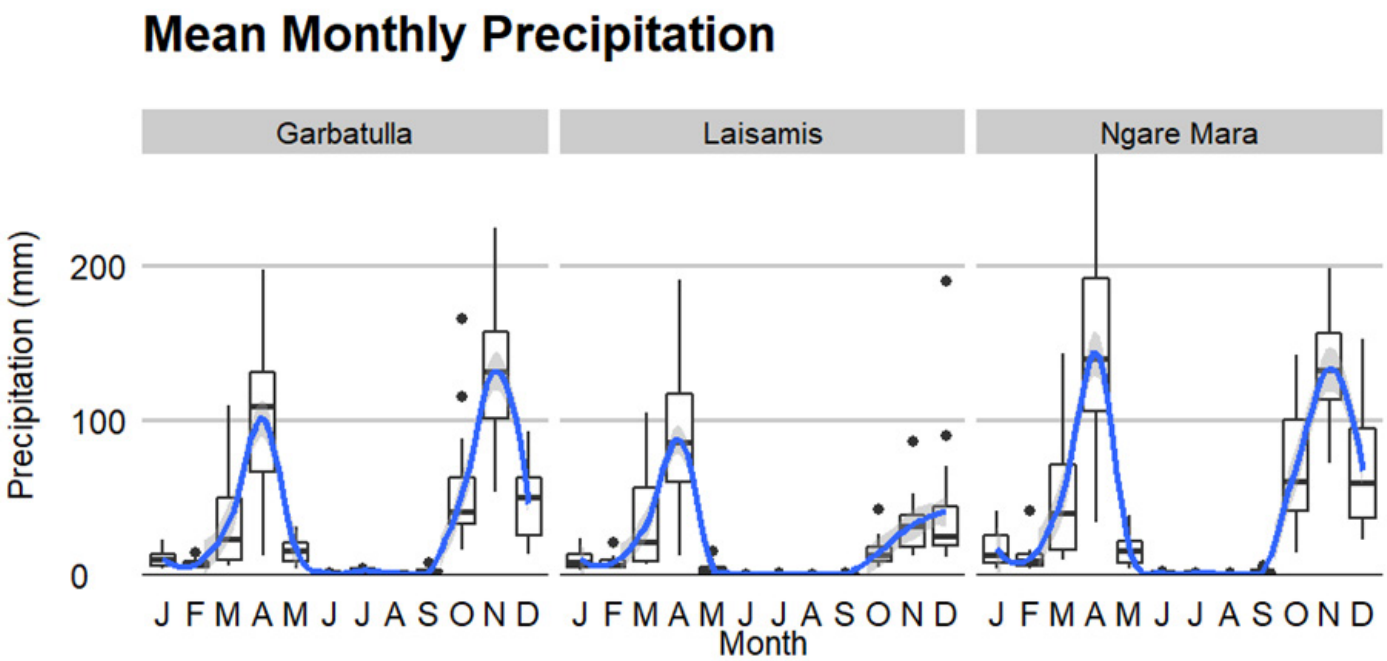


Figure 8. Mean monthly precipitation in Garbatulla, Laisamis, and NgareMara Wards.



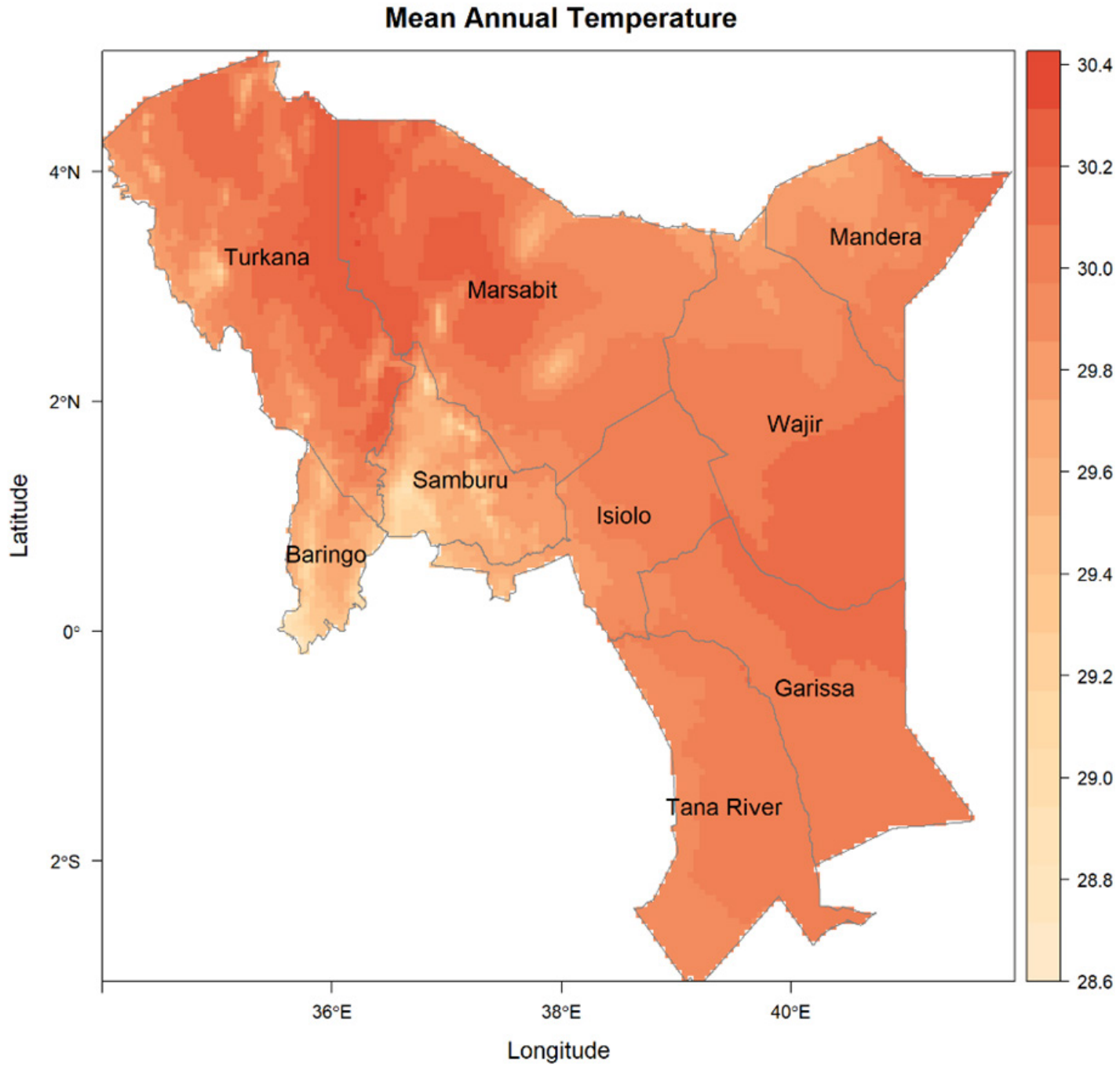
of Marsabit, including Laisamis. What is consistent across all three wards is that we can see a very clear and long first dry season (June, July, August, September) followed by a second and shorter dry season (January and February), with January especially still occasionally experiencing some rainfall.

Temperature

The hottest counties are Marsabit and Turkana, as well as parts of Wajir, while Samburu is the coolest given the higher elevation, along with small pockets in Marsabit and Turkana (Figure 9). Thus, there is far greater spatial temperature variability in Marsabit and Turkana.

The small variability in temperature is easier to visualize in Figure 10, panel a. Most counties display two temperature peaks, one in February and another one around September/October. Of all the counties, Marsabit shows the lowest range in temperature, but this is due to the aggregation of temperature data across all of Marsabit, which

Figure 9. Mean annual temperature (degrees Celsius) by county.



has relatively cool and hot pockets in most months (Figure 10, panel b).

At the ward level, focusing on the Nawiri three sentinel sites, we see a far greater differentiation in temperature compared to aggregated county monthly values. We see two peaks in temperature, around April (corresponding go the first rain peak) and September (corresponding to the start of the second rainy season) for all three wards, but much lower temperatures in NgareMara despite the fact that NgareMara and Garbatulla are both in Isiolo County and only 40 kilometers apart. The main distinction between Garbatulla and Laisamis is that the temperature drops far more in July in Garbatulla. See Figure 11.

Vegetation

Baringo is by far the greenest county, while Marsabit has the least amount of vegetation, on average (Figure 12). However, as with everything else, averaging, even on the county level, obscures the high level of spatial variability. While Marsabit, on average, has the least amount of vegetation, along with Isiolo and Samburu, it has pockets of

Figure 10. Temporal (panel a: left) and spatial variability (panel b: right) across 20 years of temperature data by month and county.

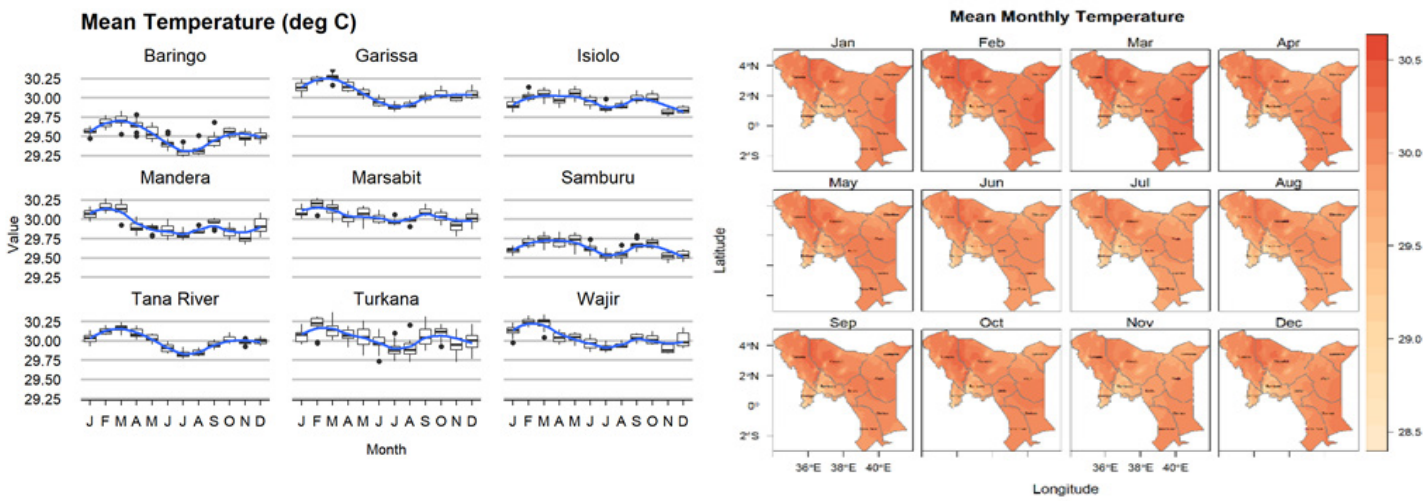


Figure 11. Monthly temperature and variability for Garbatulla, Laisamis, and NgareMara Wards.

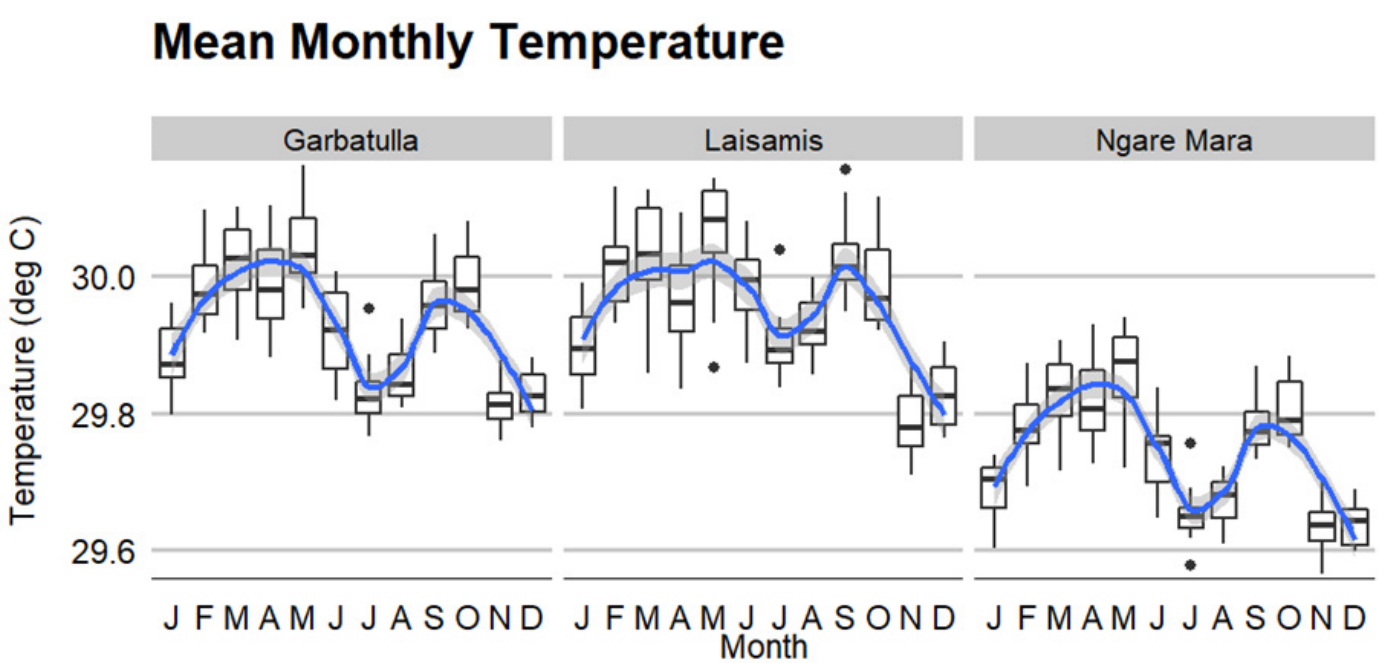
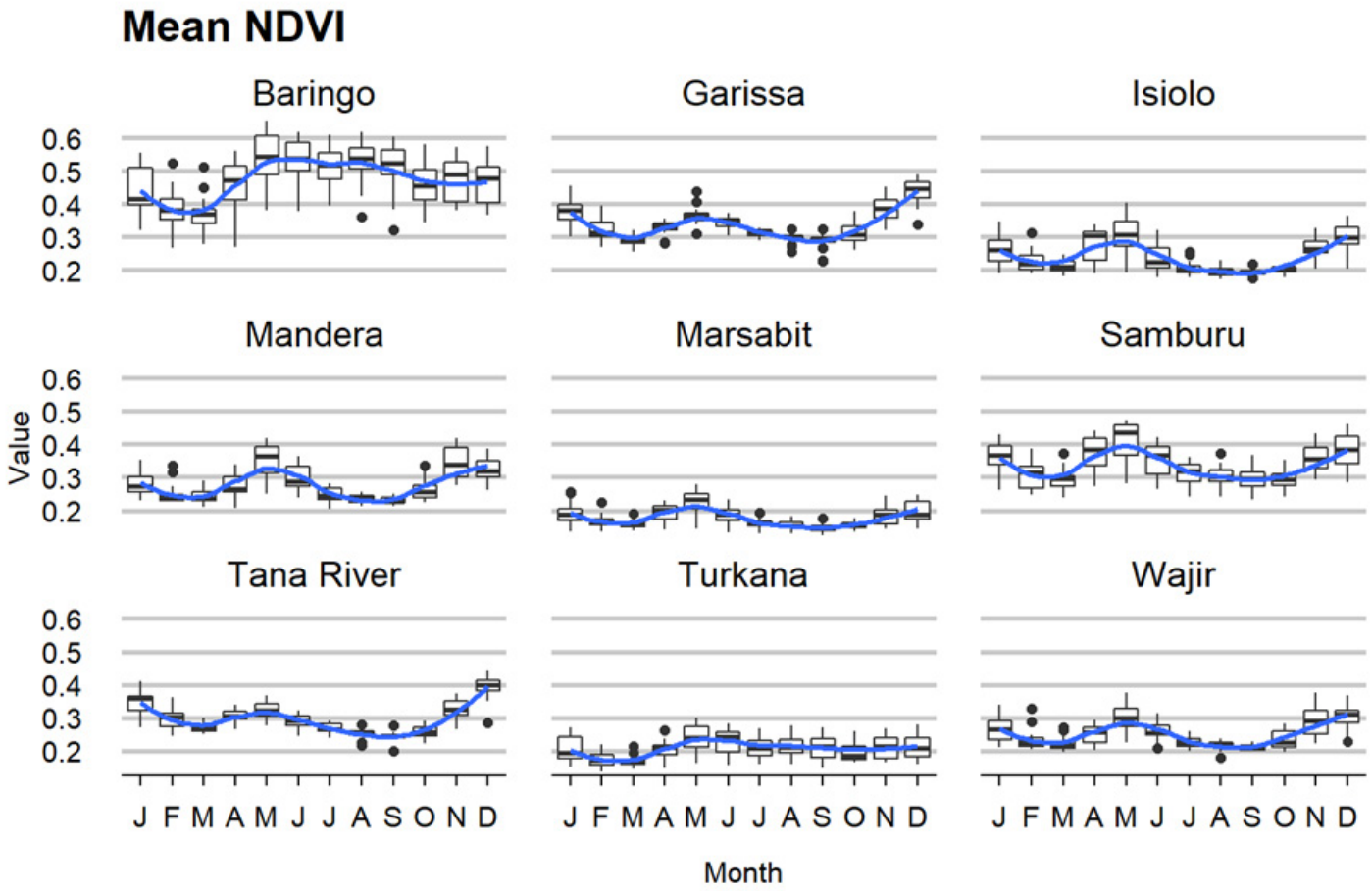


Figure 12. Variability across 20 years of NDVI data by month and county.



vegetation comparable to what can be found in Samburu and southern Garissa and Tana River (Figure 13).

As with precipitation and temperature, we also look separately at trends in vegetation in the three sentinel wards (Figure 14). Two peaks in vegetation are observed, one around April/May and a second peak in December, occurring directly after the identified peaks of rainfall. We also see that Laisamis Ward has lower levels of vegetation throughout the year compared to the other two wards.

Ward-level seasonality of climatic variables in relation to seasonal calendars

Reviewing the seasonal patterns and variability of precipitation, temperature, and vegetation in the three sentinel wards identified for the primary data collection, we can briefly summarize the seasonal characteristics of the three wards (Figure 15). In all three wards, we have two rainy seasons, almost equal in duration and total precipitation in Garbatulla and NgareMara: approximately March through May and October through December. In Laisamis (our only Marsabit ward), we have a primary and larger rainy season, also from March through May, and a smaller rainy season from October through December. There are two temperature peaks: in April, which is the middle of the first rainy season, and in September, which corresponds to the first sprinkling of rain that happens before the start of the second rainy season. Both temperature and precipitation, alongside soil quality and other environmental characteristics, drive the seasonal vegetation. There are two peaks in vegetation: in March and December, corresponding to the end of the two rainy seasons alongside the drop in temperature. Of the three wards, Garbatulla has the highest vegetation, corresponding to presence of communities who practice both livestock keeping and farming, while Laisamis has the lowest vegetation, corresponding to a preference for pastoralism.

Figure 13. Spatial distribution of monthly NDVI in the Kenyan ASALs.

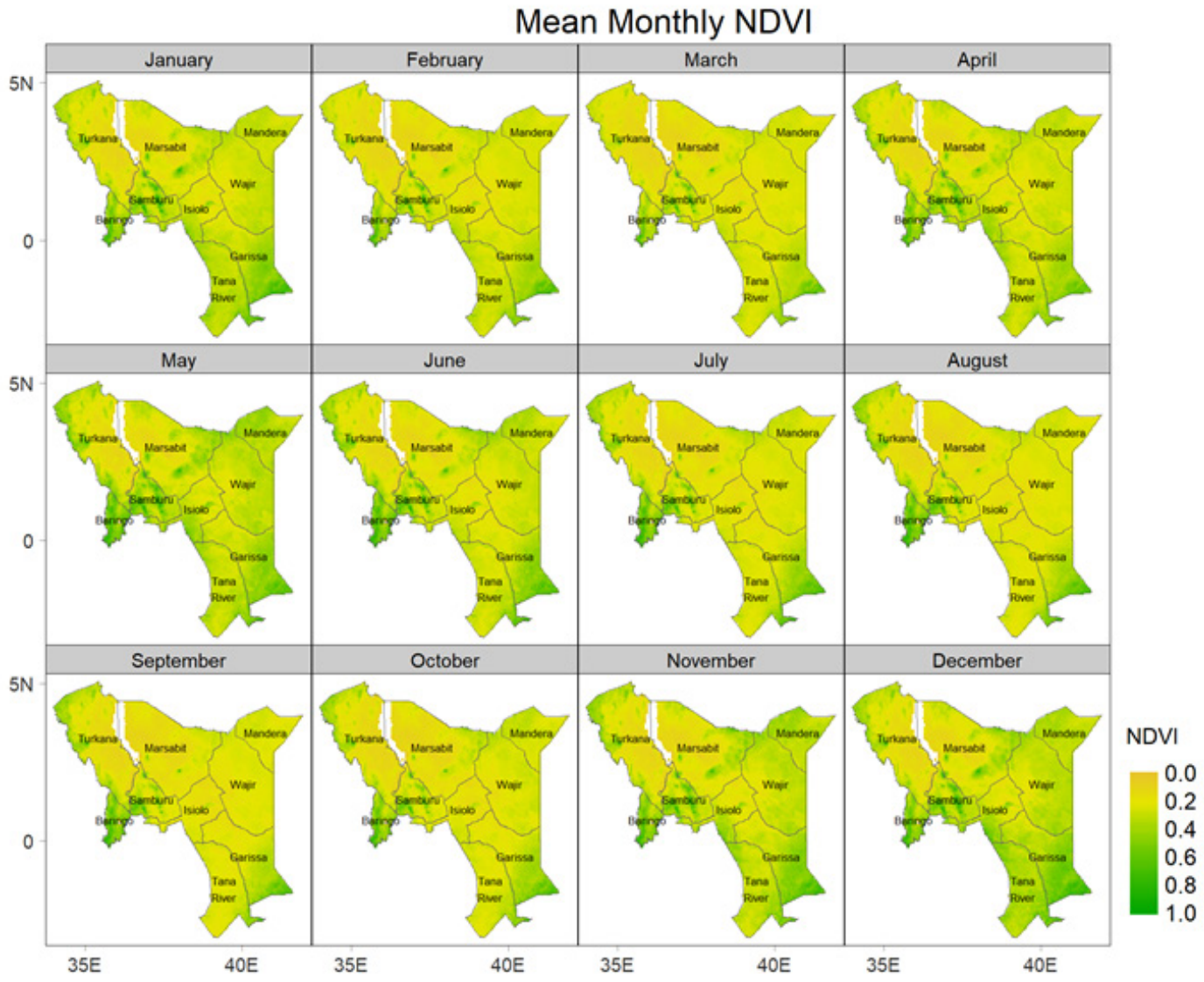


Figure 14. Monthly NDVI and variability in Garbatulla, Laisamis, and NgareMara Wards.

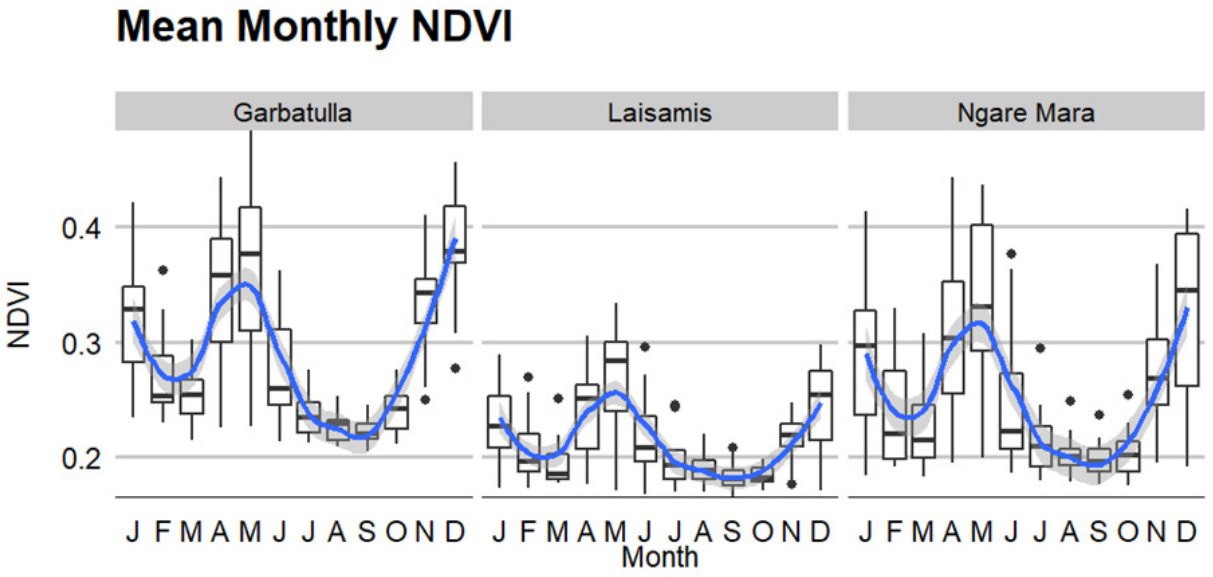
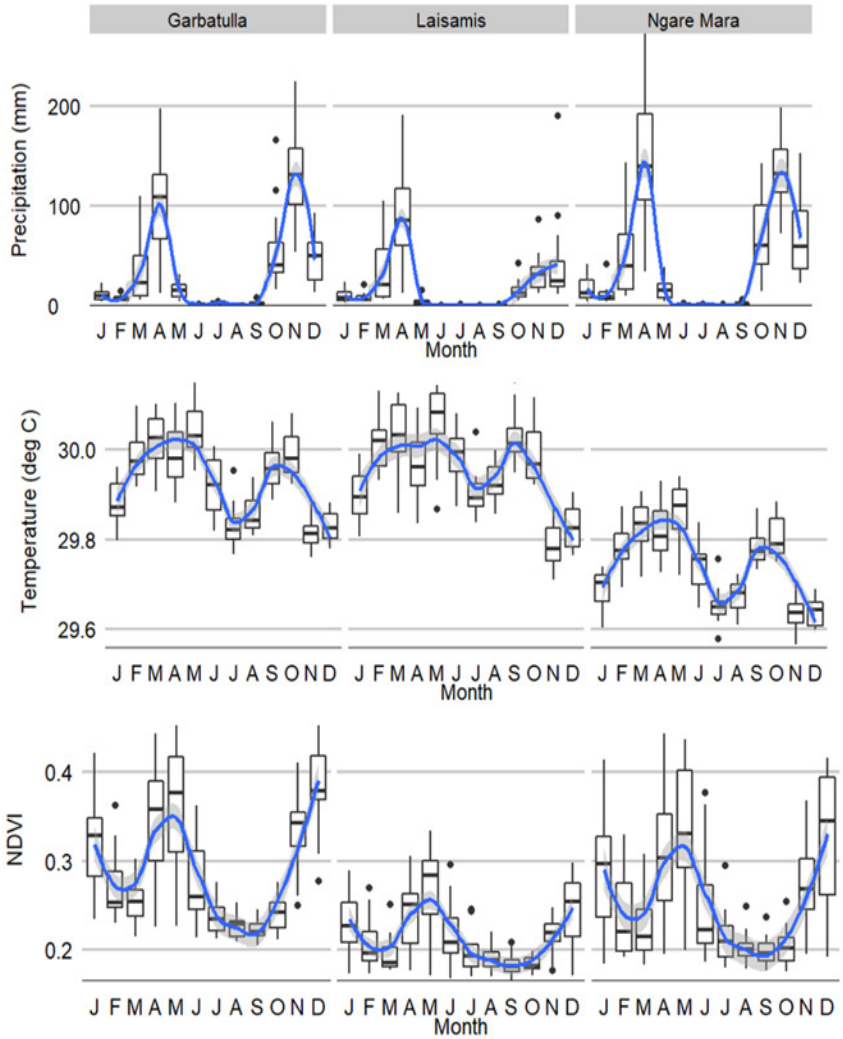
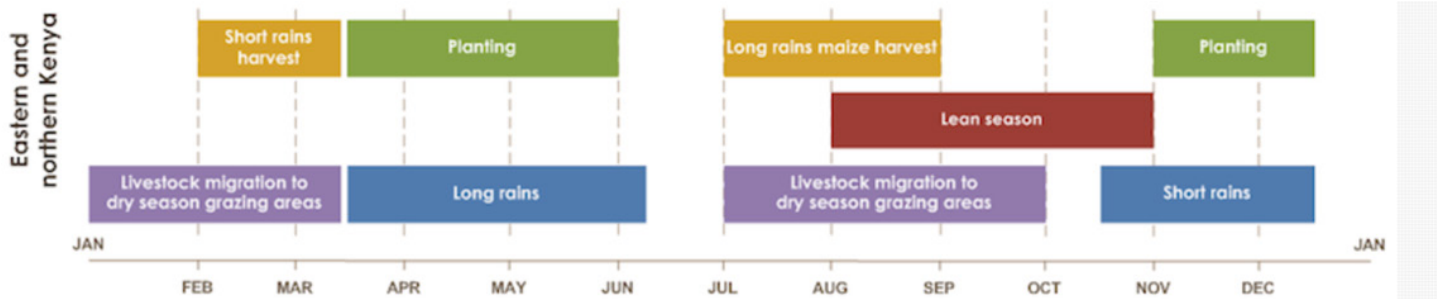


Figure 15. Precipitation, temperature, and vegetation across the three sentinel wards.



Next, we compare how the seasonal climatic pattern identified through the remote sensing data corresponds to the climatic description in the Isiolo and Marsabit Development Plans, the FEWS NET seasonal calendar for northern Kenya (Table 4), and the seasonal calendar produced by Caritas as part of the initial Nawiri workshop (Table 5). The slightly different seasonal patterns identified across these four sources highlight how variable the start time, end time, and duration of the two rainy and two dry seasons are. Both the county-level Development Plan and FEWS NET calendar identify two rainy seasons of different durations in Isiolo: "The short rain season occurs between October and December with the peak in November while the long rain occurs between March and May with the peak in April" in Isiolo (Republic of Kenya 2018) but differ on timing, with FEWS NET identifying a slightly later long rainy season from April through June but the same timing for the "short" rainy season: November and December. The county-level Development Plan for Marsabit also refers to a long and short rainy season, but gives a shorter duration for the long rainy season: "The long rain season falls between April and May while the short rain season falls between November and December" (Republic of Kenya C. G. o. M. 2018). The Nawiri seasonal calendar also reports different timing from our review of the remote sensing data, the FEWS NET calendar, and the county-level Development Plans, identifying four seasons: short dry spell from January to March, heavy rains from April to May, a long dry spell from July through September, and a short rainy season from October through December.

Table 4. FEWS NET seasonal calendar



Source: https://fews.net/file/113528.

Table 5. Seasonal calendar according to Nawiri workshop for Isiolo and Marsabit

	Jan	Feb	Mar	April	May	June	July	Aug	Sept	Oct	Nov	Dec
Rainfall	Short Dry spell			Heavy rains/ flash floods			Long dry spell			Short rains/flash floods		
Farming	Harvest (maize)	Land prep.	Planting			Weeding, Harvest (beans)	Harvest (maize)		Land prep.	Planting		Weedin g
Livestock			Calving period						Calving period			
		Migrate to dry season area		Migrate to wet season area			Migrate to dry season area			Migrate to wet season area		
Farmer-herder conflict			conflict	conflict					conflict	conflict		

The literature review partially highlights the inconsistency of the timing and size of the rainy seasons in relation to the seasons outlined in the county-level reports, FEWS NET, and the Nawiri seasonal calendar. The few studies that did present rainfall or other climatic characteristics corresponding to the timing of their nutrition data collection directly noted divergence from the static characterization of season. For example, Shell-Duncan et al. (1995) writes: "During the 12-month study period, the wet season occurred from February through April, during which time 70% of the total annual rainfall accumulated. A short wet season, which typically arrives in October or November, did not occur in this seasonal cycle" (Shell-Duncan 1995). Another author who looked at rain gauge data for their study also noted: "The customary monsoon rains, from March through June, failed, leading to conditions in which milk production was low and food was in short supply." (Little and Johnson 1987). Finally, Fratkin et al. (2004) collected data over three years and also found an inconsistent rainfall pattern across the years of data collection (Figure 16) (Fratkin, Roth et al. 2004). It is also interesting to note that both authors specify different assumed seasonal timing from Shell-Duncan, reporting the wet season (long rains) from February to April, while Little specifies that the customary wet season is from March to June. These "assumed" seasons do not even overlap.

We might also need to consider that the typical four-season breakdown for the Kenya ASALs—long rains, long dry season, short rains, short dry season—might not be appropriate everywhere in

Figure 16. Monthly rainfall (mm) in Marsabit District, 1995–97 (Fratkin, Roth et al. 2004).

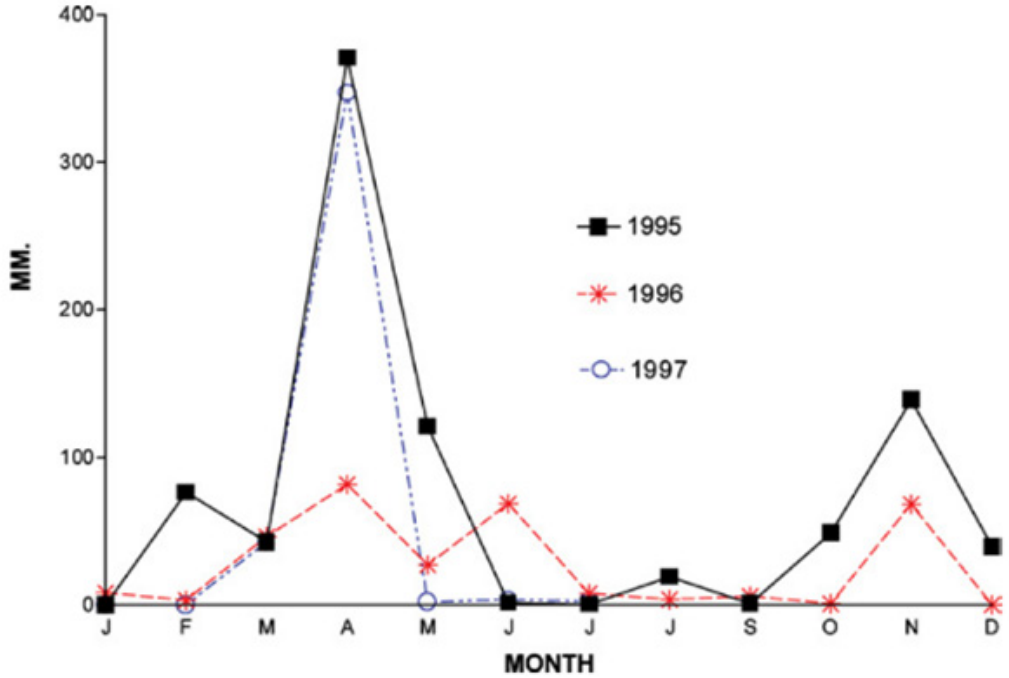


Fig. 2. Monthly rainfall in Marsabit District, 1995–97.

the ASALs. We have already discussed how there does not appear to be a distinction in rainfall between the long rains and the short rains in two of our three wards. In addition, participatory work on seasonality in Samburu identified a fifth season that they called "sparse rains" that occurs in September right before the short rains (FAO, UNICEF et al. 2020). September corresponds to the start of the second rainy season and, critically, a temperature peak. This fifth season was not mentioned in any of the other papers, which strictly spoke about the dry versus wet season, or a slight expansion on that: the long dry vs. short dry vs. long wet vs. short wet season. This short season indicating the beginning of the rains might be of particular interest considering a similar fifth season was identified in Chad and Sudan, called *rushash*. *Rushash* refers to the start of the rains when showers are very light, almost like a sprinkling, and highly dispersed, yet sufficient to cause a first light flush of new grass, also corresponding to a seasonal temperature peak (FAO and Tufts 2019, Marshak, Young et al. 2021). Another interesting observation that might have implications for participatory methods around seasonality is that women and men appeared to have different perspectives on the timing in the Marsabit study. Women reported that "light showers" started in August, while men reported that the rains start in October (FAO, UNICEF et al. 2020). This difference might relate to the difference in livelihood activities by sex and hence different environmental signs for when to begin those activities.

History and seasonality of disasters

A review of the last 20 years (2000–2020) of EM-DAT data on disasters shows a long history of multiple and frequently overlapping shocks (Table 6). For example, across the 11 counties, there are only two years with no disasters reported (2003 and 2007). Most years the Kenyan ASALs experience more than one disaster, sometimes reporting both a flood and a drought. 2019 has the greatest burden of multiple disasters, reporting floods, epidemics, droughts, and an insect infestation. And we can add a global pandemic to 2020.

When isolating the disaster data just to Isiolo and Marsabit, we note that the experience of covariate disasters does not perfectly overlap across the two counties (Table 7). For example, twice the number of droughts were reported in Marsabit compared to Isiolo (six versus three respectively), while floods and epidemics are slightly more common in Isiolo compared to Marsabit.

Table 6. List of disasters by county and year (2000–2020) (EM-DAT database)

Year	Disaster Type	Isiolo	Marsabit	Turkana	Baringo	Samburu	Moyale	Mandera	Wajir	Garissa	Tana River	Ijara
2000	Epidemic							yes	yes	yes		
2001	Epidemic								yes			
2002	Flood				yes						yes	yes
2004	Drought		yes	yes				yes	yes	yes	yes	yes
2004	Flood			yes	yes						yes	
2005	Flood	yes								yes		
2005	Epidemic	yes	yes					yes	yes		yes	yes
2006	Flood	yes		yes			yes	yes	yes	yes	yes	yes
2006	Epidemic	yes						yes	yes	yes	yes	yes
2008	Flood		yes	yes				yes	yes	yes	yes	
2008	Epidemic							yes				
2008	Drought			yes	yes	yes						
2009	Epidemic	yes		yes					yes	yes		
2009	Flood	yes		yes		yes		yes			yes	
2010	Flood	yes	yes	yes	yes	yes	yes	yes			yes	
2010	Drought	yes	yes	yes		yes	yes	yes	yes	yes	yes	yes
2011	Flood	yes	yes	yes	yes	yes	yes		yes	yes	yes	
2011	Drought		yes	yes			yes	yes	yes		yes	
2012	Flood										yes	
2013	Flood			yes	yes							
2014	Drought		yes	yes	yes	yes		yes	yes			
2015	Flood	yes	yes					yes	yes		yes	
2016	Flood		yes	yes					yes			
2016	Drought	yes	yes	yes	yes	yes		yes	yes	yes	yes	
2017	Epidemic			yes					yes	yes		
2018	Flood	yes		yes		yes		yes	yes	yes	yes	
2019	Flood	yes	yes			yes		yes	yes		yes	
2019	Drought	yes	yes	yes	yes			yes	yes	yes		
2019	Epidemic									yes		
2019	Locusts	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
2020	Flood									yes	yes	

Note: Shading is used to separate the data visually by year; epidemics include viral, bacterial, and parasitic diseases.

Table 8. Percent of floods by month and by county

	Month									
	Jan	Mar	Apr	May	Jun	Aug	Oct	Nov	Dec	Total
Baringo	12.5	25	12.5	12.5	0	12.5	0	12.5	12.5	100
Garissa	0	25	12.5	12.5	0	0	25	25	0	100
Ijara	0	0	50	0	0	0	50	0	0	100
Isiolo	0	20	20	0	0	0	30	10	20	100
Mandera	0	22.22	0	0	0	0	55.56	11.11	11.11	100
Marsabit	0	33.33	16.67	0	0	0	16.67	16.67	16.67	100
Moyale	0	20	20	0	0	0	40	20	0	100
Samburu	0	40	0	0	0	0	20	20	20	100
Tana River	0	21.43	14.29	0	7.14	0	28.57	14.29	14.29	100
Turkana	8.33	33.33	16.67	0	0	8.33	25	0	8.33	100
Wajir	0	12.5	12.5	0	0	0	37.5	25	12.5	100
Total	2.3	24.14	13.79	2.3	1.15	2.3	28.74	13.79	11.49	100

Not surprisingly, there is evidence of seasonality across most of the disaster types, but also variability across the counties (Table 8). Floods primarily occur during the two main rainy season periods (March/April and October/November/December). But there is some difference by counties as to when floods are most likely to occur. For example, in Mandera, Wajir, Moyale, Samburu, and Tana River, floods tend to happen in the second rainfall peak, while in Marsabit and Turkana they fall in the first rainfall peak. In Baringo flooding falls more consistently across the entire year, corresponding with the rainfall pattern that indicates more consistent rainfall, with a peak in March/April.

EM-DAT data report the start date of disasters. Thus, while droughts can last for multiple months, we can look at the distribution of the start month by county (Table 9). Droughts start during the two precipitation nadirs (June/July and December/January). In Isiolo, Mandera, Marsabit, Moyale, and Wajir, droughts appear to be more likely to have been reported to have started in December/January, while for the remaining counties there is a much more even distribution. This finding indicates that failure of the short rains (October, November, December) particularly contributes to the classification of a drought.

The seasonality of the reported start date of epidemics corresponds primarily to the second peak of rainfall (November), with almost half of all epidemic start dates being reported then (Table 10). This likely corresponds to the dual role of the start of the short rains (October) and peak yearly temperature, resulting in conditions conducive to the growth of pathogens and hence disease outbreaks.

Table 9. Percent of droughts by reported start month by county (2000–2020)

	Month				
	Jan	**Jun**	**Jul**	**Dec**	**Total**
Baringo	50	25	25	0	100
Garissa	40	20	20	20	100
Ijara	33.33	0	33.33	33.33	100
Isiolo	50	25	0	25	100
Mandera	50	16.67	16.67	16.67	100
Marsabit	50	16.67	16.67	16.67	100
Moyale	100	0	0	0	100
Samburu	50	25	25	0	100
Tana River	25	25	25	25	100
Turkana	42.86	14.29	28.57	14.29	100
Wajir	50	16.67	16.67	16.67	100
Total	46	18	20	16	100

Table 10. Percent of epidemics by reported start month by county (2000–2020)

	Month					
	Jan	**Feb**	**May**	**Jun**	**Nov**	**Total**
Garissa	60	0	0	20	20	100
Ijara	0	0	0	0	100	100
Isiolo	33.33	0	0	0	66.67	100
Mandera	20	20	20	20	20	100
Marsabit	0	0	0	0	100	100
Tana River	0	0	0	0	100	100
Turkana	50	0	0	0	50	100
Wajir	33.33	0	0	33.33	33.33	100
Total	30.77	3.85	3.85	15.38	46.15	100

Farmer and herder conflict seasonality

We used ACLED data to look at the seasonality of conflict events (ACLED 2019). However, we soon realized that the entire seasonal pattern of conflict was driven by the large number of observations in Turkana (Figure 17). Thus, we cannot speak to the seasonality of conflict for any other county or the ASALs more broadly, but we can say something about the seasonality of conflict in Turkana. There are two clear peaks in both events and fatalities. The first peak is in February, and the second peak is in June/April. In Turkana, these two peaks correspond to periods of low precipitation and vegetation. This seasonal pattern likely relates to several factors, including the corresponding timing of livestock migration, greater competition over key resources such as dry season pasture and water, and/or greater concentration of animals in the vicinity of watering points.

Nutrition seasonality

In this section, we use available secondary data on wasting outcomes to better understand seasonal trends and how the nutrition data might relate to climatic variables. We start by presenting findings using the sentinel monthly monitoring data on child MUAC from NDMA. These data are available for every month, which allows us to say something about seasonal patterns, but only using MUAC. The SMART data unfortunately are only available for four months in Isiolo and six months in Marsabit, and thus we rely on regression analysis with climatic variables to see if we can better understand seasonal peak timing.

NDMA

We find that in both Marsabit and Isiolo, MUAC does not show much seasonal variability for the sample as a whole (see Figure 18). The regression results confirm these findings (Figure 19), with only a few months showing a significant different MUAC value. In Marsabit, we only find a significant difference between December (with the lowest MUAC) compared to March (with the highest MUAC). Similarly, in Isiolo, a significant difference is observed between November/December (with the lowest MUAC) and March (with the highest MUAC). Thus, we find a MUAC peak corresponding to the end of the first rainy season (around March), and the lowest MUAC right around the peak/end of the second rainy season (November/December). When it comes to the inclusion of the climatic factors in the regression, we find no significant association in Marsabit, but in Isiolo a higher NDVI is associated with a higher MUAC, which corresponds to short rainy season harvest (according to the FEWS NET seasonal calendar) and the calving period (according to the Nawiri workshop seasonal calendar).

Figure 17. Predicted seasonality of farmer and herder events and fatalities (20 years of ACLED data).

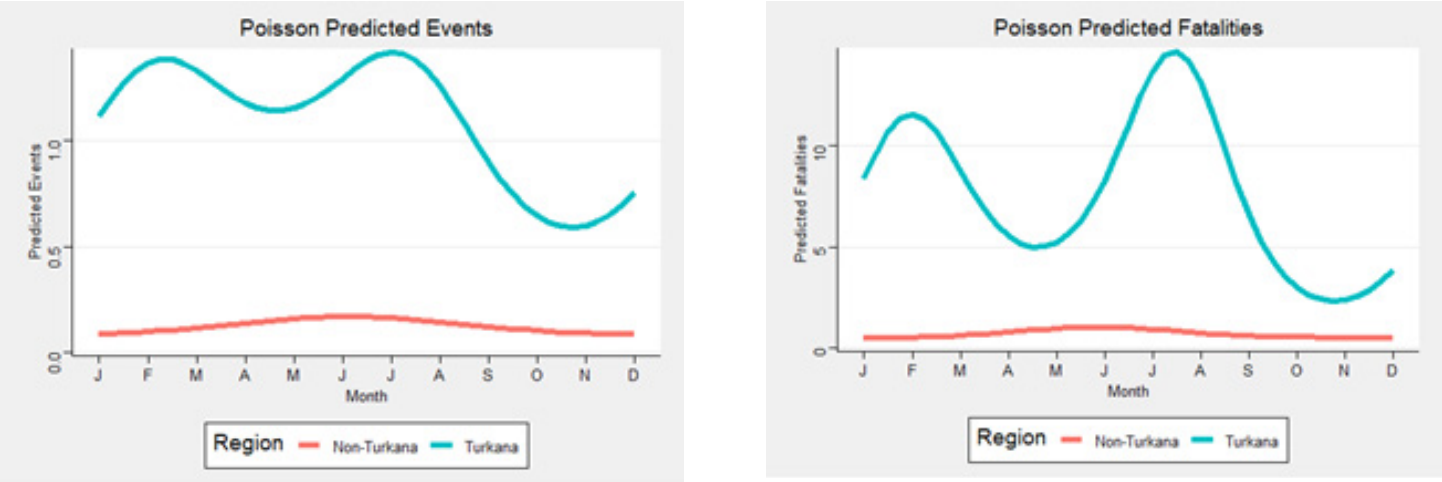
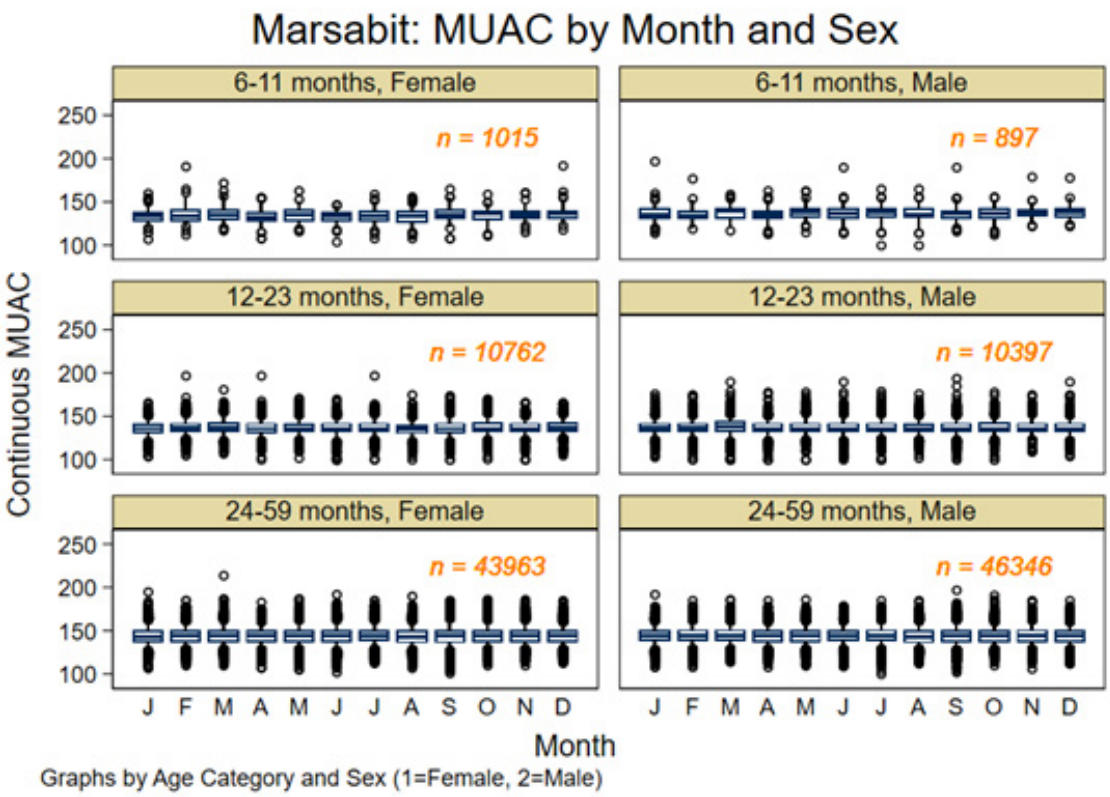


Figure 18. NDMA MUAC by month and sex for Marsabit (top) and Isiolo (bottom) Counties.



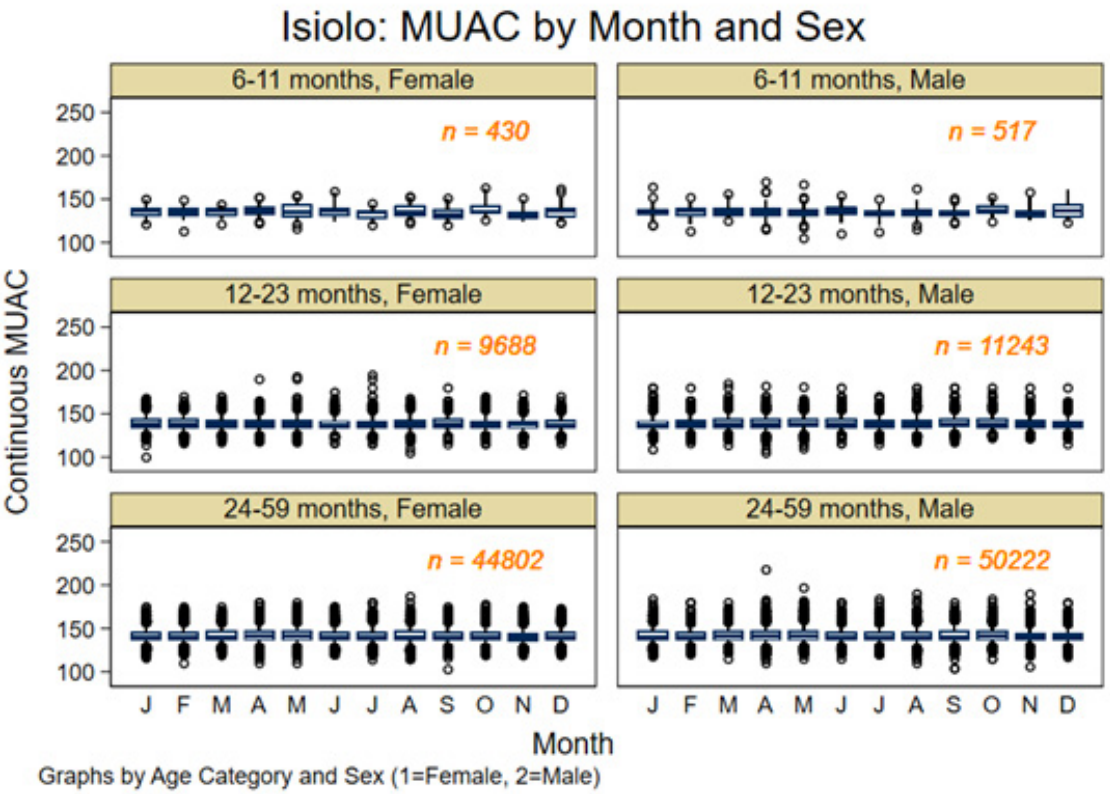
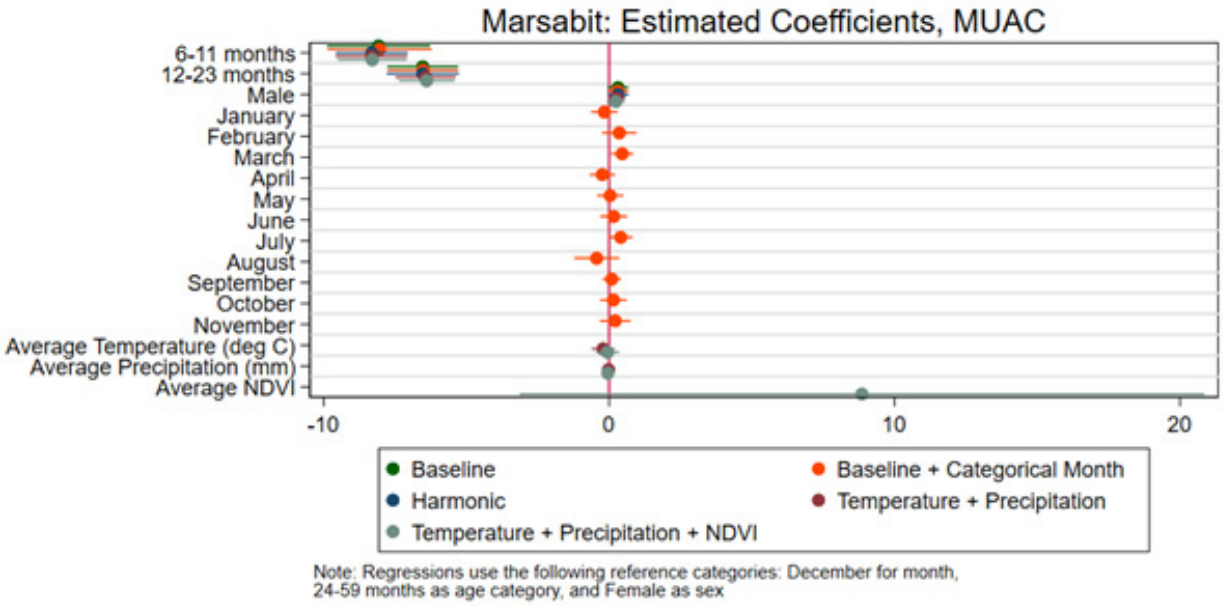
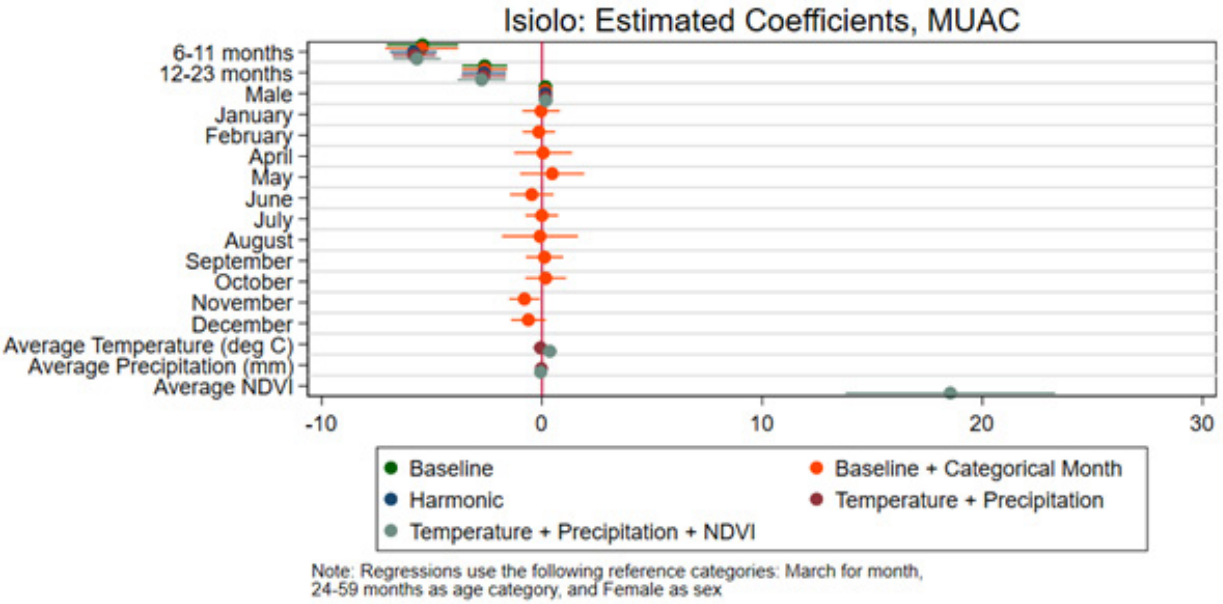


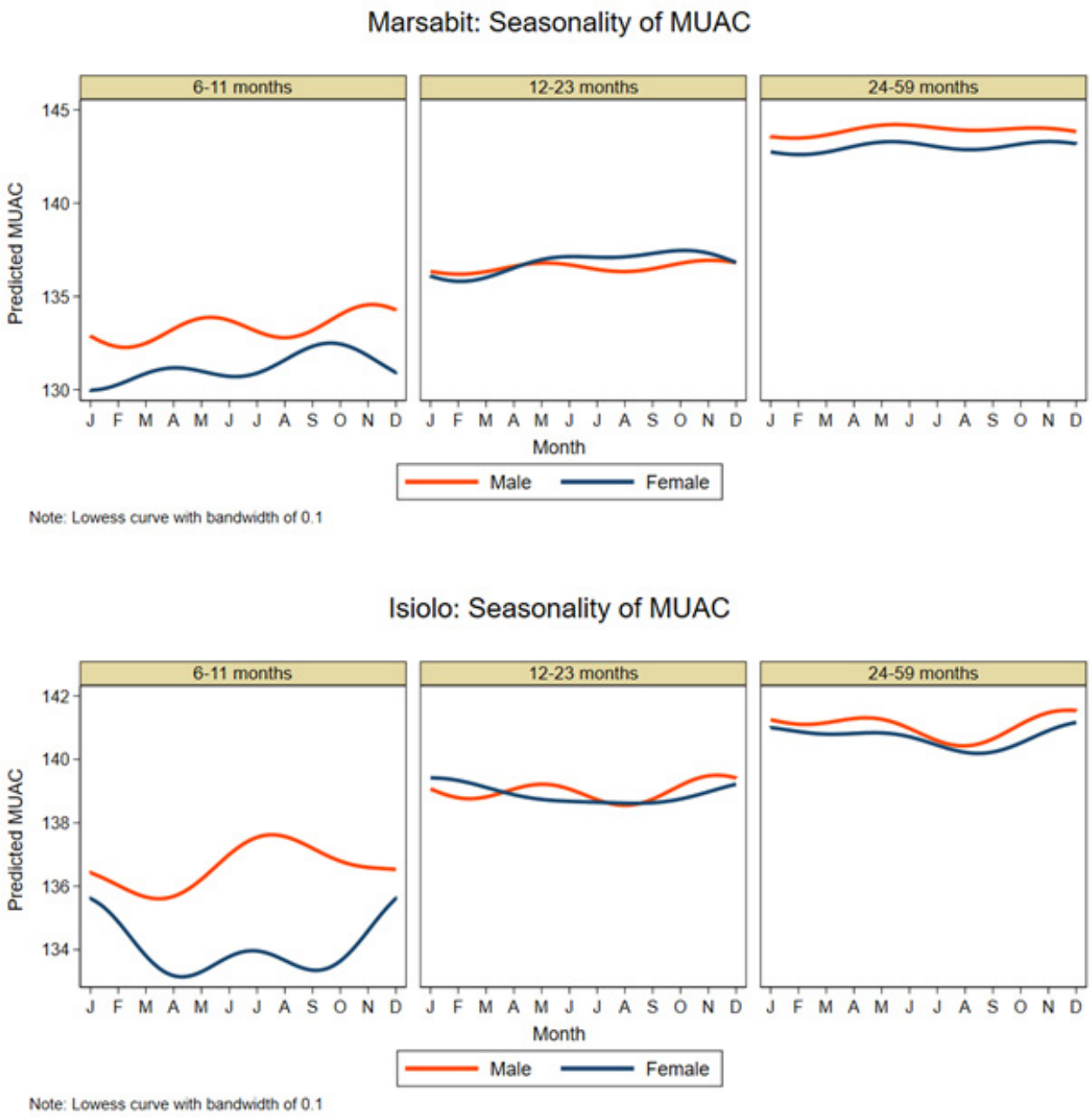
Figure 19. Regression output for MUAC NDMA data by sex and age group for Marsabit (top) and Isiolo (bottom) Counties.





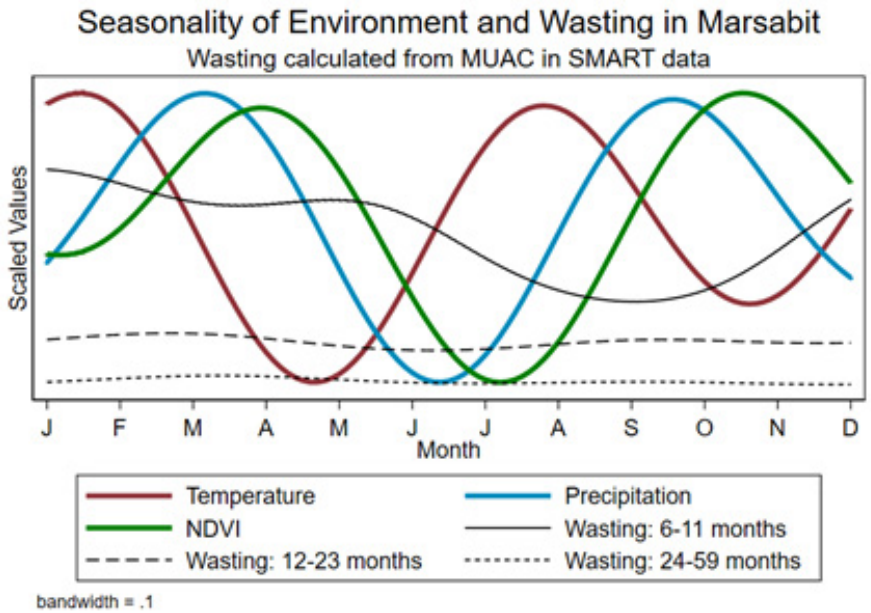
In the regression analysis, as expected, children ages 6–11 months have significantly lower MUAC compared to children 24–59 months in both Isiolo and Marsabit. There are no significant differences by sex for the sample as a whole, but on average boys have a slightly higher MUAC. The slightly better performance of boys is clearer when looking at children 6–11 months (Figure 20). In general, seasonality becomes much more pronounced when looking at this age group. In Marsabit, boys have the highest MUAC in December (end of the second rainy season), with a smaller peak in March (end of the first rainy season). Girls' peaks exhibit a slight lag, with the largest peak in October and a smaller peak in April. A completely different trend is observed in Isiolo, with MUAC dipping for boys and girls in April and October (corresponding to the temperature peaks). Thus, it is hard to draw conclusions around the seasonal timing of MUAC, except to say that it is far more seasonal for children 6–11 months and boys tend to consistently outperform girls. The latter is likely related to the lack of sex-specific standardization of MUAC.

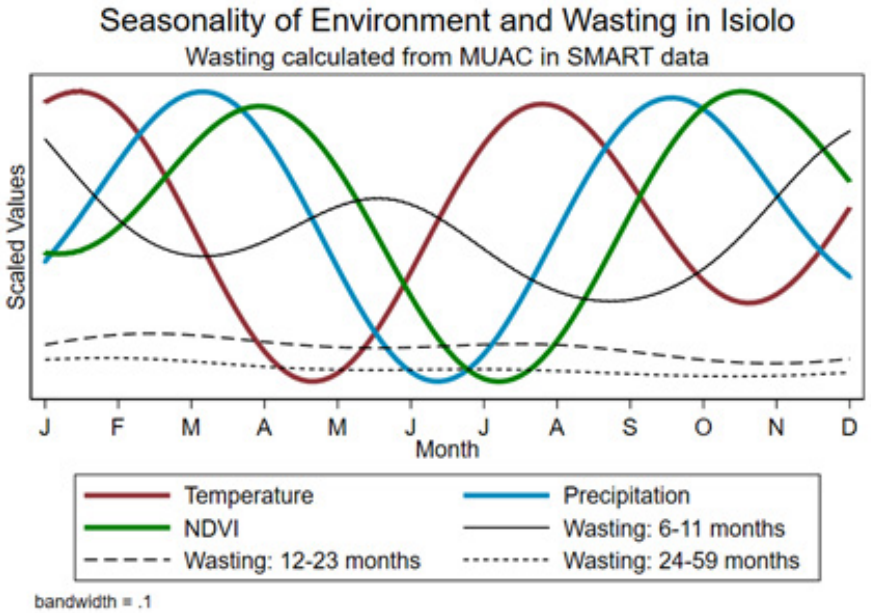
Figure 20. Seasonality of MUAC by age group and sex in Marsabit (top) and Isiolo (bottom).



When looking at wasting as a binary outcome (MUAC ≤ 125 cm vs. MUAC > 125 cm), seasonal differences become much more apparent (see Figure A1 in Annex A), particularly in Isiolo and once again particularly for children 6–11 months. Given the presence of significant seasonality with wasting (as measured by MUAC in the NDMA dataset), we use the regression output to predict the seasonal curves separately for Marsabit and Isiolo by age group (Figure 21). For children 6–11 months in both Marsabit and Isiolo, the primary peak is observed in December/January (corresponding to the lowest continuous MUAC value analysis above). This timing is associated with the short dry season and peak temperatures. A smaller secondary peak (for both counties) is observed in May/June, which is the start of the second dry season. Figure 21 further shows the inconsistency of the two peaks in relation to different climatic variables, with each peak associated with different climatic conditions and hence the lack of significance of temperature, NDVI, and precipitation in the regression analysis.

Figure 21. Predicted seasonal curves of wasting in relation to climatic data in Marsabit (top) and Isiolo (bottom).



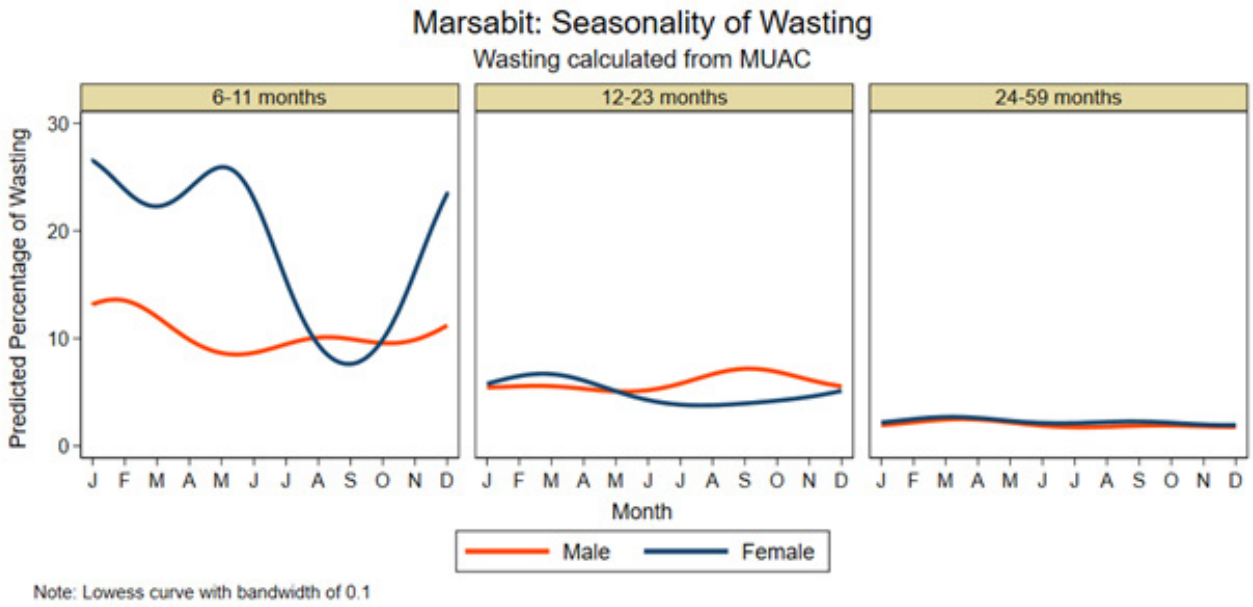


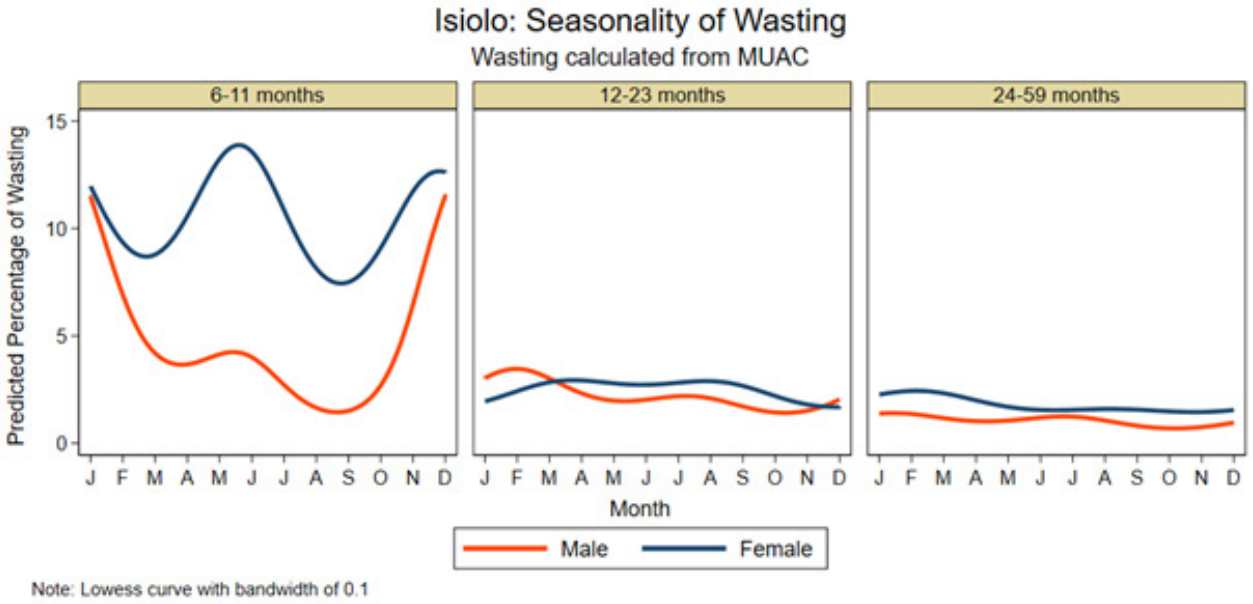
Children 6–11 months are significantly more likely to be malnourished. This time the difference between boys and girls is significant as well, with boys having a significantly higher MUAC across the entire sample (Figure A2 in Annex A). Figure 22 below further underscores the lack of a seasonal trend for older children as opposed to younger children, and that sex difference are particularly pronounced (with boys doing better) for children 6–11 months.

SMART—MUAC and WHZ

As noted earlier, the lack of data across all, or even at least most, months in the year in the SMART dataset makes analysis of seasonality impossible. Thus, we primarily rely on the regression output in relation to the climatic variables to identify the presence of seasonality and its relation to climatic differences, starting with MUAC. Unlike with the NDMA data, seasonal differences in MUAC are observed in Marsabit but not Isiolo (Figure A3

Figure 22. Predicted wasting (according to MUAC from NDMA) by age and sex in Marsabit (top) and Isiolo (bottom).





and A4 in Annex A). Most importantly, for both counties we find that boys have significantly higher MUAC, as expected children 6–11 months have the lowest MUAC, and NDVI is significantly and positively associated with a higher MUAC. Thus, children are best off (in relation to MUAC) after the rainy season is completed and during the harvest period. Analysis of wasting using a MUAC cut-off of 125 tells the same story: children 6–11 months are significantly more likely to be wasted, as are females, and wasting is significantly and negatively associated with NDVI (Figure A5 in Annex A).

Next, we replicate the same analysis using WHZ from the SMART data to better understand the presence of seasonal patterns, how they vary by age and sex, and the relationship to climatic variables. The findings mimic those of the MUAC data with two critical exceptions: according to WHZ and wasting as measured by WHZ, boys are significantly worse off and children ages 24–59 months are significantly more likely to have a lower WHZ and higher odds of being wasted compared to children 6–11 months (Figures A6, A7, and A8 in Annex A). Otherwise, a higher NDVI is significantly

associated with higher WHZ in Marsabit (not Isiolo), and significantly lower odds of a child being wasted in both Marsabit and Isiolo. There is no significant association with rainfall or temperature, when controlling for NDVI.

The positive association between NDVI and higher MUAC and WHZ in the SMART data, and lower wasting, likely captures distinctions between, as opposed to within, years, as the peak timing of NDVI (around December and May) is exactly the same timing associated with peak wasting using MUAC in the NDMA data.

Putting all the secondary data together: nutrition regressed on climate, disasters, and conflict

In this section, we present results of running all of our secondary data—temperature, NDVI, precipitation, disasters, and conflict—on our nutrition outcomes (MUAC, WHZ, wasting using MUAC, wasting using WHZ) in Isiolo and Marsabit. We briefly discuss any consistent results in the analysis. Throughout the analysis, disasters consistently dropped out of the regression, and therefore results are not presented. The dropping of the disaster data is due to the minimal overlap between the months, locations, and years for which nutrition data were available corresponding to identified disasters in EM-DAT. Conflict, on average, is associated with better nutrition outcomes, which is difficult to unpack, or is insignificant.

When exploring what is associated with MUAC (across both data sets) we find, unsurprisingly and consistently, that younger children, particularly 6–12 months, have significantly lower MUAC. There is some evidence that boys have slightly higher MUAC compared to girls. Higher NDVI is associated with higher MUAC, but only in Isiolo (Figures A9, A10, A11, and A12 in Annex A). Using the binary outcome of wasting (calculated from MUAC), some results remain consistent: older children and boys are less likely to be wasted. The main difference between the analysis on the more continuous form of MUAC versus using thresholds is that seasonality (i.e., significance of the month variables) comes out far more clearly in the binary data (Figures A13, A14, A15, and A16 in Annex A).

When it comes to WHZ, we find the opposite relationship between child demographics (age and sex) and nutrition outcomes. WHZ is higher in younger children and is at its lowest for children 24–59 months. In addition, boys have significantly worse WHZ compared to girls. NDVI, just as with MUAC, is identified with higher WHZ (Figures A17 and A18 in Annex A). The odds of a child being wasted (using WHZ) is lowest for children 6–11 months, while boys are significantly more likely to be wasted compared to girls. Higher NDVI is associated with lower odds of a child being wasted, as is a greater number of conflict events (Figures A19 and A20 in Annex A).

Secondary geospatial data

We also looked at additional secondary data that we could use to better inform our contextual understanding of Isiolo and Marsabit and could eventually incorporate into the nutrition seasonality analysis. The additional data included markets, roads, seasonal rivers, elevation, land use, and livelihood zones (Figure 23 and Figure 24).

Literature review on the seasonality of nutrition outcomes

In this section we look at the evidence base for, or at the very least evidence of consideration of, the climatic conditions and their variability in research around nutrition outcomes in the Nawiri research area. We find that despite the importance and presence of climatic variability and climatic extremes in this context, extremely few studies consider, measure, or even interpret findings with consideration for between- and within-year climatic variability.

Despite the obvious seasonal variability in the ASAL counties, only about a third of all the papers (8) made considerations for seasonal variability in their study design. All 3 of the studies utilizing more participatory methods included seasonal recall. Of the remaining 5 quantitative papers that have a design that takes season into consideration, 2 papers aggregate the data in their analysis and do not present seasonal information on nutrition, and 2 of the papers are actually based on the

Figure 23. Land use in Marsabit and Isiolo Counties.

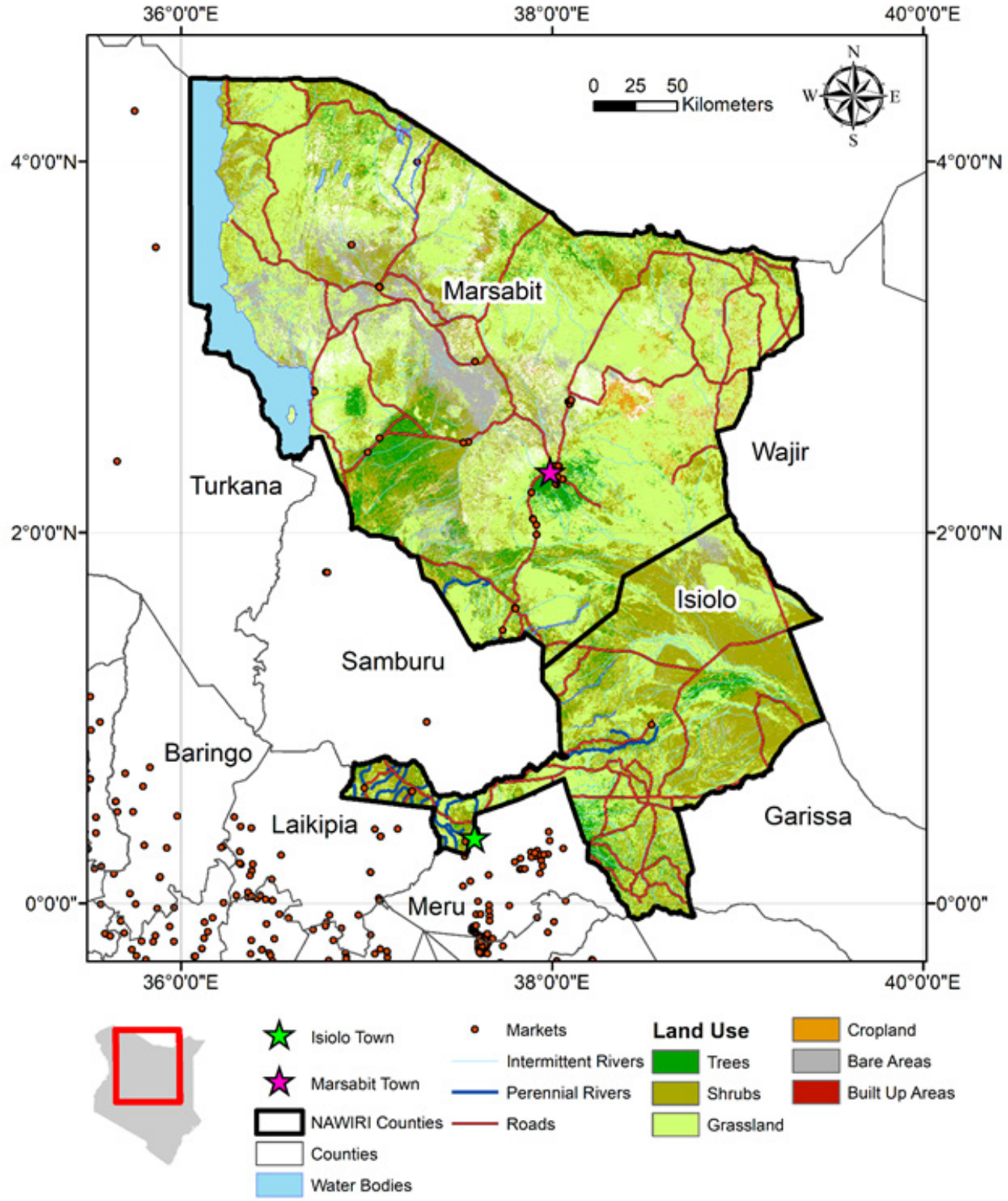
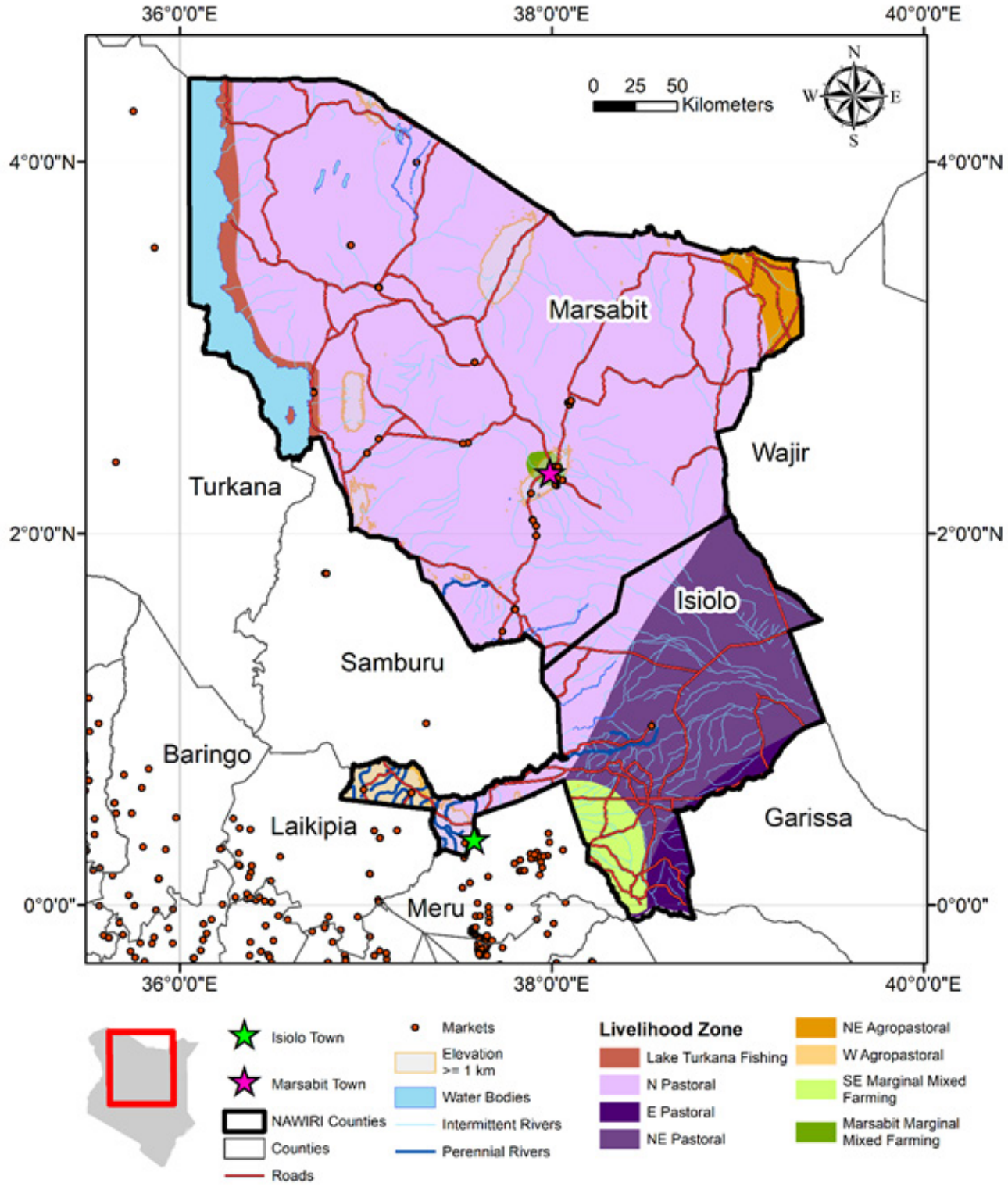


Figure 24. Livelihood zones in Marsabit and Isiolo Counties.



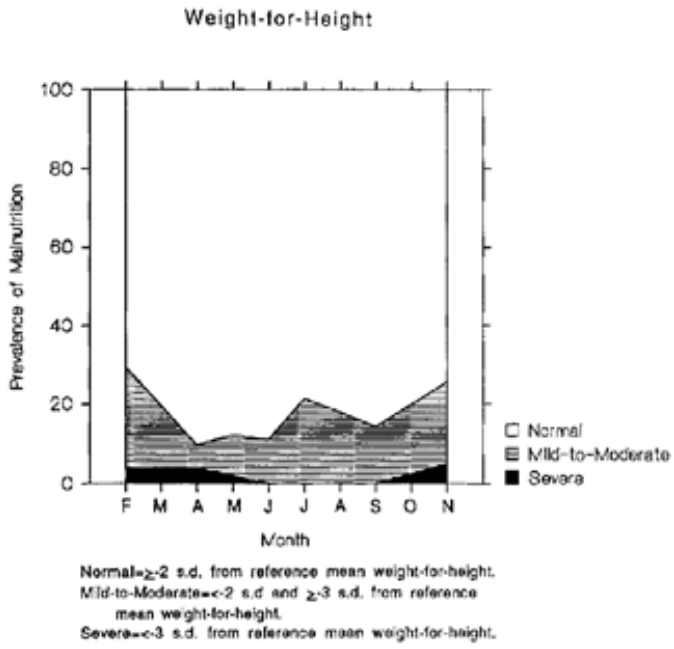
same dataset, just analyzed differently. Over a third of the papers (9) included no mention of seasonality, not even mentioning the season when the data were collected to allow the readers to frame the findings within a seasonal context. The remaining 6 articles either mentioned lack of seasonal data as a limitation or included at least one sentence describing the seasonal context of the data collection. Thus, out of 23 papers in a context of extreme variability, only 6 papers (split evenly across quantitative and qualitative methods) actually present seasonal data.

Two of the three participatory studies (two of which utilize a Link Nutrition Causal Analysis (NCA) approach) identified the dry season as the peak timing for acute malnutrition. In Marsabit, the dry season was identified as June-Sept/October (the long dry season) and February and March (short dry season) (FAO, UNICEF et al. 2020). A similar assessment was made in Isiolo: "Findings from the fieldwork (participatory methods) indicated that acute malnutrition typically occurs during the dry season or during droughts, peaking at the commencement of rains, and is linked to seasonal reductions in access to and consumption of milk" (Manners, Calo et al. 2015). The Link NCA in West Pokot focused on stunting and noted "that stunting peaks do not follow a regular seasonal trend as is the case in wasting, but the various risk factors for stunting were related to persistent rainfall failure or mild droughts reported over the years." (Mutegi and Korir 2016). Thus, while stunting was not equated to seasonal dry periods, overall, stunting was identified as linked with between-year variation in rainfall.

A study in Turkana (using 10-month longitudinal data) found no seasonal differences in WAZ, but variation in WHZ, HAZ, and MUAC-for-age. Interestingly, the authors found different seasonal trends for the three indicators. Both MUAC-for-age and HAZ decreased throughout the dry season, while WHZ increased (Shell-Duncan 1995). While these seasonal differences are significant, the magnitude of them are not. The authors thus conclude that nutritional outcomes are poor throughout the season and do not follow the same patterns as food insecurity: "The results indicate that food availability is not likely to be the sole determinant of nutritional status and that infection may be an important contributor to the high levels of nutritional and immunological stress among nomadic Turkana children" (pg. 1). Interestingly, the authors plot but do not analyze the binary forms of WHZ, wasting, and severe wasting (Figure 25 below). The data indicate two peaks of wasting. The larger peak occurs somewhere between November and February, which corresponds to the end of the dry season and start of the rainy season, and July, associated with a small secondary rainfall peak. However, caution is required in interpreting these findings as they are based on 82 children. A few years later, the authors use the same data to look at seasonal patterns, but this time aggregating the findings by wet vs. dry season. In the wet season, they find that 6% of children are wasted compared to 10% in the dry season (but not significant). However, the authors unfortunately never define how they grouped the months into seasons (Shell-Duncan and Wood 1997). The final study that actually presents nutrition data by season looks at the proportion of children with MUAC < 135 mm in Ijara across 12 months. The researchers (visually, not statistically) identify peak timing in July, which was identified as the end of the rainy season or start of the dry season (Njuguna and Muruka 2011). Altogether, the evidence points to the dry season as being a critical time for acute malnutrition, but with insufficient information on when in the dry season. Thus, the limited evidence warrants further investigation.

While two additional papers had a seasonal component to their data collection, they cannot actually say anything about seasonality because in the analysis they aggregated across seasons. For example, Little et al. (1983) writes: "Measurements from the sample of Turkana adults and children were collected during the wet season of 1981 (March and April) and the late dry season of 1981-1982 (December through March). Although we hypothesize a seasonal variation in adult body weight and child growth patterns the data in the present paper should be viewed as representing an average pattern of these variables" (Little, Galvin et al. 1983, 815) Another study, with the most impressive longitudinal data collection of them all—17 bimonthly observations across 3 years on 488 children—visually represented the seasonality of many of the drivers of child malnutrition, but never malnutrition itself. More so, the authors then proceeded to aggregate the data across "normal rainfall" periods vs. "drought" periods

Figure 25. Wasting and rainfall peaks in Shell-Duncan et al. 1995.



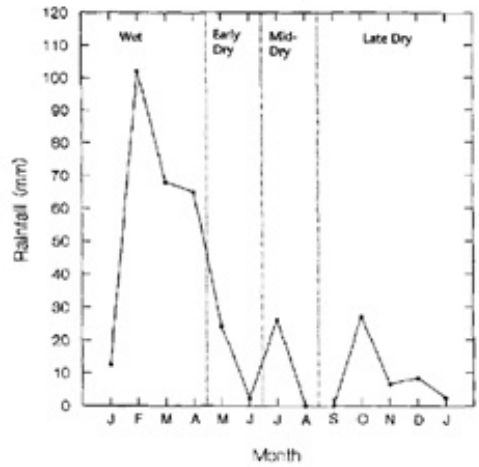


Fig. 2. Monthly variation in rainfall in South Turkana, January 1990 through January 1991.

and conducted a separate analysis on each (but still do not provide z-score means or malnutrition prevalence). Thus, what could be a treasure trove of seasonality data does not allow us to actually say anything about nutrition seasonality (Fratkin, Roth et al. 2004).

Finally, three papers included remote sensing data in their analysis to better understand how climatic trends might relate to nutrition outcomes. Two papers found that a higher proxy of vegetation was associated with a lower prevalence of malnutrition (combined stunting and underweight) (Mark, Imwatis et al. 2017) and a higher MUAC z-score (Bauer and Mburu 2017). One of those two papers also identified a significant relationship between higher temperature and higher prevalence of malnutrition (combined stunting and underweight) (Mark, Imwatis et al. 2017). And finally, higher rainfall was correlated with higher HAZ (Grace, Davenport et al. 2012). These findings correspond to a recent global review of drivers of child malnutrition. The authors found that the most consistent predictors of child malnutrition were shocks due to variations in climate conditions (as measured by temperature, rainfall, and vegetation) and violent conflict (Brown, Backer et al. 2020). However, when it comes to climatic shocks, a more nuanced approach might be necessary. As highlighted in the Livelihoods Desk Study (Stites 2021), dryland livelihoods systems are well suited to coping with dry seasons, drought, and extreme variability more generally. From a purely climatic standpoint, it is multi-year droughts that provide a more formidable stress (Livelihood Desk Study). Furthermore, as outline in the Natural Resource Management Desk Study (Birch 2020), consideration for the nature of resource management, governance systems, and disaster preparedness and mitigation mechanisms at all administrative levels can play an equally important role in determining drought impact.

6. Discussion

The Kenyan ASALs are made up of a variety of different climatic regimes, with neighboring areas exhibiting single and dual rainy peaks. While most of the analysis is aggregated on the county level, within each county there is significant spatial variability in rainfall, temperature, and vegetation given the difference in elevation within, not just between, counties. For example, while Garbatulla and NgareMara are both in Isiolo, NgareMara is much cooler, and Garbatulla is greener. Particularly important is the distinction in rainfall patters for Marsabit as a whole versus for Laisamis Ward. While Marsabit, on average, presents with two almost equally sized rainfall peaks, in Laisamis, there is a clear distinction between the amount of rain that usually falls in March–May versus October–December. Thus, while we can identify Isiolo, Marsabit, Moyale, Mandera, Wajir, Garrissa, Tana River, and Ijara (but not Baringo and Turkana) as exhibiting two clear rainfall peaks, the distribution of that rainfall within the county is extremely variable. Even in the wettest months (April and November), parts of Turkana, Marsabit, Isiolo, and Wajir still receive less than 50mm/month. A similarly high level of temporal and spatial variability is observed in temperature and vegetation. **Thus, it is critical for both programs and research to utilize remote sensing data on the most granular spatial level possible, in our case ward level rather than county level.**

There is also some inconsistency in the literature, county-level development plans, FEWS NET, and Nawiri's own understanding of the timing of the seasons. While this inconsistency is not surprising considering the observed temporal variability in climatic variables across the 20 years, **it does indicate that real-time remote sensing data are critical for defining seasons rather than resting on existing seasonal calendars that imply a consistency in the timing of the seasons**. In addition, the seasonal categories applied to Kenya's ASALs—long and short wet season and the long and short dry season—might be insufficient. From the literature, communities in Samburu identified a fifth season related to the start of the rains, but also corresponding to a temperature peak. This season occurs right before the majority of epidemics are reported, indicating that this time of year might be unique and particularly important from the standpoint of pathogen risk. **Thus, it is critical for Nawiri to understand seasonality through the perspective of local communities, as we can identify a much more nuanced seasonal breakdown by doing so.**

And while the Kenyan ASALs are highly affected by disasters (primarily droughts, epidemics, and floods), there is evidence of possible slight differences in the seasonality of those disasters across the counties of interest. Not all counties are equally affected by disasters in any one year. When they do experience the same category of disaster, the timing of that disaster varies. Floods primarily occur during the two main rainy season periods (March/April and October/November/December). However, in Mandera, Wajir, Moyale, Samburu, and Tana River, floods tend to happen during the second rainfall peak. In Marsabit and Turkana they fall in the first rainfall peak. The reported start date of droughts also shows some variability across our counties. Epidemics are also seasonal, with most epidemics reported in the second (usually termed "short") rainy season, occurring right after a time period of both extremely high temperatures and initial sprinkling of the rains, characteristics associated with a higher risk of pathogen growth.

There is a fairly uneven distribution in the number of farmer-herder conflict events that were reported by county, with Turkana having the highest level of reporting. It is difficult to say whether the difference in number of events reflects the reality in conflict across our counties, or just the reality in reporting of conflict. However, in Turkana we do see a distinct seasonal pattern, with conflicts corresponding to the dry season.

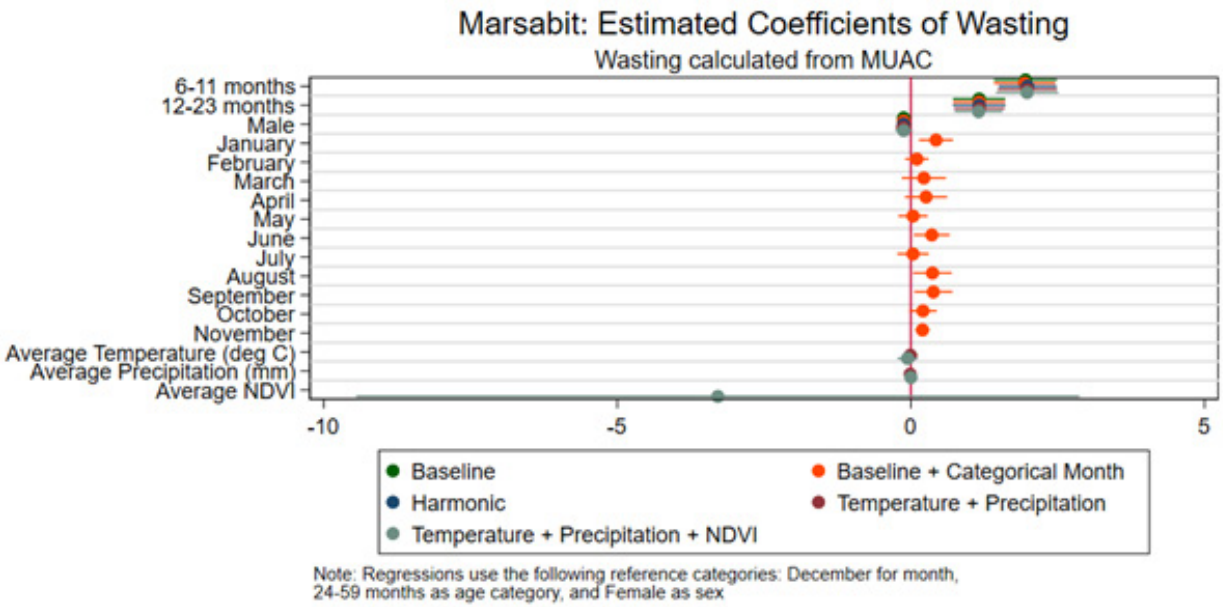
Seasonal analysis of MUAC and wasting (using MUAC) from the NDMA data indicates that peaks of wasting likely occur in December (largest peak) and in May/June (smaller peak). Both of these time periods generally correspond to the end of the rainy season, with peak precipitation generally occurring in November and April. These seasonal peaks correspond to the findings from Shell-Duncan's work in Turkana. However, most of the literature on seasonality groups data by rainy and dry season, with the dry season most consistently associated with worse outcomes. Depending on the year, December and June could both fall under either the rainy or dry season and more realistically represent the transition between rainy and dry. Thus, it is difficult to align these findings with the broader literature. The current timing of the SMART surveys is focused on the start of the dry season, with the majority of SMART surveys occurring in January and February. While this timing is not too far off, it is important to remember that, according to the secondary data, March is generally associated with one of the lowest prevalence of wasting. Thus, even a one- or two-month difference in survey timing might miss peak levels of child wasting.

There are also critical and important distinctions between MUAC and WHZ in terms of identifying the most vulnerable group. MUAC identifies girls and children 6–11 months as the most vulnerable, while WHZ identifies boys and children 24–59 months as the most vulnerable. While this is likely a product of the lack of age and sex standardization in the MUAC as opposed to WHZ data, the difference is critical for consideration for referral to treatment. More so, MUAC appears to be insufficient for looking at seasonal trends, unless the focus is only on children 6–11 months. These differences will be further explored and unpacked in the Nawiri primary data collection.

The analysis of the secondary nutrition, climatic, and shock data underscores the important role of seasonality. However, it is also clearly insufficient to rely on existing, and inconsistent, categories of seasons and timing. Instead, Nawiri and future programs/research need to take advantage of the free availability of secondary data to better situate their findings in real-time and geographically focused climatic conditions, with consideration for the fact that different nutrition indices might identify different seasonal patterns and vulnerable populations.

Annex A: Additional figures and tables

Figure A1. Regression output across multiple models on wasting (from NDMA MUAC) for Marsabit (top) and Isiolo (bottom).



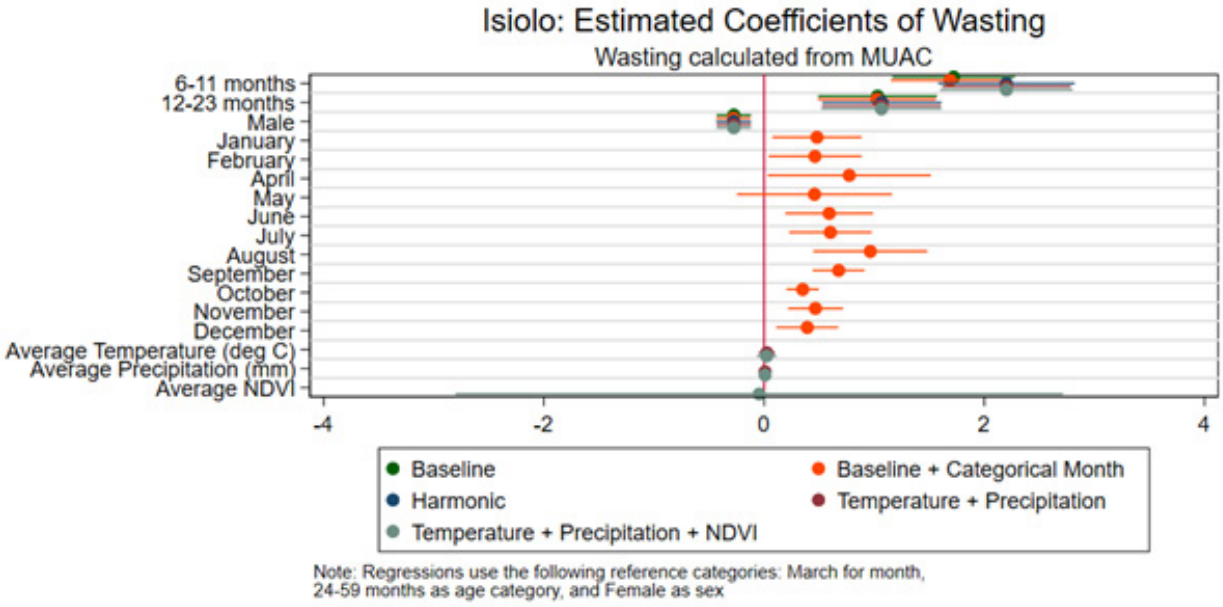
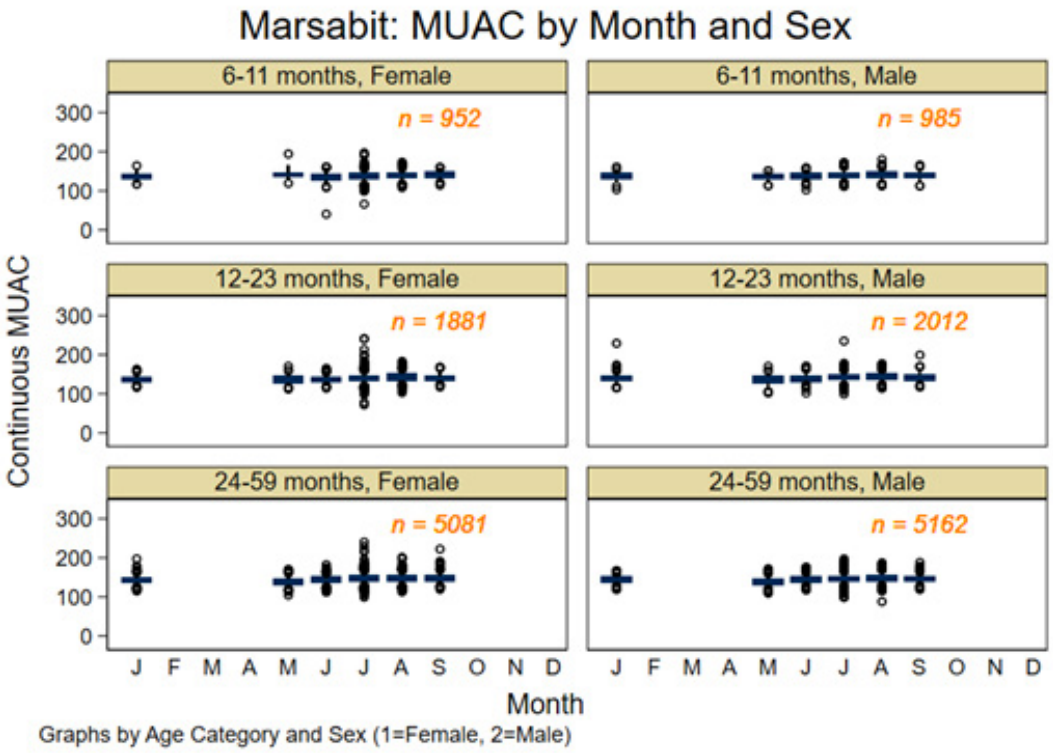


Figure A2. MUAC (collected in SMART data) in Marsabit (top) and Isiolo (bottom).



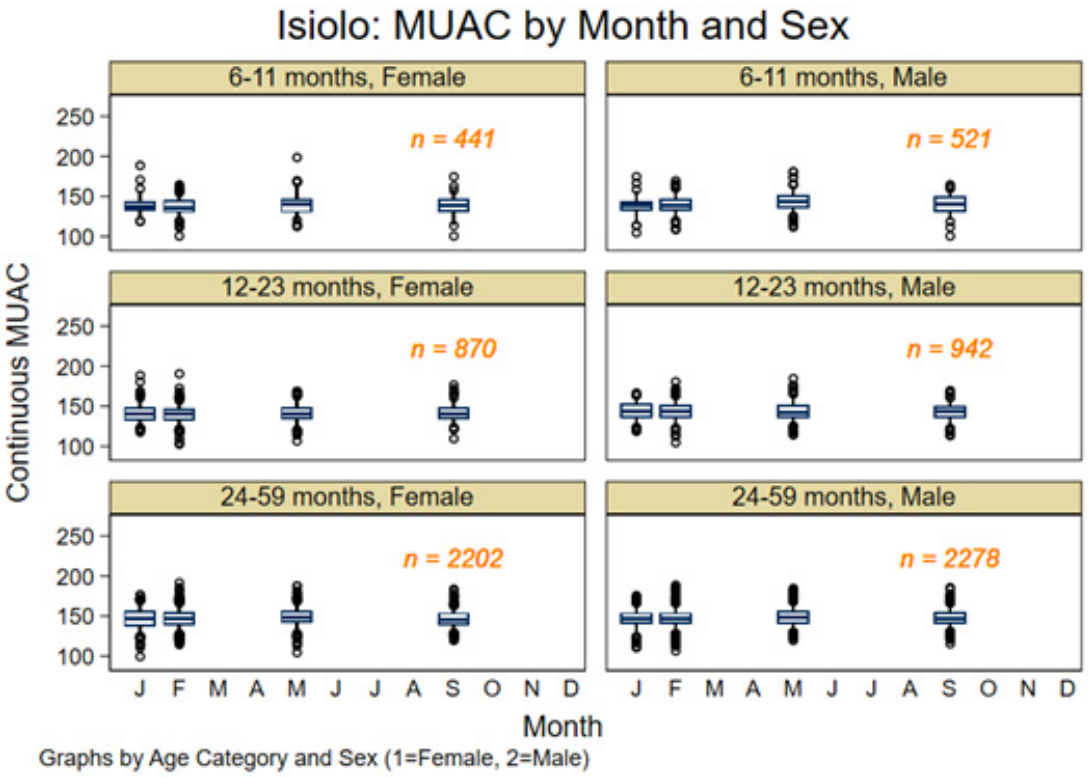
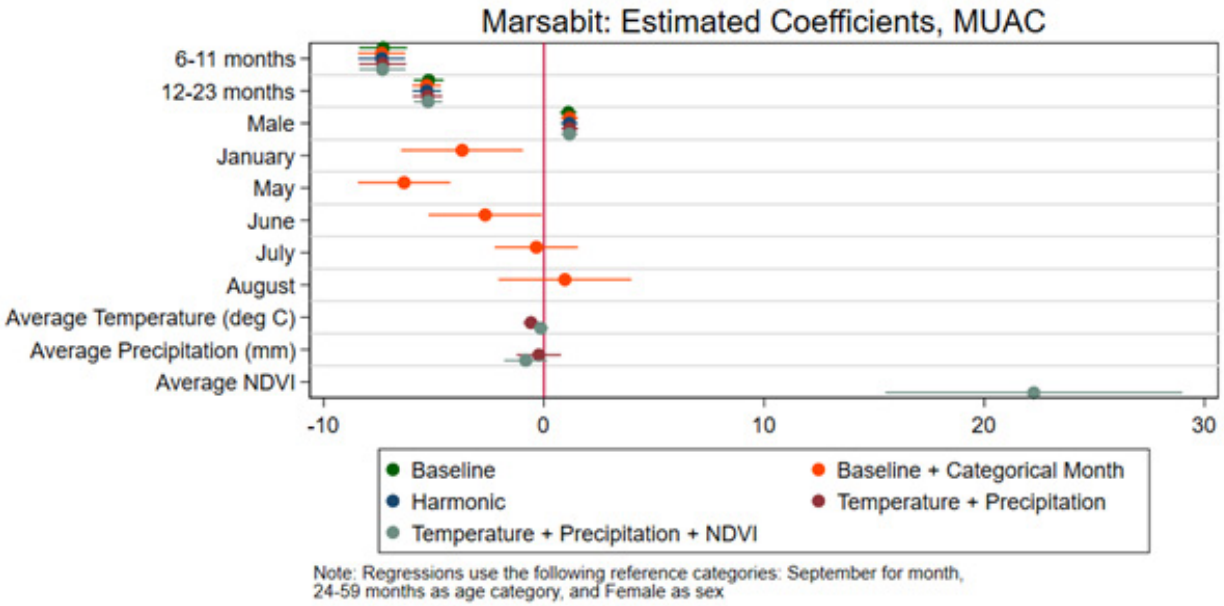


Figure A3. Regression output on MUAC (from SMART) for Marsabit (top) and Isiolo (bottom).



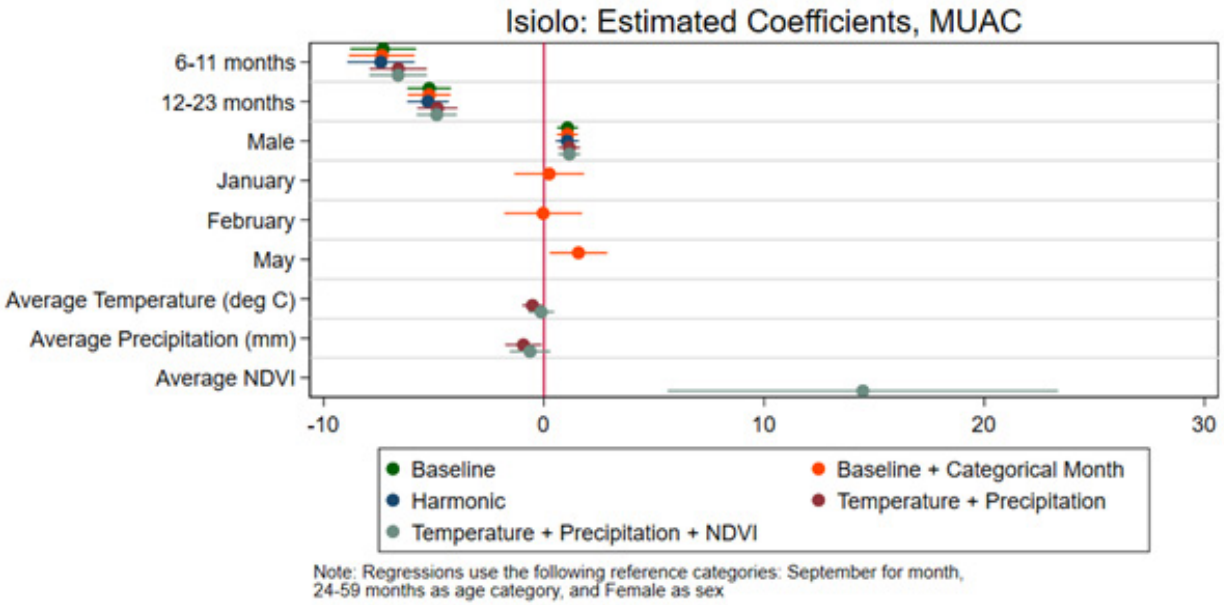
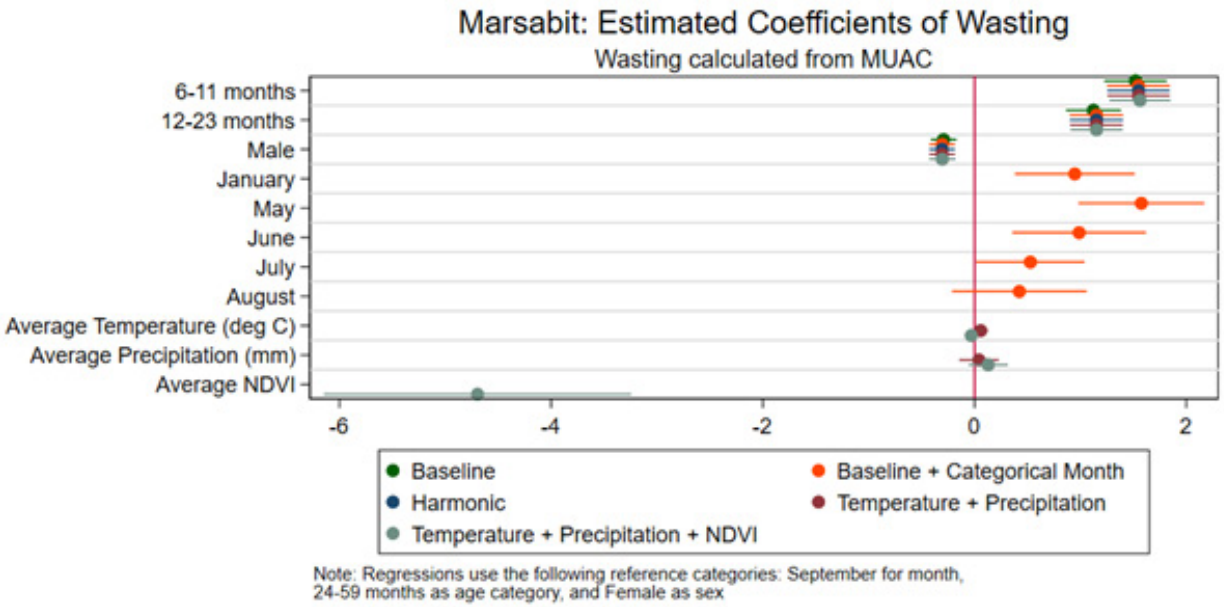


Figure A4. Regression output on wasting (from NDMA) for Marsabit (top) and Isiolo (bottom).



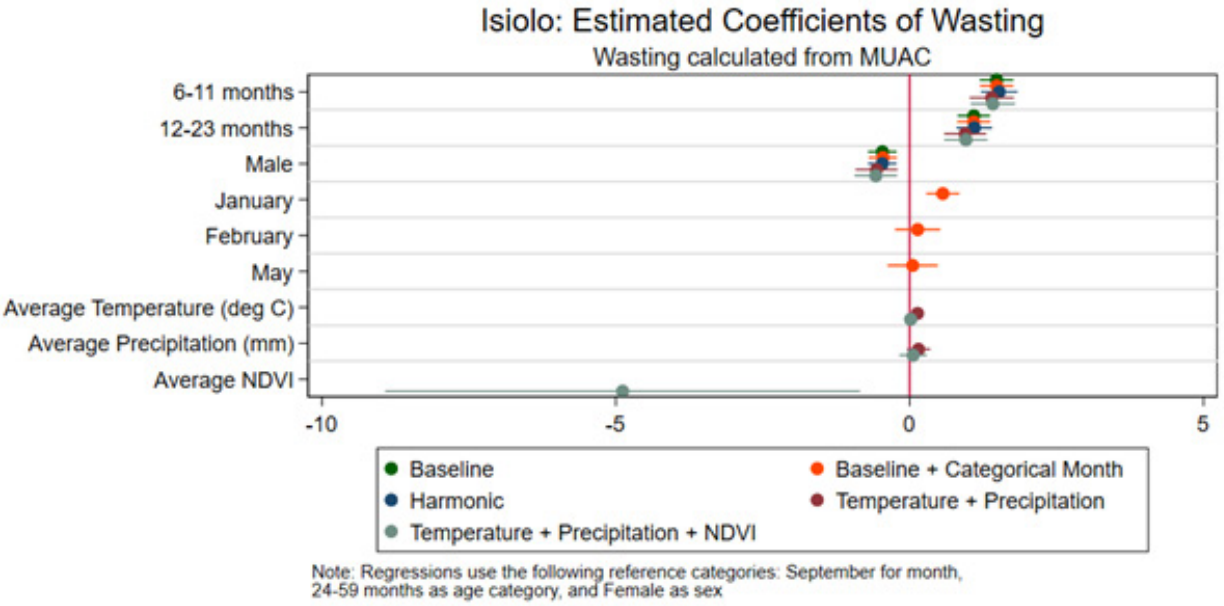
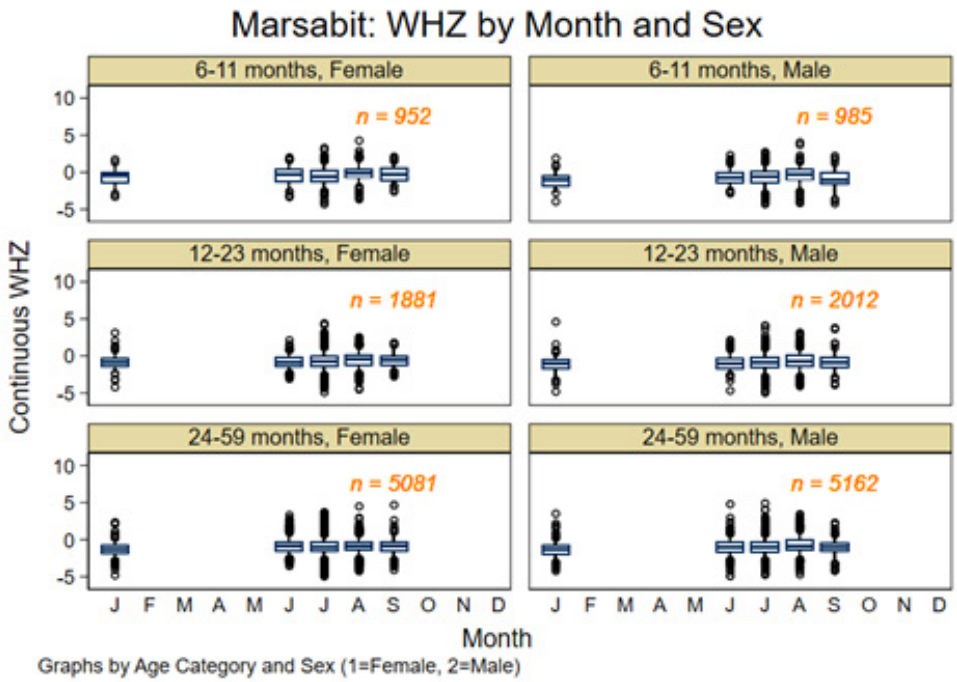


Figure A5. WHZ (collected in SMART data) in Marsabit (top) and Isiolo (bottom).



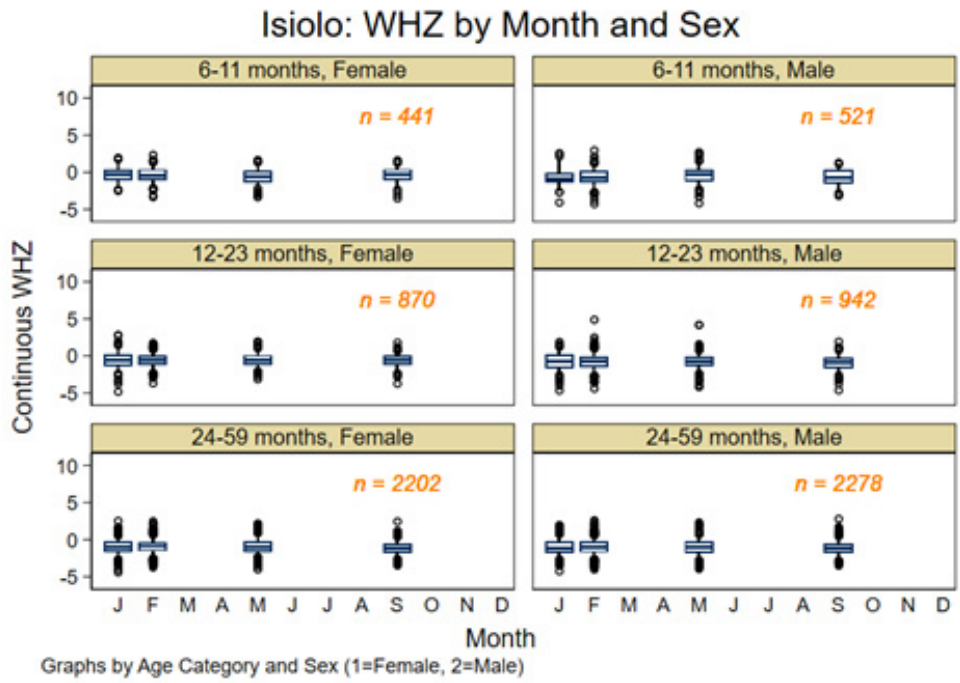
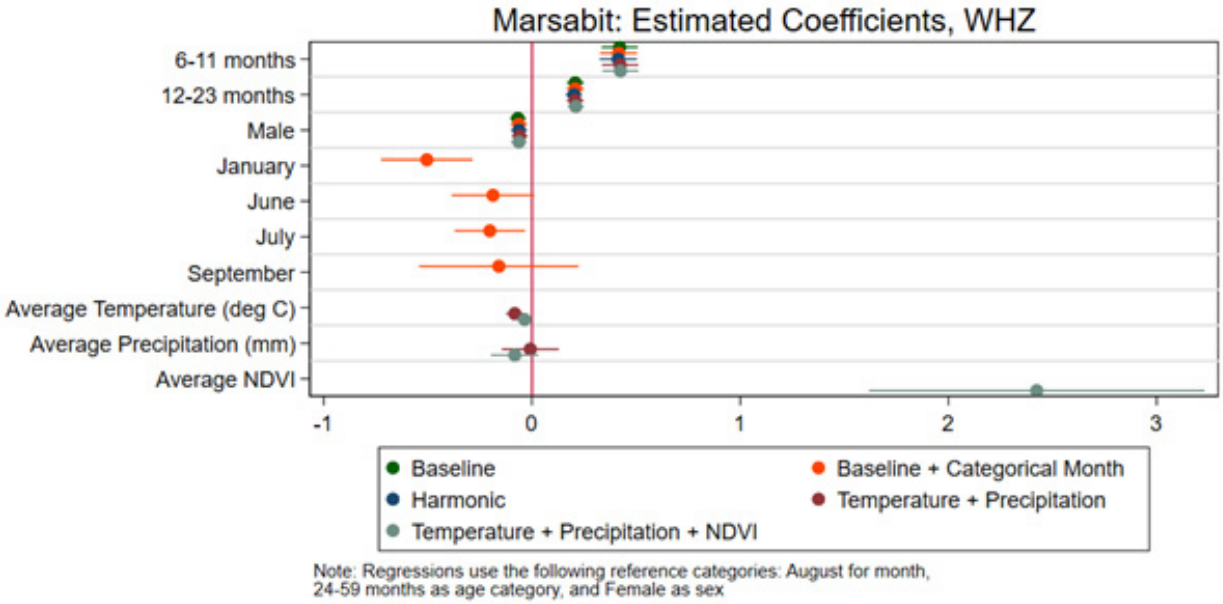


Figure A6. Regression output on WHZ (from SMART) for Marsabit (top) and Isiolo (bottom).



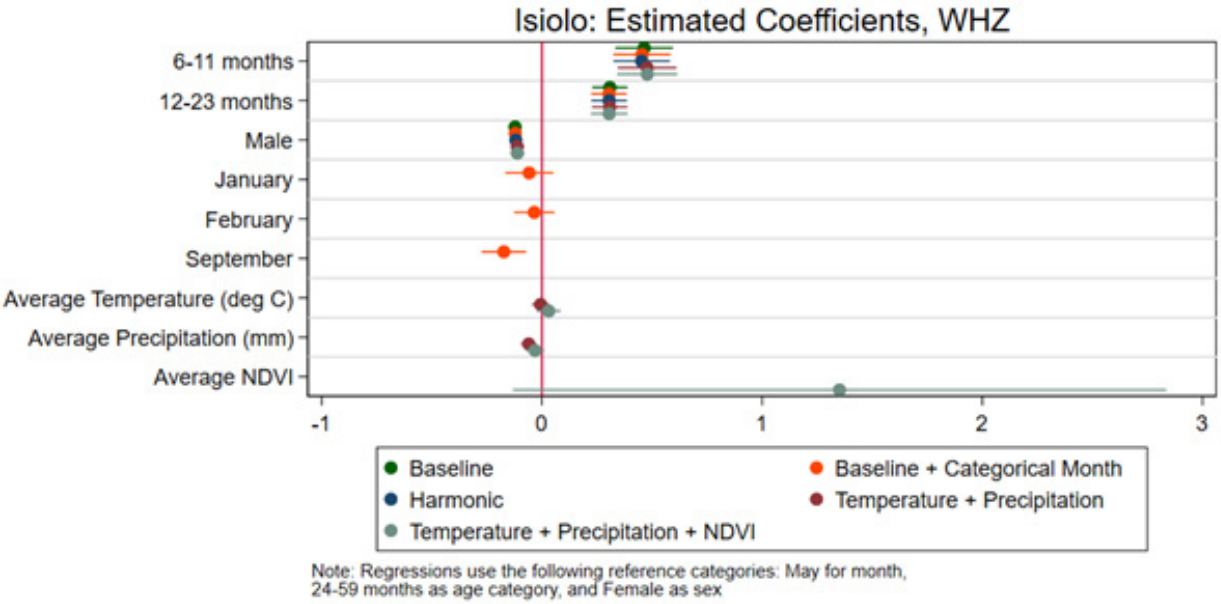


Figure A7. Regression output on wasting (from SMART WHZ) for Marsabit.

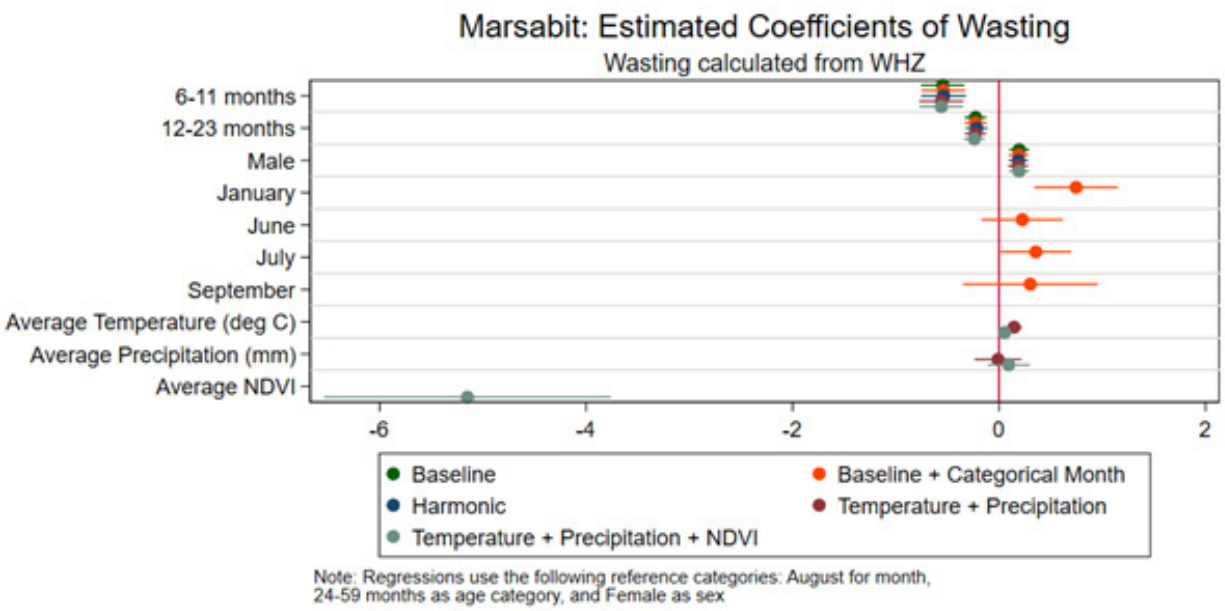


Figure A8. Regression output on wasting (from SMART WHZ) for Isiolo.

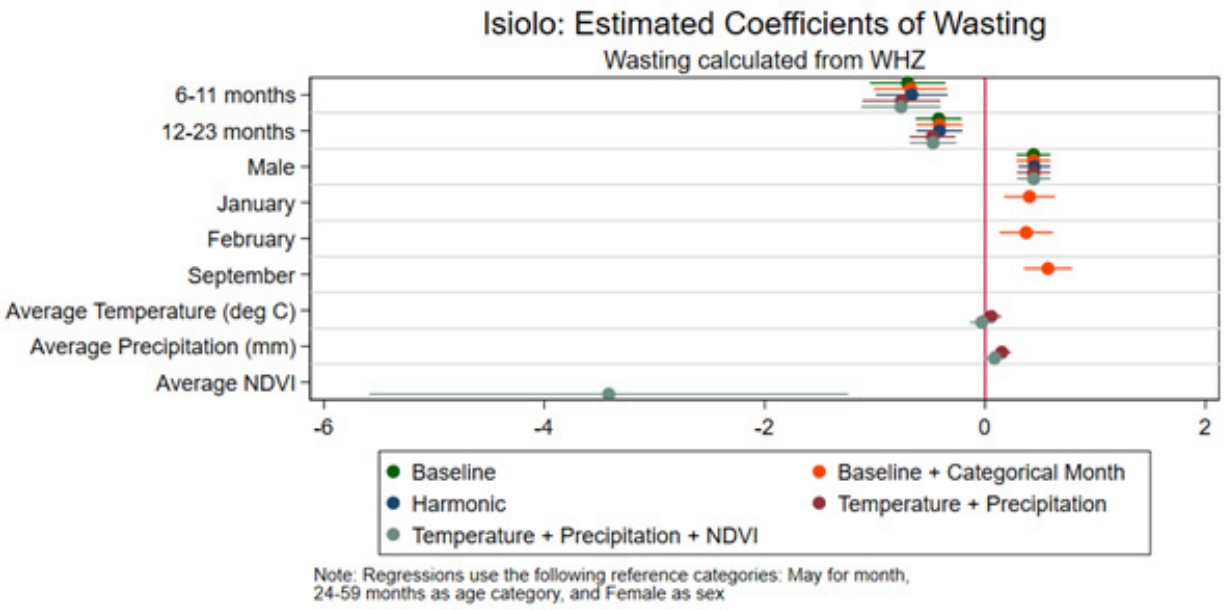


Figure A9. Full analysis on MUAC (NDMA data) in Isiolo.

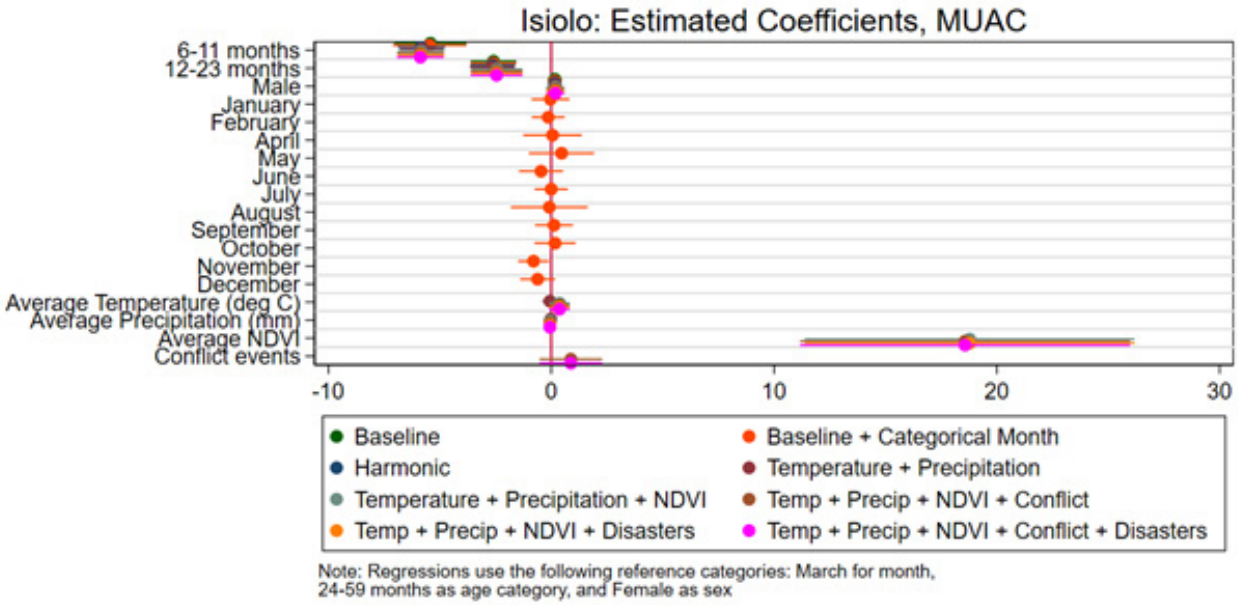


Figure A10. Full analysis on MUAC (using SMART data) in Isiolo.

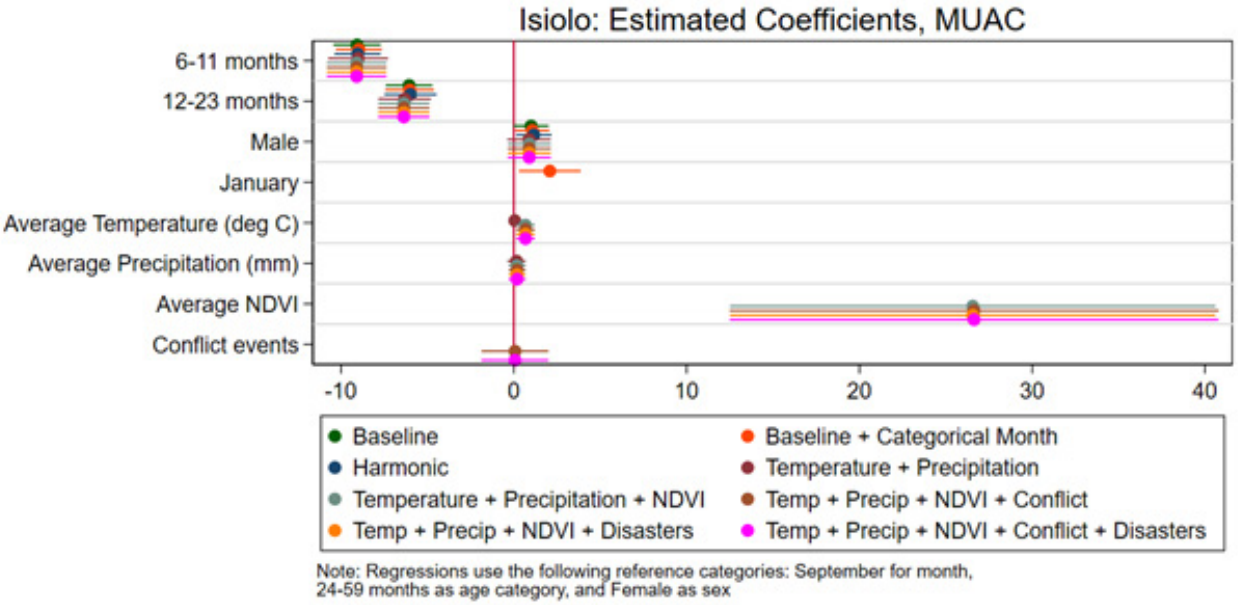


Figure A11. Full analysis on MUAC (NDMA data) in Marsabit.

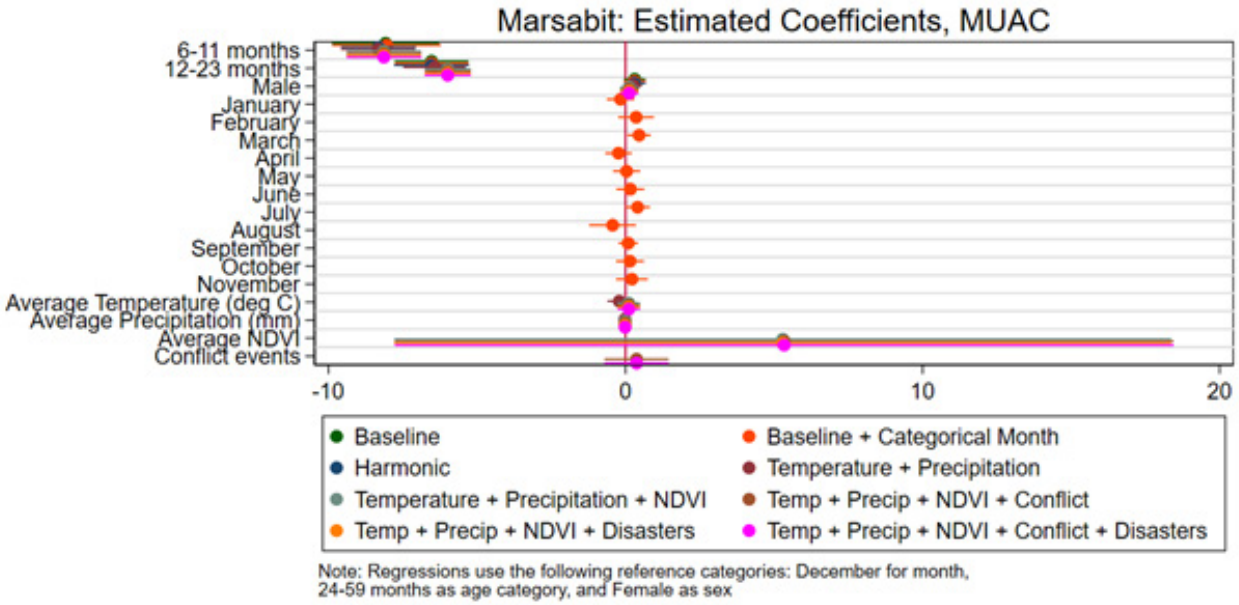


Figure A12. Full analysis on MUAC (using SMART data) in Marsabit..

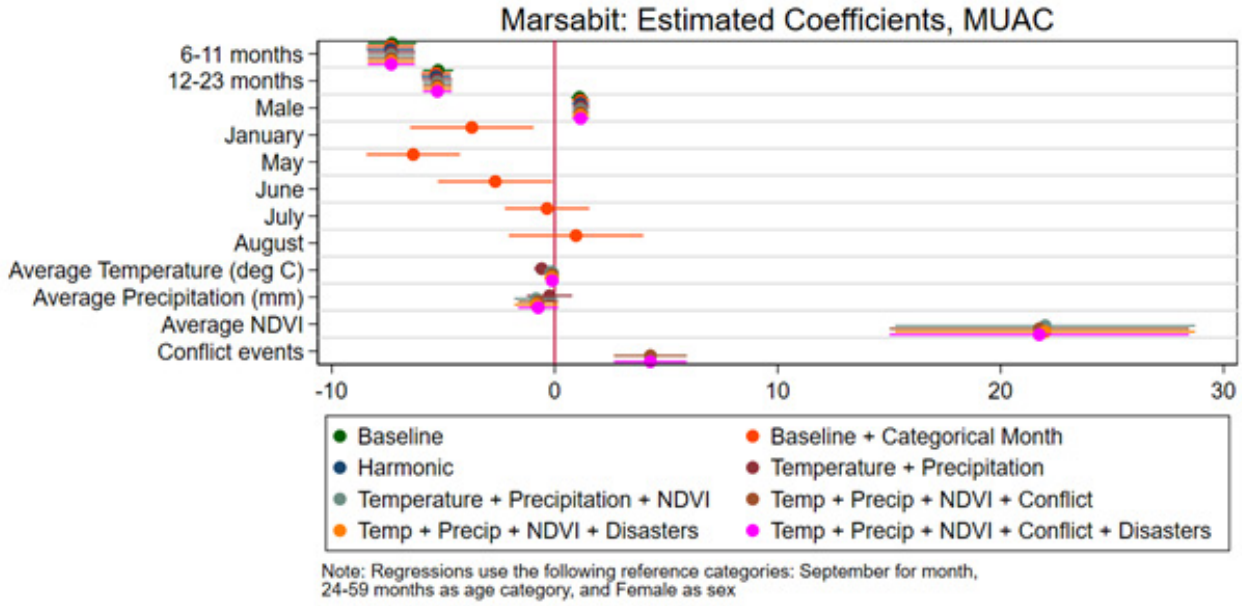


Figure A13. Full analysis on wasting (calculating using MUAC NDMA data) in Isiolo.

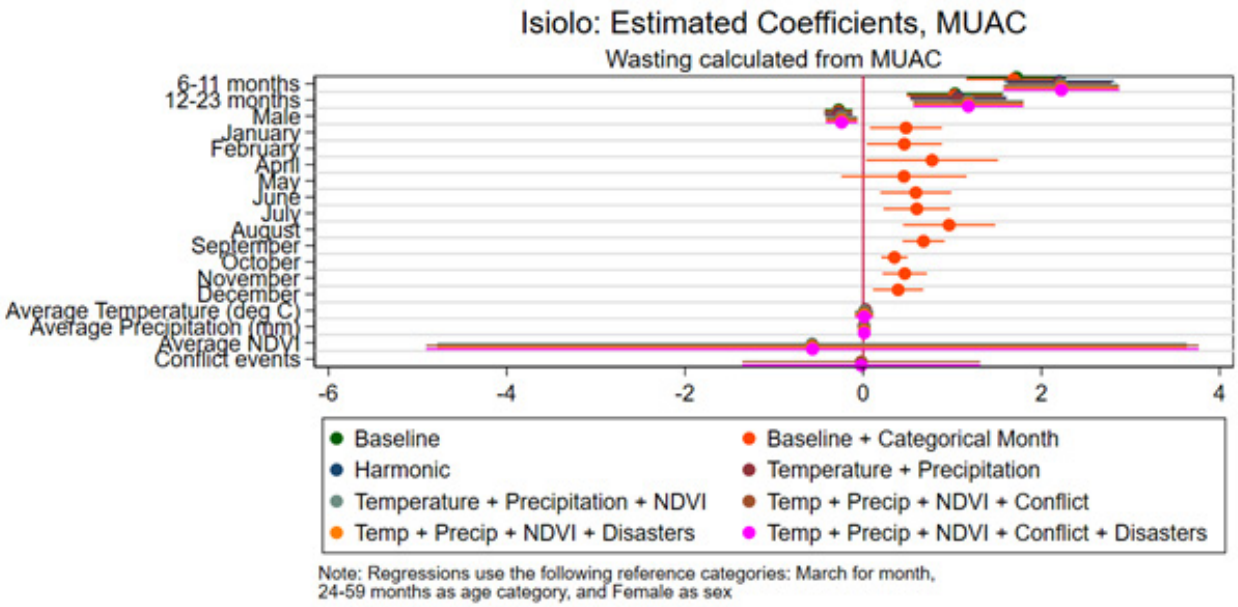


Figure A14. Full analysis on wasting (using MUAC SMART data) in Isiolo.

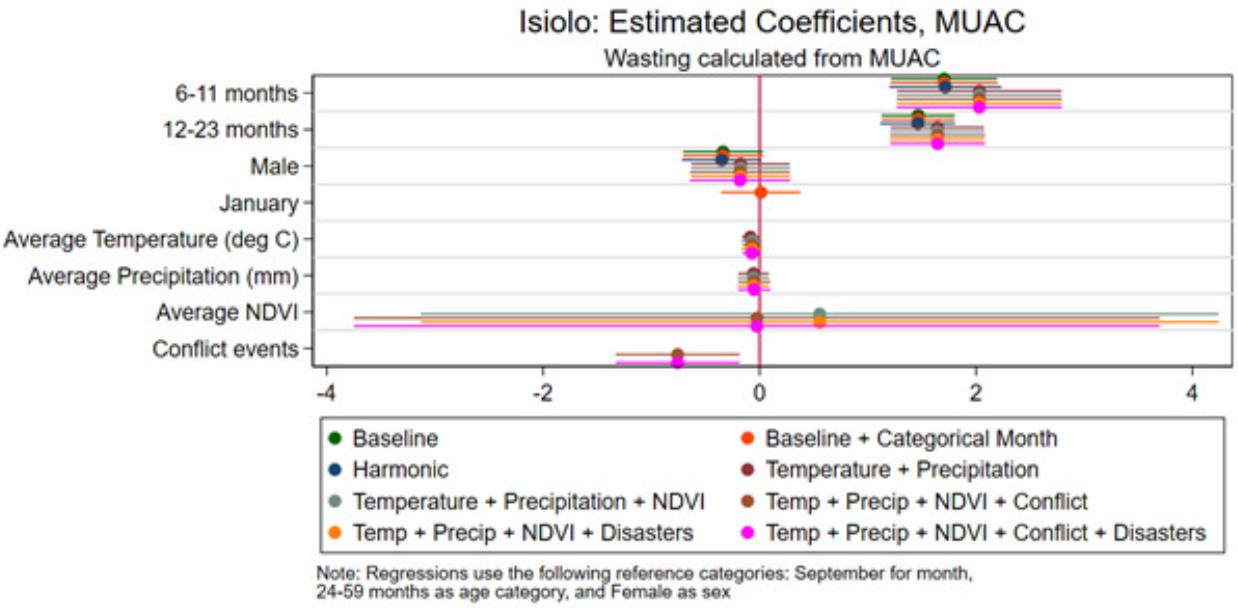


Figure A15. Full analysis on wasting (using MUAC NDMA data) in Marsabit.

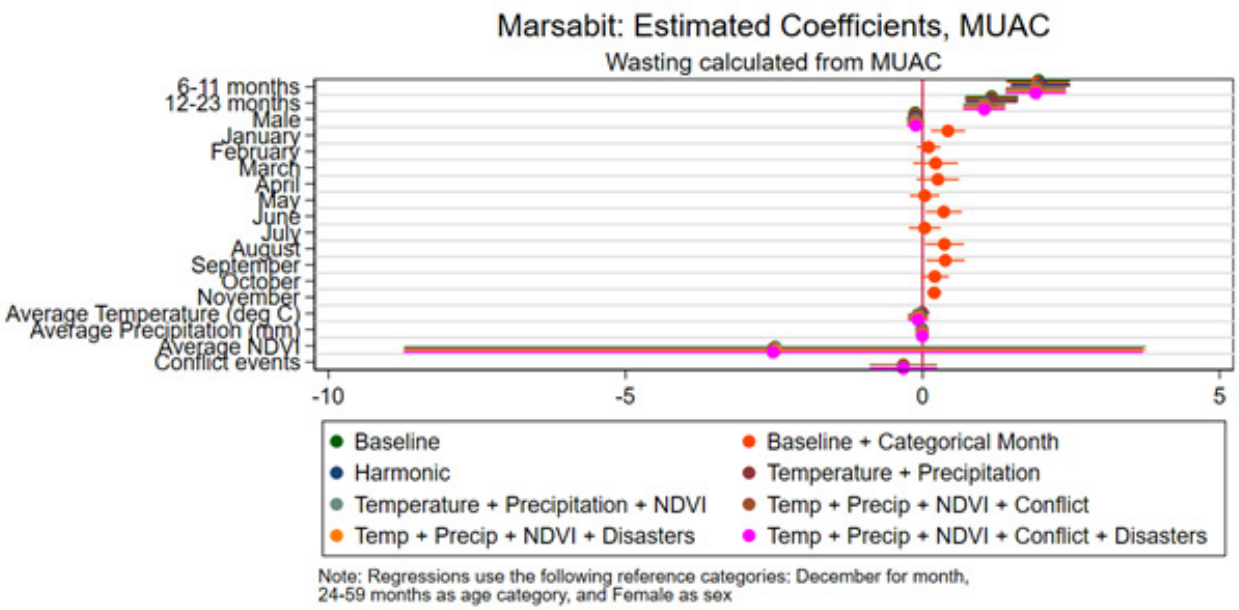


Figure A16. Full analysis on wasting (using MUAC SMART data) in Marsabit.

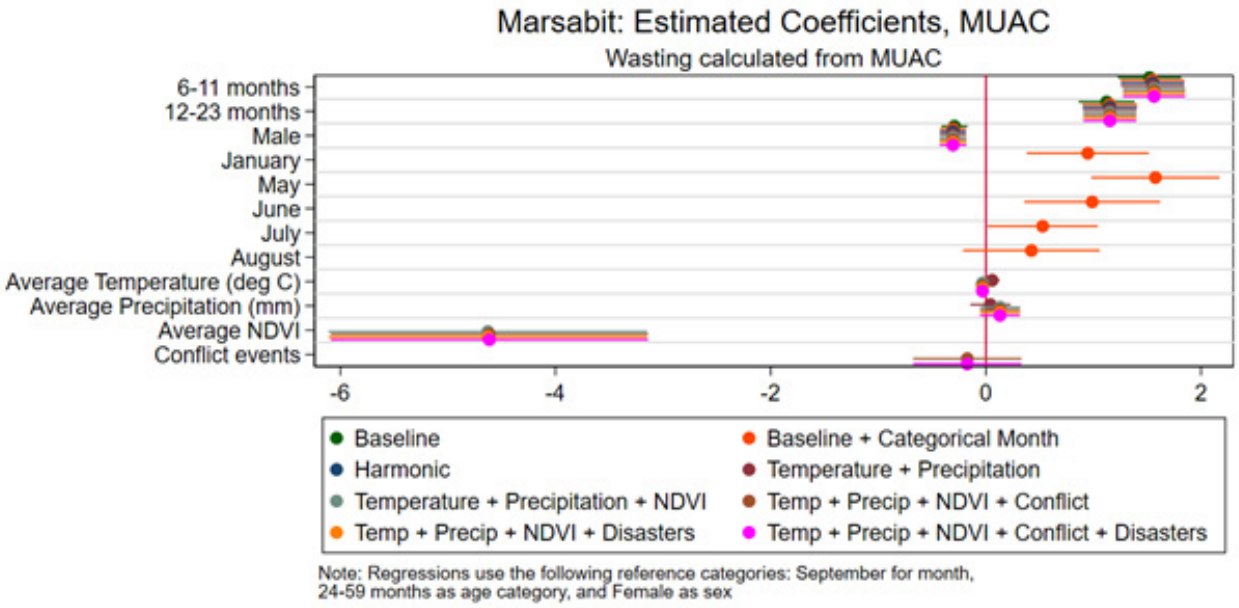


Figure A17. Full analysis on WHZ in Isiolo.

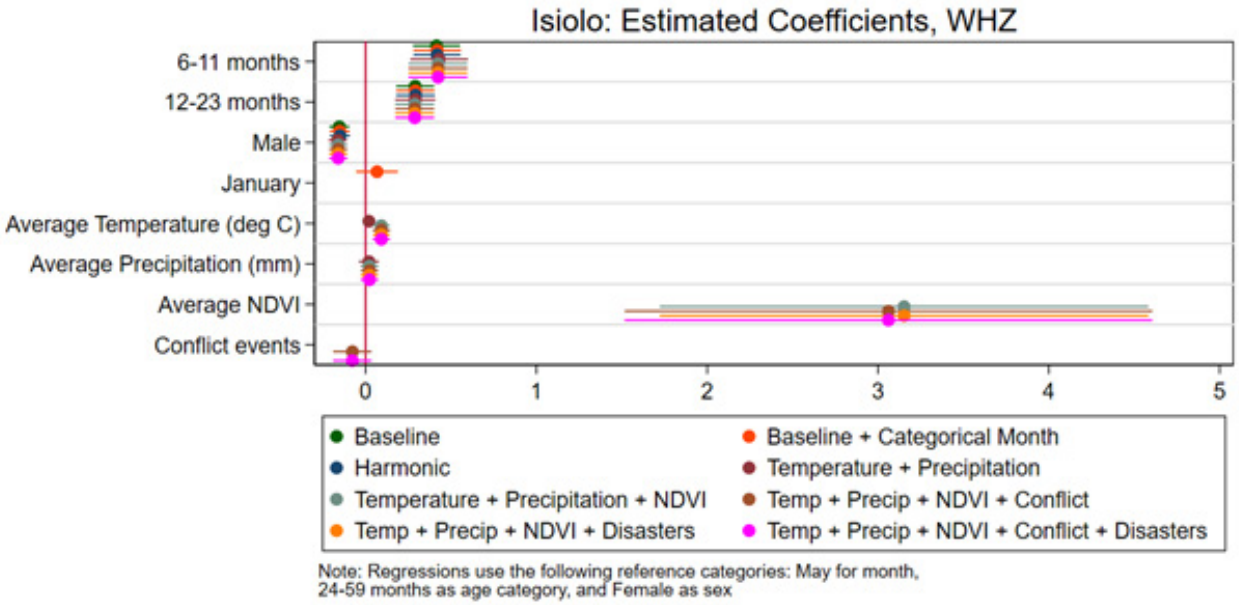


Figure A18. Full analysis on WHZ in Marsabit.

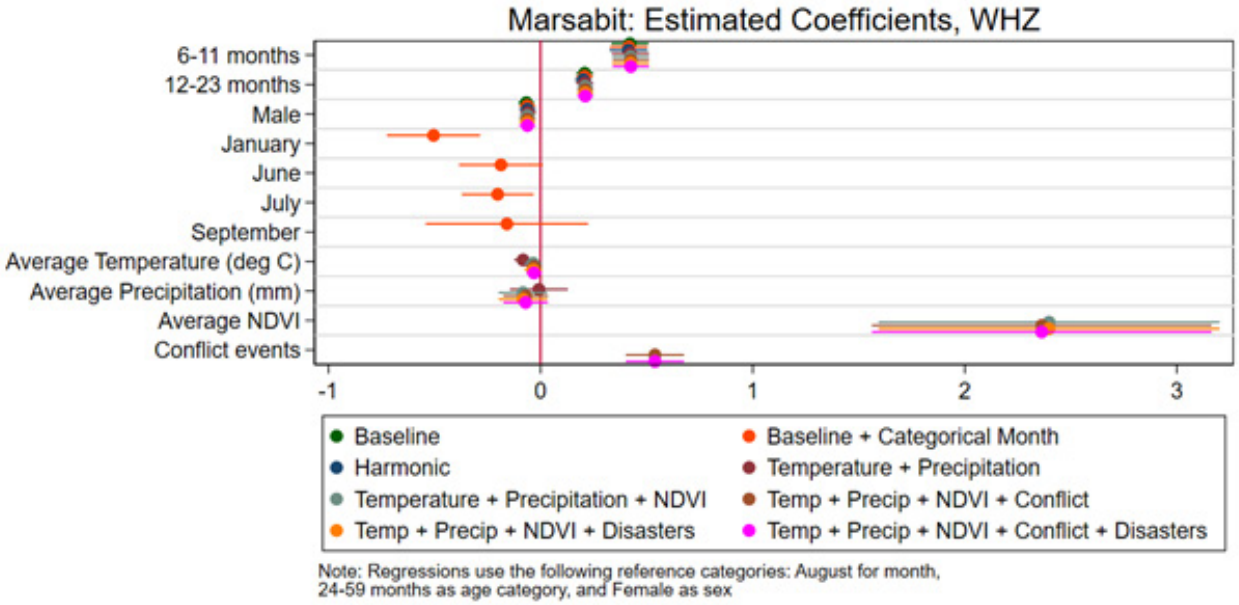


Figure 19. Full analysis on wasting (using WHZ) in Isiolo.

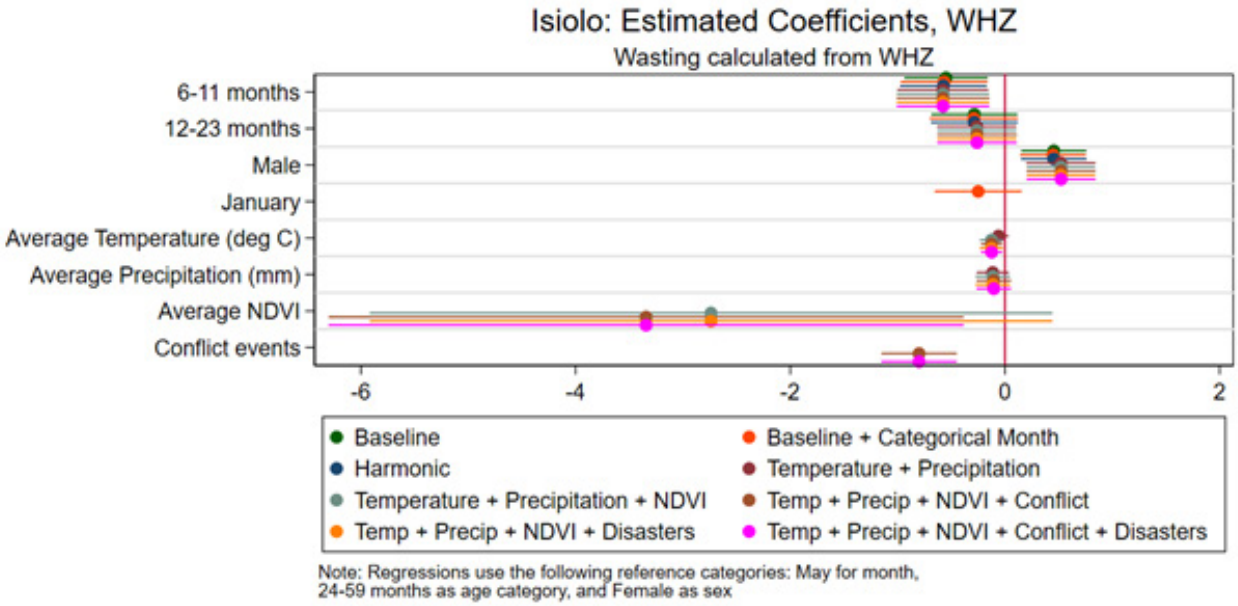
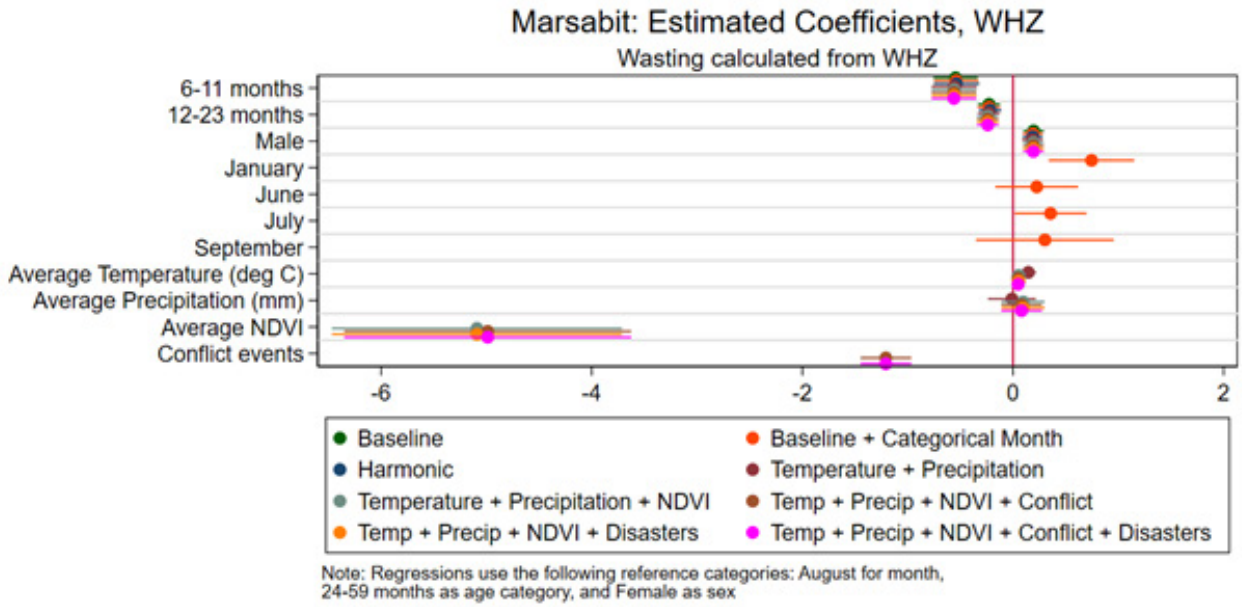


Figure 20. Full analysis on wasting (using WHZ) in Marsabit.



References

Abatzoglou, J. T., S. Z. Dobrowski, S. A. Parks and K. C. Hegewisch (2018). «TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958-2015.» Sci Data 5: 170191.

ACLED (2019). "Armed Conflict Location & Event Data Project (ACLED) Codebook."

Bauer, J. M. and S. Mburu (2017). «Effects of drought on child health in Marsabit District, Northern Kenya.» Econ Hum Biol 24: 74-79.

Birch, I. (2020). Desk review: Natural resource management and nutrition. Nawiri program, Nairobi.

Brown, M. E., D. Backer, T. Billing, P. White, K. Grace, S. Doocy and P. Huth (2020). «Empirical studies of factors associated with child malnutrition: highlighting the evidence about climate and conflict shocks.» Food Security 12(6): 1241-1252.

Centre for Research on the Epidemiology of Disasters (CRED). EM-DAT: The OFDA/CRED International Disaster Database. Brussels, Belgium: Catholic University of Leuven. http://www.emdat.be/

Didan, K. and A. Barreto (2016). NASA MEaSUREs Vegetation Index and Phenology (VIP) Vegetation Indices Monthly Global 0.05Deg CMG. N. EOSDIS, Land Processes DAAC.

ESRI (2010). «Digital chart of the world.» Retrieved June 17, 2020, from http://worldmap.harvard.edu/data/geonode:Digital_Chart_of_the_World.

FAO and Tufts (2019). "Twin peaks: The seasonality of acute malnutrition, conflict, and environmental factors in Chad, South Sudan, and the Sudan." Rome and Boston, Food and Agricultural Organization.

FAO, UNICEF and Washington State University (2020). "Marsabit County, Kenya seasonality of malnutrition: Community knowledge on patterns and causes of undernutrition in children and women in Laisamis." Rome.
FEWS NET (2018). Livelihood Zones.

Fratkin, E., E. A. Roth and M. A. Nathan (2004). «Pastoral sedentarization and its effects on children's diet, health, and growth among Rendille of Northern Kenya.» Human Ecology 32(5): 531-559.

FSD Kenya. (2019). «Kenya market locations.» Retrieved June 17, 2020, from https://data.humdata.org/dataset/kenya-markets.

Funk, C., P. Peterson, M. Landsfeld, D. Pedreros, J. Verdin, S. Shukla, G. Husak, J. Rowland, L. Harrison, A. Hoell and J. Michaelsen (2015). «The climate hazards infrared precipitation with stations--a new environmental record for monitoring extremes.» Sci Data 2: 150066.

Database of Global Administrative Areas (GADM) (2012). Database of global administrative areas, Version 2.0.
Grace, K., F. Davenport, C. Funk and A. M. Lerner (2012). «Child malnutrition and climate in Sub-Saharan Africa: An analysis of recent trends in Kenya.» Applied Geography 35(1-2): 405-413.

Herrmann, S. M. and K. I. Mohr (2011). «A continental-scale classification of rainfall seasonality regimes in Africa based on gridded precipitation and land surface temperature products.» Journal of Applied Meteorology and Climatology 50(12): 2504-2513.

Hutchinson, C. and S. Hermann (2008). "The future of arid lands - revisited: A review of 50 years of drylands research." Paris, France, UNESCO Publishing.

ICPAC (2017). «Kenya - Roads.» Retrieved June 17, 2020, from http://geoportal.icpac.net/layers/geonode%3Aken_roads#more.

Information Technology Outreach Services (ITOS) and US Agency for International Development (USAID) (2021). "Kenya - subnational administrative boundaries." Humanitarian Data Exchange. Available online: https://data.humdata.org/dataset/ken-administrative-boundaries.

Kratli, S. (2015). Valuing variability. New perspectives on climate resilient drylands development, IIED.
Little, M., J. Galvin and M. Mugambi (1983). «Cross-sectional growth of nomadic Turkana pastoralists.» Human Biology 55(4): 810-830.

Little, M. and B. R. Johnson (1987). «Mixed-longitudinal growth of nomadic Turkana pastoralists.» Human biology 59(4): 695-707.

Lloyd, C. T., H. Chamberlain, D. Kerr, G. Yetman, L. Pistolesi, F. R. Stevens, A. E. Gaughan, J. J. Nieves, G. Hornby, K. MacManus, P. Sinha, M. Bondarenko, A. Sorichetta and A. J. Tatem (2019). «Global spatio-temporally harmonised datasets for producing high-resolution gridded population distribution datasets.» Big Earth Data 3(2): 108-139.

Manners, K., M. Calo, I. Awino and J. Korir (2015). «Undernutrition risk factors and their interplay with nutrition outcomes: nutrition causal analysis pilot in Kenya.» Field Exchange 49.

Mark, B., A. Imwatis and K. Harison (2017). «Spatial variability of malnutrition and predictions based on climate change and other causal factors: A case study of North Rift ASAL counties of Kenya.» Journal of Earth Science & Climatic Change 8(10).

Marshak, A., A. Venkat and E. N. Naumova (2021). «How seasonality of malnutrition is measured and analyzed.» International Journal of Environmental Research and Public Health.

Marshak, A., H. Young and E. N. Naumova (2021). «Seasonality of wasting in eastern Chad: A story of two peaks.» in progress.

Marshak, A. (2021c). "Immediate and underlying drivers: the immediate and underlying drivers of child malnutrition in the Kenyan ASALs." Feinstein International Center. July 2021.

Mutegi, K. and J. Korir (2016). «Nutrition sensitive multi-sectoral planning: Experiences on Link Nutrition Causal Analysis Kenya.» Field Exchange (51): 149.

Njuguna, J. and C. Muruka (2011). «Diarrhoea and malnutrition among children in a Kenyan district: A correlation study.» Journal of Rural and Tropical Public Health 10: 35-38.

Ocholo, S. (2021a). Malnututrition hotspot mapping analysis for the Nawiri project in Isiolo County. Nawiri program, Nairobi.

Ocholo, S. (2021b). Malnutrition hotspot mapping analysis for the Nawiri project in Marsabit County. Nawiri Program, Nairobi.

Raleigh, C., A. Linke, H. Hegre and J. Karlsen (2010). «Introducing ACLED: An armed conflict location and event dataset.» Journal of Peace Research 47(5): 651-660.

RCMRD Kenya (2015). «Kenya SRTM 30 meters.» RCMRD Geoportal. Retrieved June 17, 2020, from http://geoportal.rcmrd.org/layers/servir%3Akenya_srtm30meters.

RCMRD Kenya (2017). «Kenya Sentinel2 Land Use Land Cover 2016.» RCMRD Geoportal. Retrieved June 17, 2020, from http://geoportal.rcmrd.org/layers/servir%3Akenya_sentinel2_lulc2016#more.

Republic of Kenya, C. G. o. I. (2018). "Isiolo County integrated development plan 2018-2022."

Republic of Kenya, C. G. o. M. (2018). "Marsabit County integrated development plan 2018-2022."

Saverio, K., O. H. Eldirani and H. Young (2013). "Standing wealth: Pastoralists livestock production and local livelihoods in Sudan." Khartoum, Feinstein International Center, Friedman School of Nutrition Science and Policy at Tufts University.

Shell-Duncan, B. (1995). «Impact of seasonal variation in food availability and disease stress on the health status of nomadic Turkana children: A longitudinal analysis of morbidity, immunity, and nutritional status.» American Journal of Human Biology 7: 339-355.

Shell-Duncan, B. and J. W. Wood (1997). «The evaluation of delayed-type hypersensitivity responsiveness and nutritional status as predictors of gastro-intestinal and acute respiratory infection: A prospective field study among traditional nomadic Kenyan children.» Journal of Tropical Pediatrics 43: 25-32.

Stites, E. (2020). Nawiri desk study: Livelihood systems in Isiolo and Marsabit County. Nawiri program, Nairobi.

Stites, E. and E. Dykstra-McCarthy. (2020). Gender gap analysis on Isiolo and Marsabit. Nawiri program, Nairobi.

UNICEF (1990). "Strategy for improved nutrition of children and women in developing countries. A UNICEF policy review." New York, UNICEF.

UNICEF and USAID (2006). Measuring Mortality, Nutritional Status, and Food Security in Crisis Situations: SMART Methodology. Version 1. April 2006

WRI (2007). «Kenya GIS data.» Retrieved June 17, 2020, from https://www.wri.org/resources/data-sets/kenya-gis-data.

Young, H. (2020). "Nutrition in Africa›s drylands: A conceptual framework for addressing acute malnutrition." Boston, Feinstein International Center, Friedman School of Nutrition Science and Policy at Tufts University.

Nawiri