Adaptation: Towards Security in the Face of Instability

A study of adaptation strategies using a multiple regression model with interaction terms for smallholder food security in Tanzania

Industrial Ecology
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CMAP Precipitation and GHCN_CAMS Gridded 2m Temperature (Land) data provided by the NOAA PSL, Boulder, Colorado, USA, from their website at ***https://psl.noaa.gov***[1]

The National Oceanic and Atmospheric Administration publicly provides scientific data used throughout the world and its work is thus featured in countless critical studies.

[1] Accessed the 27th of May 2021 via the following web pages:
Mean precipitation from https://psl.noaa.gov/data/gridded/data.cmap.html
Mean air temperatures from https://psl.noaa.gov/data/gridded/data.ghcncams.html

Summary

In this thesis, national survey data and a historical weather model are combined in order to explore the relationship between weather shocks and food insecurity in rural Tanzania. The effects of existing climate change adaptation strategies on this relationship are explored through multiple regression analysis in order to ascertain how small-scale farmers in Tanzania may prepare for the worsening climate. Household data on agricultural practices, diets and geographical locations based on survey data were linked to local climate data from a global historic weather model. A composite measure of household weather shock exposure based on exposure to periods of unusually low precipitation and periods of unusually low temperatures was used in conjunction with the household Food Consumption Score to measure the relationships between climate adaptation strategies, weather shocks and food insecurity. This analysis takes advantage of the large volume of survey data from the Living Standards Measurement Study - Integrated Surveys on Agriculture Project and allows the measurement of the statistical performance of adaptation practices while accounting for control variables. The study finds that the interaction terms of livestock diversity and intercropping with weather shocks do significantly correlate with a reduced impact on food security. Furthermore, a reduction in livestock diversity appears to further help maintain household food security in the face of adverse weather conditions, likely signifying that households compensate for these conditions through the slaughter or sale of livestock. Livestock thus appears to function as a sort of insurance against extreme weather impacts on food security. These practices represent actionable strategies that smallholders with limited available resources can utilize to reduce vulnerabilities in the face of a changing climate.

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Introduction

Although the exact level of future climate change isn't certain, there is consensus that it will lead to more extreme weather across the globe, as this is increasingly linked to the emission of greenhouse gases[IPCC, 2022]. Considering the scale of the threat to human livelihoods, great efforts are required in order to stem the tide. Because of past greenhouse gas emissions, some degree of climate change has now become unavoidable, as the delayed effects of radiative forcing kick in. This necessitates adaptation to these coming changes.

Climate change will likely decrease the crop yields of farmers across the globe by 2050 [Wing et al., 2021]. Crops are especially vulnerable to extreme weather conditions, which climate change exacerbates. Crops have limited tolerances for extreme weather and yields can be negatively impacted by extreme weather. Combined with projections of world wide population growth, especially in Africa, and increased per capita demand placed on food production, climate change and weather shocks will put additional pressures on an already strained system [Serraj & Pingali, 2018].

Subsistence farmers and other smallholders are especially vulnerable to rainfall and temperature conditions because agriculture on this scale relies on stable and predictable rainfall and temperature patterns throughout the growing and harvesting seasons. This is most relevant in regions that depend more on rainfall and less on irrigation for the watering of crops. A second reason why these farmers are vulnerable to these changes is that such farmers also tend to have less access to capital, which can impede their ability to make changes in their business to mitigate the impacts of extreme weather [Benson, 2021].

The vulnerability of agriculture to climate change is projected to be most severe in Sub-Saharan Africa and South America, two regions which are very vulnerable to weather shocks in the current climate, and will thus be even more vulnerable after the climate changes.[Richardson et al., 2018] This region's vulnerability to these disruptions is further exacerbated by the causal link between weather shocks and civil conflict which has been found in Sub-Saharan Africa [Burke et al., 2009; Maystadt & Ecker, 2014]. This regional effect mirrors the more general correlation between food prices and political instability in low and middle income countries, and potentially further food insecurity in the case of conflict [Barrett 2013, Brinkman and Hendrix 2011, Lagi et al. 2011, Bellemare 2012]. Lastly, as reduced crop yields diminish food supply and cause increased local food prices, people are affected not just by the physical effects of food shortages, but also by the psychosocial effects of food uncertainty [Timmer 2012]. Via these mechanisms, climate change threatens to destabilize Sub-Saharan Africa.

The rainfall and temperature sensitivity of crops make them vulnerable to weather shocks: weather extremes in temperature and precipitation. There has been a rise in the number of extreme wet and extreme dry periods in East Africa, and the prevalence of extreme wet days is projected to rise in the future [Vizy & Cook, 2012]. Observed reductions in precipitation in the March-May rainy season in East Africa have been linked to rising Indian ocean temperatures. As global temperatures rise, these dry spells can therefore be expected to exacerbate in the future. [Lyon, & DeWitt, 2012] However, the extreme temperature range in Africa is expected to decline somewhat in the future, as a result of the rising minimum temperatures. This rise is connected to the rising temperatures at night. [Climate Change, 2014] To summarize, the literature expects extreme weather events to become more common, even if the range of temperatures narrows somewhat.

Studying the adaptation of agriculture to extreme weather requires detailed data on the adoption of specific agricultural practices in regions most vulnerable to these weather shocks. Within the East-African nations, Tanzania provides an interesting case to research the effects of extreme weather on food security. Tanzania's agriculture is predominantly rain-fed with relatively little access to irrigation, which can be expected to make it more sensitive to extreme precipitation shocks. Another reason for selecting Tanzania is the availability of data: Its national panel survey has periodically gathered data on households' diets and agricultural practices.

The potential of weather shocks, and specifically droughts, to harm the population of Tanzania exceeds that of other nations due to a confluence of factors:

- Only 2.3% of Tanzania's cultivated land is equipped for irrigation [FAO, 2016] making crops potentially more sensitive to droughts and floods.
- 69% of the population lives in rural areas [FAO, 2016]
- Agriculture employs 91% of rural and 73% of all households [Wineman et al., 2020]
- Tanzania's population is projected to grow 89% from 2024 to 2050 [PRB, 2024]
- Tanzanian farmers predominantly grow maize, up to 80% of which is grown and consumed locally[Wilson & Lewis, 2018]. Maize however is vulnerable to droughts during the flowering and grain-filling growth stages, which can lead to serious yield losses[Baijukya et al., 2020].
- 26.4% of the population of mainland Tanzania could not afford their basic needs and one in eight Tanzanians were deemed extremely poor by the National Bureau of Statistics Tanzania[NBS, 2020]. This lack of financial means necessarily restricts the strategies available to them for mitigating the impact of weather shocks on food security.

In short, Tanzanian smallholders must find affordable ways to feed a rapidly growing poor and rural population while their crops are sensitive to droughts in a climate whose stability is waning. This provides a monumental challenge, and any support this study may provide in finding actionable solutions is worth every effort.

Heavy rainfall events and droughts are both projected to increase for Tanzania (with a high confidence for a global warming level of 2°C and higher according to the IPCC [2017]. Droughts are projected to be more common, last longer and be more intense, and their prevalence has already doubled since 2005 while being especially severe during the summer [IPCC, 2022]. The rainfall in the March-May rainy season is vital in Tanzania, especially for the growing of maize, sorghum and millet as well as the growing of rice. This constitutes the main growing season for the majority of Tanzanian crops. [FAO, 2025] As stated previously, this season is projected to experience reduced precipitation, which will thus have a significant impact on Tanzanian agriculture.

Climate change projections generally predict a wetter climate in eastern Africa, but with significant changes in the timing of rainy seasons in Tanzania. This constitutes a reversal of the historic trend. The rainy seasons would shift: shortening the spring rainy season while simultaneously lengthening the fall rainy season. [Climate Change 2014, Cook & Vizy 2012 B]

The limited financial means of rural smallholders in Tanzania requires a focus on affordable strategies for coping with extreme weather. Adapting to the threat of weather shocks using only the means available to these smallholders limits us to a handful of options, which will be outlined below. Tanzania's agriculture sector is dominated by smallholders, a dry climate and relatively little irrigation [Brüntrup et al., 2018]. Consequently, it will be valuable to know which adaptation strategies appear to reduce the impact of a worsening climate. Because of the low amounts of capital available to these farmers, most high-tech climate adaptation strategies are unlikely to be widely adopted in the near-future [Brüntrup et al., 2018]. Low-tech strategies for reducing the impact of climate shocks are likely more fruitful, and worth exploring. These include intercropping, diversifying types of crops, cattle-rearing and taking up work for wages in order to be less reliant on agriculture. Other adaptation strategies exist, but these in particular distinguish themselves because they are measurable from the data of the Tanzanian National Panel surveys, which provides a very large dataset and thus the ability to find statistically significant links.

This study seeks to ascertain which weather shocks diminish food security in Tanzania, and how adaptation strategies mitigate the impact of those shocks on food security. In order to explore the effectiveness of these adaptation strategies, this work will attempt to answer the following research question:

"Which climate adaptation strategies reduce the impact of extreme weather on the food security of smallholders in Tanzania?"

Current research in the scientific literature concerning these adaptation strategies generally suffers from two problems which this study seeks to address [see table 1]:

- It is difficult to distinguish their moderating impact on weather shock induced food security from their direct correlation to food security. This distinction is necessary to distinguish strategies which can be expected to be particularly effective in future scenarios where weather shocks are more prevalent/severe.
- Their method for measuring food insecurity is indirect (e.g. measuring food prices, food expenditure or retarded child growth) rather than being based on dietary data from survey results. This adds a layer of uncertainty regarding the final impact on the nutritional wellbeing of these households.

In order to avoid these issues, this study will calculate interaction terms and a Food Consumption Score for each household respectively, which will be explained in the Methods chapter.

	Includes Tanzania	Measures moderation	Measures food security directly
Haile et al., 2018	Yes	No	No
Ajefu & Abiona, 2020	No	Yes	Yes
Arslan et al., 2017	Yes	No	Yes
Bozzola et al., 2020	No	Yes	No
Brander et al., 2021	Yes	No	Yes
Demeke et al., 2011	No	No	Yes
Eriksen et al., 2005	Yes	No	No
Gebre et al., 2023	Yes	No	Yes
Kubik & Maurel, 2016	Yes	No	No
Letta et al., 2018	Yes	No	No
Matsuura et al., 2023	No	Yes	Yes

Table 1: A brief overview of similar studies regarding extreme weather, food security and smallholders

Despite the fact that National Panel Survey data from 2008 forward has been available, which includes detailed questions about household nutrition, we can see [see table 1] that many studies regarding food security instead rely on less direct methods for determining food security. These range from household food expenditure to maize yields or the stunted growth of children.

Notably, Ajefu & Abiona [2020] do study how the impacts of drought-induced food insecurity are mitigated by a significant factor: Land tenure security. Their study however, concerns Malawi instead of Tanzania, and has a singular focus on this one mitigating variable, rather than studying a range of adaptation strategies. This present study seeks to specifically study adaptation strategies that are readily available for smallholders with limited access to credit and facilities. Any insights derived from this research question can thus help identify relatively affordable and achievable solutions for these households, which do not require systemic changes that are outside the control of individual smallholder households. Existing studies almost exclusively focus on solutions through policy suggestions of systemic changes, which lies outside the control of the people directly impacted by the impacts of extreme weather.

Several adaptation strategies exist and are implemented by a significant number of farmers, which will be analysed in this study. These can reduce vulnerability to weather shocks in different ways. To study the effects of changes over time, national panel survey data is especially useful, because it tracks data for given households over time. The present study is therefore constrained by the data available in this National Panel Survey in the questions that can be answered. Due to the inclusion of geographic data in the survey, the households can also be linked to local weather data. As for the agricultural practices of smallholders, the survey includes questions concerning the specific crops grown on each plot of land and livestock. It also includes data on members of the household working for wages outside of the household.

Kubik & Maurel [2016] suggest that income diversification strongly mitigated the impact that weather shocks had on internal migration in Tanzania. This may be explained by households becoming less dependent on local climate conditions, as it allows these households to earn an income that can be used to buy food from farmers that are less impacted by local weather. They did not measure the impact on food security, however, which offers an opportunity for research.

Bozzola and Smale [2020] meanwhile show that smallholders in Kenya respond to droughts by increasing the diversity of their crops. Increasing *crop diversity,* which is to say the number of unique crop species grown on a farm, may help these farmers in the following manner: Different crops have different weather preferences and tolerances for temperatures and precipitation, thus making a specific set of weather conditions less likely to negatively affect all the crops grown on a farm. The different crops may also be grown and harvested in different periods of time than each other, making it less likely that extreme weather in one point of time affects all the crops cultivated by the entire household. In these ways, using different types of crops may reduce the impact of weather shocks based on their type, timing or intensity. Testing whether this adaptation strategy statistically reduces vulnerability to weather shocks may help to assess whether this response appears effective. Bozzola and Smale [2020] do conclude in their research that this is the case in Kenya, making it more plausible that such a mitigating relationship also holds for Tanzania.

Livestock diversity, meaning the number of unique species of livestock reared by a household, may help mitigate vulnerability. Van Keulen and Schiere [2004] lists potential benefits of crop-livestock combination acting as a buffer against trade, price and climate fluctuations, a diversified income source and investment option, a solution for weeds, erosion and low-quality roughages, as well as other benefits and a list of drawbacks.

Many types of livestock are kept over several years, and can thus help bridge short periods of food scarcity by acting as a form of wealth storage, since livestock can be sold or slaughtered when most needed to alleviate food insecurity. This might explain the buffer function against trade, price and climate fluctuations.

Livestock may be fed using feedstocks of crops or with by-products and waste, or a mix of both. The use of by-products and waste helps prevent situations where crop failures also lead to issues feeding livestock, because the feedstock becomes more expensive. This latter issue is illustrated by the strong drops in livestock prices that have been linked to droughts in Somalia, hurting farmers who relied solely on livestock sales for their income [Maystadt & Ecker, 2014]. However, The drop in livestock prices also coincided with an increase in cereal prices, suggesting that an income based on both livestock and cereal may be more resistant to weather shocks. This helps contextualize the function of livestock as a diversified income source. Diverse income/investment sources require low correlations of the underlying investments.

Lastly, the manure produced by livestock helps reduce the need to buy artificial fertilizer for crop cultivation. This reduces the economic burden on households. Through these mechanisms, rearing livestock can be expected to reduce the impact of weather shocks on food security.

Growing multiple crops on the same plot of land, known as *intercropping,* which is the practice of cultivating different species of crops on the same plot of land, may help reduce vulnerability to ecological disruptions by increasing drought-resistance[Rusinamhodzi et al., 2012]. Fields that are intercropped might also be less vulnerable to crop-specific pests and pests and diseases in general [Trenbath, 1993]. The resistance to pests and diseases helps mitigate climate risk, since extreme climate conditions make more crops vulnerable to pests and diseases [He et al, 2025]. Previous research has shown some increased resilience for Tanzanian smallholders that apply intercropping along with complementary adaptation strategies [Arslan et al., 2017]. These findings regarding intercropping and crops suggest that there may be a statistical link between intercropping and reduced vulnerability to weather shocks of smallholder food security, which this work aims to establish.

Considering the wealth of data available through the National Panel Survey, it is likely possible to draw statistical conclusions about the impact of these practices on food security in Tanzania. In 'Welfare effects of weather variability' [Haile et al., 2018] regarding Tanzania, Uganda & Ghana, a very similar question is explored using panel data. This research shows how panel data can be used to assess the viability of adaptation strategies. They do not measure the impact on food security however, electing to use household food consumption expenditure as a proxy for household welfare. The underlying assumption is that smallholders are restricted in their purchase of preferred foods on the market by the household income from excess food production, sold on the market. This study is very useful as a contrast to this one because of its similar approach and data usage, but the assumptions do leave room for further research using the data from those surveys regarding nutrition and diet directly in order to measure food security with increased confidence.

Current studies that do study actionable adaptation strategies and food security in Tanzania suffer from another limitation: They do not measure the statistical moderation of these adaptation strategies on the relationship between weather shocks and food security [see Table 1]. Instead, their direct correlation with food security is used. This can obfuscate the causal links underlying correlations: Are households experiencing changes to their food security as a result of an adaptation strategy or are they responding to worsening conditions by changing strategies? Studying the moderating effect, i.e. how an adaptation strategy reduces the impact of weather shocks on food security, it is instead possible to infer which strategies are likely to improve food security in a changing climate undergoing more extreme weather in the future. Doing so with a focus on readily available adaptation strategies for Tanzanian smallholders fills a gap in the current scientific literature.

Methods

Data sources

The weather data used in this work come from the CMAP and GHCN+CAMS gridded global weather models. These models are based on weather station data, satellite data and inference of missing values by the respective authors. The CMAP:CPC precipitation enhanced dataset was derived from a monthly analysis of a 17-year timespan using 5 kinds of satellite images (GPI, OPI, SSM/I scattering, SSM/I emission and MSU) as well as gauge data by Xie & Arkin [1997]. This dataset was gathered and enhanced by blending NCEP/NCAR reanalysis precipitation values with the observed data. The GHCN+CAMS monthly mean air temperature dataset was created to better integrate reanalysis data with observed data, with reduced biases. Fan & van den Dool [2008] used data from 1948 onwards combining two large sets of weather station observation data (namely GHCN and CAMS: Global Historical Climatology Network version 2 + Climate Anomaly Monitoring System) with several complicated interpolation methods in order to complete the dataset along the spatial and temporal dimensions.

The survey data comes from the National Panel Survey Tanzania from the Tanzania National Bureau of Statistics as part of the Living Standards Measurement Study (LSMS). This survey contains questionnaires concerning the household and its agriculture. Specifically, survey waves 2 and 3 (2010-2013) were used, as they contained the relevant data and the individuals of the households could be tracked among both waves. Using two consecutive surveys allows both delayed effects and immediate short term effects of adaptation strategies to be observed. This decision helps detect anomalous correlations, where the correlation coefficient changes drastically within a few years time.

The following section outlines the variables that were included for this analysis, a summary of all these variables can be found in *table 4*, including the way they are calculated.

Food Insecurity

The food security of a household was measured by using the Food Consumption Score, the most common food security indicator used by the world food program [VAM Resource Centre, 2024]. Other studies concerning food security have used this measure [Ajefu & Abiona, 2020], or a similar measure [Matsuura et al., 2023] to calculate household food insecurity. These measures sum the number of times over a 7 day period that one or more members of the household consumed food of a given food group, with weights assigned to each food group. This method was selected due to the availability of household data in the National Panel Survey, which posed this exact question to each household. In order to obtain a measure of food insecurity, the food consumption score of a household was subtracted from the maximum possible value, 112. This was done in order to invert the score from a food security score to a food insecurity score. Using the standard methodology, there are two thresholds associated with this score: between a ‘poor’ and ‘borderline’ diet, at a value of 21, and between a ‘borderline’ and ‘acceptable’ diet, at a value of 35.5 [VAM Resource Centre, 2024]. The impact of using other measures of food security will be explored as part of further analysis.

Food consumption group	Standard thresholds	Food insecurity (*I*) thresholds
Poor food consumption	0 - 21	91 - 112
Borderline food consumption	21 - 35.5	76.5 - 91
Acceptable food consumption	35.5 - 112	0 - 76.5

Table 2: Food consumption group thresholds

Weather Shocks

Since the aim of this model is to test how different adaptation strategies affect the relationship between weather shocks and food security, a clearly visible relationship between these two variables will make further analysis more clear, by making the impacts of adaptation strategies easier to detect. It is uncertain what types of weather shocks have relatively high impacts on food security in Tanzania, except that the dry climate and scarcity of irrigation suggests that droughts may have an outsized impact. It is also uncertain which methods for measuring food security are most effective at detecting the consequences of weather shocks. Furthermore, it is unknown how long after the occurrence of weather shocks an impact on food security can be measured.

In order to account for the relative impacts of different types of weather shocks, the weather shock variable *w* will function as a predictor variable composed of weights attached to the four types of weather shocks: extreme cold weather, extreme hot weather, extreme droughts and extreme precipitation.

Several changes were necessary to the climate data in order to shape it to a form suitable to analyze weather shocks. Each grid cell of the temperature and precipitation gridded weather models that overlaps with the territory of Tanzania were used as climate regions, and the households contained in those regions were compared to that weather data. The data for each region was adjusted for the long-term trends by subtracting the trend from the data. The local temperature and precipitation trends were obtained by fitting the dataset to a linear regression model. Since shocks are defined by unusual deviations, data falling within the standard deviation of the trend was not considered to be a shock of any kind. The weather shock threshold is defined as 1 standard deviation. Four different types of shocks are recognized: low/high temperature shocks and low/high precipitation shocks. Rather than using an integer count of the number of shocks, this analysis uses the sum of the standard deviations of these weather shocks from the norm in excess of the weather shock threshold (see equations 2-5) . This means that more extreme weather shocks have more weight in the calculation than less extreme weather shocks for determining the predictor variable *w*. The weighting of different types of weather shocks is outlined in *equation 1*.

In this analysis, weather shocks in the lean period (November-February) are intentionally ignored, as these are unlikely to affect the growth of crops. This lean period is based on the most common food crops grown in Tanzania. The accuracy of this assumption is tested by comparing the difference in results when including the lean period.

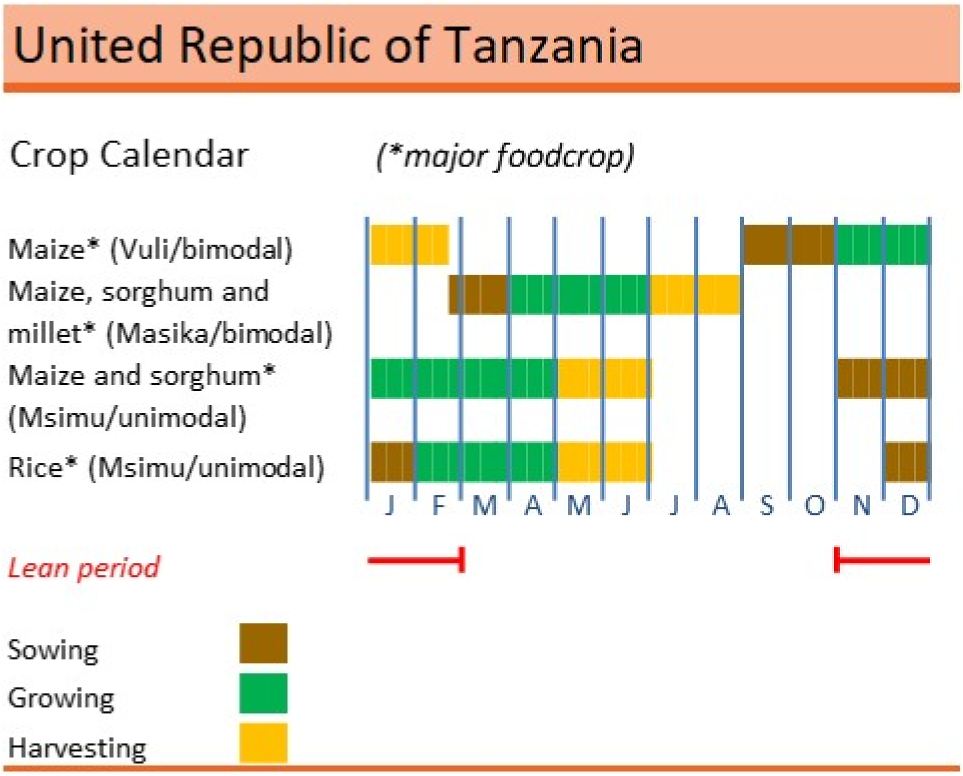

Figure 1: Tanzania’s common crop calendar and the lean period [FAO, 2025]

There are four different types of weather shocks whose impact on food security will be tested: unusually high temperatures, unusually high precipitation, unusually low temperatures and unusually low precipitation. Before the moderating impact of adaptation strategies can be measured, the significance of the different types of weather shock in affecting household food security in Tanzania specifically will first be established. Brewser, in their introduction to climate change [2023], delineates the following types of weather shocks as direct results of climate change: Droughts, Heatwaves, Floods, Wildfires and Tropical Cyclones. Tanzania is situated in a geographical band along the equator which does not experience such tropical cyclones[NASA, 2006]. The impact of wildfires on food security in Tanzania might well be worth investigating, though this falls outside the scope of this work. The extremes for both precipitation and temperatures will be tested for correlations with food security in order to ascertain their threat in the context of smallholder food security in Tanzania.

A multiple regression analysis of these four types of weather shocks and household food security will be used to determine which types of weather shocks significantly affect food security for the smallholders included in this dataset, the other types of shocks will be excluded from further analysis. The chosen weather shock types will then be weighted according to their correlation coefficient to food insecurity to form a predictor variable. The purpose of this weighting method is to give higher weights to those types of weather which appear from the data to most severely impact the food security of these households.

The variable *w* is thus a predictor variable based on weather shocks, and it is used to predict food insecurity. It is based on the intensity of recent local weather shocks leading up to a given month and is calculated as follows:

$$w(y_n) = A \cdot Lt(y_n) + B \cdot Ht(y_n) + C \cdot Lp(y_n) + D \cdot Hp(y_n)$$

Equation 1

Where *w* is the weather shock exposure variable, y_n is the month of the survey, *Lt* is the intensity of low temperature weather shocks leading up to that month, *Ht* is the intensity of high temperature weather shocks leading up to that month, *Lp* is the intensity of low precipitation shocks leading up to that month and *Hp* is the intensity of high precipitation shocks leading up to that month. These last four variables are calculated as seen in equations 2-5. Lastly, A, B, C and D are the weights applied to the 4 different types of weather shocks to determine the predictor variable *w* based on weather shocks.

$$Lt(y_n) = \sum_{i=0}^{M} max(\frac{\overline{K} - Ky_{n-i}}{\sigma_K} - T,\ 0)$$

$$Ht(y_n) = \sum_{i=0}^{M} max(\frac{Ky_{n-i} - \overline{K}}{\sigma_K} - T,\ 0)$$

$$Lp(y_n) = \sum_{i=0}^{M} max(\frac{\overline{P} - Py_{n-i}}{\sigma_P} - T,\ 0)$$

$$Hp(y_n) = \sum_{i=0}^{M} max(\frac{Py_{n-i} - \overline{P}}{\sigma_P} - T,\ 0)$$

Equations 2-5

M is the number of months before the date of the household interview during which local weather shocks count towards the predictor variable and *K* is the measured local monthly temperature in Kelvin and *P* is the measured local monthly precipitation in mm. $\overline{K}$ and $\overline{P}$ are the long term local trend averages for temperature measured in Kelvin and monthly precipitation measured in mm, respectively. *T* is the threshold value, the number of standard deviations from the local long-term trend weather needs to be in order to be classified as a weather shock.

Adaptation strategies

Crop diversity and livestock diversity were both measured by taking the number of unique species that were grown by a household. Wage work was measured by counting the percentage of household members that worked outside of the household for a wage up to 12 months before the interview. Lastly, intercropping was measured by taking a households' different plots of land, subdivided by the different crops grown on them, and counting the percentage that were grown intercropped as opposed to separately. See table 3 for the exact questions from the questionnaire which were used to construct these variables.

‘Wage work’	*“Did you do any wage work during the last 12 months? (i.e. work for someone else for pay)”*	Household Section E: LABOUR | 13
‘Intercropping’	*“Was cultivation intercropped?”*	Agriculture Section 4: Crops by plot | 4
‘livestock diversity’	*“Did this household own any [ANIMAL] in the last 12 months?”*	Agriculture Section 10A: Livestock | 2
‘crop diversity’	*“CROP”*	Agriculture Section 4: Crops by plot | index

Table 3: National Panel Survey questions used for measuring adaptation strategies

The selected four strategies (‘wage work’, ‘intercropping’, ‘livestock diversity’ and ‘crop diversity’) for reducing the impact of weather shocks have been included in two distinct ways each: directly, and indirectly as interaction terms (see below). The latter aims to measure how these strategies may reduce or exacerbate the effect of extreme weather on food security, while the former aims to show how food insecurity directly correlates with these strategies. Direct correlation could in theory be caused by a relationship where an adaptation strategy directly impacts the productivity of the farm, or a relationship where food insecurity leads households to adopt or avoid these adaptation strategies. This assumes that both variables in such a relationship are not merely the consequences of another variable that is missing from the analysis. This assumption can only be justified when the socioeconomic status of households is taken into account as a control variable. Otherwise strategies such as the rearing of diverse livestock could accidentally act as a measure of socioeconomic status instead and thus correlate to increased food security. Aside from livestock diversity, another variable measuring the change in livestock diversity between the two included waves of survey is included. This variable serves to highlight the effects of the recent sale or slaughter of livestock by the household. Another assumption is that households would already have adopted any of these strategies if those directly led to increased food security irrespective of weather shocks and socio-economic status. This assumption naturally leads any positive direct correlations between adaptation strategies and food insecurity to be interpreted as a form of adaptation, where the household adopts new strategies to combat food insecurity.

Control Variables

In order to prevent other common factors affecting economic vulnerability from distorting the results, they were included in the linear regression model as control variables. The included control variables are: the maximum education level in years obtained by any member in the household, the size of the household, the average age of the household, the ratio of women among the household and the time of the interview. The maximum education level serves as a proxy for Socioeconomic status. Similar research most often uses Household Size, Age, Gender, Literacy and Wage labor as control variables, with varying other additions, when using regression to explore weather shock impacts on smallholder food security [Demeke et al., 2011; Maharjan & Joshi 2011; Feleke et al., 2005]. Although it is not within the scope of this research to explore the relationships between these variables and food security, they are nonetheless included in order to distinguish their effect on weather shock vulnerability from that of the adaptation strategies and interaction terms. This prevents situations where one such variable which is correlated to both an adaptation strategy and the households' vulnerability to weather shocks causes an apparent correlation between those latter two variables. These variables are included in Table 4, along with other variables.

Definition of variables

As part of this research, data was analyzed concerning weather shocks, food security, adaptation strategies (wage work, livestock diversity, crop diversity & intercropping), interaction terms and control variables (education, family size, ages, female ratio, time). The table below lists how these were defined. These do not include the variables used to represent the moderating impact of adaptation strategies as discussed earlier. These follow a method outlined further below, in the *Empirical Strategy* section.

Unit	**Definition**
Wage Work (dependent variable)	The percentage of household members that performed work for a wage in the last 12 months before the interview
Livestock diversity (dependent variable)	The number of livestock species for which there was at least one animal owned by the household
Crop diversity (dependent variable)	The number of unique crop species grows by the household
Intercropping (dependent variable)	This is calculated by taking, for each plot of land, each crop there grown. Out of these, this variable counts the percentage that were intercropped
Maximum education (control variable)	The highest accredited degree of education attained by any member of the household, expressed in the number of years this education would nominally require. This includes pre-primary education
Family size (control variable)	The number of persons in the household
Ages (control variable)	The average (mean) age of the members of the household
Female ratio (control variable)	The ratio of women in the household
Time (control variable)	The date at which the household was interviewed
Weather Shocks (independent variable)	The sum of the intensity of weather shocks over a period of three and a half years (42 months) in the households' region

Food Insecurity (dependent variable)	The Food Consumption Score based on the frequency of consumption of different food groups (weighted) by the household
Interaction terms (dependent variable)	Each interaction term is the product of a adaptation strategy ('wage work', 'intercropping', 'livestock diversity' & 'crop diversity') and weather shocks

Table 4: A summary of included variables

Descriptive statistics

Variable	2010		2012	
	mean	std. dev.	mean	std. dev.
crop diversity	2.628	1.278	2.657	1.352
max education	8.292	3.149	8.550	3.256
livestock diversity	3.213	2.827	1.245	0.702
wage work	0.082	0.175	0.184	0.262
intercropping	0.614	0.406	0.596	0.411
family size	6.954	4.435	6.019	3.483
female ratio	0.512	0.181	0.513	0.194
Average age	24.872	11.493	25.443	12.840
food insecurity	58.561	17.746	57.656	18.881
low temperature shocks	0.734	0.893	1.310	1.562
high temperature shocks	1.119	1.074	0.965	1.125
low precipitation shocks	0.633	0.685	0.868	1.041
high precipitation shocks	0.260	0.400	0.672	1.136
weather shocks	4.490	2.816	7.126	4.289

Table 5: Means and standard deviations of the various variables in the dataset

Table 5 reveals the mean values and standard deviations for the measured variables across all individuals included in this dataset, across both waves of the survey that were included (2010 and 2012). From 2010 to 2012, crop diversities, highest education levels, individuals working for wages, the ratio of women and average ages of households trended upward. Meanwhile, the diversity of livestock, the implementation of intercropping, family sizes and food insecurity decreased. Finally, these individuals experienced more unusually cold, unusually wet and unusually dry weather conditions leading up to 2012 than 2010, but less unusually warm weather conditions. These weather conditions were highly variable between households, showing relatively high standard deviations.

Empirical strategy: Interaction terms

As discussed, this study seeks to uncover which actionable smallholder adaptation strategies moderate the impact of weather shocks on food security in Tanzania. In order to measure the moderating effect of crop diversity, wage work and other farming practices on the relationship between weather shocks and food insecurity, new variables were added named 'interaction terms'. The interaction terms are constructed by taking the product of two main effects, namely the weather shock intensity and one adaptation strategy. These are the regressed along with the main effects towards the 'Food Insecurity' variable. The goal is to measure to what degree these farming practices reduce the strength of the relationship between weather shocks and food security. Each interaction term is the product of one adaptation strategy and weather shocks intensity, leading to a composite variable.

Interaction term	Proxy for
Wage Work * Weather Shock intensity	How supplementary incomes from wage labor increases or reduces the vulnerability of a households' food security to local weather shocks, by enabling the household to buy food from the market
Livestock diversity * Weather Shock intensity	How rearing one or more species of livestock may allow a household to reduce the impact of local weather shocks on it's food security by providing an alternative source of food and/or income
Crop diversity * Weather Shock intensity	How relying on more crop species mitigates the vulnerability of a households' food production to local weather shocks by increasing agricultural resilience against specific weather conditions
Intercropping * Weather Shock intensity	How the practice of intercropping makes the household food production more robust in the face of adverse weather by improving soil, water and other environmental conditions and reducing pests

Table 6: The purpose of each interaction term

These interaction terms are analyzed in conjunction with the variables from which they are constructed in a multiple regression analysis, in order to differentiate direct correlations and the effects of statistical moderation.

Testing parameters & weights

In order to test the impact of selecting a different measure for household food security, three other methods for measuring dietary quality are tested. These are alternatives to the dependent variable 'food security'. These alternatives serve to test the sensitivity of the results to the method chosen for measuring food security. The alternative methods used as part of this analysis are the following:

- The percentage to which the household diet reached the standards for food groups outlined by the **EAT-Lancet** reference diet. For this analysis, average food densities and weights[2] were used in order to standardize data expressed in weight, volume and 'number of pieces' in the interviews.

- The number of months in the year leading up to the interview, during which the household reportedly experienced **food scarcity** to the point where there was insufficient food to feed the entire household. This is another, more simplified approach towards measuring food security, though it only considers the quantity of food, not the nutritious qualities of said food.
- The reported application of **rationing measures** by the household. For this category, all forms of rationing were weighted equally except for the cases where the household went '[…] a whole day and night without eating anything', which was counted as weighing as much as all forms of rationing combined. Like the previous method, this only considers the quantity of food, not its nutritious qualities.

Three choices regarding weather shock definition may also impact the results of this analysis and are thus tested with altered values as well. These alternative definitions serve to test how sensitive the results are to the definitions used for the parameters:

- The number of standard deviations from the mean weather used as a threshold over which weather shocks are counted; 0.5/(1)/2
- The number of months over which weather shocks values are summed in order to make a predictor for food insecurity; 36/(42)/48
- The weight given to each type of weather shock; +1/(0)/-1

This analysis will serve to test how robust the results are in the face of alternative approaches and decisions made by the author. In order to facilitate meaningful comparisons between the coefficients of different variables, the variables will be normalized as part of the regression analysis. In this case the method of normalization for each variable subtracts its mean value from the variable and divides the remainder by its standard deviation, thereby ensuring that the normalized variables each have a mean of 0 and a standard deviation of 1.

Initial run of the model (with equal parameters)

In order to test the core correlation of this study, namely between weather shocks and food security, the model is initially run with the following parameters:

- All types of weather shocks are included and weighted equally
- The three methods for measuring food security are all included and weighted equally
- The predictor variable w is calculated using weather shocks occurring over a period of 24 months prior to the household interview. (M=24)

The results of this first run of the model served to identify whether the model would run into problems regarding data, collinearity and sample sizes. The results from this initial run led to the exclusion of the maximum and minimum monthly temperatures from the weather shock predictor variable, due to their overlap with the average monthly temperatures.

[2] https://www.aqua-calc.com/calculate/food-volume-to-weight, as accessed in july 2021

Results

Coefficients of weather shock types

Multiple regression including all four types of weather shock (low/high temperature and low/high precipitation) correlated to food insecurity (as measured using the Food Consumption Score method) yielded the following results (table 7):

	Coefficient	p-value
Low temperature	2.1415	0.0000
High temperature	0.0151	0.9626*
Low precipitation	3.4671	0.0000
High precipitation	-0.8440	0.0094

Table 7: Multiple regression results correlating the types of weather shocks to food insecurity (FCS)

Two types of weather shocks are found to have significant positive correlations with food security: Low temperature shocks and low precipitation shocks. These two types of shocks are therefore included in the calculation of the predictor variable *w*, and their respective weights *A* and *C* are equal to the coefficients found here, namely 2.1415 and 3.4671 respectively. No weight was given to the other two types of weather shocks. The equation used to determine the predictor variable from weather shocks is thus as follows:

$$W(y_n) = \sum_{i=0}^{42} 2.1415 \cdot max(\frac{\overline{K} - Ky_{n-i}}{\sigma_K} - 1,\ 0) + 3.4671 \cdot max(\frac{\overline{P} - Py_{n-i}}{\sigma_P} - 1,\ 0)$$

Equation 6: Weather shocks variable quantification

The results of the multiple regression analysis of the independent variables, interaction terms and control variables as relating to the household food security score are shown in table 8. The food insecurity constant was found to be 64.3445, which is the food insecurity value expected in this model for a hypothetical household for which all variables are equal to 0. The regression coefficients can be understood to augment this starting value.

Quantity (survey wave specific)	Regression Coefficient	Normalized Reg. Coeff.
Local Weather shocks intensity (2012)	1.6034	0.3642
Livestock diversity (2010)	0.4515*	-0.0590
Livestock diversity (2012)	1.8548	0.1003
Livestock diversity change (2012 - 2010)	1.4033	0.0837
Intercropping (2010)	1.6233*	0.0349*
Crop diversity (2010)	1.4775	0.1000
Livestock diversity * weather shock intensity (interaction, 2012)	-0.5152	-0.2267
Intercropping * weather shock intensity (interaction, 2010)	-0.7941	-0.1222
Crop diversity * weather shock intensity (interaction, 2010)	-0.1432*	-0.0767*
Maximum education (2010) (SES proxy)	-0.5554	-0.0926
Maximum education (2012) (SES proxy)	-0.7217	-0.1245
Wage earning fraction of household (2010)	4.9028	0.0456
Family size (2012)	-0.5182	-0.0956
Ratio of women in household (2010)	-1.4666*	-0.0140*

Table 8: Results of the Multiple Regression Model connecting given variables to food insecurity (2012)
** not significant (p>0,05)*

Observing the calculated relationships between local weather shocks, adaptation strategies, control variables and food insecurity, we can see that local weather shocks, livestock diversity, crop diversity and wage earning work all show positive correlations with food insecurity, while the interaction terms show negative correlations with food insecurity instead. Notably, a reduction in livestock diversity between 2010 and 2012 shows a significant positive correlation with food security. Meanwhile, the size of a given household correlates negatively with food insecurity, with the remaining control variables having no statistically significant correlations to it. The strongest predictors for food insecurity are weather shocks, followed by the interaction term for livestock diversity and weather shocks.

Consequences of selected parameters and weights

In order to test relative importance of different parameters, it was tested how the relative coefficient change when an uncertain/arbitrary parameter is changed in either direction. This was done after an initial run where all arbitrary parameters are weighted equally, which serves as the basis for this test. The tested input parameters are the following:

- The selection of different food security variables E, F & R (EAT-Lancet, Food Consumption Score and implementation of rationing measures)
- The weights of different types of weather shocks (low/high precipitation and low/high temperature)
- The threshold for counting extreme weather as a weather shock
- The time horizon for counting weather shocks leading up to the date of a given survey

Each of the parameters was increased or decreased in order to see how this affects the correlations under study.

Variable	Food Insecurity measure method				Changes to Weather Shock weights								Shock time period		Shock threshold	
	Unaltered	Rationing	EAT-Lancet	Scarcities	A+1	A-1	B+1	B-1	C+1	C-1	D+1	D-1	36 months	48 months	0.5	2
maximum education 2010	-0.093	-0.045*	-0.09	-0.069	-0.092	-0.096	-0.092	-0.093	-0.094	-0.092	-0.093	-0.094	-0.099	-0.094	-0.094	-0.095
maximum education 2012	-0.124	-0.091	-0.142	-0.04*	-0.124	-0.126	-0.122	-0.127	-0.125	-0.124	-0.13	-0.121	-0.122	-0.126	-0.118	-0.136
weather shocks 2012	0.364	-0.034*	0.341	-0.045*	0.331	0.391	0.389	0.292	0.38	0.335	0.318	0.344	0.297	0.352	0.37	0.079*
livestock diversity 2010	-0.059	-0.022*	0.013*	-0.049	-0.056	-0.073	-0.055	-0.079	-0.064	-0.056	-0.063	-0.071	-0.082	-0.067	-0.01*	-0.103
livestock diversity 2012	0.1	-0.04*	0.11	0.081*	0.073*	0.111	0.131	0.056*	0.11	0.077*	0.11	0.077*	0.049*	0.097	0.244	0.005*
intercropping 2010	0.035*	0.113	0.049*	0.058*	0.032*	0.029*	0.063*	-0.017*	0.033*	0.033*	-0.012*	0.04*	0.017*	0.043*	0.082*	-0.048*
intercropping 2012	-0.021*	-0.042*	-0.058*	0.028*	-0.018*	-0.014*	-0.003*	-0.026*	-0.021*	-0.019*	-0.013*	-0.002*	-0.002*	-0.035*	-0.012*	-0.021*
crop diversity 2010	0.1	-0.057*	-0.023*	-0.124	0.094	0.1	0.149	0.063	0.101	0.095	0.063*	0.103	0.073	0.102	0.071*	0.057
crop diversity 2012	-0.039*	0.019*	-0.033*	-0.061*	-0.052*	-0.012*	-0.054*	-0.012*	-0.026*	-0.051*	0.005*	-0.056*	-0.026*	-0.048*	-0.096*	0.001*
wage work 2012	-0.005*	0.085	0.011*	0.064	-0.001*	-0.01*	0.003*	-0.01*	-0.007*	-0.001*	-0.013*	0.007*	0.002*	-0.003*	0.002*	-0.014*
wage work 2010	0.046	0.04*	0.066	0.015*	0.051	0.041*	0.047	0.046	0.043	0.051	0.045	0.053	0.056	0.051	0.052	0.05
family size 2010	0.027*	0.031*	-0.011*	0.098	0.033*	0.023*	0.022*	0.038*	0.024*	0.032*	0.031*	0.037*	0.033*	0.033*	0.032*	0.051*
family size 2012	-0.096	0.037*	0.043*	0.018*	-0.094	-0.098	-0.09	-0.101	-0.096	-0.094	-0.098	-0.097	-0.093	-0.093	-0.09	-0.104
ratio of women 2010	-0.014*	0.009*	-0.011*	0.045*	-0.013*	-0.015*	-0.015*	-0.014*	-0.015*	-0.013*	-0.015*	-0.013*	-0.01*	-0.016*	-0.019*	-0.011*
ratio of women ratio 2012	-0.001*	0.011*	-0.103	-0.043*	-0.002*	0.001*	0.003*	-0.003*	-0.0*	-0.002*	-0.0*	-0.002*	-0.0*	-0.002*	0.003*	-0.003*
livestock diversity interaction 2012	-0.227	0.131*	-0.114*	-0.146	-0.183	-0.257	-0.257	-0.186	-0.245	-0.188	-0.246	-0.191	-0.146	-0.231	-0.352	-0.195
livestock diversity interaction 2010	-0.07*	-0.062*	-0.097	0.071*	-0.086*	-0.036*	-0.053*	-0.052*	-0.057*	-0.084*	-0.058*	-0.059*	-0.031*	-0.052*	-0.125	-0.001*
intercropping interaction 2010	-0.122	-0.084*	-0.112	-0.084*	-0.128	-0.109	-0.142	-0.066*	-0.116	-0.128	-0.061*	-0.119	-0.105*	-0.142	-0.146	0.013*
crop diversity interaction 2010	-0.077*	0.022*	0.032*	0.115	-0.062*	-0.085*	-0.153	-0.001*	-0.083*	-0.064*	-0.009*	-0.082*	-0.018*	-0.079*	-0.011*	0.038*
intercropping interaction 2012	0.021*	0.117*	0.035*	-0.009*	0.014*	0.014*	-0.005*	0.034*	0.022*	0.015*	-0.0*	0.009*	-0.013*	0.036*	0.002*	0.102
crop diversity interaction 2012	0.049*	-0.044*	-0.01*	0.115*	0.075*	0.001*	0.074*	0.009*	0.025*	0.073*	-0.013*	0.074*	0.023*	0.068*	0.106*	-0.025*
Δ livestock diversity (2012-2010)	0.084	0.012*	0.014*	0.069	0.074	0.1	0.088	0.092	0.091	0.075	0.09	0.09	0.094	0.09	0.071	0.104

Table 9: Impact on correlation coefficients of changes to the parameters
*(*red text indicates insignificance at $p < 0.05$)*

There was one coefficient which had a significant correlation but in the opposite direction when using reported food Scarcities instead of the Food Consumption Score to determine food insecurity: Crop diversity (2010) correlated negatively with food insecurity in that scenario instead of positively. All other significant correlations in this analysis maintained their direction. The default values for the weather shock weights *A*, *B*, *C* and *D* were 2.1514, 0, 3.4671 and 0 respectively, and each of these values was increased by 1 and decreased by 1 to test how this change affected the results.

The initial run of the model

The correlation between weather shocks and food security in the initial run of the model appeared stronger when less weight was given to droughts and/or extreme heat, and when more weight was given to extreme cold. The correlation coefficients between Weather Shocks and Food Insecurity in this run, using equal weights for all 4 types of weather shocks were as follows: (all four of these values were statistically significant)

Shocks-Insecurity coefficient	Shocks: across 36 months	Shocks: across 42 months
Including lean period	2.0768	1.9998
Excluding lean period	2.7321	2.3340

Table 10: Initial model shock-insecurity coefficients

By using the parameters as intended and outlined in the *methods* chapter, the strongest factor among the different types of weather shock appears to be droughts, with no discernible negative impacts from unusually high rainfall. The increased weight for droughts and the increasing of the range of time over which weather shocks were counted, increased this specific correlation.

Any deviation from the default weather shock threshold of ‘1’ appears to weaken the core correlation which is central to this study, namely that between weather shocks and food security. A defined shock threshold of 1 standard deviation from the local trend was maintained as a requirement for weather to qualify as a shock.

Projections of future Tanzanian shocks

In their article, Luhunga models projected climate changes on a regional level within Tanzania. [Luhunga, 2015] For all studied seasons, the model finds a likely decrease or lack of change in the number of consecutive dry days per time period for many regions. Meanwhile some isolated areas are likely to experience an increase in consecutive dry days, including parts of Lake Victoria and regional highlands. There is a great deal of regional differentiation in this model, which is based on a CMIP climate model.

However, there is a so-called ‘East African climate paradox’ when comparing models to empirical data: CMIP models have consistently projected increases in rainfall in East Africa, but empirical evidence has found an opposite trend of increasing droughts so far. [Ongoma et al., 2018] Considering this paradox, there is great uncertainty about the reliability of projections based on these models. As a crude alternative, the historic trend in weather shocks can be linearly extrapolated as an alternative based on empirical data from Tanzania. This simple approach does not capture the complexities of future climate change, but it avoids the problem that arises specifically when addressing climate change in east Africa. At the very least it can serve as a hypothetical example to illustrate how climate change might change food security outcomes in Tanzania.

Baxter and colleagues [Baxter et al., 2023] studied the sedimentary record of Lake Chala (Tanzania and Kenya) to analyse the links between precipitation, temperature and CO2 concentrations over a period of 75.000 thousand years. They find that in the current interglacial climate, temperature rises are linked with exacerbated droughts, which agrees with the empirical data from recent decades. This evidence thus appears to support a continuing trend that follows the empirical data rather than the climate model projections (CMIP). They conclude that this data supports the prediction that there will be more widespread water scarcity across the horn of Africa.

Considering the climate data from 1980 to 2020 in Tanzania, the trend for droughts remains roughly flat (see table 10), while the trend for unusually cold weather has increased over this time period. This can be used to calculate the average increase in weather shock intensity in Tanzania using the existing formula. It needs to be emphasized that the projections and models are uncertain regarding the future climate of East Africa.

These are the results obtained from a linear regression on the two relevant types of weather shocks from 1980 to 2012 across Tanzania based on the year.

Linear regression results	Low Precipitation Shocks	Low Temperature Shocks
Trend	0.000737	0.0181
Intercept	-0.893	-35.1

Table 11: Linear regression results for the significant weather shocks of both types over time

Should the linear trend of low precipitation and low temperature weather shocks continue, we would expect households to experience 43% more weather shocks by 2050 when compared to 2012. Such an increase in extreme weather would increase the positive impact of climate adaptation practices. Such a scenario is represented here by increasing the projected weather shock variable of the example household by 43%.

Household food insecurity predictors

The results of the main analysis were used to construct the following final equation:

$$I(p) = 64.34 + 1.85L + 1.4\Delta L + 1.48O + 4.9E - 0.56S10 - 0.72S12 - 0.52F + W\cdot(1.6 - 0.52L - 0.79X)$$

Equation 7: Predictive model

I = Food Insecurity (p = prediction)
L = livestock diversity
Δ*L* = Change in livestock diversity
O = crop diversity
E = Wage earning fraction of household
S = Socioeconomic Status proxy (maximum education)
F = Family size
W = weather shocks
X = Intercropping

The equation for predicting food security contains five parts: a constant, the direct impact of studied strategies, the impact of control variables, the impact of weather shocks, and finally the mitigating effect of strategies on weather shock impact.

This equation serves as a linear model for estimating the food security outcome for a given household based on the known statistically significant predictors outlined in this study. It could thus be used to make predictions for households given changes in their situation, and it can be used to predict reasonable expectations for improvements in household food security after adopting strategies to mitigate insecurity. It could in theory be used to give bespoke advice to households seeking to improve their food security given their unique characteristics. Naturally such advice would then need to be supplemented with more comprehensive analysis.

In order to show the impact of the variance in measured household data, figure 2 shows a sensitivity analysis based on a change in any given input variable of one standard deviation from the mean, based on the equation outlined above. For each variable changed as part of the sensitivity analysis, all other variables were kept constant at their mean value.

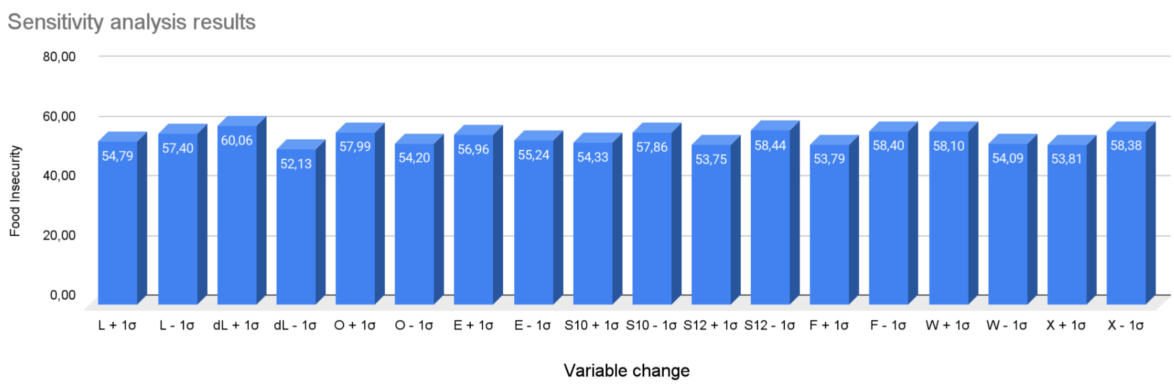

Figure 2: Sensitivity analysis results based on variation of inputs by one standard deviation

As an illustration of this equation, an anonymous individual was randomly selected from among the individuals included in the dataset. The selected individual lived in a household with the following characteristics: they held 2 species of livestock, down 1 from one from the previous survey wave. They grew 3 types of crops. 60% of their individual crop-fields were intercropped. One out of the four members in the household received wages from work outside the household. The highest achieved education of a member of the household was the equivalent of 9 years of study, in both waves of the survey. They experienced weather shocks with an intensity score of 4.31 leading up to the second wave of the survey.

Given these variables, the model predicts a food insecurity score of 59. The actual food insecurity score calculated for this individual was 52, from a Food Consumption Score of 60. The calculation of the predicted score using the main equation is as follows:

$$58.7 = 64.34 + 2*1.85 - 1*1.4 + 3*1.48 + 0.25*4.9 - 9*0.56 - 9*0.72 - 4*0.52 + 4.31*(1.6 - 2*0.52 - 0.6*0.79)$$

Based on the linear trend for weather shocks in Tanzania, we can substitute a different value for the *weather shocks intensity* value in order to simulate a rough estimate of the changing circumstances by 2050. Assuming a 43% increase in weather shocks intensity would yield the following projection (all else being equal):

$$59.2 = 64.34 + 2*1.85 - 1*1.4 + 3*1.48 + 0.25*4.9 - 9*0.56 - 9*0.72 - 4*0.52 + 6.16*(1.6 - 2*0.52 - 0.6*0.79)$$

We can observe that the impact on this particular household is minimal in this simulation, because the livestock diversity and intercropping practices offset the majority of the impact of weather shocks.

Interpretation & Discussion

This present study investigates the complex relationships between weather shocks, agricultural practices and food security among smallholders in Tanzania. A linear regression model with interaction terms is applied to investigate the effectiveness of various climate adaptation strategies available to smallholders in Tanzania. The National Panel Survey provided data concerning agricultural practices, diets and control variables, while a gridded global historical weather data model from the National Oceanic and Atmospheric Administration (NOAA) provided the basis for the identification and analysis of local weather shocks as discussed in *Methods - Data Sources* and *Methods - Weather Shocks*.

Food insecurity

Using the panel survey data, the households were assigned food insecurity scores according to the Food Consumption Score methodology. Among the analyzed households, 88% had an acceptable diet in the 2010-2011 wave of surveys, with almost 8% having a borderline diet and 4% having a poor diet. For the same households in the 2012-2013 wave of surveys, nearly 86% have an ‘acceptable’ diet, with more than 9% having a ‘borderline’ diet and roughly 5% having a ‘poor’ diet. This shows an increase in food insecurity between these two waves of the survey.

The mean value for the food insecurity (I) for the households in this sample changed from 58.561 to 57.656 in these waves of the survey. The threshold defining a borderline household diet lies 1 standard deviation higher than the mean (1.011 in 2010-2011 & 0.998 in 2012-2013) while the threshold defining a poor household diet lies 1.8 standard deviations higher than the mean (1.828 in 2010-2011 & 1.766 in 2012-2013). The measurement that roughly 87% of households had an acceptable diet lines up with the expectations regarding a normal distribution, where a limit of up to 1 standard deviation above the mean corresponds to a limit at the 84th percentile in the distribution.

Weather shock impacts on food security

Weather shocks have a significant impact on food security for smallholders in Tanzania. Even in the initial run of the model, using equal weights for all types of weather shocks and measures of food security, this relationship is statistically significant. The initial results show that this relationship is indeed more pronounced when weather shocks in the lean period (November-February) were excluded from analysis, thereby validating that decision. [see table 10] In the definitive model, this exclusion was thus maintained. Similarly, the conventional threshold of 1 standard deviation for defining weather shocks was maintained for all further analysis, and further analysis found that altering this value did not improve the correlation between weather shocks and food security. Doing so would have been controversial, since the definition of weather shocks using 1 standard deviation from the mean is based on the consensus among researchers.

Based on the coefficients of weather shocks to food insecurity, droughts and unusually low temperatures are shown to have significant impacts on the food security and dietary composition for smallholders in Tanzania. No significant relationship between warm weather shocks and food insecurity was found. This is somewhat surprising considering that Burke et al. has shown that even in the United States, crop production appears quite vulnerable to extreme heat despite the ongoing climate adaptation efforts they identified. [Burke et al., 2016] It is possible that the crops grown by Tanzanian farmers are better suited for extremely warm temperatures than those grown by farmers in the United States.

High precipitation weather shocks did have significant correlation with food insecurity, but the relationship is found to be negative, meaning that unusually high amounts of precipitation correlated to improved food security. Unusually dry weather is found to be the most impactful type of weather shocks, based on the high correlation coefficient between low precipitation shocks and food insecurity. Haile et al. [2018] found dry weather to be the most harmful type of weather shock in Tanzania, which agrees with the results obtained here. This may be explained due to the relatively dry climate in Tanzania on average, which means that unusually high local precipitation is still within healthy margins for most crops grown by smallholders. The region also has a relatively low amount of irrigation, making crops more dependent on rainfall. It remains to be seen whether climate change may make flooding more detrimental for Tanzanian smallholders, as flooding is projected to become a more severe problem for African agriculture.[IPCC, 2022]

The benefits of food production diversification and intercropping

The results obtained by multiple regression analysis suggest that higher levels of livestock diversity reduce the impact of weather shocks on food security. The same can’t be said (with statistical certainty) for crop diversity, based on these results. The academic literature helps to put these results into perspective: Based on the same panel survey data combined with weather data, Haile et al. [2018] concludes that Tanzanian weather shocks (dry spells, wet spells and heat waves) are associated with reduced rural household consumption expenditure. This latter statistic is used as a proxy for household welfare in that study. In essence, it is argued that weather shocks resulting in reduced harvests would thereby reduce the amount of produce households could sell, thereby reducing the income they had available to purchase more preferential food products from the market. In accordance with the findings here, they found dry spells to have the most pronounced effect. They stated that they were unable to disentangle sensitivity and adaptation effects regarding the moderating effects of crop and livestock diversity on weather shock induced food insecurity of households. That is where this present study manages to add to the existing conclusions, through the successful use of interaction terms. A study of food security in Ethiopia [Bakhtsiyarava & Grace, 2021] corroborates the improvement in food security of diversification. They find that increased crop diversity and livestock diversity increase food security based on the height and weight of children for their age in a household. This provides similar evidence that does not rely on panel survey data and makes the evidence of this statistical relationship more robust. This is only a direct relationship and does not draw conclusions about the moderating effect of these diversification on weather shock induced food insecurity.

However, Bakhtsiyarava & Grace [2021] find that crop diversity may in fact make farmers more vulnerable to droughts. They speculate this to be the result of both diminished food security as well as changes in childcare practices. This finding helps to contextualize the insignificant result concerning crop diversity: since droughts are the most significant drivers of food insecurity in Tanzania, they were given a correspondingly high weight in the analysis. Add to this the fact that wet spells and heat waves were excluded from the analysis due to the lack of statistically significant evidence that they caused reduction in food security, and it becomes clear that droughts are given a lot of weight in this context. The insight that crop diversity may make farmers more susceptible to droughts helps explain why crop diversity did not significantly reduce the impact of weather shocks on food security in this model. In fact, the results from the analysis of the impact of parameters and weights provides some support for this thesis: When unusually high temperatures were included in the calculation of weather shocks, a significant effect was found where crop diversity indeed reduced the impact of weather shocks on food security (see table 9, column 'B+1'). Shifting the focus away from droughts and towards heat waves thus reveals the positive effects of crop diversity. In Tanzania however, dry weather clearly poses a major risk to their food security, and investing into increased crop diversity may not be advisable in this context. Further research might investigate the effects of all four types of weather shocks on the food security of smallholders using different farming practices, including interaction terms.

One other interaction term yielded significant results: Intercropping, just like increased livestock diversity, appears to protect households by reducing the impact of weather shocks on their food security. This is also supported in the literature: Arslan et al [2017] find that intercropping maize and legumes provides yield benefits that are robust in the face of weather shocks when they are combined with organic fertilizer and soil and water conservation practices in Tanzania. This suggests that intercropping may reduce vulnerability to weather shocks best when combined with other specific adaptation strategies. However, their study was limited only to the growing of maize, and with legumes in the case of intercropping. This current study expands the scope by including all smallholders regardless of the specific crops grown. Similar complementary strategies may require more research, specifically by looking at sample data from smallholders which employ multiple complementary climate adaptation strategies. In any case however, intercropping maize with legumes appears to be a viable adaptation strategy in the face of increasing weather volatility for Tanzanian smallholders.

Livestock diversification - an anomaly?

Although livestock diversity reduced household vulnerability to weather shocks, food security correlated positively with high livestock diversity in the previous survey wave and negatively with the concurrent wave of survey. The hypothesis for the unexpected results concerning livestock is that maintaining livestock makes households more vulnerable to weather shocks, but households can slaughter or sell their livestock when times are tough to improve their food security. Selling livestock would provide a household with extra funds with which staple foods can be bought from the local market. This points to a likely delayed effect of livestock rearing on food security and weather shock vulnerability.

The moderating effect of selling livestock was also a factor in Gebre et al. [2023], where it was assessed along with five other adaptation strategies including diversifying income and the employment of drought-tolerant maize. This categorical study compared Tanzanian households that did adopt these strategies to those that did not and found the 'adopters' group to be twice as likely to attain food-security as the 'non-adopters' group. Their results also provided some proof that the vulnerable households that did not follow these strategies would have been as food-secure as the other group if they had adopted the strategies in question. This is to underscore the point that the adoption of these strategies is the key factor determining the food security outcomes, as opposed to these two variables both being the result of a third factor. This provides support for the interpretation that a direct causal link between the adoption of these strategies and increased food security exists. A limitation of that study is the lack of interaction terms to fully distinguish the direct effects of the adaptation strategies, the moderating effects, and the effects of the control variables.

Direct correlations to food security

Similar to this present study, Matsuura et al. [2023] use panel survey data and gridded weather data to investigate the empirical links between weather shocks, climate adaptation strategies and food security in Bangladesh. They find that weather shocks drive crop and income diversification of rural households. This supports the finding that weather shocks elicit a response from households: these households are more likely to adopt climate adaptation strategies when exposed to weather shocks. Their study does not provide evidence on whether these strategies proved effective in reducing the impact of weather shocks, merely that they were adopted by households that faced weather shocks. Since this data concerns households in Bangladesh, these findings suggest that the positive correlation between weather shocks and crop/livestock/income diversification may be found in many vulnerable countries across the world.

The correlations obtained in this study between adaptation strategies and food security may support this finding. The direct correlations, thus excluding the interaction terms, are positive, with the caveat that livestock diversity has a more complicated relationship with food security as was discussed previously. Crop diversity and wage work have significant positive correlations with food insecurity, which can be explained as a response from households to food insecurity. This does not directly imply causation, as the correlations between weather shocks and a subsequent adoption of adaptation strategies was not investigated in this regression model, but the results certainly don't clash with the interpretation offered by Matsuura et al.

Control Variables

The proxy variable for Social Economic Status (education) is negatively correlated with food insecurity, a likely affirmation that SES makes households less vulnerable. This conclusion is also borne out of the results of Gebre et al.[2023]. Since the proxy variable is included in the model and accounted for, the variable measuring the wage earning fraction of the household should not be taken as an indication of economic success, but a separate indicator of adaptation. The positive correlation with food insecurity suggests that members of the household take up jobs in times of crisis in order to supplement meager harvests. What is surprising however, is that no significant correlation was found between the corresponding weather shock interaction term and food security. If we take this to mean that wage labor does not significantly reduce vulnerability to weather shocks, as would be consistent with previous conclusions regarding variables showing the same pattern, then the explanation may be found in local spikes in food prices. The rising food prices caused by bad local harvests may undermine the protection that wages would otherwise give to smallholders against weather shocks. Further research might illuminate whether this observation differs in areas with reliable access to foreign markets. In lieu of more detailed data, this is merely a hypothesis. In any case, the data suggest that wage work is indeed an adaptation strategy rather than a control variable, although they do not suggest it is particularly effective in practice.

The other control variable that positively affects food security is the size of the household. This size of a household correlates negatively with its food insecurity, suggesting that larger families are better able to gain access to nutrition. On one extreme end of the spectrum, households that are smaller due to the presence of a single parent may be more challenged economically and in terms of available labor. On the other extreme, Tanzanian households regularly include extended families over more than two generations. The practice of polygamy is also not uncommon in Tanzania. It can be speculated that families with secure nutrition may be more successful in attracting additional family members by extended family members moving in, by marriages and by having more children when access to food is sufficient. More data is needed to confirm these causal relations.

The correlations concerning the ratio of women in the household yielded insignificant results. The existence of positive gender-effects was expected, but failed to reach the threshold for statistical significance outside of the initial run of the analysis. Its inclusion served to minimize the error in the model in order to obtain more clear results for the climate adaptation strategies, but it was also meant to support the results from gender studies. More thorough research on this topic serves to highlight not only the effect of the ratio of women in a household, but also their level of empowerment. [Kihiu, 2021] found that Kenyan households where women were more empowered had significantly better food consumption scores (FCS) than those where women were not. The fact that such a similar study using FCS found a significant relationship is likely due to the measurement of empowerment rather than merely the ratio of women in the household.

Robustness of results

The results obtained in this study have been checked against a range of parameters in order to test how well they hold up. This should give some insight into the degree to which the outcomes of this research are dependent on the decisions made during the setup of this thesis. In general, results which remain statistically significant over a wide range of alternative tests are considered highly robust. Such robust results include the reduction in food insecurity associated with socioeconomic status (using education level as a proxy), which holds up in 15 out of 16 tests in both waves of the survey. The complicated relationships between livestock diversity, food insecurity and weather shocks also appear quite robust, including the effects of reductions in livestock diversity. Furthermore, the fact that family size, employment for wages outside the household and exposure to weather shocks all correlate to food (in)security is maintained in 13 out of 16 tests performed for this analysis. Less robust are the correlation between crop diversity and food security. As is the moderating effect of intercropping on the impact of weather shocks on food security. These statistical relationships are observed in 11 out of 16 tests each.

This same analysis also shows which decisions in the setup of the research are most consequential in terms of altering the results. Most altered parameters that were tested had a limited impact on the significance or direction of the results. These changes include: small changes to the weights of different types of weather shocks, altering the number of standard deviations that acts as a threshold when defining weather shocks, and changes to the exact amount of time over which weather shocks are considered relevant to the food security of a household. In these tests, at least 9 out of 11 significant correlations are maintained, with one exception: increasing the threshold for defining weather shocks to 2 standard deviations reduced this number to 8 out of 11.

Far more consequential is the selection of a method for measuring food security in the first place. Using self-reported implementation of rationing measures in particular proved to obfuscate many of the results obtained in this research. The significant effect of socioeconomic status on food security was the only result that was maintained when switching to this method. Comparing the household diet to the EAT-Lancet reference diet or counting the reported instances of recent food scarcity as a method for measuring food security also led to noticeable changes in the results of the regression analysis, with only 6 or 3 of the significant correlations surviving the changes respectively. This shows that the results of similar studies hinges to a large degree on the exact method by which food insecurity is defined and measured. The Food Consumption Score is only one of many alternatives in the field of food security, and other methods not explored here, such as household reports on perceived food insecurity or stunted growth measured among children are likely to impact the results of any study concerning food insecurity outcomes. Such choices may lead to varying or even contradictory results across studies, which is complicated by the fact that there is no academic consensus about the best way to measure food insecurity.

In order to test the hypothesis that households slaughter or sell their livestock in order to compensate for the negative impact of weather shocks on food security, a new variable was added to the model and tested in the regression model: The change in households' livestock diversity between the two waves of the survey. The results do support the hypothesis, as a reduction in livestock diversity between the two waves correlated with reduced food insecurity. This is in line with the expectations under the assumption that families slaughter and/or sell livestock in times of distress to increase their food security. When considering the positive correlation between food insecurity and the maintenance of livestock, livestock appears to act as a type of insurance: Smallholders accept slightly lower food security most of the time in order to have the option to mitigate the worst impacts of extreme weather conditions.

Limitations and opportunities for further research

Despite the insights from this study, there are several limitations that limit the conclusions and the degree of certainty which can be derived from it.

The first limitation of the present study is the limited timespan over which survey data was included, as a result of the changes made to the questionnaires over the years. These changes made answers from questionnaires from some of these surveys incompatible with one another. One consequence of this is that the period over which weather shocks were counted fully overlaps with the time period between the first and second waves of the survey used in this study. This makes it harder to compare the effects of weather shocks from one wave to another. In the current setup, weather shocks experienced from 2008 to 2010 are included in the calculations of weather shocks for both waves of the survey. Shortening the period over which shocks are counted is not advised, as this would ignore the delayed effects of damage done to harvests on household food security. Using questionnaires from a broader time period also allows researchers to test whether exposure to weather shocks leads to a response from households, such as the increased adoption of adaptation strategies. This present study does find positive correlations between weather shock exposure and the application of adaptation strategies. Further research may measure the changes in adoption rates after exposure to weather shocks and expand the time period over which these effects are measured.

Another limitation is the use of a single predictor based on different types of weather shocks: further research may use interaction terms to test the degree to which adaptation strategies reduce the impact of each of the four types of weather shocks separately. This appears especially promising for research including the effects of crop diversity. The inclusion of extremely high temperatures and precipitation may help contrast the climate adaptation practices of smallholders in various weather conditions.

The definition of weather shocks in terms of standard deviations from a long term local climate trend, as opposed to absolute values, also introduces limitations. It obfuscates the effects of absolute temperatures and precipitation when these are part of the long term trend. When the local weather is rapidly trending away from the norm, farmers may well be hard-pressed to adapt and thus suffer from reduced food security. This can’t be distinguished from the results in this study.

Furthermore, the lack of a consensus regarding the future projections for weather shocks in Tanzania makes it difficult to estimate just how immediate the need for climate adaptation against extreme weather is for the smallholders in Tanzania. The differences between projections of extreme weather in East-Africa and the empirical data has been documented in the academic literature, and this paradox creates great uncertainty regarding the extent of future extreme weather risk. This thesis finds that climate adaptation strategies do broadly appear effective in reducing the impact of unusually low temperatures and precipitation, but it is unclear whether these specific types of extreme weather will become more or less prevalent in the coming decades. Further research in the field of climate modeling could dispel this uncertainty by constructing a weather model that better fits the empirical data while taking into account the future effects from climate change in the region.

Finally, aggregating data from across Tanzania necessarily sacrifices geographic resolution. A country as large and diverse as Tanzania may include different regional microclimates, which could be analyzed separately in order to obtain recommendations specific to these regions. In this context, it may be especially valuable to make a distinction between regions which experience unimodal rainfall patterns as opposed to bimodal rainfall patterns.

Conclusions

International commitments to end hunger throughout the world may be complicated by the negative effects of climate change on smallholders. The results of this study suggest that the diversification of livestock and the practice of intercropping both reduce the impact of weather shocks on household food security in Tanzania. In contrast, increasing crop diversity does not appear to have the same beneficial effect, possibly owing to an increased vulnerability to droughts specifically. Supplementing farm labour with income from wages earned outside the household also does not appear to reduce vulnerability to weather shocks, possibly due to a local spike in food prices.

Weather shocks show a clear impact on food security in Tanzania, while other factors appear to improve security, such as the social economic status of the household. The results show that the households most affected by food insecurity tend to also be the households which adopt some of the studied climate adaptation strategies, namely crop diversity, livestock diversity, and income from outside the household, suggesting a response to adverse climate conditions.

Despite the paradoxical outcomes of CMIP-models, predictions regarding climate change by the IPCC [2017] suggest that Tanzania will likely face more extreme droughts and floods in the future. Droughts and cold weather are found to reduce food security in this study thus it is expected that adaptation to droughts will become even more important in the future, and so will the farming practices that reduce vulnerability. As such, farming practices that have drawbacks in mild climate conditions but offer increased security during extreme conditions, such as rearing diverse livestock, may become more attractive to smallholders in Tanzania in the future. Through linear regression this study found that there is a correlation between food insecurity and two types of weather shocks: unusually low precipitation and unusually low temperatures.

This study adds to a growing body of evidence that specific farm practices protect smallholders against climate change and protect the food security of smallholders in regions vulnerable to weather shocks. Efforts to adapt to climate change will be more likely to achieve results if they promote farming practices that are resilient in the face of weather shocks. The relatively dry climate and low levels of irrigation in Tanzania make the mitigation of the impact of dry weather especially crucial. Drought-resistant farming practices are therefore on the forefront of climate adaptation.

Literature

Ajefu, J. B., & Abiona, O. (2020). The Mitigating Impact of Land Tenure Security on Drought-Induced Food Insecurity: Evidence from Rural Malawi. *The Journal of Development Studies, 56(12)*

Arslan, A., Belotti, F., & Lipper, L. (2017). Smallholder productivity and weather shocks: Adoption and impact of widely promoted agricultural practices in Tanzania. *Food Policy*, 69

Baijukya, F. P., Sabula, L., Mruma, S., Mzee, F., Mtoka, E., Masigo, J., Ndunguru, A., Swai, E. (2020). *Maize production manual for smallholder farmers in Tanzania.*

Bakhtsiyarava, M., & Grace, K. (2021). Agricultural production diversity and child nutrition in Ethiopia. *Food Security*, *13 (6)*

Barrett, C. B. (2013). Food or Consequences: Food Security and Its Implications for Global Sociopolitical Stability. *Food Security and Sociopolitical Stability*. Oxford University Press.

Baxter, A. J., Verschuren, D., Peterse, F., Miralles, D. G., Martin-Jones, C. M., Maitituerdi, A., Van der Meeren, T., Van Daele, M., Lane, C. S., Haug, G. H., Olago, D. O., & Sinninghe Damsté, J. S. (2023). Reversed Holocene temperature–moisture relationship in the Horn of Africa. *Nature (London)*, *620*(7973)

Bellemare, M. F. (2015). Rising Food Prices, Food Price Volatility, and Social Unrest. *American Journal of Agricultural Economics*, 97(1)

Benson, T. (2021). *Disentangling food security from subsistence agriculture in Malawi.* International Food Policy Research Institute (IFPRI).

Bozzola, M., & Smale, M. (2020). The welfare effects of crop biodiversity as an adaptation to climate shocks in Kenya. *World Development, 135*

Burke, M. B., Miguel, E., Satyanath, S., Dykema, J. A., & Lobell, D. B. (2009). Warming increases the risk of civil war in Africa. *Proceedings of the National Academy of Sciences - PNAS, 106(49)*

Brander, M., Bernauer, T., & Huss, M. (2021). Improved on-farm storage reduces seasonal food insecurity of smallholder farmer households – Evidence from a randomized control trial in Tanzania. *Food Policy*, *98*

Brewer, T. (2023). *Climate Change : An Interdisciplinary Introduction* (First edition.). Springer Nature Switzerland AG.

Brinkman, H. J., & Hendrix, C. S. (2011). *Food Insecurity and Violent Conflict: Causes, Consequences, and Addressing the Challenges*

Brüntrup, M., Schwarz, F., Absmayr, T., Dylla, J., Eckhard, F., Remke, K., & Sternisko, K. (2018). Nucleus-outgrower schemes as an alternative to traditional smallholder agriculture in Tanzania – strengths, weaknesses and policy requirements. *Food Security, 10(4)*

Burke, M and Emerick, K., 2016. Adaptation to Climate Change: Evidence from US Agriculture. *American Economic Journal: Economic Policy*, 8 (3)

Cook, K. H., & Vizy, E. K. (2012 B) Impact of climate change on mid-twenty-first century growing seasons in Africa. *Climate Dynamics, 39* (12)

Demeke, A. B., Keil, A., & Zeller, M. (2011). Using panel data to estimate the effect of rainfall shocks on smallholders food security and vulnerability in rural Ethiopia. *Climatic change, 108*(1)

Eriksen, S. H., Brown, K., & Kelly, P. M. (2005). The dynamics of vulnerability: locating coping strategies in Kenya and Tanzania. *The Geographical Journal*, *171*(4)

Fan, Y., and van den Dool, H. (2008), 'A global monthly land surface air temperature analysis for 1948-present', *J. Geophys. Res., 113*

FAO (2025), Figure: *United Republic of Tanzania crop calendar (major foodcrop) and lean period*, reference date 22-January-2025, accessed via: https://www.fao.org/giews/countrybrief/country.jsp?code=TZA&lang=ar

FAO (2016), *AQUASTAT Country Profile – United Republic of Tanzania.* Food and Agriculture Organization of the United Nations (FAO). Rome, Italy

Feleke, S. T., Kilmer, R. L., & Gladwin, C. H. (2005). Determinants of food security in Southern Ethiopia at the household level. *Agricultural Economics, 33*(3)

Gebre, G. G., Amekawa, Y., Fikadu, A. A., & Rahut, D. B. (2023). Do climate change adaptation strategies improve farmers' food security in Tanzania?. *Food Security*, 15(3)

Haile, B., Signorelli, S., Azzarri, C., & Johnson, T. (2018). Welfare effects of weather variability: Multi-country evidence from Africa south of the Sahara. *PloS One*, *13*(11)

He, Z., Ding, X., & Lu, Q. (2025). Research on the Impact of Meteorological Disaster Shocks and Risk Perception on Farmers' Cooperative Pest and Disease Control Behavior. *Agriculture, 15*(6)

IPCC (2014): *Climate Change 2014 – Impacts, Adaptation and Vulnerability:* Part B: Regional Aspects: Working Group II Contribution to the IPCC Fifth Assessment Report. Cambridge University Press.

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

Kihiu, E. (2021). *Gender, access to agricultural resources and food security in Kenya*. Kenya Institute for Public Policy Research and Analysis.

Kubik, Z., & Maurel, M. (2016). Weather Shocks, Agricultural Production and Migration: Evidence from Tanzania. *The Journal of Development Studies, 52(5)*

Lagi, M., Bertrand, K. Z., & Bar-Yam, Y. (2011). *The food crises and political instability in North Africa and the Middle East*.

Letta, M., Montalbano, P., & Tol, R. S. J. (2018). Temperature shocks, short-term growth and poverty thresholds: Evidence from rural Tanzania. *World Development*, *112*

Lyon, B. and DeWitt, D. G., (2012) A recent and abrupt decline in the East African long rains. *Geophysical Research Letters, 39* (2)

Luhunga, P. M. (2025). Projected changes in climate extremes over Tanzania. *Scientific Reports*, *15*(1)

Maharjan, K. L., & Joshi, N. P. (2011). Determinants of household food security in Nepal: A binary logistic regression analysis. *Journal of Mountain Science, 8*

Maystadt, J.F., & Ecker, O. (2014). Extreme Weather and Civil War: Does Drought Fuel Conflict in Somalia through Livestock Price Shocks? *American Journal of Agricultural Economics, 96(4)*

Matsuura, M., Luh, Y., & Islam, A. H. Md. S. (2023). Weather shocks, livelihood diversification, and household food security: Empirical evidence from rural Bangladesh. *Agricultural Economics, 54*(4)

NASA (2006), Historic Tropical Cyclone Tracks. *Image of the Day for November 2*. National Aeronautics and Space Administration, Earth Observatory: https://earthobservatory.nasa.gov/images/7079/historic-tropical-cyclone-tracks

NBS (2020), *HOUSEHOLD BUDGET SURVEY 2017/18. FINAL REPORT*. National Bureau of Statistics Tanzania (NBS). Tanzania Integrated Household Budget Survey

Ongoma, V., Chen, H., & Gao, C. (2018). Projected changes in mean rainfall and temperature over East Africa based on CMIP5 models. International Journal of Climatology, 38(3)

PRB (2024), *2024 World Population Datasheet: Eastern Africa*. Population Reference Bureau (PRB) https://2024-wpds.prb.org/africa/#eastern-africa

Richardson, K.J., Lewis, K.H., Krishnamurthy, P.K. (2018) Food security outcomes under a changing climate: impacts of mitigation and adaptation on vulnerability to food insecurity. *Climatic Change 147*

Rusinamhodzi, L., Corbeels, M., Nyamangara, J., & Giller, K. E. (2012). Maize−grain legume intercropping is an attractive option for ecological intensification that reduces climatic risk for smallholder farmers in central Mozambique. *Field crops research, 136*

Serraj, R., & Pingali, P. (2018). *Agriculture & Food Systems To 2050.* World Scientific Publishing Co.

Trenbath, B. R. (1993). Intercropping for the management of pests and diseases. *Field crops research, 34*(3-4)

Van Keulen, H., & Schiere, J., (2004) Crop-livestock systems: old wine in new bottles.

Vizy, E. K. and Cook, K. H., (2012) Mid-twenty-first-century changes in extreme events over northern and tropical Africa. *Journal of Climate, 25* (17)

VAM Resource Centre (2024), *Food Consumption Score & Food Consumption Score Nutritional Analysis, Guidance Note*. Last accessed 12-’24 at: https://resources.vam.wfp.org/data-analysis/quantitative/food-security/food-consumption-score. Doc.: https://docs.wfp.org/api/documents/WFP-0000158062/download/

Wilson, R. T., & Lewis, J. (2015). The maize value chain in Tanzania. *A report from the Southern Highlands Food Systems Programme*

Wineman, A., Jayne, T. S., Isinika Modamba, E., & Kray, H. (2020). The changing face of agriculture in Tanzania: Indicators of transformation. *Development Policy Review*, *38*(6)

Wing, I.S., De Cian, E., Mistry, M.N., (2021) Global vulnerability of crop yields to climate change. *Journal of Environmental Economics and Management*, 109.

Xie, P., Arkin, P.A., (1997), Global precipitation: A 17-year monthly analysis based on gauge observations, satellite estimates, and numerical model outputs. *Bull. Amer. Meteor. Soc., 78*