ESSAYS ON THE ECONOMICS OF CLIMATE SHOCKS, FOOD SECURITY, AND SUSTAINABLE AGRICULTURE

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ESSAYS ON THE ECONOMICS OF CLIMATE SHOCKS, FOOD SECURITY, AND SUSTAINABLE AGRICULTURE

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“Nothing in life is as important as you think it is, while you are thinking about it.”

Daniel Kahneman

For my mother, Eleni and my daughter, Koralia.

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ACLED Armed Conflict Location and Event Data Project

DRC Democratic Republic of Congo

ESS Ethiopia Socioeconomic Survey

FEWS NET Famine Early Warning Systems Network

FIES Food Insecurity Experience Scale

GDP Gross Domestic Product

HDDS Household Dietary Diversity Score

HFIAP Household Food Insecurity Access Prevalence

HFIAS Household Food Insecurity Access Scale

IPC Integrated Food Security Phase Classification

MAE Mean Absolute Error

ML machine learning

NDVI Normalized Difference Vegetation Index

PPVT Peabody Picture Vocabulary Test

PSNP Productive Safety Net Program

RF Random Forest

RMSE Root Squared Error

SAPs Sustainable Agricultural Practices

SNNP Southern Nations and Nationalities People's Region

SPEI Standardized Precipitation Evapotranspiration Index

XGBoost Extreme Gradient Boosting

YLS Young Lives Study

SUMMARY

This dissertation studies climate change and its impact on sustainable development in Africa. My first essay is on the impact on droughts on children's educational outcomes and health outcomes. I compile a panel dataset on Ethiopian children and monthly precipitation data to find that droughts decrease children's likelihood of being enrolled in school and negatively affect grade completion. Results also show that droughts increase stunting and thinness among children and increase household food insecurity. My second essay analyzes factors that help determine when farmers in Ethiopia adopt Sustainable Agricultural Practices (SAPs) such as crop rotation and mixed cropping. I find that receiving agricultural assistance encourages farmers to adopt crop rotation and that both SAPs have a powerful impact on reducing food insecurity among households. In my third essay, I use machine learning machine learning (ML) techniques to predict food insecurity in four countries in Africa. Since food insecurity results from complex interactions between economic shocks, climate change and regional conflict, I compile high frequency data on these indicators. I estimate two commonly used ML models, namely, Random Forest (RF) and Extreme Gradient Boosting (XGBoost) to predict food insecurity at district level. I find that the most important factors in predicting food insecurity are food price and vegetation indices. Overall I find that climate shocks, which are occurring at a high frequency and intensity, have detrimental effects on children's education, health and overall well-being. Sustainable agriculture will help farmers cope better with climate shocks and alleviate food security in the continent.

CHAPTER 1

INTRODUCTION

In 2015, almost 200 countries across the world jointly signed the Paris Agreement to address the growing threat of climate change and to limit the rise in global warming. Climate change has significantly altered weather patterns across the world. Declining rainfall and rising temperatures are making already dry regions drier. Droughts have affected more people around the world in the past four decades than any other type of natural disaster. They have an adverse impact on a country's economy, environment, public health, transportation, tourism, and other sectors[1] and they are particularly devastating in countries dependent on agriculture. Droughts have become more frequent and more intense especially in African countries and for this reason there is a need for evaluating the impact of droughts on well-being in such countries. We study the effect of droughts on children's well-being and specifically on their educational outcomes, since droughts tend to affect children disproportionately more than adults[1]. Additionally, we explore possible mechanisms that drive these results, finding that food insecurity is one of the most important factors during a drought that affects children.

The global population is projected to reach 9.7 billion by the year 2050.[2] The rising population entails increased food consumption and presents significant challenges for agriculture amplified by the effects of climate change, land degradation, and declining resources[2]. Unsustainable land management results in loss of agricultural land due to desertification, salinization, soil erosion[3], while affecting smallholder farmers, who depend on agriculture to make a living and constitute the majority of 800 million people worldwide

[1] https://www.nrdc.org/stories/drought-everything-you-need-know#increasing

[2] United Nations - Department of Economic and Social Affairs (https://www.un.org/en/desa/world-population-projected-reach-98-billion-2050-and-112-billion-2100)

that face hunger.[3] On the one hand, there is an urgent need to provide food for the increasing global population, but on the other hand it is important to conserve the environment and natural resources through promoting sustainable and climate resilient agricultural practices for holist agricultural development. We focus on the need for sustainable agriculture considering that agricultural production must increase by 60 percent by 2050 to meet global food demand [4]. Agriculture intensification has increased food production, but the focus on a few crops has resulted in biodiversity losses, increased pest pressure, soil erosion, soil organic matter losses, and greenhouse gas emissions. The adoption of sustainable agriculture systems or practices has the potential to ensure food security through sustainable agricultural yields and maintain environmental sustainability[5]. Additionally, growth in the agriculture sector has been shown to be at least twice as effective in reducing poverty as growth in any other sector[4] especially in developing countries, reinforcing the need for rendering agriculture systems more productive and less wasteful, through SAPs. Sustainable land management aims at improving our understanding on better management of the use of land and natural resources[6] and includes the use of agricultural practices that are economically and environmentally sustainable that can ensure a useful approach to tackling food insecurity.

Finally, we focus on the need for predicting food insecurity as it constitutes a major global challenge affecting millions of people worldwide. Almost 690 million people are hungry according to the Food and Agriculture Organization (2020)[5], while the number of undernourished people worldwide has been increasing in recent years, depending greatly on factors such as climate, location, and socio-economic conditions. Climate change poses a significant threat to food security by affecting agricultural productivity, water availability, and natural resources through increasing temperatures, altering weather patterns, and greater frequency of some extreme events such as droughts.[6] Additionally, conflict events

[3] United Nations (https://www.who.int/news)
[4] USAID Agriculture and Food Security (https://www.usaid.gov/agriculture-and-food-security)
[5] FAO (https://www.fao.org/sdg-progress-report/2020/en)
[6] ipcc - Food Security (https://www.ipcc.ch/srccl/chapter/chapter-5/)

and increases in food prices lead to further deterioration of food insecurity particularly in regions such as sub-Saharan Africa. The complex interactions of conflict, poverty, extreme weather, climate, and food price shocks (see [7]; [8]) affect food insecurity. Predicting food insecurity can lead governments and humanitarian organizations to obtaining information on the number of people that are food insecure, and therefore make informed and timely decisions on relevant policies and programs. To achieve targeted prevention, policies require the use of machine learning tools to predict food crises that will emerge in terms of time and location [9]. We use ML to predict the prevalence of food insecurity [10], since application of ML in this field can lead to informed decisions and timely interventions and can guide policy-making and program implementation towards mitigating hunger. The analysis in all 3 essays is based on data from Africa, because it is one of the regions most vulnerable to the impacts of climate change. Droughts, which are becoming more frequent and severe, directly affect agricultural productivity, and food security in Africa and understanding these dynamics is essential for developing effective adaptation strategies.

CHAPTER 2

IMPACT OF DROUGHT ON CHILDREN'S EDUCATIONAL OUTCOMES

2.1 Overview and Literature Review

In Africa, droughts are increasingly threatening the livelihoods of many in countries such as Ethiopia, and others in the horn of Africa. This chapter analyzes the impact of droughts on children's education in Ethiopia, a country ranked number one among the most drought prone countries in the world.[1] Ethiopia is one of the poorest countries in the world with a per capita gross national income of $890. Among the more than 100 million who live in the country, 80 percent live in rural areas and are engaged in agricultural or other pastoral activities.[2] Thus agriculture forms the backbone of the country's economy. Nearly 20 percent of Ethiopians are poor with incomes below the national poverty line. Global warming has played a pivotal role in increasing the frequency and severity of droughts in Ethiopia [11]. Previously Ethiopia used to experience drought every ten years or so, but in recent years, the frequency of droughts has increased to almost one in every three years. In the last two decades, Ethiopia has experienced major droughts in 2000, 2002–2003, 2006, 2011, 2015-2017, and 2021-2022.

Chuta (2014) found that shortage of rainfall in Ethiopia led to reduced agricultural output, which resulted in children leaving school and engaging in daily work [12]. Drought also led to death of livestock, which led to reduced nutrition among children and adversely affected their educational outcomes. Children in households reporting drought were more likely to have dropped out of primary schools in Ethiopia [13]. The amount of time children allocated to domestic activities, unpaid activities and paid labor were each found to have a positive effect on the probability of children dropping out of school. The impact of droughts

[1] World Atlas-Most prone countries in the world
[2] https://www.worldbank.org/en/country/ethiopia/overview

on cognitive achievement among children in Ethiopia was studied, and it was found that test scores of children from drought affected households were lower compared to other children [14]. Exposure to drought reduced a child's cognitive skills by 0.18 standard deviations. School enrollment and Peabody Picture Vocabulary Test (PPVT) were negatively affected by drought shocks in Ethiopia [15]. For each additional summer drought in early childhood, the child had 16 percent lower odds of completing schooling [16]. Moreover, droughts in Mexico reduced male school attendance by almost three percentage points [17]. Rainfall shocks in drought-prone region in Kenya had substantial negative effects on the cognitive development and educational achievement of girls [18].

On the other hand, there were no significant effects of droughts in Ethiopia on either school enrollment or on children's test scores [19]. Children in India reported a lower likelihood of work in drought years, and that children were more likely to attend school during drought [20], and it was estimated that children aged 11-13 completed about 0.2 more years of schooling for every drought they experienced whereas children who experienced more rainfall during school years had lower overall years of schooling as adults. A drought in Zimbabwe increased the probability that girls advanced in school, due to lower opportunity costs to education [21], while argued that the drought's positive impact on school attendance came through there being less demand for children's time outside of school. In Table 2.1, we list recent studies investigating the impact of droughts and rainfall shocks on children's educational outcomes in Ethiopia and other developing countries.

In this paper, we use a unique panel dataset on Ethiopian children that spans between 2009 and 2017. The data is compiled as part of the Young Lives Study (YLS) project, an international longitudinal study of childhood poverty led by the Department of International Development at the University of Oxford. An important contribution of the paper is that we combine the panel data on children with monthly rainfall data. We compile data from the global Standardized Precipitation Evapotranspiration Index (SPEI) to to identify droughts in different regions in Ethiopia.

Table 2.1: Impact of Drought on Children's Educational Outcomes: Overview of Literature

	Country	Variable	Natural Shock	Impact
Chuta (2014)	Ethiopia	School attendance	Shortage of rain	Negative
Berhane et al. (2015)	Ethiopia	Cognitive achievement	Drought	Negative
Woldehanna and Hagos (2015)	Ethiopia	Completion of primary education	Drought	Negative
Baloch and Behrman (2016)	Ethiopia	Enrollment PPVT scores	Drought	No effect
Randell and Gray (2016)	Ethiopia	Complete any schooling School attendance	Drought	Negative
Nguyen and Nguyet (2018)	Ethiopia	Enrollment Test scores	Drought	No effect
Shah and Steinberg (2015)	India	School attendance	Drought	Positive
Arceo-Gómez et al. (2020)	Mexico	School attendance	Drought	Negative
Nordstrom and Cotton (2020)	Zimbabwe	School enrollment Grade progression	Drought	Positive
Nübler et al. (2021)	Kenya	Cognitive development Educational achievement	Shortage of rain	Negative

Note: The list in Table 1.1 is not exhaustive of the literature but contains recent studies (2010 onwards) which have analyzed the impact of droughts on children's educational outcomes. Literature on the impact of rainfall shocks experienced in utero and during the first few years of life is not covered here; see Hyland and Russ (2019) and Randell and Gray (2019) for a review of this literature.

Our results show that droughts negatively affected children's educational outcomes. Droughts decreased enrollment levels by more than 36 percent and slowed grade progression in schools. In order to understand how droughts may affect schooling outcomes, we also study the impact of droughts on a child's living conditions including food security and well-being, on child's health using stunting scale, and on the time spent by a child on education, sleeping, paid activities, domestic tasks and household chores. In Figure 2.1, possible pathways affecting educational outcomes are presented. We find that with the onset of droughts, children's well-being declined, incidence of stunting increased since many households experienced an increase in food insecurity. Girls and children living in rural areas were severely affected by drought in terms of living conditions and health.

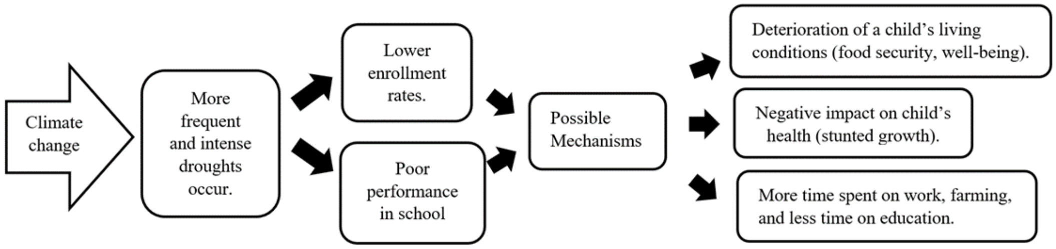

Figure 2.1: Possible ways in which Droughts may affect Educational Outcomes.
Note: Figure 1.1 includes possible pathways affecting educational outcomes that are considered in the current study.

2.2 Data

2.2.1 Young Lives Study Panel Data

The YLS data has several features that make it particularly appropriate for the proposed analysis. YLS uses a multi-stage sampling process to collect data from 20 sites across Ethiopia which are predominantly poor. Villages within each site are randomly selected and so are the households within each village. Although data is not representative nationally, data collection sites reflect heterogeneity of location, ethnicity, and religion in population. We use YLS data on children born in 2001-2002.Data on these children was compiled from rounds in 2009-2010, 2013-2014 and 2016-2017 (latest round) when the children were about 8, 12 and 15 years old respectively. The YLS has a low attrition rate of about 2 percent.[3] On removing observations with missing values, we have a sample of 1,093 children per round. Very few households in the panel, less than 1 percent, migrated during the three rounds. Table 2.2 shows summary statistics of key variables during the three rounds.

Data on Children's Educational Outcomes

YLS collects data on enrollment in school and the grade completed at the time of the interview. Only about 64 percent of children around age eight were enrolled in school in

[3] Outes-Leon and Dercon (2009) found that the attrition in YLS panel data is highly unlikely to bias inferences.

the 2009-2010 round. That percentage increased to 97 percent in 2013-2014, when these children were about 12 years old. Most children in the sample had not completed grade one at the age of eight. At the age of 12, children completed grade three and at the age of 15, they had completed grade five. We calculate relative grade as the ratio of the grade a child has completed divided by the grade the child should have completed based on the child's age [22]. Thus, a relative grade of less than one indicates that the child has not been able to complete a grade at the expected age. For example, in 2016-2017, an average relative grade of 0.773 indicates that for children who should have completed grade 8 at the time of the interview, had actually completed 6.18 grades, which means that they were about 2 grades behind on average.

Data on Mechanism Variables

We also compile data on other variables such as children's well-being, health and their time allocation. The household food insecurity index describes the food situation in the last 12 months using a scale 1-4, where 4 indicates more food insecure households; on average, the food insecurity index was slightly above 2 in all three years. The survey also asks children about their well-being status. The well-being score of one indicates a very poor quality of life and that of nine indicates very good living conditions. In our sample, the score was between 5 and 6, indicating good quality of life in all three rounds. We also compile data on the time a child spends on a variety of daily activities, namely, i) hours spent at school, studying at home, and doing homework, ii) sleeping, iii) working outside household on paid tasks, iv) working on household tasks that generate income such as farming, cattle herding and shepherding and v) time on household chores such as cooking and cleaning. Time spent on education varied between 5 to 7 hours and time for sleeping was between 9 to 10 hours per day. Children spent almost no time working for paid tasks in the first two rounds, but by the time they were 15 years old, they spent on average 0.2 hours on paid tasks. Children spent on average two hours on domestic tasks (such as farming, cattle herding and shepherding which generated income) and two hours daily on household chores.

Data on Household Characteristics

More than 87 percent households were male headed with the average age of household head between 43 and 50 years. The average household size was about six members. The average education level among fathers was grade four and for mothers it was grade two. We also compile data on changes in households since the previous round, in terms of death, or illness of a parent and/or other household member and divorce or separation. Since the YLS is conducted predominately in poor areas, the average wealth index was between 0.3 and 0.4. Productive Safety Net Program (PSNP) is a welfare program in support of the Government of Ethiopia's program that provides food and or cash to food insecure households in exchange for labor on rural infrastructure projects or direct transfers to households that cannot to participate in physical labor activities. About 30 percent of households received PSNP in 2009-10 and that percentage declined to 14 percent in 2016-17.

Table 2.2: Summary statistics of Panel data from the Young Lives Survey in Ethiopia.

No. of Obs. (1093 per round)	2009-2010		2013-2014		2016-2017	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Educational Outcomes						
Enrollment (yes=1, no=0)	0.640	0.480	0.971	0.169	0.939	0.240
Grade completion (0-10)	0.618	0.757	3.427	1.767	5.862	2.117
Relative grade	0.617	0.756	0.743	0.387	0.773	0.280
Mechanism Variables						
Food insecurity (1-4)	2.333	0.724	2.252	0.653	2.187	0.632
Child's subjective well-being (1-9)	5.397	1.961	5.818	1.818	5.919	1.562
Stunting z-score (0-2)	0.246	0.533	0.321	0.561	0.323	0.597
Time spent on education (hours per day)	5.801	2.940	7.135	1.860	7.254	2.344
Time spent on sleep (hours per day)	9.654	1.007	9.265	0.989	8.757	0.959
Time spent on paid work (hours per day)	0.001	0.030	0.050	0.388	0.169	1.083
Time spent on domestic tasks (hours per day)	1.720	2.225	1.749	2.006	1.783	2.136
Time spent on household chores (hours per day)	1.648	1.355	1.839	1.245	2.231	1.426
Control Variables						
Child's age (in years)	8.098	0.329	12.09	0.325	15.056	0.309
Height for age z-score (0-2)	-1.187	1.079	-1.438	0.947	-1.306	1.095
Male household head (yes=1, no=0)	0.940	0.238	0.870	0.336	0.906	0.292
Household head's age (in years)	43.472	9.106	46.746	9.119	50.164	9.165
Father's education level (1-15)	3.265	4.040	4.008	4.221	4.045	4.360
Mother's education level (1-14)	2.391	3.538	2.526	3.615	2.637	3.746
Hhd. Health shock (yes=1, no=0)	0.497	0.500	0.274	0.446	0.189	0.392
Household size (2-16)	6.503	1.843	6.294	1.807	6.226	1.761
No. children ¡ 6	1.092	0.826	0.756	0.802	0.608	0.735
No. children 6 – 18	1.841	1.238	1.795	1.091	1.618	1.050
Rural (yes=1, no=0)	0.726	0.446	0.726	0.446	0.724	0.447
Wealth index (0-1)	0.334	0.180	0.372	0.174	0.401	0.165
PSNP (yes=1, no=0)	0.302	0.459	0.212	0.409	0.142	0.349

Note: Source: Authors' calculations using the YLS data.

2.2.2 Climatic Data to Identify Regional Droughts

We compile rainfall data from the global SPEI database of the Climatic Research Unit of the University of East Anglia. The SPEI uses monthly difference between precipitation and potential evapotranspiration to measure a simple climatic water balance. Ethiopia experiences three seasons per year: (i) Kiremt (June to September), (ii) Bega (October to January) and (iii) Belg (February to May). We consider drought occurrence during Ethiopia's two grain growing seasons, namely Belg and Kiremt. Grain production (including mainly corn, wheat, sorghum, barley, and teff) greatly depends on rainfall patterns during the Belg season. The country receives much of its rainfall in the months of July and August (Kiermt season), though rainfall amounts vary across regions. The YLS compiles data from three to five sites in five regions in Ethiopia, namely, Tigray, Amhara, Oromia, Southern Nations and Nationalities People's Region (SNNP) and Addis Ababa City Administration. [4]

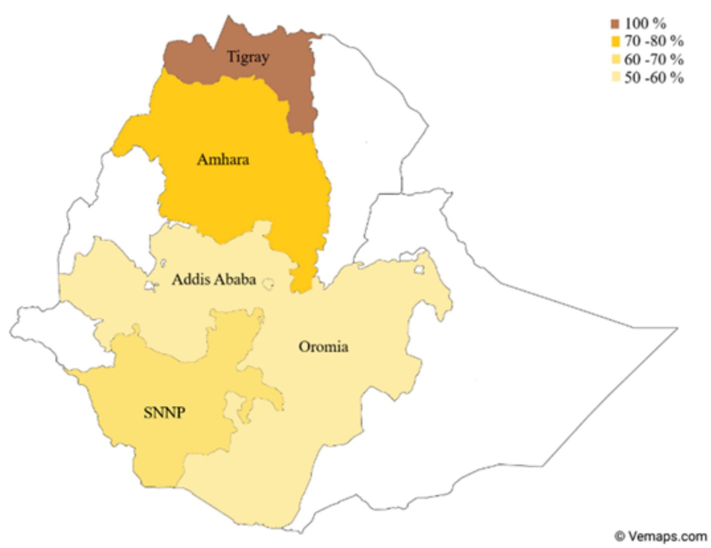

Figure 2.2: Regional Variation of Droughts in Ethiopia based on SPEI data.
Note: Figure templates used are from Vemaps.com. The figure shows the percentage of sites in a region which experienced drought based on SPEI data. The non-shaded parts indicate the regions, for which there is no data available in YLS.

[4]Sentinel site names are not used by YLS to protect the children's anonymity. For an approximation of sites' locations, we are using latitude-longitudinal coordinates based on the YLS study sites map and the description for each site (https://www.younglives.org.uk/sites/default/files/migrated/ETHIOPIA-SurveyDesign-Factsheet-Jan18_0.pdf). The GPS coordinates have been determined for each region site using https://www.gps-coordinates.net/

Typically SPEI value of less than -0.5 indicates a drought (see Appendix Table A1); we identify that a particular site has experienced drought in a particular season if the monthly average SPEI value for that season is less than or equal to -0.5. Table A2 in the Appendix shows that in 2009, all 20 sites experienced drought in at least one season in a year whereas in 2013, only 10 of the 20 sites experienced drought.

Figure 2.2 shows the percent of sites in a region, which experienced drought during the three rounds. As seen in the figure, droughts were more common in Tigray and less so in Addis Ababa. Tigray has sub-tropical climate with an extended dry period of 9 to 10 months and a maximum effective rainy season of 50 to 60 days. It is the only region in our sample which experienced drought during all three rounds. Droughts in Tigray severely affected agricultural production, since about 80 percent of the population in the region are farmers residing in rural areas. Amhara, which receives 80 percent of total rainfall of Ethiopia, is one of the most fertile regions. All survey sites in Amhara experienced drought in 2013, but only one site had drought in the last round in 2016.

2.3 Empirical Strategy and Results

In order to examine the relationship between droughts and a child's educational outcomes, we estimate the following baseline model:

$$Y_{irt} = \alpha_1 + \beta_1 * Drought_{rt} + \beta_2 * X_{irt} + \beta_3 * H_{irt} + \mu_i + \nu_r + \xi_t + \epsilon_{irt} \tag{2.1}$$

In Equation (2.1), Y denotes the educational outcome variable (enrollment, grade completion and relative grade) of child i, in region r, and in year t. *Drought* is a binary (yes or no) variable denoting whether there was a drought at the site where the household was located, X is a vector of child characteristics (age, age squared, lagged health-to-age z-scores) and H is a vector household characteristics (household head's gender and age, father's and mother's education, lagged household shocks, household's size, number of children, lagged wealth index and whether the household was in a rural area and whether it benefited from the PSNP welfare program in the last 12 months).[5] We include child fixed effects μ_i, region fixed effects ν_r, and year fixed effect ξ_t; ϵ_{irt} denotes the error term at child-level. We control for region fixed effects to capture differences in regional characteristics such as soil quality that may affect agricultural production.

2.3.1 Impact on Educational Outcomes

Table 2.3 summarizes estimates of the baseline model. Column 1 shows estimates for child's enrollment (yes or no) based on a logistic regression model. We consider the impact of drought on the number of grades completed using a Poisson regression model (Column 2) and on relative-to-age grade attainment (Column 3). Impact of drought on grade completion is assessed after controlling for the fact that the child was enrolled in school in the previous round.[6]

Table 2.3: Impact of Drought on Children's Education.

Educational Outcomes	Enrollment	Grade Completion	Relative Grade
	(1)	(2)	(3)
Drought	-1.010**	-0.043***	-0.059***
	(0.405)	(0.013)	(0.017)
Obs.	1,332	3,279	3,279
Obs. per round	444	1,093	1,093
Child, Year and Region FE	Y	Y	Y

Robust standard errors (clustered at child level) in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: Appendix Table A4 shows estimates for all control variables in the model. In logit model (1) used for enrollment, only the observations for which there has been a variation in enrollment among rounds are included.

[5] Although the YLS has data on school type (government funded, public, community or private), we do not control for this variable in our model due to more than 500 missing observations per round.

[6] The YLS also administered the PPVT, which measures a child's vocabulary and mathematics tests. We estimated Equation (1) using PPVT and math test scores as our dependent variables and found that there was no significant impact of drought on both variables in our sample (See Appendix Table A3). Nguyen and Nguyet (2018) also found that there were no significant effects of droughts in Ethiopia on children's test scores.

We find that droughts significantly affected children's schooling outcomes. Children who experienced drought saw a decrease in the log-odds by 1, that is, their odds of being enrolled were more than 36 percent lower than those who did not experience drought. School enrollment was found to be negatively affected by droughts in Ethiopia ([13], [15]). Another study tested whether enrollment in schools increased if schools were more likely to serve lunches during droughts in India [20]. However, no evidence to support this wa found. In fact, it was found that lunches were more likely to be provided in positive rainfall years, when districts had more resources. In Ethiopia, we found a decline in enrollment during drought years which may be partly explained by the fact that many schools closed during drought years. For instance, during the drought of 2016 over 9,000 primary schools in Ethiopia were partly closed and 1.2 million children were missing on education as schools were closed in the worst affected areas.[7]

Additionally, during droughts children also saw a significant decrease in their absolute grade. The difference in the logs of expected counts of grade decreased by 0.043, which corresponds to 4.2 percent decrease in the grade scale. Moreover, relative-to-age grade completion decreased by 0.05. This suggests, for example, that children above 16 years old would have lost an entire grade if they experienced a drought in the previous rounds. A drought in Mexico decreased school attendance among children aged 12 to 17 years [17]. Moreover, rainfall shocks indicative of meteorological drought at ages when children should be starting primary school negatively affected their grade completion [18].

Appendix Table A4 shows detailed results. Columns 3, 6 and 9 describe our baseline model and show that the control variables have expected signs. A child's lagged health-for-age score had a positive impact on enrollment and grades. Parents' education positively affected educational outcomes. Parental shocks such as illness and death had a negative impact on grades. Enrollment was positively affected when a household received PSNP welfare support.

[7] https://reliefweb.int/report/ethiopia/ethiopia-drought-schools-closing-livestock-dying-and-wells-drying

2.3.2 Drought's Impact on Children's Living Conditions and Time Allocation

There are several channels through which droughts tend to affect children's educational outcomes. Severe droughts significantly reduce households' income and may force households to migrate and children to drop out of school. For example, household wealth declined in regions with intense droughts in Mauritania [23]. Droughts and the subsequent decline in income forced children to spend more time working for paid jobs, farming or pastoral activities and/or helping with domestic chores. As a result, children tended to drop out of school and/or lag in their grade progression. Droughts in Central Mexico led to children dropping off from school and increasing their work participation [24]. Droughts also have an adverse impact on a child's physical health. Droughts had a significant impact on children's height at a young age, which adversely affect their school completion rates [25].

Table 2.4: Impact of Drought on Children's Living Conditions, Health, and Time Allocation.

	Living Conditions	Health		Time	Allocation			
	Food Insecurity	Well Being	Stunting	Paid work	Domestic tasks	Chores	Education	Sleep
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Drought	0.067***	-0.031*	0.071	0.078**	0.008	-0.196***	0.138	-0.099**
	(0.014)	(0.017)	(0.072)	(0.036)	(0.076)	(0.063)	(0.102)	(0.049)
Obs.	3,279	3,279	1,257	3,279	3,279	3,279	3,279	3,279
Obs. per round	1,093	1,093	419	1,093	1,093	1,093	1,093	1,093
Child, Year and Region FE	Y	Y	Y	Y	Y	Y	Y	Y

Robust standard errors (clustered at child level) in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: Appendix Table A5 shows estimates for all control variables in the model. In Poisson model (3) used for stunting, only the observations for which there has been a variation in stunting scale among rounds are included.

In order to understand the mechanism by which droughts may impact children's educational outcome, we estimate the model in equation (1) by alternately using data on a child's i) living conditions including food insecurity and subjective well-being, ii) health using stunting scale and iii) time spent on activities, as dependent variables.[8] Results are summarized in Table 2.4.

Droughts had an adverse impact on children's living conditions. The food insecurity index increased by 7 percent among drought affected households. Drought like conditions tended to negatively affect children's general health and increased food insecurity in households [13]. These children were less likely to enroll in primary school and often dropped out of school to work outside the house. Students reporting poor diet quality were less likely to do well in school [26]. Children who lived in households reporting very low food security had 0.65 times the odds of meeting expectations for reading and 0.62 times the odds of meeting expectations for mathematics. Although drought increased food insecurity in households, we did not find a significant difference in the incidence of stunting among children. However, the YLS also compiles data on subjective assessment of children's well-being. The well-being score of one indicates a very poor quality of life and that of nine indicates very good quality of life. Estimates in Table 4 show that children's well-being was significantly affected by droughts, with an expected decrease of 3 percent in the well-being scale. Rainfall shocks in early life affected cognitive development and self-reported health among children [18].

We found that children's time spent on activities was significantly affected by droughts. During natural calamities like a drought, households are often forced to take children out of school and ask them to work domestically or on paid jobs to supplement household income. We found that on average, children spent 0.078 hours more on paid work in drought affected areas. Our results are consistent with previous study, who found that less rainfall in Ethiopia entailed reduced agricultural output, so that children often had to leave school and had to work as daily labor [12]. Children had up to 34 percent more chance to be employed within five years after a natural shock [27]. We also found that children who experience

[8] YLS also collects data on household shocks such as death of livestock and crop failure. We found that there was no significant impact of drought on death of livestock but there was a significant impact on crop failure. However, data on crop failure has many missing observations so our sample size was reduced so much so that we had to force convergence to get estimates.

drought spend less time for household chores including cooking and cleaning. This may be attributed to the fact that drought leads to a scarcity of water and other resources, reducing the need for related chores. Additionally, during droughts, economic activities might shift, with families focusing more on finding income sources rather than maintaining household chores. Therefore, children might be involved in other activities to support the family financially, which in our study is consistent with the increase in time for paid work. Moreover, in some cases communities affected by drought receive aid and support from governments or other organizations, and this external support can alleviate some of the daily burdens on families, reducing the need for children to engage in chores. However, we found that children in households which had experienced drought spent significantly less time on sleep which may explain their slow progress in grade completion.

2.3.3 Gender Differences

Evidence in the literature suggests that the impact of natural shocks on educational outcomes and activities may differ for boys and girls. To account for heterogeneity between genders, we use an interaction term ($Drought_{rt} * Female$) in Equation (2.1)[9].

$$Y_{irt} = \alpha_1 + \beta_1 * Drought_{rt} * Female + \beta_2 * X_{irt} + \beta_3 * H_{irt} + \mu_i + \nu_r + \xi_t + \epsilon_{irt} \tag{2.2}$$

Estimates of Equation (2.2) are summarized in Table 2.5. We find that drought had a significant negative impact on enrollment for girls indicating that their odds of being enrolled were about 21 percent lower when they experienced drought. Drought also had a significant negative impact on girls' grade completion and relative grade. Droughts resulted in reduced school attendance among girls [17]. Parents tend to value less girls education compared to boys since girls are expected to marry and leave the household [28]. Drought

[9]We could not check for gender differences among siblings, because YLS gives a unique id to each child and we could not identify children living in the same household.

exposure during early life of girls was significantly associated with lower levels of education [29].

Table 2.5: Impact of Drought on Girls' Outcomes.

	Educational Outcomes			Living Conditions	Health		Time	Allocation			
	Enrollment	Grade Completion	Relative Grade	Food Insecurity	Well Being	Stunting	Paid work	Domestic tasks	Chores	Education	Sleep
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Drought	-1.565**	-0.045**	-0.052**	0.055***	-0.038	0.279**	0.026	0.005	-0.263***	0.034	0.061
*Female	(0.784)	(0.018)	(0.024)	(0.018)	(0.024)	(0.137)	(0.044)	(0.085)	(0.082)	(0.128)	(0.066)
Obs.	1,332	3,279	3,279	3,279	3,279	1,257	3,279	3,279	3,279	3,279	3,279
Obs. per round	444	1,093	1,093	1,093	1,093	419	1,093	1,093	1,093	1,093	1,093
Child, Year and Region FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Robust standard errors (clustered at child level) in parentheses *** p< 0.01, ** p< 0.05, * p< 0.1

Note: Appendix Table A7 shows estimates for all control variables in the model. In Poisson model (3) used for stunting, only the observations for which there has been a variation in stunting scale among rounds are included.

As seen in Table 2.5, the food insecurity index increased by almost 6 percent and stunting scale increased by 28 percent for girls in drought affected areas. Exposure to extreme drought led to reduced height in girls [29]. According to a study on the impact of malnutrition on academic performance of children in Ethiopia, the odds of good academic performance were lower among girls than boys [30]. We also found a significant decrease in the amount of time girls spent on chores in households affected by droughts.

2.3.4 Rural versus Urban Differences

To account for heterogeneity between rural and urban areas, we use an interaction term ($Drought_{rt} * Rural$) in Equation (1), indicating drought for rural areas to capture differences between their outcomes.

$$Y_{irt} = \alpha_1 + \beta_1 * Drought_{rt} * Rural + \beta_2 * X_{irt} + \beta_3 * H_{irt} + \mu_i + \nu_r + \xi_t + \epsilon_{irt} \quad (2.3)$$

Estimates in Table 2.6 show that children living in rural areas had 33 percent lower odds of being enrolled. Both absolute and relative grades of children in rural areas were significantly negatively affected. The food insecurity index increased by more than 7 percent and children's well-being scale decreased by similar magnitude. Children living in rural areas saw a significant decrease (0.3 hours per day) in time spent on education and an increase in the time spent on paid work outside the house (0.08 hours per day).

Table 2.6: Impact of Drought on Children's' Outcomes in Rural Areas.

	Educational Outcomes	Living Conditions			Health		Time	Allocation			
	Enrollment	Grade Completion	Relative Grade	Food Insecurity	Well Being	Stunting	Paid work	Domestic tasks	Chores	Education	Sleep
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Drought	-1.096**	-0.027*	-0.052***	0.071***	-0.074***	0.109	0.081*	0.136	-0.152**	-0.295**	0.007
*Rural	(0.449)	(0.016)	(0.018)	(0.016)	(0.020)	(0.077)	(0.046)	(0.089)	(0.073)	(0.120)	(0.055)
Obs.	1,332	3,279	3,279	3,279	3,279	1,257	3,279	3,279	3,279	3,279	3,279
Obs. per round	444	1,093	1,093	1,093	1,093	419	1,093	1,093	1,093	1,093	1,093
Child, Year and Region FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Robust standard errors (clustered at child level) in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note: Appendix Table A7 shows estimates for all control variables in the model. In Poisson model (3) used for stunting, only the observations for which there has been a variation in stunting scale among rounds are included.

Similar differences between rural and urban areas were found in several studies. Drought caused a more severe decline in children's cognitive achievement in rural India [31]. A study on the nutritional status and prevalence of malnutrition in students in rural schools showed that students with stunted growth had a significantly higher number of absences in school relative to students with adequate nutritional status[32]. Malnutrition among students in Ethiopia led to poorer academic performance among student from rural residences compared with those from urban areas [30].

2.3.5 Impact due to Higher Frequency of Droughts

So far in our analysis, drought is measured as a binary variable (yes or no) indicating whether the site in which the child resided experienced a drought or not. Instead, in this section, we estimate the impact of the frequency, that is, the number of droughts on children's outcomes. Estimates in Table 2.7, show that an additional drought decreased the odds of being enrolled by 45 percent. Grade completion and relative grade were also negatively affected. Children who experienced more frequent droughts saw an increase in time spent on domestic tasks which might be attributed to increased farming activities during subsequent dry seasons to minimize crop loss.

Table 2.7: Impact of Drought Frequency on Children's' Outcomes.

	Educational Outcomes	Living Conditions			Health		Time	Allocation			
	Enrollment	Grade Completion	Relative Grade	Food Security	Well Being	Stunting	Paid work	Domestic tasks	Chores	Education	Sleep
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
No. of Droughts	0.791*** (0.287)	-0.038*** (0.010)	-0.074*** (0.016)	0.030*** (0.011)	0.020 (0.014)	0.115** (0.056)	0.031 (0.025)	0.142** (0.061)	-0.209*** (0.045)	-0.115 (0.076)	0.020 (0.040)
Obs.	1,332	3,279	3,279	3,279	3,279	1,257	3,279	3,279	3,279	3,279	3,279
Obs. per round	444	1,093	1,093	1,093	1,093	419	1,093	1,093	1,093	1,093	1,093
Child, Year and Region FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Robust standard errors (clustered at child level) in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note: Appendix Table A7 shows estimates for all control variables in the model. In Poisson model (3) used for stunting, only the observations for which there has been a variation in stunting scale among rounds are included.

We also see a significant increase in food insecurity index and that with every additional drought stunting among children increased by nearly 12 percent. In Ethiopia, Belg rainfall has been found to declining over the past decades and climate models predict changes in kiremt rainfall, ([33] and [34]). These changing rainfall conditions are expected to impact child nutrition. Some regions in Ethiopia may see an increase in stunting rates associated with declining rainfall and more frequent and severe drought conditions [35].

2.3.6 Estimates using Alternative Self-Reported Data on Droughts

In addition to the SPEI data as drought indicator, we have some information on droughts in the YLS. The survey asked households whether they recall having experienced a drought since the previous round of the survey. The survey does not define what constitutes a drought and we do not have information on when the drought happened since the survey rounds were 3 to 4 years apart, so the recall period is considerably long. The YLS technical note warns that households answers are based on perceptions meaning that they do not show whether a negative event has actually occurred or not. As a result, there is a greater measurement error involved in YLS data on droughts and hence we relied on more accurate climatic data in our main analysis. However, in this section, we use the YLS data where households report experiencing one/multiple droughts since the last round.

Table 2.8: Impact of Drought Children's Education using self-reported data.

	Educational Outcomes	Living Conditions			Health		Time	Allocation			
	Enrollment	Grade Completion	Relative Grade	Food Insecurity	Well Being	Stunting	Paid work	Domestic tasks	Chores	Education	Sleep
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Drought	-0.408*	0.012	0.028	0.096***	-0.049***	-0.036	-0.015	0.101	0.044	-0.168	-0.057
(self-reported)	(0.232)	(0.017)	(0.020)	(0.014)	(0.016)	(0.064)	(0.041)	(0.096)	(0.065)	(0.127)	(0.051)
Obs.	1,332	3,279	3,279	3,279	3,279	1,257	3,279	3,279	3,279	3,279	3,279
Obs. per round	444	1,093	1,093	1,093	1,093	419	1,093	1,093	1,093	1,093	1,093
Child, Year and Region FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Robust standard errors (clustered at child level) in parentheses *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$

Note: Appendix Table A8 shows estimates for all control variables in the model. In Poisson model (3) used for stunting, only the observations for which there has been a variation in stunting scale among rounds are included.

We re-estimate our baseline model in Equation (2.1) and compile results in Table 2.8. Children in households reporting a drought saw a 0.41 decrease in the log-odds, indicating that the odds of being enrolled when experiencing drought were 0.67 times that of a child who did not experience drought since the last round. However, drought showed no statistically significant impact on either absolute or relative grade attainment. There was a significant increase in food insecurity and a decrease in well-being in households that reported they experienced droughts since the previous round. There were no significant differences in the time spent by children on different activities. Overall, we found that results based on climatic data were statistically more significant than those based on self-reported drought experiences.

2.4 Contribution and Limitations

In this chapter, we examined the impact of drought on educational outcomes and well-being among children in Ethiopia. We used a rich panel data which followed 2000 children in different regions of Ethiopia over nearly eight years. An important contribution of the paper was combining the YLS panel data with monthly rainfall data in Ethiopia. We used high-frequency SPEI based on climatic data to identify drought affected areas in Ethiopia. Our analysis investigated how droughts affected a variety of outcomes such enrollment, grades, health, food insecurity and time spent by children. We found that droughts had a significant adverse impact on children's education, and that in drought affected areas they were less likely to be enrolled in school.

However, there are certain limitations in the current analysis and we plan to extend it further in the future. For instance, we have not included data on conflict though Ethiopia witnessed conflicts during this period which may have adversely affected children's educational outcomes and well-being. Additionally, we would like to evaluate other mechanisms. For instance, we would like to find out whether droughts or other climate shocks such as floods led households to marry off young girls in return for dowry to make up for the loss of income. The current analysis will be enriched by these and other extensions.

CHAPTER 3

SUSTAINABLE AGRICULTURE PRACTICES: EXPLORING FACTORS INFLUENCING ADOPTION AND IMPACT ON FOOD SECURITY

3.1 Overview and Literature Review

In Ethiopia, agriculture is the backbone of the economy and constitutes the largest sector, and about 74 percent of the countries' farmers are small family farmers [36], who account for about 96 percent of the total area cultivated.[1] Agricultural sector accounts for more than 50 percent of Gross Domestic Product (GDP) and employs more than 85 percent of the labor force. Agricultural products constitute more than 80 percent of Ethiopia's exports, which is one of the highest shares in Sub-Saharan Africa. Agriculture is a top of priority sector in the Government of Ethiopia's ten-year economic development plan (2021-2030).[2] The agricultural sector is expected to grow at 6.2 percent per year over the next decade. Ethiopia's agriculture-based economy is mainly based on grain production, namely teff, maize, wheat, barley, and sorghum [36]. However, grain yields are relatively low due to poor land management, and insufficient supplies of fertilizer and improved seeds.[3] Ethiopia is also one of Africa's leading coffee producers, contributing to 26 percent of the total value of the country's exports.

In the interim, Ethiopia has been severely affected by food insecurity for decades. According to the World Food Program, an estimated 20.1 million people in Ethiopia require food support.[4] Food insecurity and malnutrition are still a major concern across Ethiopia despite important development gains over the past two decades, reducing poverty and ex-

[1]Farming In Ethiopia, Agriculture Crops, Livestock — Agri Farming (https://www.agrifarming.in/farming-in-ethiopia-agriculture-crops-livestock)

[2]Ten Years Development Plan (https://faolex.fao.org/docs/pdf/eth215704.pdf)

[3]Ethiopia-Agricultural Sector (https://www.trade.gov/country-commercial-guides/ethiopia-agricultural-sectors)

[4]World Food Program (https://www.wfp.org/countries/ethiopia)

panding investments in basic social services. In 2015, more than 60 percent of smallholder farms were found to live below the national poverty line [36]. Over 80 percent of Ethiopians live in rural areas and are heavily dependent on rain-fed agriculture, where productivity is still low due to overuse of natural resources and climate change. As a result, Ethiopia faces a reduction of per capita food production [37]. Limited food production and poor agricultural productivity have been attributed to land degradation [38], often caused by unsustainable agricultural practices.

SAPs encourage farming in a way that can protect, aid, and expand natural resources.[5] Among different SAPs, the two important ones are crop rotation, and mixed cropping [39]. Crop rotation is the practice of cultivating different sequences of crops on the same plot of land [40], while the planned rotation may vary from a growing season to a few years or even longer periods. It can have a major impact on soil health, due to emerging soil ecological interactions and processes that occur with time [41]. Crop rotation is the cheapest and the most effective way to improve crop yields and soil fertility, as well as reduce the opportunity for disease and pests to take hold, since their development cycles get interrupted by changing crops [40]. In Ethiopia, crop rotation systems are mostly used for cereals production [41]. Another practice practiced mainly by smallholders is mixed cropping, by which farmers produce crops simultaneously on the same farm. Mixed cropping practice leads to better yield compared to monoculture, since the fertility of the soil improves when the soil absorbs a variety of nutrients for multiple crops to grow. In case of loss in one crop there is another crop to cover for nutritional needs or provide income.

Sustainable agriculture practices are examined as important pathways to ensuring food and livelihood security among rural households in Ethiopia [42]. Previous studies have examined the relationship between SAPs and food security in African countries. The impact of diversifying crop production in Zambia has been studied and it is found necessary to ensure food availability [43]. The implementation of crop diversification and agroforestry

[5] National Agricultural Library (https://www.nal.usda.gov/farms-and-agricultural-production-systems/sustainable-agriculture)

is associated with higher food security status of smallholder households [44]. Crop diversification had positive and significant effect on household food security among rural farm households in Ethiopia [45]. Moreover, participation of farmers in agroecological trainings and farmer discussion groups for the adoption of agroecological practices including crop diversification and soil management practices had been found to increase food security according to [46]. Households who practiced mixed crop systems improved 50 percent of productivity and farm income in the highlands of Ethiopia compared to smallholders that did not undertake this practice [47].

The chapter reveals that among the most important agricultural determinants of adopting crop rotation is receiving agricultural assistance, whereas for mixed cropping is cultivating irrigated crops. Additionally, for adopting both SAPs, cultivated area and production on consumption ratio are significant. SAPs are found to have a powerful impact in reducing food insecurity. Therefore, this study recommends that it is important to determine future policies to reinforce SAPs adoption and improve food security.

3.2 Theoretical background

Most of previous research has identified the need for SAPs; however, an important contribution of this study is that it uses a unique panel data which extends from 2011 to 2016 to identify determinants of adopting crop rotation and mixed cropping, while analyzing SAPs' impact on food security in Ethiopia. Moreover, in order to determine whether a household experiences food insecurity conditions, we use multiple food insecurity indicators, which are calculated based on households' information on food consumption to further analyze whether farmers who adopted sustainable agricultural practices consistently succeeded in reducing household food insecurity (Figure 3.1). Relying on one food insecurity measure may not capture insecurity completely as these measures depend on several factors such as the frequency of experiences indicating food insecurity in household. We first include glsfies that has a 12-month recall period, where frequency is not captured. Therefore, we estimate Household Food Insecurity Access Prevalence (HFIAP) and Household Food Insecurity Access Scale (HFIAS) score in our study that can provide further insight on not only whether the household experiences food insecurity, but also on the frequency of food insecurity experiences which is important in classifying household as mild, moderate, severe food insecure. Consistency in results can verify the food insecurity conditions estimated in a household.

We offer a unique integrated approach on decoding the mechanisms that lead households to SAPs' adoption, while evaluating households' food conditions and examining whether SAPs can improve food security in a household. Identifying SAPs as means to improve food security at the household level, can provide valuable insight for policymakers and organizations leading to tailored interventions to meet the unique needs of different households, such as providing targeted agricultural assistance within the local context and socio-economic factors that influence food security.

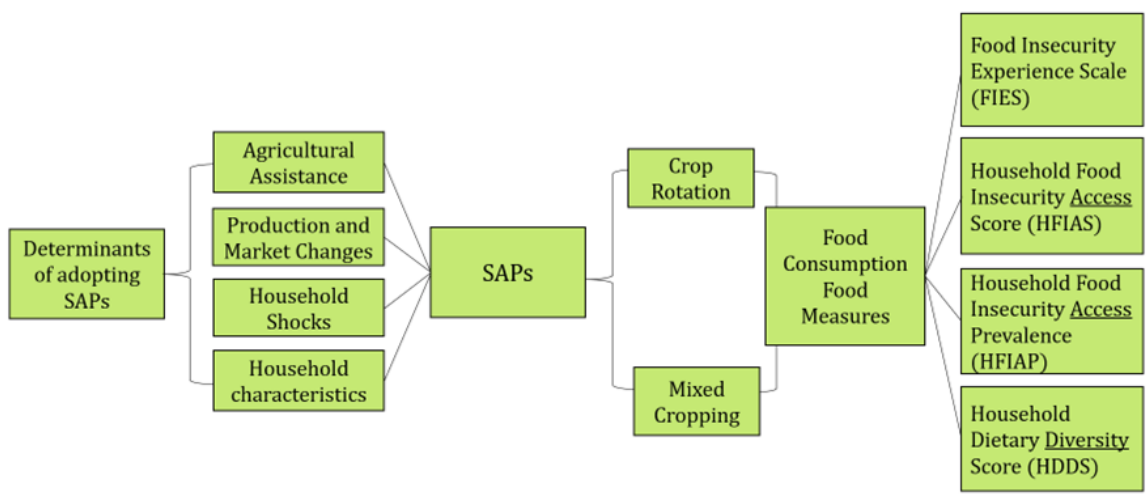

Figure 3.1: Mechanism Flow Chart.

The remaining sections of the paper are structured as follows. Section 3.3 describes data on households, SAPs, and food insecurity measures and empirical model specification. Section 3.4 presents regression estimates based on panel data models used to identify determinants of adopting SAPs, impact of SAPs on food security and discussion on findings, and Section 3.5 includes conclusion.

3.3 Data and Methodology

3.3.1 Ethiopia Socioeconomic Survey (ESS) Panel Data

In this paper, I use a unique panel data on Ethiopian households, located in rural and small-town areas [6], that spans between 2011 and 2016, and has not been extensively explored in previous studies.

Data are obtained from the ESS[7], which was implemented by the Central Statistical Agency of Ethiopia and Living Standards Measurement Study – Integrated Surveys on Agriculture team and includes three waves.

The ESS is a long-term project responding to the data needs of Ethiopia, given the dependence of a high percentage of households on agriculture. It collects information on agricultural assistance, household-level characteristics, as well as economic features.[8] An important contribution of this chapter is that the same households are included over time in the ESS. Through this, factors important for adopting SAPs over an extended period are identified. Additionally, the impact of the frequency of adopting SAPs on household food security is evaluated.

The ESS is the first panel survey combines a multi-topic household questionnaire with detailed data on agriculture.[9] The ESS began as the Ethiopia Rural Socioeconomic Survey in 2011/12, which is the first wave of data collection including rural and small-town areas. The second and third waves were carried out in 2013/2014 and 2015/16, respectively.

We consider two SAPs namely crop rotation and mixed cropping. According to Table

[6]The sample includes households in the most populous regions such as Amhara, Oromiya, SNNP, and Tigray and in small regions including Afar, Benshangul Gumuz, Dire Dawa, Gambella, Harari, and Somalie regions. (World Bank)

[7]The World Bank - Microdata Library: 1) Wave 1 - (ESS) 2011-2012 (https://microdata.worldbank.org/index.php/catalog/2053/get-microdata on [08/14/2022], 2) Wave 2 - ESS 2013-2014 (https://microdata.worldbank.org/index.php/catalog/2247/get-microdata) on [08/14/2022], 3) Wave 3 - ESS 2015-2016 (https://microdata.worldbank.org/index.php/catalog/2783/get-microdata) on [08/10/2022]

[8]https://microdata.worldbank.org/index.php/catalog/2053/study-description

[9]https://microdata.worldbank.org/index.php/catalog/2053/study-description

3.1, about 81 percent of the households use crop rotation in 2011-12, whereas almost 83 percent in 2013-14 and almost 82 percent adopted crop rotation during 2015-16 period. The percentage range of the households that applied mixed cropping decreases over time from 63 in 2011-12 to almost 58 percent in 2015-16.

Additionally, to identify factors, which are significant for SAPs implementation, I am comparing agricultural, production and household characteristics of the household for adopters and in-and-out adopters versus non-adopters[10] (Appendix Figure A1) for crop rotation and mixed cropping.

Table 3.1: Summary statistics of Data from the Ethiopia Socioeconomic Survey.

	2011-12		**2013-14**		**2015-16**	
Variables (1,425 Observations)	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
SAPs						
Crop Rotation(Yes=1, No=0)	0.813	0.390	0.830	0.376	0.821	0.383
Mixed Crop (Yes=1, No=0)	0.632	0.483	0.613	0.487	0.575	0.494
Food Measures						
Food Insecurity Experience Scale (FIES) (0-3)	0.592	0.946	0.449	0.842	0.577	0.925
HFIAS (0-18)	1.727	3.275	1.215	2.726	1.635	3.139
HFIAP (1-4)	1.619	1.069	1.458	0.935	1.563	0.987
Household Dietary Diversity Score (HDDS) (0-12)	5.066	1.611	5.483	1.729	5.490	1.549
Agricultural Characteristics						
Agricultural Assistance (Yes=1, No=0)	0.730	0.444	0.775	0.417	0.801	0.400
Irrigated crop (Yes=1, No=0)	0.149	0.357	0.134	0.341	0.131	0.337
Cultivated Area (0 - 9.98 ha)	1.859	1.928	1.577	1.651	1.569	1.614
Production on Consumption (ratio)	0.678	0.221	0.663	0.224	0.694	0.223
Market Conditions						
Increase of food prices (Yes=1, No=0)	0.222	0.416	0.126	0.332	0.180 .	0.385
Household Shocks						
Economic Shock (Yes=1, No=0)	0.079	0.270	0.046	0.209	0.073	0.260
Drought Shock (Yes=1, No=0)	0.160	0.367	0.072	0.259	0.316	0.465
Family Shock (Yes=1, No=0)	0.162	0.369	0.113	0.317	0.224	0.417
Household Characteristics						
Male Household Head (Yes=1, No=0)	0.839	0.367	0.828	0.377	0.816	0.388
Educated Household Head (Yes=1, No=0)	0.398	0.490	0.399	0.490	0.416	0.493
Household Size (1-17)	5.387	2.044	5.508	2.094	5.509	2.171

Source: Authors' calculations using the ESS data.

[10]I consider a farmer as adopter when he adopts each of the two SAPs at least once during 2011-2016 period and as non-adopter when he uses no SAPs during 2011-2016 period.

3.3.2 Data on Control Variables

As control variables the following are included: agricultural characteristics (agricultural assistance, irrigated crop, cultivated area), production and market conditions (portion of production on consumption and increase in food prices), household shocks including economic (income loss or death of livestock), drought, and family (death or illness) shock. Moreover, we control for household characteristics such as household head's gender and education level and household size. Almost 73 percent of households receive agricultural assistance in the first round and there is an increase in households participating in extension programs[11] to almost 80 percent during 2015-16. The portion of irrigated crops ranges from 13 to 15 percent and the cultivated area from 1.6 ha to 1.9 ha. For production, a variable defining the portion of household's production on consumption is included varying between 66 to 69 percent. To evaluate the impact of SAPs on food measures, we control for market conditions' changes, and a variable indicating whether there has been an increase of food prices is considered. There is a reduction over the years on increase of food prices ranging from 18 to 22 percent. Further control variables are included such as household shocks, indicating that up to 8 percent of the households have experienced income loss or death of livestock, more than 30 percent have experienced drought and 22 percent have experienced family shock during the last round. More than 80 percent of households are male headed in all three rounds and 40 percent of household heads could read or write or had attended school. The average household size is about five members.

[11] Agricultural extension programs contribute to improving farming, improving commercialization, educating farmers, conserving natural resources, promoting new technology, promoting sustainable agriculture, and disseminating information across various settings.

3.3.3 Data on SAPs - Differences between households

Crop Rotation

Among 3,699 farmers that adopt crop rotation during the survey period from 2011 to 2016, 82 percent receive agricultural assistance, whereas among 576 non-adopters almost 46 percent receive agricultural assistance (Appendix Figure A1). This may be attributed to the fact that receiving any form of agricultural assistance provides farmers with knowledge on benefits of adopting crop rotation or information on how to implement the practice. Moreover, only 12 percent of adopters of crop rotation cultivate irrigated crops. The cultivated area is significantly higher for adopters reaching 1.7 hectares on average. Adopters of crop rotation use more than 66 percent on their own consumption, whereas the magnitude for non-adopters is higher, exceeding 77 percent. A possible explanation for lower consumption when crop rotation is adopted might be that it can contribute to a more balanced and sustainable farming system, where less of the farm's own production needs to be consumed by the farmers themselves, allowing for more produce to be available for the market. Non-adopters of crop rotation have experienced drought at 28 percent, whereas less than 17 percent of adopters did. Finally, more than 40 percent of farmers who adopt crop rotation can read or write or have attended school, whereas this percent is lower than 34 for non-adopters, indicating than education level is important in adopting the practice. Almost 80 percent of households of both adopters and non-adopters have male head.

Mixed Cropping

Regarding mixed cropping, 76 percent of the 3,130 adopters of mixed cropping during the survey period from 2011 to 2016, received agricultural assistance and more than 79 percent of the 1,145 non-adopters received agricultural assistance (Appendix Figure A1). Moreover, 16 percent of adopters of mixed cropping use irrigated crops, whereas only 8 percent of non-adopters do. On the other hand, the percentage of adopters of mixed cropping allocate 69 percent of their production on consumption, which differs significantly from the non-adopters' percent, which is below 65. By growing a variety of crops, farmers can meet their daily requirements for pulses, oil seeds, fibers, and more, directly from their fields, leading to a self-sufficient farming approach. Finally, almost 39 percent of farmers who adopt crop rotation can read or write or have attended school, whereas this percent is higher by 6 percent for non-adopters, indicating than education level is not as important in adopting the practice as for crop rotation. The majority of the households (more than 80 percent) are male headed both for adopters and non-adopters.

3.3.4 Measuring Food Insecurity

Food insecurity is often described as a situation in which people do not have physical, social, and economic access to sufficient, safe, and nutritious food to meet their dietary needs and food preferences for an active and healthy life.[12] In the past years, a traditional approach of food insecurity included simple measures such as national food production, food grain storage, national food self-sufficiency, and food aid [48]. However, this paper includes newly developed food insecurity measures that can describe the actual food situation in a household, considering parameters such as information on the number of meals per day or the variety of food consumed. We use multiple food insecurity indicators to obtain an integrated approach of the food situation in each household such as: i) Food Insecurity Experience Scale, ii) Household Food Insecurity Access Prevalence and Scale Score, and iii) Household Dietary Diversity Score to capture food conditions in a household.

FIES

FIES[13] includes eight key questions regarding the experiences of the respondent's household focusing on difficulties in accessing food due to resource constraints. The FIES ques-

[12] Food and Agriculture Organization of the United Nations (https://www.fao.org/hunger/en/)

[13] Food and Agriculture Organization of the United Nations (https://www.fao.org/in-action/voices-of-the-hungry/fies/en/)

tions relate to self-reported food-related behaviors with experiences on food insecurity and the composed scale covers a range of severity of food insecurity, while capturing food insecure situations. We adapt the questionnaire based on our data (Appendix Table A2, ESS) and calculate the FIES for each household. The FIES ranges from 0 to 3, where 0 indicates a food secure, 1 mild food insecure, 2 moderate food insecure and 3 severely food insecure household. In the current sample, FIES mean values range from 0.5 to 0.6 indicating food secure to mild food insecure households (Table 2.1).

HFIAS and HFIAP

HFIAS is used to estimate the prevalence of food insecurity in the United States annually [49]. HFIAS has been used outside the United States and particularly in Africa to measure and analyze food insecurity within households (see [50]; [51]), since it provides a valuable approach for assessing the prevalence of food insecurity, including the access component and detecting changes in food insecurity over time.

HFIAS can capture and quantify responses, related to food insecurity predictable reactions, through a survey. The questionnaire consists of nine occurrence questions that represent a generally increasing level of severity of food insecurity, and nine "frequency-of-occurrence" questions.[14] These questions are based on perceptions of food vulnerability or stress and behavioral responses to insecurity. Two types of indicators are used that can elucidate the characteristics and changes in household food insecurity: HFIAS and HFIAP.

Using the questionnaire based on ESS Data (Appendix Table A3, ESS), we calculate the HFIAS for each household, using a range of 0-18. The higher the score, the more food insecure is the household, whereas lower score entails less food insecurity. The HFIAS score is a continuous variable, used to capture smaller increments of changes over time. The HFIAP Status indicator is used to report household food insecurity prevalence and is reported in addition to HFIAS. The HFIAP indicator takes values 1-4 and categorizes

[14] International Dietary Data Expansion Project (https://inddex.nutrition.tufts.edu/data4diets/indicator/household-food-insecurity-access-scale-hfias)

households into four levels of household food insecurity: food secure, mild food insecure, moderately food insecure, and severely food insecure. Households are categorized as increasingly food insecure as they respond affirmatively to more severe conditions and if they experience those conditions more frequently. For the sample of households included in this paper, HFIAS and HFIAP range from 1.2 to 1.7 and 1.5 to 1.6 respectively (Table 3.1) indicating food secure to mild insecure households.

HDDS

The HDDS[15] is used as an indicator at a population level of household food access, and it can be described as the number of food groups consumed by a household over a given reference period. The HDDS indicator provides information on a household's ability to access food and specifically includes 12 food groups (Appendix Table A4). Each food group is assigned a score of 1, if is consumed or 0, if not and the household score will range from 0 to 12, based on the total number of food groups consumed by the household. The HDDS is based on a recall of food groups consumed by the household in the previous 24 hours. We use information on types of food during the past week.[16] We are using the HDDS indicator in conjunction with HFIAS to understand household access to certain food groups [52]. However, the HDDS has not been validated as a proxy for micronutrient adequacy, and the number of food groups that may constitute a sufficiently diverse is not defined. Thus, there is no sufficiently diverse diet at the household level or a universally accepted cut-off that can be used to discriminate between households that have a sufficiently diverse diet from those that do not.[17] In this paper, HDDS is between 5 to 5.5 and improved in 2012-13 and 2014-15, indicating and improvement on food diversity (Table 2.1).

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[15]International Dietary Data Expansion Project (https://inddex.nutrition.tufts.edu/data4diets/indicator/household-dietary-diversity-score-hdds)

[16]The adjustment of the reference period is unlikely to cause imperfect recall. Also, it is important to note that all groups of food may not be consumed in a 24-hour period, even if they may be available, which allows estimating HDDS for a longer than the suggested period.

[17]International Dietary Data Expansion Project (https://inddex.nutrition.tufts.edu/data4diets/indicator/household-dietary-diversity-score-hdds)

3.3.5 Empirical model specification

Determinants of applying SAPs – Panel Regression Model

An econometric model is applied to assess the impact of households' socioeconomic characteristics on the adoption of crop rotation and mixed cropping. The above characteristics include receiving agricultural assistance and production allocation information, whether crop are irrigated and the cultivated area, experiencing economic or drought shock and household's characteristics (head male, education level, size). The estimates for adopting SAPs (yes or no) are based on a logistic regression model.[18] The estimated logit model is described by the equation below:

$$\log \frac{\mathbf{P}(SAP_{it} = 1)}{1 - \mathbf{P}(SAP_{it} = 1)} = \alpha_1 + \beta_1 \cdot A_{it} + \beta_2 \cdot P_{it} + \beta_3 \cdot S_{it} + \beta_4 \cdot H_{it} + \mu_i + \xi_t + \epsilon_{it} \quad (3.1)$$

In Equation (3.1), $\mathbf{P}(SAP_{it} = 1)$ denotes the probability of adopting sustainable agricultural practices, specifically crop rotation or mixed cropping. A is a vector representing agricultural characteristics (such as agricultural assistance, irrigated crop, and cultivated area), P is a variable indicating production allocation (portion of production used for consumption). S is a vector representing economic and drought shocks experienced, and H is a vector including household characteristics (such as head male, education level, and size). Additionally, μ_i represents household fixed effects, capturing heterogeneity at the household level, and ξ_t denotes year fixed effects, accounting for temporal variations.

Household fixed effects are included in the model to control for heterogeneity at the household level and account for time-invariant differences that may be correlated with omitted variables in our data affecting SAPs adoption, such as farm income or access to credit.[19]

[18] In logit model, the sample includes the observations for which there has been a variation in adopting SAPs among rounds.

[19] According to Atube et al. (2021), access to credit, annual farm income, and time taken to market influenced adoption of planting improved seeds.

Impact of SAPs on Food Insecurity - Panel Regression Model

For the estimation of the impact of adopting SAPs on FIES and HFIAP categorical variables, I use a fixed effects Poisson regression model. The Poisson probability mass function is given by:

$$\mathbf{P}(Y_{it} = k) = \frac{e^{-\lambda_{it}} \lambda_{it}^{k}}{k!} \tag{3.2}$$

In Equation (3.2), $\mathbf{P}(Y_{it} = k)$ represents the probability of Y_{it} taking the value k, where Y denotes FIES or HFIAP measures in household i at year t. λ_{it} denotes the event rate corresponding to household i at year t, as described in Equation (3.3), which is equal to both the mean and the variance of Y_{it}.

$$\log \lambda_{it} = \alpha_1 + \beta_1 SAP_{it} + \beta_2 F_{it} + \beta_3 S_{it} + \beta_4 X_{it} + \mu_i + \xi_t + \epsilon_{it} \tag{3.3}$$

SAPs denotes the frequency of adopting each of the sustainable agricultural practices.[20] Increased frequency of adopting crop rotation can help maintain soil fertility and improve crop yield especially over an extended time period. In the model the following control variables are included: F indicating increase in food prices, S is a vector denoting shocks that the household experiences and specifically family shock, economic or drought shock, and H is a vector of household characteristics (e.g., household head's gender, head's education, household's size). Moreover, I include μ_i term, representing household fixed effects and include year fixed effects ξ_t.

Additionally, an OLS panel regression model is included to identify whether SAPs are major determinants of HFIAS and HDDS measures, as described in Equation (3.4).

$$Y_{it} = \alpha_1 + \beta_1 SAP_{it} + \beta_2 F_{it} + \beta_3 \cdot S_{it} + \beta_4 \cdot X_{it} + \mu_i + \xi_t + \epsilon_{it} \tag{3.4}$$

In Equation (3.4), Y_{it} denotes HFIAS and HDDS measures of household i in year t. The

[20] I aim at capturing the subsequent effect of adopting SAPs.

independent variables are included as described in Equation (3.3).

3.4 Results and Discussion

The current paper has two main objectives. First, I examine the determinants of applying crop rotation and mixed cropping and second the implication of these SAPs on household food insecurity.

3.4.1 Determinants of applying SAPs

There is evidence that different factors such as demographic, institutional, and socio-economic factors are important factors in adoption of agricultural technologies [53].

However, there is no evidence available as to comparing factors in affecting different agricultural practices adoption namely crop rotation and mixed cropping. The purpose of this study is to identify the underlying factors affecting the adoption of these two sustainable agricultural practices adoption using a unique panel data from Ethiopia over the years 2011 to 2016. In Ethiopia and specifically in regions where smallholder farming systems are characterized by poor soil fertility and low levels of agricultural technology use, there is a need for understanding the determinants of these two commonly used sustainable agricultural practices, since it can further lead to targeted policies and advocate for increased funding and support to sustainable agricultural practices adoption.

According to the findings, impact of the included characteristics vary between adopters and non-adopters depending on the SAPs adopted. According to the results (Table 3.2), participating in an extension program or receiving agricultural advising increases the odds of adopting crop rotation by more than 38 percent. Extension programs help farmers in Ethiopia to produce more food in a variety of contexts and higher agricultural yields are experienced due to extension services. According to [54], agricultural extension services have been found to have a positive impact on crop rotation use and more specifically farmers who used the agricultural extension service were 34 percent more. Moreover, [55] have found that farmers are only willing to adopt practices if paid, although as they suggest there are still gaps in the literature regarding the analysis of farmers' behavior regarding sustainable agriculture. An increase on the portion of production allocated on consumption entails that farmers are less likely to adopt crop rotation. Moreover, farmers with extended cultivated area by 1 hectare, have almost 18 percent higher odds of adopting crop rotation, whereas allocating greater portion of production in consumption by 10 percent decreases the odds by almost 7 percent. Farmers are also 2.5 times more likely to adopt crop rotation when experiencing an economic shock, since for example they may choose to rotate crops due to changing commodity prices[21]. Oftentimes, crop rotation can help farmers maintain soil fertility and increase yields, which is beneficial when output prices are low and can help them reduce the need for chemical fertilizers and pesticides, when input prices are high [56]. Moreover, an increase in household size and a more educated head of the house renders adopting the practice more likely. When the household head can read or write or has attended school is 1.43 times more likely to adopt crop rotation suggesting that higher education level positively influenced agricultural technology adoption.

On the other hand, likelihood of adopting mixed cropping is not affected by whether farmers receive agricultural assistance. However, when farmers cultivate irrigated crops entails that they are 1.71 times more likely to adopt mixed cropping. Experiencing drought decreases the likelihood of adopting mixed cropping, which happens due to the fact that irrigated crops, such as maize, peppers and onions are more often used in mixed cropping [57]. Drought is a major challenge for Ethiopia, especially for farmers, leading to irrigation issues in Ethiopia through reducing the availability of water sources for irrigation, such as rivers, wells, and reservoirs. Allocating greater portion of production on consumption by 10 percent entails that is more likely to adopt mixed cropping increasing odds by more than 4 percent and an increase in the cultivated area by 1 ha increases the likelihood of adopting mixed cropping by more than 5 percent. Adopting mixed cropping for households

[21] USDA - Economic Research Service (https://ers.usda.gov/topics/farm-practices-management/crop-livestock-practices/soil-tillage-and-crop-rotation.aspx)

Table 3.2: Determinants on adopting SAPs.

Variables	Crop Rotation (Logit)			Mixed Cropping (Logit)		
	(1)	(2)	(3)	(4)	(5)	(6)
Agricultural Characteristics						
Agricultural Assistance (Y/N)	0.301***	0.354***	0.323***	0.057	0.057	0.044
	(0.101)	(0.103)	(0.104)	(0.072)	(0.072)	(0.073)
Irrigated Crops (Y/N)	0.026	0.050	0.097	0.549***	0.534***	0.538***
	(0.153)	(0.154)	(0.158)	(0.090)	(0.090)	(0.090)
Cultivated Area (ha)	0.159***	0.169***	0.163***	0.053***	0.052***	0.052***
	(0.039)	(0.039)	(0.039)	(0.015)	(0.015)	(0.015)
Production on Consumption (ratio)	-0.580***	-0.644***	-0.690***	0.441***	0.427***	0.433***
	(0.199)	(0.201)	(0.205)	(0.126)	(0.127)	(0.127)
Household shocks						
Economic Shock (Y/N)	-	0.715***	0.906***	-	-0.096	-0.039
		(0.164)	(0.170)		(0.113)	(0.114)
Drought Shock (Y/N)	-	0.086	0.044		-0.152*	-0.163**
		(0.120)	(0.122)		(0.080)	(0.080)
Household characteristics						
Male Household Head (Y/N)	-	-	0.115	-	-	0.727***
			(0.251)			(0.179)
Educated Household Head (Y/N)	-	-	0.358**	-	-	-0.011
			(0.172)			(0.081)
Household size	-	-	0.264***	-	-	0.116***
			(0.047)			(0.024)
Observations	780	780	780	1,715	1,715	1,715
Year and Household FE	Y	Y	Y	Y	Y	Y

Robust standard errors in parentheses (clustered at household level) *** $p<0.01$, ** $p<0.05$, * $p<0.1$

experiencing drought shock is 0.85 times that of not experiencing drought. Moreover, a male head increases the odds of adopting mixed cropping, and an increase in household size by one more member entails a 12 percent odds increase.

Overall, different factors affect whether crop rotation or mixed cropping will be applied based on the current findings. Adopting crop rotation is more likely when receiving agricultural assistance, whereas for mixed cropping cultivating irrigated crops is significant. Cultivated area is important for adopting both SAPs, with greater impact on adopting crop rotation. Portion of production in consumption is important for adopting both SAPs, but with negative effect in crop rotation and positive in mixed cropping.

Household size is an important positive factor for adopting both SAPs, whereas higher level of education leads to higher odds of adopting crop rotation, and having male head of the household means that it is more likely for a household to adopt mixed cropping.

3.4.2 Impact of SAPs on Food Insecurity

According to our findings (Table 3.3), increasing frequency of crop rotation entails that food insecurity is expected to have a rate 0.9 times that of not adopting the practice using FIES measure (Columns 1 and 2) and 0.93 times when using HFIAP (Columns 5 and 6) scales.[22] Crop rotation can have a major impact on soil health, due to emerging soil ecological interactions and processes that occur with time [41] and is considered as a promising way to improve food security under a changing climate. Crop rotation besides being one of the cheapest practice, it is also considered the most effective agricultural control strategies used in preventing the loss of soil fertility, as well as reducing the opportunity for disease and pests to take hold, since their development cycles get interrupted by changing crops [40]. Smallholder agriculture production, which involves crop rotation, contributed to food and nutrition security in Ethiopia by providing food and income sources, and enhancing dietary diversity and quality [58]. The adoption of sustainable agriculture practices including crop rotation helps to reduce the use of agrochemicals and synthetic fertilizers, while improving agricultural productivity and profitability [5]. Additionally, a recent survey of Malawi, which is one of the more food insecure and malnourished countries in Africa, revealed that sustainable agriculture strategies can help in improving food security and nutrition through cultivating multiple crops [59]. Regarding other control variables, a food price increase entails that food insecurity has expected rate 1.35 times that of experiencing no change in food prices. Drought also is found to increase the expected rate of food insecurity in a household which equals to 1.7 times that of not experiencing drought.

Similarly, adopting mixed cropping is found to decrease food insecurity. Specifically, higher frequency of adoption of mixed cropping leads FIES scale to decrease by almost 4 percent, and HFIAP by 1.5 percent. HFIAS also is lower by 0.013 when farmers use mixed cropping. These findings concur with previous studies, which demonstrated a positive re-

[22] According to our findings, for HFIAS the impact of is not significant. This may be attributed to the fact that HFIAS measure is more sensitive to capturing smaller increments of changes over time, which was not achieved for crop rotation, since the effect may be more clearly captured in the long-term.

Table 3.3: Impact of SAPs on Food Insecurity Measures.

Variables	FIES (Poisson)		HFIAS (OLS)		HFIAP (Poisson)	
	(1)	(2)	(3)	(4)	(5)	(6)
SAPs adoption						
Crop Rotation (Frequency)	-0.100***	-	-0.013	-	-0.073***	-
	(0.033)		(0.015)		(0.012)	-
Mixed Cropping (Frequency)	–	-0.057***	-	-0.016*	-	-0.026***
	-	(0.014)	-	(0.008)	-	(0.005)
Market Conditions						
Increase of food prices (Y/N)	0.287***	0.288***	0.062***	0.062***	0.146***	0.145***
	(0.017)	(0.017)	(0.013)	(0.013)	(0.008)	(0.008)
Household shocks						
Economic Shock (Y/N)	0.348***	0.343***	0.065***	0.064***	0.177***	0.175***
	(0.023)	(0.023)	(0.021)	(0.021)	(0.011)	(0.011)
Drought Shock (Y/N)	0.520***	0.511***	0.056***	0.056***	0.197***	0.198***
	(0.020)	(0.020)	(0.012)	(0.012)	(0.008)	(0.008)
Family Shock (Y/N)	0.175***	0.176***	0.026**	0.026**	0.094***	0.095***
	(0.015)	(0.015)	(0.010)	(0.010)	(0.007)	(0.007)
Household characteristics						
Male Household Head (Y/N)	0.552***	0.552***	0.037	0.037	0.227***	0.228***
	(0.050)	(0.051)	(0.033)	(0.033)	(0.019)	(0.019)
Educated Household Head (Y/N)	-0.166***	-0.159***	-0.004	-0.004	-0.029***	-0.027***
	(0.023)	(0.023)	(0.013)	(0.013)	(0.008)	(0.008)
Household size	0.032***	0.033***	0.001	0.001	0.006***	0.007***
	(0.006)	(0.006)	(0.004)	(0.004)	(0.002)	(0.002)
Observations	2,213	2,213	4,274	4,274	4,274	4,274
Year and Household FE	Y	Y	Y	Y	Y	Y

Robust standard errors in parentheses (clustered at household level) *** $p<0.01$, ** $p<0.05$, * $p<0.1$

lationship between cultivating multiple crops and food security of the household (see [60]; [61]; [62]). Crop diversification has a negative and significant effect on Household Food Insecurity Access Score [63]. Adopting the mixed cropping agricultural practice in Nigeria, has resulted on improving food production and income for small farmers, while promoting diversification of agricultural productions and securing the regularity of returns throughout the season as well as safety net against climatic uncertainties [64]. [45] have suggested that households that cultivate multiple crops are better assured of food availability compared to households who practice mono cropping, since it was related to dietary diversification and negatively related to food insecurity. Another benefit from growing multiple crops in improving food security can be manifested through better management of price and production risks [65], since growing more than one crop species in a single season gives the farmers more options and helps them to manage price and production risks better as compared to less diversified farming systems. Moreover, households who practiced mixed crop systems were found to improve 50 percent of productivity and farm income in the highlands of Ethiopia compared to smallholders that did not undertake this practice [47].

Additionally, we estimate the effect of SAPs on food diversity. According to the outcomes (Table 3.4) crop rotation leads to a decrease of 0.017 in food diversity, whereas mixed cropping increases food diversity scale by 0.014. A possible explanation for this may be that crop rotation occurs in cereals, so if a household uses production for its own consumption, then food diversity decreases, whereas adopting mixed cropping offers a variety of food groups such as cereals, legumes and oilseeds. Farm production diversity was consistently and positively associated with household dietary diversity [66].

Table 3.4: Impact of SAPs on Food Diversity.

Variables	**HDDS (OLS)**	
	(1)	(2)
SAPs adoption		
Crop Rotation (Frequency)	-0.017*	-
	(0.010)	
Mixed Cropping (Frequency)	-	0.014**
		(0.006)
Market Conditions		
Increase of food prices (Y/N)	0.004	0.003
	(0.008)	(0.008)
Household shocks		
Economic Shock (Y/N)	-0.001	-0.001
	(0.011)	(0.011)
Drought Shock (Y/N)	-0.001	0.001
	(0.008)	(0.008)
Family Shock (Y/N)	0.013*	0.012
	(0.008)	(0.008)
Household characteristics		
Male Household Head (Y/N)	-0.004	-0.005
	(0.020)	(0.020)
Educated Household Head (Y/N)	0.024***	0.025***
	(0.009)	(0.009)
Household size	0.006**	0.006**
	(0.003)	(0.003)
Observations	4,274	4,274
Year and Household FE	Y	Y

Robust standard errors in parentheses (clustered at household level) *** $p<0.01$, ** $p<0.05$, * $p<0.1$

3.5 Contribution and Limitations

In this chapter, we examine the determinants for adopting sustainable agricultural practices, namely crop rotation and mixed cropping, and their impact on food security. The contribution of this work is that we include different food insecurity measures estimated using household data. We use a unique household panel data on Ethiopia and find that food insecurity significantly decreased when households adopted sustainable agricultural practices. We would like to extend the analysis by including data on climate shocks such as drought or flooding, which affect SAPs adoption and food insecurity. Also, we do not include data on specific crops that are cultivated at each household, which can provide further insight on SAPs adoption and levels of food security. Crop rotation has some advantages over mixed cropping, such as easier weed control, lower labor and input costs, and higher market value for some crops; we would like to include these factors in our analysis.

CHAPTER 4

FORECASTING FOOD INSECURITY USING MACHINE LEARNING

4.1 Overview and Literature Review

This chapter explores machine learning to predict food insecurity, offering insight into the factors, time and location of food insecurity events, using verifiable data in 4 African countries for the period 2020 to 2023. We use a function approximation approach, i.e., $y = \hat{f}(x_1, ..., x_{10})$, to explore how accurately we can estimate food insecurity given information on economic, environmental, climate and conflict data. The idea is to compare function approximation approach with time series forecasting methods. Based on preliminary tests we have conducted with smaller dataset, there is evidence that function approximation may perform better, which in turn may indicate a Markov approach where the history plays little role compared to the current state. This will be further verified with extensive experiments. We analyze data of almost 4 years including monthly assessments on district-level food insecurity outcomes together with monthly covariates that capture known drivers of food insecurity. We explore how machine learning can help to address these challenges using a unique dataset including monthly economic, environmental, climate and conflict data. The predictions are generated using Multinomial Logistic Regression as our baseline model, and we further use RF and XGBoost models to evaluate, and identify the most important features in predicting food insecurity.

Previous studies have used ML to predict food security indicators. Geo-located data on child nutrition have been used along with localized climate and governance indicators to map locations where droughts have the largest effects on child health outcomes, including stunting [67]. Moreover, another study has shown how a RF model, that is trained on open access data can be used for contemporaneous prediction and near-future food security outcomes aiming at informing early warning systems [68]. Moreover, historical Integrated Food Security Phase Classification (IPC), available at the subnational level, for food crisis prediction, led to an algorithm that outperforms the IPC own forecasts, while using training the data on a series of geospatial and administrative indicators [69].

According to Food and Agriculture Organization of the United Nations' Global Report (2023)[1] on crop prospects and food situation, erratic rains caused impairment of 2023 production prospects in East Africa. Moreover, this report concludes that the two previous successive years of widespread drought have caused a devastating impact on food security, which was further weakened by conflicts. The list of the top 10 countries facing the most acute food insecurity and hunger crisis in the world include South Sudan, Sudan, Somalia and Democratic Republic of Congo (DRC), which lie on East and Central Africa.[2] Almost more than half of 38 African countries are experiencing some level of acute food insecurity is concentrated in the above four countries, which we include in this chapter (Figure 4.1).

South Sudan has been facing an economic downturn, floods, and civil insecurity. Despite ongoing humanitarian aid, a significant portion of the population continues to experience food insecurity. Furthermore, factors such as stagnant agricultural production, consecutive years of widespread flooding, and increased organized violence at the subnational level since 2020 lead to increasing inflation rates and inadequate food supplies. Approximately 7.76 million people, which covers nearly 70 percent of the total population, were anticipated to face severe acute food insecurity from April to July 2023.[3]

Sudan has been experiencing conflict, displacement, and high food prices resulting in severe localized food insecurity. Due to conflict that erupted in mid-April 2023, almost 19.9 million people, over 40 percent of the population, are expected to need emergency

[1] Food and Agriculture Organization of the United Nations' Global Report (2023) https://openknowledge.fao.org/server/api/core/bitstreams/15af07ad-1452-4e61-82b5-dfde52c14ad0/content

[2] World Food Program USA (https://www.wfpusa.org/articles/global-food-crisis-10-countries-suffering-the-most-from-hunger/)

[3] Food and Agriculture Organization of the United Nations' Global Report (2023) https://openknowledge.fao.org/server/api/core/bitstreams/15af07ad-1452-4e61-82b5-dfde52c14ad0/content

food assistance. This situation led to an increase in the already high food prices.[4]

Somalia is experiencing drought conditions and civil insecurity entailing an exceptional shortfall in overall food production and supplies. Over 35 percent of the population, were estimated to experience severe acute food insecurity between April and June 2023. The leading causes of this crisis is include the consecutive poor rainy seasons since late 2020 and increased conflict since early 2021.[5]

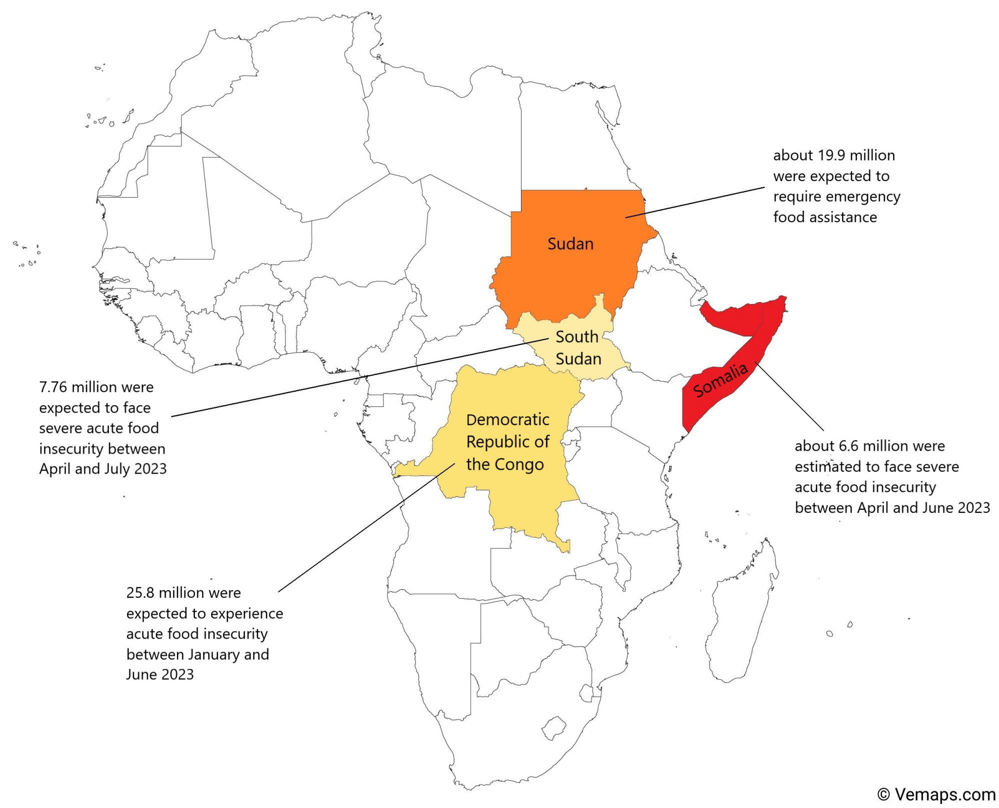


Figure 4.1: Countries included in the current study.

DRC is confronting civil insecurity in its eastern regions and high food prices. The October 2022 IPC analysis projected that over 25 percent of the population would face acute food insecurity between January and June 2023. Intensified conflict in the northeastern

[4]Food and Agriculture Organization of the United Nations' Global Report (2023) https://openknowledge.fao.org/server/api/core/bitstreams/15af07ad-1452-4e61-82b5-dfde52c14ad0/content

[5]Food and Agriculture Organization of the United Nations' Global Report (2023) https://openknowledge.fao.org/server/api/core/bitstreams/15af07ad-1452-4e61-82b5-dfde52c14ad0/content

provinces has hindered harvest completion entailing reduced food availability.[6]

The paper is structured as follows. Section 2 introduces the data, section 3 describes the empirical strategy, Section 4 presents key results and discussion, and section 5 concludes.

4.2 Data

4.2.1 Food Insecurity Data

We obtain historical data on food insecurity from monthly assessments performed across 66 districts in 4 developing countries over the period from 2020 to 2023. Our approach allows us to evaluate the accuracy of our model, while making predictions for all districts, where covariates are available. Table 4.1 includes the number of observations and districts per country. We use food insecurity data obtained from Famine Early Warning Systems Network (FEWS NET).[7] Food insecurity is measured using the IPC system, which is an analytical framework that follows evidence based guidelines to qualitatively classify the severity of food insecurity and prescribe policies to mitigate risk [70]. The IPC scale includes five phases of food insecurity: (1) minimal, (2) stressed, (3) crisis, (4) emergency and (5) famine. The FEWS NET data are reported at a sub-national level at quarterly frequency from 2020 to 2023, and then every four months afterwards. For the months with no report values, we are using monthly predictions of FEWS NET. We are also including the IPC rating scale, which reflects the actual on-the-ground conditions inclusive of any humanitarian assistance.

Mean values of the food insecurity index per country[8] are presented in Figure 4.2. South Sudan is experiencing the highest levels of food insecurity indicating crisis during the examined period, which in May 2023 is characterized by an emergency phase. Sudan faces minimal to stressed food insecurity conditions until May 2022, whereas afterwards the food

[6] Food and Agriculture Organization of the United Nations' Global Report (2023) https://openknowledge.fao.org/server/api/core/bitstreams/15af07ad-1452-4e61-82b5-dfde52c14ad0/content

[7] FEWS NET (https://fews.net/data/acute-food-insecurity)

[8] We use the average monthly value of food insecurity phase of the included districts per country.

Table 4.1: Descriptives of coverage in the current study.

Country	Coverage Observations	Time (months)	Districts
South Sudan	644	46	14
Sudan	736	46	16
Somalia	966	46	21
DRC	690	46	15
Total	3036		66

Source: Authors' calculations on the data.

insecurity increases and becomes stressed with temporal signs of emergency during 2023. Somalia experiences a food situation above stressed and below crisis levels until March 2022, whereas afterwards and until the end of October 2023 the food situation worsens with the country experiencing crisis to emergency conditions. DRC faces below but close stressed food insecurity conditions during the examined period.

4.2.2 Data on Control Variables

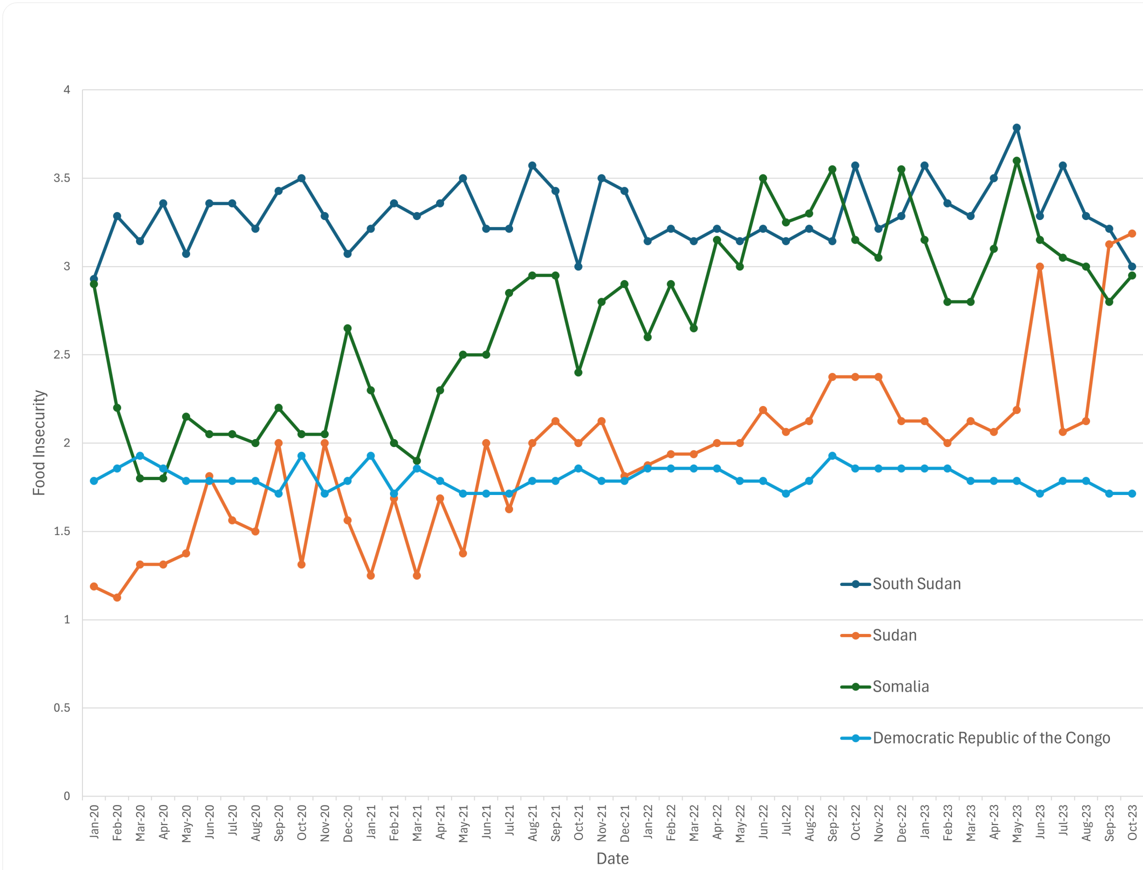
We forecast transitions into food insecurity using monthly district level key covariates. Moreover, we further include features at country level. Table 4.2 includes the summary statistics of our data.

District Level Factors

- **Food Price Index**

  Changes in the food price index can directly lead to food insecurity by increasing the cost of living for vulnerable households (see [71]), and rising prices may indicate whether fiscal space is sufficient or constrained, potentially due to episodes of conflict [72]. We use monthly sub-national food price indices using World Bank Data[9] to capture these important dynamics.

[9]THE WORLD BANK (https://microdata.worldbank.org/index.php/catalog/4509/study-description)



Source: Authors' calculations on the data.

Figure 4.2: Food Insecurity for four countries during the period from January 2020 to October 2023.

- **Violent Conflict**

  Violent conflict significantly influences food insecurity causing disruption of social systems and obstructing access [69]. Moreover, it may indicate underlying factors contributing to food insecurity. Events, such as riots and protests may reflect an ailing economy, while violent attacks on civilians can lead to displacement and disrupt food production and distribution [73]. We use the count of conflict events from Armed Conflict Location and Event Data Project (ACLED)[10] to predict food insecurity.

[10] ACLED (https://acleddata.com/data-export-tool/)

- **Climate and Environmental**

  We use remote sensing data to track climate and environmental factors affecting food production. Food production depends on soil moisture content, which can be monitored through rainfall and evapo-transpiration of the water balance equation [69]. We use SPEI data[11] to identify drought conditions. We also proxy for food plant health directly using the Normalized Difference Vegetation Index (NDVI) data[12], which is a commonly-used satellite-imagery-based measure of vegetation coverage (see [74]). Additionally, we include NDVI anomaly, which can provide valuable insight on the changes in global crop production in districts and time periods when they experienced significant drought conditions.[13]

Table 4.2: Summary Statistics.

	S.Sudan		**Sudan**		**Somalia**		**DRC**	
Variables	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Outcome								
Food Insecurity (1-5)	3.295	0.574	1.921	0.643	2.703	0.738	1.816	0.706
Control								
District Level								
Food Price Index (USD)	0.031	0.016	0.057	0.046	0.002	0.001	0.001	0.001
Conflict	0.418	0.835	4.321	7.553	1.680	2.542	1.642	4.530
SPEI	-1.066	1.151	-0.405	1.286	-1.246	1.795	-0.455	0.103
NDVI	0.491	0.176	0.215	0.118	0.247	0.110	0.717	0.103
NDVI Anomally	0.042	0.053	0.018	0.028	0.004	0.046	0.007	0.027
HA(0-1)	0.186	0.390	0.287	0.453	0.128	0.335	0.002	0.038
Country Level								
Population (million)	14.363	0.450	46.027	1.300	17.293	0.572	95.121	3.347
GDP (billion USD)	6.647	1.060	32.469	3.580	10.020	0.582	59.942	7.054
Inflation Rate (%)	22.043	16.028	209.753	89.578	5.421	1.038	12.051	4.239
COVID-19 Cases	11,846	6,920	42,115	22,945	17,588	10,669	57,998	37,779
Obs.	644		736		966		690	

Source: Authors' calculations on the data.

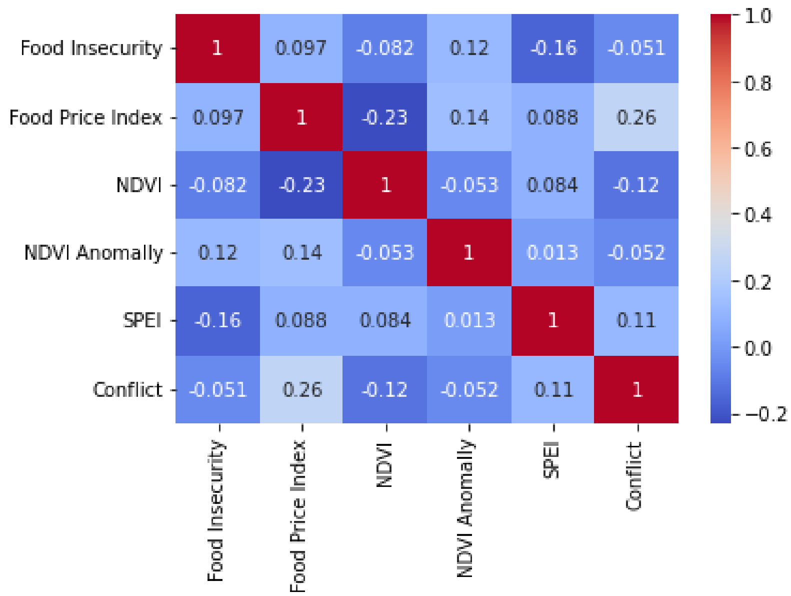
Figure 4.3 describes the correlation among the indicators that are included at district

[11] Global SPEI database(https://spei.csic.es/database.html)

[12] Global Agricultural Monitoring (https://glam1.gsfc.nasa.gov/)

[13] see https://docs.digitalearthafrica.org/en/latest/data_specs/NDVI_Anomaly_specs.html

level. As seen in the table, there is no strong linear correlation between features, which entails faster algorithm learning, higher interpretability and reduced bias.[14] Food insecurity is highly correlated with SPEI and NDVI Anomaly. Negative correlation is found for food price index and NDVI, entailing that higher NDVI leads to lower food prices, whereas positive correlation is found for conflict events and food price index.



Source: Authors' calculations on the data.

Figure 4.3: Correlation among features at district level.

Country Level Factors

- **Population**

  We are including country yearly population data[15] during the examined period from January 2020 to October 2023.

- **GDP**

  GDP, defined as the monetary value of all goods and services produced in a coun-

[14] https://medium.com/analytics-vidhya/correlation-and-machine-learning-fee0ffc5faac
[15] https://www.statista.com/statistics/805605/total-population-sub-saharan-africa/

try in a specific time period, is used as a tool to measure the economic strength of the countries. We use yearly GDP data[16] to capture differences among countries in predicting food insecurity related to their economies output, size and health.

- **Inflation Rate**

  One of the most urgent issues that Africa is confronting is the need to tackle decade-high levels of inflation.[17] In the current paper, we include inflation rate data[18] at a country level.

- **COVID-19 Cases**

  The time frame of the current study is covering the years of the pandemic beginning early 2020. As an extension to our approach presented in Section 4.5, we further estimate our models including as additional feature monthly COVID-19 cases at country level.[19]

According to Table 4.2, Sudan has the highest food price index, whereas for the other three countries we observe similar levels of food price index. Number of conflict events is higher in Sudan, whereas Somalia and DRC experience 2 events on average per month. SPEI values indicate that Somalia and South Sudan experience greater dry conditions on average during the examined period. NDVI is similarly lower for Sudan and Somalia, whereas NDVI anomaly is found to be highest for South Sudan. Sudan has an extremely high inflation rate, whereas for the other three countries inflation rate ranges from 5.4 to 22 percent. The greatest number of COVID-19 cases was found in DRC.

4.3 Empirical Strategy

We use Multinomial Logistic Regression as our baseline model and we further use RF and XGBoost for predicting food insecurity phase at district level. We further evaluate our

[16]https://www.statista.com/statistics/805564/gross-domestic-product-gdp-in-sub-saharan-africa/
[17]https://www.imf.org/en/Blogs/Articles/2022/10/20/africas-inflation-among-regions-most-urgent-challenges
[18]https://www.statista.com/statistics/805570/inflation-rate-in-sub-saharan-africa/
[19]https://ourworldindata.org/covid-cases

models, while identifying the significance of the examined covariates.

4.3.1 Baseline Model: Multinomial Logistic Regression

Multinomial logistic regression is used for modeling the relationship between food insecurity classes, which includes five classes and our independent variables. The model uses a logistic function to model the relationship between the included features and the probabilities of each phase of food insecurity and estimates the log-odds of each phase. The probability of each outcome is modeled as:

$$p_{ij} = \frac{e^{\sum_{k=1}^{K} a+b_{kj}X_{kji}}}{\sum_{j=1}^{J} e^{\sum_{k=1}^{K} a+b_{kj}X_{kji}}} \tag{4.1}$$

where i denotes the number of observations, j denotes food insecurity classes and k is included for our independent variables. We train the model using the 80 percent of the whole sample, and predict the probabilities of each category for the remaining 20 percent of our observations. The analysis breaks the food insecurity phase variable down into a series of comparisons between five categories. In our case, the analysis consists of four comparisons, which includes compare the first category with all the remaining four. The predicted food insecurity phase is the one with the highest probability.

4.3.2 RF

RF is a collection of Random Trees. A Random Tree is formed by a stochastic process. Classification trees of RF are simple representations of classifying instances. The data are described as:

$$(x, Y) = (x_1, x_2, x_3, ..., x_k, Y) \tag{4.2}$$

where Y is the food insecurity phase based on IPC scale and x the vector, which is composed of our input variables x_1, x_2, x_3 etc. In our case, the leaves of the trees represent one of the food insecurity classes. According to the developer of the algorithm of

Random Forest, the tree complexity has a crucial effect on its accuracy [75]. Tree complexity is measured by one of the following metrics: tree depth and number of attributes used. Therefore, we perform a grid search to identify the best parameters indicating the number of trees, maximum tree depth and the optimal number of features. A multitude of decision trees is constructed at training time, which outputs the phase of each observation of the training set. Each tree of the RF predicts a food insecurity phase outcome and in the end the forest classifies each observation according to the predictions of all trees, which are finally aggregated through majority voting. Each tree grows with a training set, which is formed by 80 percent of cases sampled at random from the original data. The number of features equals 6 for the construction of each tree. In this study, 600 trees construct the RF and the maximum depth of trees equals to 20.

4.3.3 XGBoost

XGBoost operates on decision trees and it is described as the mathematical structure where our input features x_i are weighted for each observation i and predict food insecurity y_i. The choice model of XGBoost are decision tree ensembles, including a set of classification and regression trees, which is different compared to decision trees since a real score is associated with each of the leaves, allowing richer interpretations. XGBoost grows many decision trees sequentially that each aim to predict the residuals not yet explained by the previous trees. Specifically, boosting starts by estimating an initial regression tree, for the outcome, y_i, then shrinks it by the learning rate, which in our case equals to 0.1. XGBoost instead of training the best possible model on the data, it trains thousands of models on various subsets of the training dataset and then vote for the best-performing model. The learning process behind XGBoost[20] includes an objective function that needs to be minimized [76]. The objective function (4.3) combines the training loss and a regularization term, which is used to prevent overfitting.

[20] XGBoost (https://towardsdatascience.com/the-notorious-xgboost-c7f7adc4c183)

$$Objective(T) = \sum l(y_i, y_{pred,i}) + \sum \Omega(f) \tag{4.3}$$

where T denotes the ensemble of decision trees, $l(y_i, y_{pred,i})$ is a differentiable convex loss function that measures the difference between the true food insecurity phase y and the predicted food insecurity phase y_{pred}, y_i is the true food insecurity phase, for instance i, $y_{pred,i}$ is the predicted food insecurity phase for instance i, and $\Omega(f)$ is the regularization term applied to each tree f in the ensemble T. XGBoost creates an iterative ensemble of decision trees that gradually minimizes the objective function. In each iteration, a new tree is added to the ensemble, and the objective function is optimized. Essentially, the prediction of the food insecurity phase after adding m trees equals the sum of the prediction up to $m-1$ trees and the new tree added in the m-th iteration. XGBoost uses gradient descent and in each iteration, the first and second-order derivatives of the loss function are calculated with respect to the predicted food insecurity phase. Then, in the m-th iteration, the best tree f_m that minimizes the objective function. An intuitive introduction to boosting can be found in previous paper [77].

4.4 Results and Discussion

4.4.1 Predictive Models for Food Insecurity

Food crises impose heavy human costs that are likely to increase in light of worsening climatic drivers and growing populations [69]. Experts identify three main causes for food insecurity: conflict, economic shocks and extreme weather events.[21] To build the predictive models, we have collected data covering all three dimensions: data on number of conflict-related events, economic information (food price index, GDP and inflation) and data on drought occurrence and vegetation (SPEI, NDVI, NDVI Anomaly). For each food insecurity phase for a given district and time window, we associate as independent variables

[21] FSIN. Global Report on Food Crises 2020 (https://www.wfp.org/publications/2020-global-report-food-crises)

the corresponding food price indices, conflict events, economic and climatic conditions. We evaluate our models using the following metrics: Accuracy, Precision, Recall, Root Squared Error (RMSE), Mean Absolute Error (MAE), training time and prediction time (Table 4.1).

Multinomial Logistic Regression model performed poorly indicating that approximately 57 percent of the total number of predictions are predicted correctly. Precision, which is given by the ratio of the true positive cases to the total positive cases (true and false predicted), is found at highest level of 0.62 for the first class, indicating higher ability of our model to identify food insecurity minimal conditions. Recall, which is given by the ratio of true positive cases to the sum of the true positive and the false negative cases, is found 0.79 for the third class, meaning that our model has higher ability of identifying most instances of food insecurity crisis.[22]. RMSE and MAE are estimated at 0.8 and 0.46 respectively and training time is less than 0.4 seconds.

Table 4.3: Models Performance Metrics.

Metrics	**Multinomial Logistic Regression**	**RF**	**XGBoost**
Accuracy (%)	56.91	75.16	73.68
Precision	0.58	0.75	0.73
Recall	0.57	0.75	0.74
RMSE	0.80	1.54	1.49
MAE	0.46	0.27	0.28
Training Time (sec)	0.36	9.64	2.34
Prediction Time (sec)	$< 10^{-2}$	1.12	0.02

We further apply two classification models: RF and XGBoost. Both models indicate higher accuracy in prediction compared to our baseline model.

RF indicates the highest accuracy of 75.16 percent with precision for all classes that exceeds 70 percent. Specifically, the model is found to have higher ability of 78 percent

[22]In Table 3 the weighted average of precision and recall for all class is reported.

to identify cases under food insecurity stressed conditions. Additionally, training time is below 10 seconds. Figure 4.3 shows the classification results using RF. The lowest accuracy is found in predicting food insecurity emergency conditions cases, which are classified at 50 percent correctly, and 48 percent as crisis conditions cases. On the other hand, our model classifies correctly minimal food insecurity conditions cases at almost 70 percent, over 80 percent of stressed conditions cases and 78 percent of crisis conditions cases. There is a contribution in the incorrectly classified cases, indicating that in the model further parameters may need to be included to improve the model's performance.

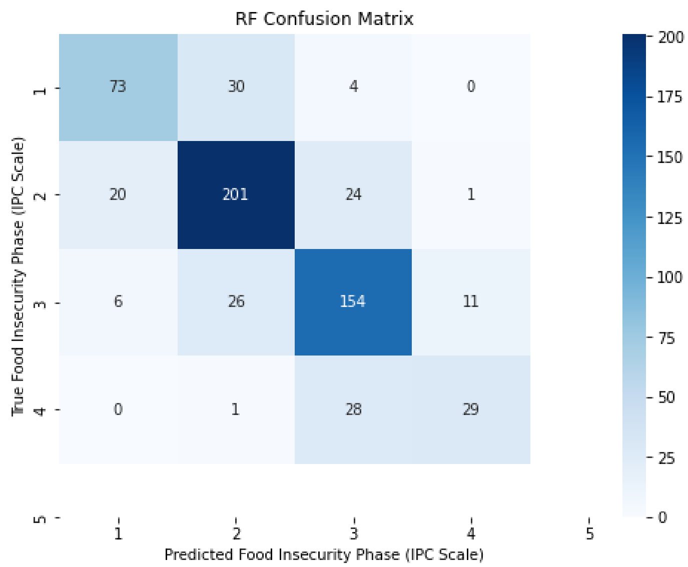


Figure 4.4: Confusion Matrix of RF.

XGBoost indicated accuracy of 73.68 percent. The highest precision is found for stressed food insecurity conditions class at 78 percent and the lowest for the emergency class at below 60 percent. RMSE and MAE are found similar to glsrf, whereas training time that is required for XGBoost is lower. In Figure 4.4, the confusion matrix of XGBoost is included according to which almost 70 percent of the minimal food insecurity cases, more than 82 percent of stressed cases, and almost 75 percent of crisis condition cases are classified correctly. However, the model classifies correctly less than 50 percent of the emergency cases, and identifies the remaining cases as crisis food insecurity cases. Transitions in the state of the food security can be forecasted using open data XGBoost with the strongest performance for longer lead times [78]. XGBoost model was more capable of capturing food security related complex interactions and the comparison with random forest models showed that it yielded a slightly higher performance, especially for crisis-onset predictions [79] .

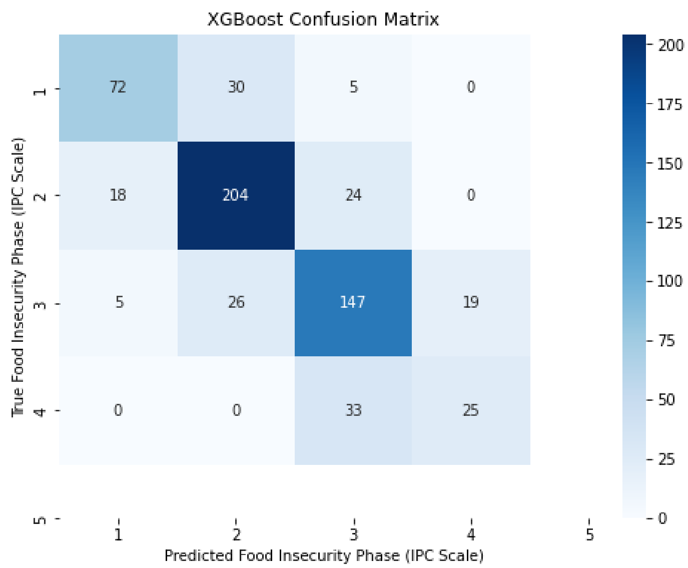


Figure 4.5: Confusion Matrix of XGBoost.

In conclusion, we find that RF and XGBoost perform similarly, with RF being slightly more accurate, but requiring more time for prediction compared to XGBoost.

4.4.2 Evaluation of Features

We further evaluate the features of our models. For RF model, the features' importance is extracted from the trained model, showing the relative importance of each feature in the construction of the RF. Figure 4.5 quantifies the contribution of each feature to the RF model's prediction.

Our findings using RF model, indicate as the most important feature in predicting food insecurity the food price index. High and rising food prices are considered the most frequent barriers to adopting healthier diets [80]. Food-insecure households spent less on food, reporting poor and worsening diet quality and more limited access to meat, fresh vegetables and fresh fruit.[23] Moreover, market food prices have been used to forecast food insecurity [81]. We include food price index in our model to capture food price dynamics, since it tracks changes in food prices over time, while aggregating prices of various food commodities (such as grains, dairy, meat, and oils) to provide an overall measure. We consider that food price data can be used to predict food insecurity and initiate timely interventions.

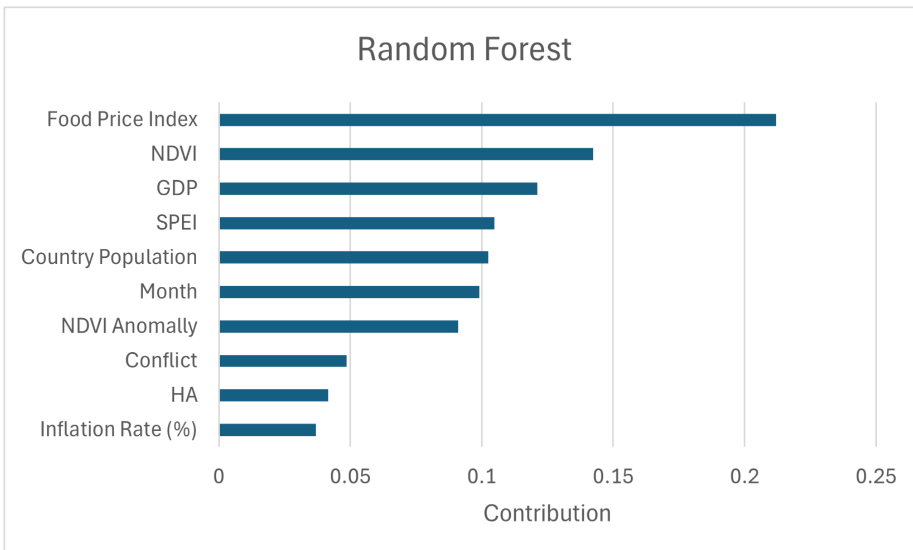


Figure 4.6: Features' Importance in RF contribution.

By including price trends, and market dynamics, we build our predictive models that can pinpoint regions or population groups at risk of food insecurity. This information can guide targeted interventions, such as food assistance programs or income support measures, to alleviate the impacts.

Climate and environmental features including SPEI and NDVI, are found to be important factors in predicting food insecurity. Soil moisture-related variables were the most important predictors for the shorter lead time, and socio-economic variables the most im-

[23]Drewnowski, A. et al. Mapping COVID-19 Risk Factors by King County Zip Codes: June to July 2020, Research Brief 6, Washington State Food Security Survey, 2020, (https://go.nature.com/3BFoWqc)

portant for the longer lead time [78]. Some of the key drivers for transitions in food security, such as soil moisture, NDVI, and rainfall, can be monitored and forecasted in high temporal and spatial resolution and with relatively high accuracy. glsndvi has been also used to predict optimal harvest time for maize harvest [82]. NDVI and NDVI anomaly have been used to measure the performance of the agricultural season and they have made predictions on food insecurity in 6 countries [81].

GDP is also found important in predicting food insecurity. Constraints on agricultural production and infrastructure affect food insecurity in African countries, where agriculture's share in GDP is large [83] . Additionally, less-skilled labour-intensive agriculture, which is less productive, cannot provide enough food for all as well as generate substantial income for farmers [84]. Increases in GDP per capita have been found to be correlated with declines in individual food security [85]. However, despite economic growth and increases in per capita GDP in Africa, access to food is still a challenge for many populations due to persistent and high levels of income inequality, maintaining large numbers of people moderately or severely food insecure [84]. For our RF model, country's population is found to be an important feature as well as the month of prediction.

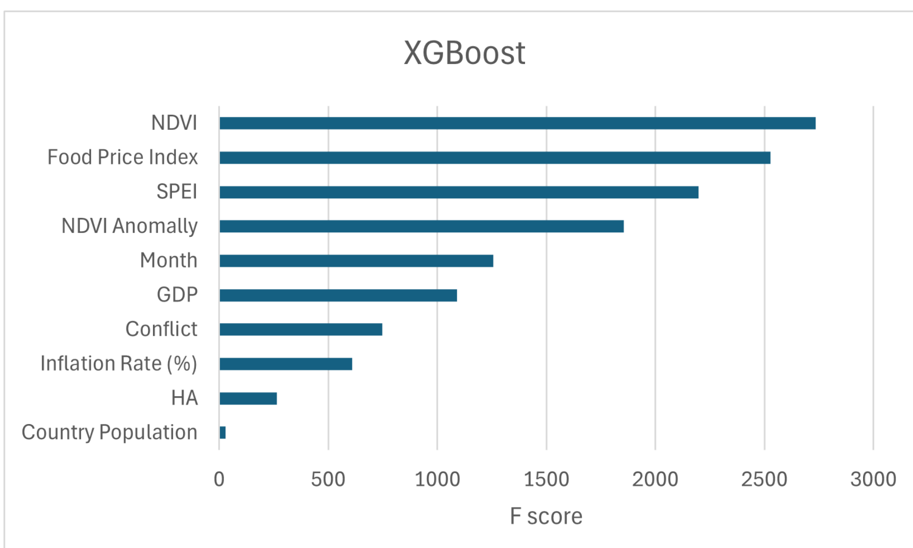


Figure 4.7: Features' Importance in XGBoost model.

Figure 4.6 presents features' importance for XGBoost using F score, which counts the number of times a feature is used to split the data across all trees in the model. Each time a feature is used in a tree's split, it contributes one count to its F score. Therefore, a higher F score indicates that the feature is used more frequently in the splits, suggesting it has a stronger influence on the model's predictions. According to our findings, NDVI and food price index have the highest frequency of appearance in the trees, entailing that they are considered more important because they are used more often in the splits. NDVI anomally, month and GDP are the next most important features.

The results using both models, although not numerically comparable, indicate that economic and climate and environmental features are the most important in predicting food insecurity. However, XGBoost does not use country population in the splits, whereas the same feature in RF has high contribution is RF's formation.

4.4.3 Sensitivity Analysis

Train-Test Split

So far, we have used in our models 80 percent training and 20 percent testing data for several reasons such as avoiding overfitting and to examine whether our model generalizes to unseen examples. We test whether our results are sensitive to this split by using 50 percent as training set and 50 percent as test data. Our results are included in the following table:

Table 4.4: Models Performance Metrics using 50/50 split.

Metrics	**Multinomial Logistic Regression**	**Random Forest**	**XGBoost**
Accuracy (%)	56.91	71.2	68.18
Precision	0.57	0.71	0.68
Recall	0.57	0.71	0.68
RMSE	1.98	3.33	3.11
MAE	0.45	0.32	0.35
Training Time (sec)	0.13	0.85	1.40
Prediction Time (sec)	$< 10^{-2}$	0.21	0.02

According to our findings, the accuracy levels are lower and there is also an increase in RMSE when we use a 50-50 split instead of a 80-20 spilt of data. Using smaller portion of the data as training set, leads to relatively lower performance in our models.

Food Insecurity Forecasting with Predictive Features

In our previous estimations, we have used both predictive (e.g. climate related) and contemporaneous(e.g., food prices, conflict) indicators to predict food insecurity in our model. Some of the contemporaneous indicators such as food prices or conflict may be outcomes resulting from severe food insecurity. Therefore, we further separate indicators and estimate our model including only climate related indicators.

Table 4.5: Models Performance Metrics using predictive features.

Metrics	**Multinomial Logistic Regression**	**Random Forest**	**XGBoost**
Accuracy (%)	55.10	69.74	70.72
Precision	0.56	0.69	0.70
Recall	0.55	0.70	0.71
RMSE	0.56	1.38	1.40
MAE	0.48	0.33	0.32
Training Time (sec)	0.39	5.21	2.97
Prediction Time (sec)	$< 10^{-2}$	0.31	0.02

Table 4.5 describes the results indicating lower, but similar accuracy compared to our initial model, in which all indicators were included. Additionally, in terms of features' importance, both RF and XGBoost models identified NDVI, SPEI, and NDVI Anomaly as most important predictors.

4.5 Further Extensions

The period covered in the current study included the pandemic years. COVID-19 posed additional challenges, such as border closures, lockdowns, and curfews disrupting supply chains, and affecting markets and farmers, and African countries heavily rely on food imports, making them vulnerable to export bans.

Table 4.6: Models Performance Metrics including COVID-19 cases.

Metrics	Multinomial Logistic Regression	Random Forest	XGBoost
Accuracy (%)	52.26	75.66	74.34
Precision	0.55	0.75	0.74
Recall	0.55	0.76	0.74
RMSE	0.75	1.52	1.52
MAE	0.48	0.27	0.28
Training Time (sec)	0.23	2.26	1.48
Prediction Time (sec)	$< 10^{-2}$	0.13	$< 10^{-2}$

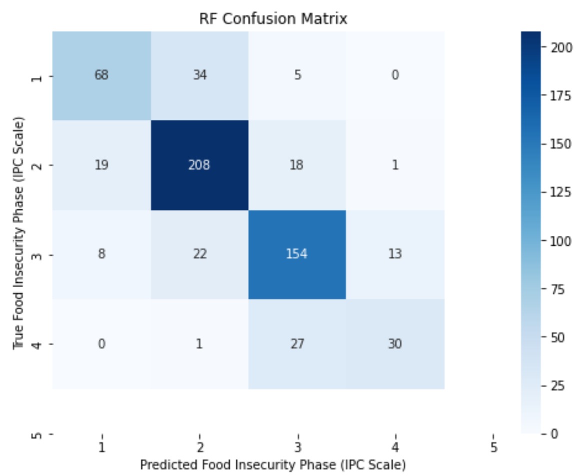


Figure 4.8: Confusion matrix of Random Forest model when we include COVID-19 cases.

We re-estimate our models by including an additional data on COVID-19 cases at country level for the years 2020-2023. We also include a lag variable for the food price index.

Table 4.6 shows models performance, which is similar but indicating slightly greater accuracy for bothRF and XGBoost. RF again indicates the highest accuracy. According to Figure 4.8, for RF model food insecurity emergency conditions cases are correctly classified by 1.2 percent more compared to our initial model and stressed cases by 5 percent. However, minimal food insecurity conditions cases are predicted correctly by 6 percent less. For XGBoost, the result indicate that almost 52 percent of food insecurity emergency cases are predicted correctly. Additionally, stressed and crisis food insecurity cases are predicted correctly at slightly higher percent compared to the initial model.

Further, we evaluate the features finding that in RF model COVID-19 Cases attribute

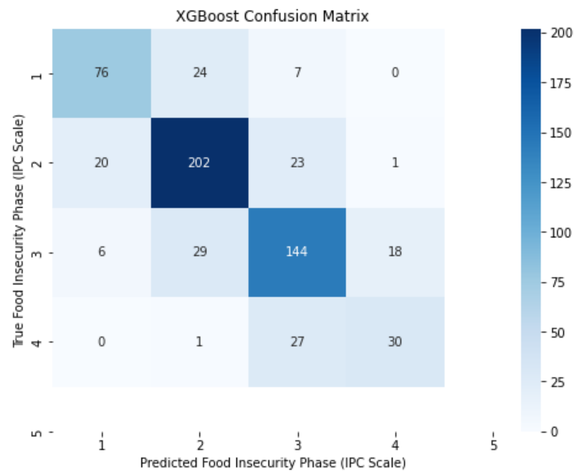


Figure 4.9: Confusion matrix of XGBoost model when we include COVID-19 cases.

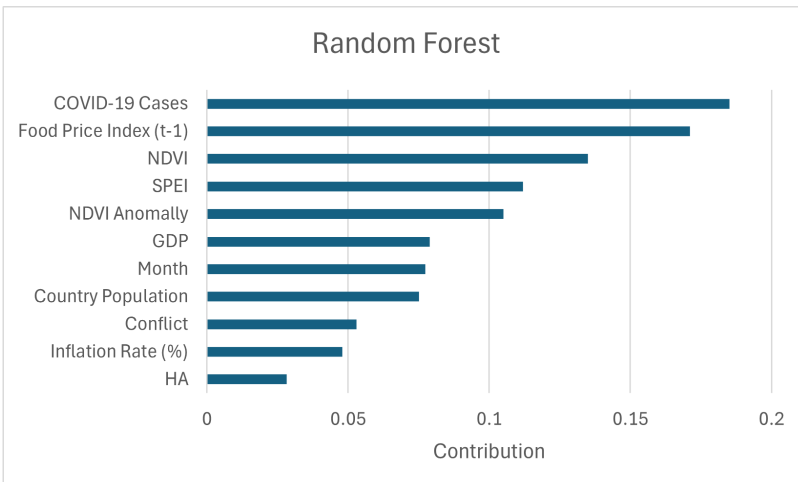


Figure 4.10: Features' Importance in Random Forest contribution.

indicated the greatest contribution (Figure 4.10). In XGBoost model, COVID-19 cases also indicated high F-score being the third most important feature in the splits (Figure 4.11). Our preliminary results, indicate that COVID-19 cases provide valuable insight in predicting food insecurity and therefore it should be further considered at this time frame in future work.

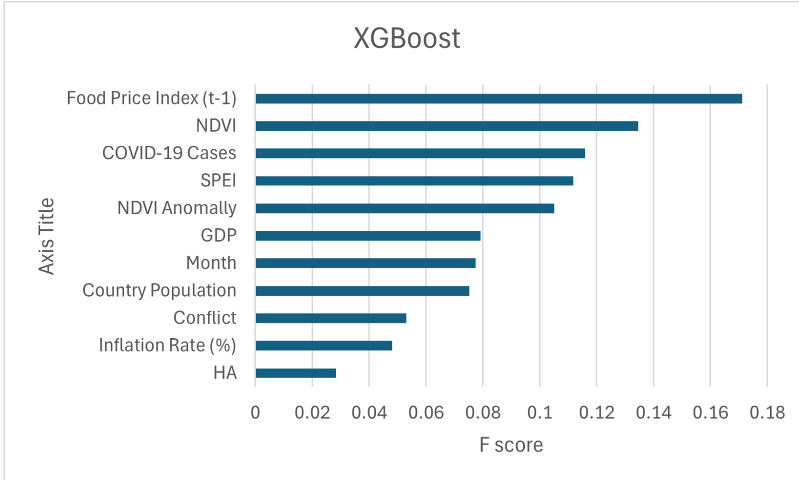


Figure 4.11: Features' Importance in XGBoost contribution.

4.6 Contribution and Limitations

Food insecurity imposes heavy human costs that are likely to increase in light of worsening climatic drivers and growing populations. In this context, models that can predict food insecurity levels of a district based on the suggested features opens important opportunities to mitigate and avoid the worst outcomes. We combined data from several sources to capture the main drivers of food insecurity, and we provide evidence on how the ML approach can be leveraged to better predict the underlying factors that highly cause food insecurity. We find that information on food price index, vegetation and climate data can be used to predict food insecurity, and these outcomes can be used to detect future crisis outbreaks and may help increase lead time for action. This research contributes to using machine learning for future food crisis in the particular context of including climate, agricultural, food price index and conflict data, supporting early interventions, and it may help to develop more effective policies to ensure food security. We further included COVID-19 cases per country since our study is conducted during the pandemic, which slightly improved models accuracy, and identified COVID-19 cases as important feature to predict food insecurity for both models. However, there are limitations in the current study. For example, the data on conflict that we have used includes many different events which may not be related to food insecurity affecting the models accuracy of prediction. Using specific conflict events, may lead to higher accuracy especially for the emergency cases. Additionally, we have included COVID-19 cases attribute, but at country level, whereas using district level data on COVID-19 cases could improve models' accuracy in predicting food insecurity.

CHAPTER 5
CONCLUSIONS AND FUTURE WORK

There is growing evidence that climate change is resulting in an increase in the frequency, intensity, and duration of natural hazards, such as droughts. This study highlights the adverse impact of droughts on children's well-being in Africa and specifically Ethiopia, where droughts have become longer and more frequent. Vulnerable populations in low-income countries including children, ethnic and religious minorities are more likely to be impacted by natural disasters. This work offers valuable evidence on the negative impact of drought on children's educational outcomes, living conditions, health and time allocation. We find that droughts had a significant adverse impact on children's education, and that in drought affected areas children are less likely to be enrolled in school. We find that these children spent nearly 0.078 additional hours daily on paid work. Children who continue to be enrolled in school lag behind in grade completion with the onset of a drought. In rural areas, particularly, children tend to spend much less time on education. Children in drought affected areas live in households with high food insecurity and often report a decline in their overall well-being. With every additional drought stunting among children, especially among girls, increases by more than 27 percent. Future work will include controlling for conflict events which can severely affect children's educational outcomes and expanding more on the mechanisms on how droughts affect education.

In the second essay, we evaluate the effectiveness of SAPs interventions on food security in households, while identifying areas for improvement in policies and programs. Additionally, incentives that give the opportunity to farmers grow diverse crops, secure future food supply and adapt to climate change are redirected. According to the findings, different factors are important in adopting each practice, which needs to be considered in determining future policies to reinforce SAPs' adoption. For example, receiving agricultural assistance has found to increase the likelihood of adopting crop rotation, since it provides farmers with knowledge on benefits of adoption. However, for mixed cropping receiving agricultural assistance is not found as important. Oftentimes, extension programs in Ethiopia may encourage farmers to adopt crop rotation more than mixed cropping, depending on the local agro-ecological and socio-economic conditions [86]. Identifying differences between factors that promote SAPs adoption can inform future policies. Moreover, we evaluate the impact of adopting crop rotation and mixed cropping on food security using different food measures. Our results reveal the powerful impact of SAPs on reducing food insecurity. Both SAPs are found to decrease food insecurity by up to 10 percent, through higher crop yields, ensuring a stable food supply, while promoting resilience to climate change by mitigating its adverse effects on crops and ecosystems. Adopting crop rotation and mixed cropping can offer a holistic approach to addressing food security challenges and can lead to food insecurity mitigation, while contributing to building more food-secure food systems for present and future generations. Extension of the current work will include information on types of crops or drought occurrence using drought indices, which can play a significant role in adopting sustainable agricultural practices.

In the third essay, we used machine learning models to predict food insecurity in four African countries. We used logistic regression as a baseline model and then applied RF and XGBoost models, which resulted in up to 75 percent accuracy in prediction. We further evaluated features' importance in each model finding that economic and environmental and climate features are very important in predicting food insecurity. Specifically, we have found that food price index and NDVI were the most important predictors in both models. These findings reinforce the need for committed efforts to improve access to food security, as well as the socio-economic well-being in developing countries, and promote policies and interventions that put special focus on alleviate the identified the causes of food insecurity. However, in our future analysis we would like to improve prediction accuracy for districts at emergency food insecurity state by compiling specific conflict data at district level. For example, conflict data could specifically include events leading to supply chain disruption. Future work will also include COVID-19 related data at district level. We would like to extend our analysis and forecast food insecurity in other countries.

Appendices

APPENDIX A

TABLES

Table A.1: Identifying droughts using SPEI values.

Drought Classification	*SPEI values*
No Drought	greater than -0.5
Mild Drought	-0.5 to -0.99
Moderate Drought	-1.00 to -1.49
Severe Drought	-1.50 to -1.99
Extreme Drought	-2.00 or less

Source: Classification based on McKee et al., (1993) and Paulo et al., (2012).

Table A.2: Number of Sites in a region with Drought.

Survey Year	Amhara (4 sites)	Tigray (4 sites)	Oromia (4 sites)	SNNP (5 sites)	Addis Ababa (3 sites)
2009	4	4	4	5	3
2013	4	4	0	2	0
2016	1	4	3	3	2

Note: This table describes the number of sites per region that experience drought per round. There is drought when a site experiences at least one dry season identified using the monthly mean SPEI value (SPEI < -0.5).

Table A.3: Impact of Drought on Children's Education.

	PPVT score	Mathematics test score
	(1)	(2)
Drought	-0.573	0.164
	(0.689)	(0.771)
Age	24.79***	13.09***
	(4.318)	(3.568)
Age sq.	-0.863***	-0.332***
	(0.152)	(0.123)
HAZ (t-1)	1.950***	0.857*
	(0.544)	(0.445)
Hhd. Male	2.443	0.490
	(1.553)	(1.497)
Hhd. Age	-0.0709	-0.0570
	(0.088)	(0.067)
Father Edu	0.294	0.131
	(0.261)	(0.243)
Mother Edu	-0.477	0.119
	(0.503)	(0.443)
Parental Shock	1.426**	0.762
	(0.707)	(0.681)
Hhd. Size	0.176	0.692*
	(0.384)	(0.404)
No. children ¡ 6	-0.556	-1.115*
	(0.678)	(0.609)
No. children	-0.122	-0.535
6-18	(0.490)	(0.441)
Rural	-5.657	0.720
	(4.005)	(5.936)
Wealth index (t-1)	4.564	6.968*
	(3.722)	(3.791)
PSNP	0.380	-0.592
	(1.001)	(0.921)
Obs.	2,454	2,454
Obs. per round	818	818
Child FE	Y	Y
Year and Region FE	Y	Y

Robust standard errors (clustered at child level) in parentheses *** p< 0.01, ** p<0.05, * p<0.1

Table A.4: Impact of Drought on Children's Education.

Educational Outcomes	Enrollment			Grade Completion			Relative Grade		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Drought	-1.098***	-1.047***	-1.010**	-0.000	-0.027**	-0.043***	-0.109***	-0.051***	-0.059***
	(0.399)	(0.394)	(0.405)	(0.013)	(0.012)	(0.013)	(0.016)	(0.015)	(0.017)
Age	3.139***	3.064***	2.042	1.130***	0.907***	0.563***	-	-	-
	(0.397)	(0.409)	(1.414)	(0.030)	(0.038)	(0.167)			
Age sq.	-0.122***	-0.118***	-0.163***	-0.035***	-0.027***	-0.032***	-	-	-
	(0.017)	(0.017)	(0.047)	(0.001)	(0.001)	(0.005)			
HAZ (t-1)	0.434**	0.583***	0.547***	0.047***	0.035***	0.032***	0.046***	0.042***	0.040***
	(0.174)	(0.188)	(0.191)	(0.013)	(0.012)	(0.012)	(0.014)	(0.014)	(0.015)
Hhd. Male	-	-0.683	-0.671	-	-0.022	-0.014	-	-0.028	-0.026
		(0.430)	(0.452)		(0.031)	(0.031)		(0.039)	(0.041)
Hhd. Age	-	0.004	0.000	-	0.001	0.001	-	0.003	0.003
		(0.025)	(0.027)		(0.002)	(0.002)		(0.003)	(0.003)
Father Edu	-	0.159*	0.183**	-	-0.012*	0.013*	-	0.005	0.005
		(0.090)	(0.091)		(0.007)	(0.007)		(0.007)	(0.007)
Mother Edu	-	-0.176	-0.162	-	0.023	-0.025*	-	-0.026	-0.028*
		(0.190)	(0.211)		(0.015)	(0.015)		(0.016)	(0.017)
Parental Shock	-	-0.079	-0.097	-	-0.028*	-0.028*	-	-0.032	-0.031
		(0.243)	(0.250)		(0.016)	(0.016)		(0.019)	(0.019)
Hhd. Size	-	0.266**	0.281**	-	0.011	0.010	-	0.015	0.016
		(0.131)	(0.132)		(0.009)	(0.008)		(0.011)	(0.011)
No. children < 6	-	-0.360	-0.396*	-	-0.023	-0.021	-	-0.003	-0.003
		(0.232)	(0.231)		(0.017)	(0.017)		(0.019)	(0.020)
No. children 6-18	-	-0.103	-0.101	-	-0.008	-0.006	-	-0.007	-0.007
		(0.140)	(0.144)		(0.013)	(0.012)		(0.014)	(0.014)
Rural	-	-11.626***	-12.654***	-	-0.097	-0.044	-	-0.021	0.013
		(1.147)	(1.184)		(0.112)	(0.110)		(0.279)	(0.276)
Wealth index (t-1)	-	-1.177	-1.131	-	-0.032	-0.057	-	-0.033	-0.030
		(1.452)	(1.451)		(0.087)	(0.088)		(0.113)	(0.115)
PSNP	-	1.408***	1.393***	-	-0.004	-0.017	-	-0.028	-0.027
		(0.391)	(0.401)		(0.025)	(0.025)		(0.032)	(0.033)
Obs.	1,332	1,332	1,332	3,279	3,279	3,279	3,279	3,279	3,279
Obs. per round	444	444	444	1,093	1,093	1,093	1,093	1,093	1,093
Child FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year and Region FE	N	N	Y	N	N	Y	N	N	Y

Robust standard errors (clustered at child level) in parentheses *** p< 0.01, ** p<0.05, * p<0.1

Table A.5: Impact of Drought on Children's Living Conditions, and Time Allocation.

	Living Conditions	Health		Time	Allocation			
	Food Insecurity	Well Being	Stunting	Paid work	Domestic tasks	Chores	Education	Sleep
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Drought	0.067***	-0.031*	0.071	0.078**	0.008	-0.196***	0.138	-0.099**
	(0.014)	(0.017)	(0.072)	(0.036)	(0.076)	(0.063)	(0.102)	(0.049)
Age	-0.131*	0.032	0.837	0.081	-0.029	0.184	0.822	-0.581**
	(0.077)	(0.087)	(0.620)	(0.159)	(0.475)	(0.330)	(0.661)	(0.251)
Age sq.	0.002	0.002	-0.009	0.013	-0.006	-0.010	-0.063***	0.028***
	(0.003)	(0.003)	(0.015)	(0.009)	(0.016)	(0.012)	(0.022)	(0.009)
HAZ (t-1)	0.016	-0.006	0.110**	0.009	0.121**	-0.078*	0.063	0.035
	(0.010)	(0.012)	(0.049)	(0.026)	(0.053)	(0.042)	(0.077)	(0.033)
Hhd. Male	-0.005	0.015	0.074	-0.053	0.147	-0.204*	-0.510***	0.128
	(0.029)	(0.030)	(0.154)	(0.060)	(0.140)	(0.106)	(0.194)	(0.091)
Hhd. Age	0.001	0.002	0.012	-0.001	0.001	-0.006	0.009	0.000
	(0.002)	(0.002)	(0.011)	(0.002)	(0.007)	(0.008)	(0.011)	(0.005)
Father Edu	-0.021***	0.004	-0.027	0.004	-0.017	-0.004	-0.013	-0.000
	(0.004)	(0.005)	(0.026)	(0.009)	(0.025)	(0.017)	(0.039)	(0.015)
Mother Edu	-0.016	-0.000	0.013	-0.006	-0.038	0.082	-0.058	-0.044
	(0.012)	(0.012)	(0.039)	(0.019)	(0.046)	(0.050)	(0.078)	(0.033)
Parental Shock	0.046***	-0.038**	0.040	0.019	0.247***	-0.093*	-0.103	0.045
	(0.013)	(0.015)	(0.066)	(0.041)	(0.075)	(0.055)	(0.103)	(0.044)
Hhd. Size	-0.012	0.019**	0.031	-0.040*	-0.006	-0.090***	0.172***	-0.022
	(0.007)	(0.008)	(0.038)	(0.021)	(0.041)	(0.032)	(0.055)	(0.025)
No. children <6	0.042***	-0.032**	0.033	-0.001	-0.039	0.068	-0.275***	-0.002
	(0.013)	(0.014)	(0.062)	(0.026)	(0.073)	(0.052)	(0.103)	(0.044)
No. children	0.023***	-0.010	0.038	0.040**	-0.025	0.041	-0.170**	0.001
6-18	(0.009)	(0.011)	(0.048)	(0.018)	(0.051)	(0.037)	(0.070)	(0.032)
Rural	-0.494***	0.020	-1.683***	0.052	0.853	-0.926**	-2.252***	0.473
	(0.118)	(0.054)	(0.307)	(0.113)	(0.664)	(0.387)	(0.644)	(0.456)
Wealth index (t-1)	0.060	0.093	0.248	-0.158	0.737	0.499	-0.054	-0.522**
	(0.078)	(0.088)	(0.407)	(0.174)	(0.475)	(0.330)	(0.648)	(0.259)
PSNP	0.016	-0.049**	-0.225*	-0.098	0.125	-0.085	0.447***	-0.042
Obs.	3,279	3,279	1,257	3,279	3,279	3,279	3,279	3,279
Obs. per round	1,093	1,093	419	1,093	1,093	1,093	1,093	1,093
Child, Year and Region FE	Y	Y	Y	Y	Y	Y	Y	Y

Robust standard errors (clustered at child level) in parentheses *** p< 0.01, ** p<0.05, * p<0.1

Table A.6: Impact of Drought on Girls' Outcomes.

	Educational Outcomes			Living Conditions	Health		Time	Allocation			
	Enrollment	Grade Completion	Relative Grade	Food Security	Well Being	Stunting	Paid work	Domestic tasks	Chores	Education	Sleep
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Drought	-1.565**	-0.045**	-0.052**	0.055***	-0.038	0.279**	0.026	0.005	-0.263***	0.034	0.061
*Female	(0.784)	(0.018)	(0.024)	(0.018)	(0.024)	(0.137)	(0.044)	(0.085)	(0.082)	(0.128)	(0.066)
Age	2.008	0.568***	-	-0.123	0.031	0.878	0.088	-0.028	0.167	0.836	-0.591**
	(1.365)	(0.168)		(0.078)	(0.087)	(0.618)	(0.159)	(0.475)	(0.327)	(0.660)	(0.251)
Age sq.	-0.164***	-0.032***	-	0.003	0.002	-0.009	0.013	-0.006	-0.011	-0.063***	0.028***
	(0.048)	(0.005)		(0.003)	(0.003)	(0.015)	(0.009)	(0.016)	(0.012)	(0.022)	(0.009)
HAZ (t-1)	0.555***	0.031***	0.040***	0.017*	-0.006	0.105**	0.011	0.121**	-0.078*	0.066	0.032
	(0.190)	(0.012)	(0.015)	(0.010)	(0.012)	(0.050)	(0.026)	(0.053)	(0.042)	(0.077)	(0.033)
Hhd. Male	-0.746	-0.015	-0.029	-0.001	0.015	0.081	-0.043	0.148	-0.204*	-0.491**	0.103
	(0.457)	(0.031)	(0.041)	(0.029)	(0.030)	(0.157)	(0.061)	(0.140)	(0.107)	(0.194)	(0.092)
Hhd. Age	-0.004	0.001	0.003	0.001	0.002	0.011	-0.001	0.001	-0.005	0.009	0.000
	(0.026)	(0.002)	(0.003)	(0.002)	(0.002)	(0.011)	(0.002)	(0.007)	(0.008)	(0.011)	(0.005)
Father Edu	0.168*	0.012*	0.005	-0.021***	0.004	-0.027	0.005	-0.016	-0.003	-0.012	-0.001
	(0.091)	(0.007)	(0.007)	(0.004)	(0.005)	(0.026)	(0.009)	(0.025)	(0.017)	(0.039)	(0.015)
Mother Edu	-0.190	0.024	0.029*	-0.016	-0.000	0.014	-0.007	-0.038	0.083*	-0.059	-0.042
	(0.222)	(0.015)	(0.016)	(0.012)	(0.012)	(0.040)	(0.019)	(0.046)	(0.050)	(0.078)	(0.033)
Parental Shock	-0.076	-0.029*	-0.030	0.045***	-0.038**	0.035	0.019	0.247***	-0.092*	-0.101	0.042
	(0.242)	(0.016)	(0.020)	(0.013)	(0.015)	(0.065)	(0.041)	(0.075)	(0.055)	(0.103)	(0.044)
Hhd. Size	0.267**	0.010	0.015	-0.011	0.019**	0.028	-0.038*	-0.006	-0.092***	0.175***	-0.025
	(0.131)	(0.008)	(0.011)	(0.007)	(0.008)	(0.038)	(0.021)	(0.041)	(0.031)	(0.055)	(0.025)
No. children <6	-0.388*	-0.020	-0.001	0.040***	-0.031**	0.036	-0.004	-0.039	0.072	-0.281***	0.004
	(0.222)	(0.017)	(0.020)	(0.013)	(0.014)	(0.061)	(0.026)	(0.073)	(0.052)	(0.104)	(0.044)
No. children	-0.086	-0.006	-0.006	0.022**	-0.010	0.043	0.038**	-0.025	0.042	-0.174**	0.004
6-18	(0.146)	(0.012)	(0.014)	(0.009)	(0.010)	(0.048)	(0.018)	(0.050)	(0.037)	(0.070)	(0.032)
Rural	-10.934***	-0.048	0.006	-0.482***	0.026	-1.740***	0.101	0.856	-0.865**	-2.155***	0.324
	(1.317)	(0.111)	(0.278)	(0.117)	(0.055)	(0.294)	(0.112)	(0.666)	(0.387)	(0.656)	(0.466)
Wealth index (t-1)	-1.093	-0.045	-0.019	0.043	0.096	0.303	-0.179	0.735	0.522	-0.093	-0.481*
	(1.448)	(0.088)	(0.114)	(0.078)	(0.088)	(0.404)	(0.172)	(0.475)	(0.329)	(0.645)	(0.258)
PSNP	1.475***	-0.014	-0.022	0.010	-0.047**	-0.214*	-0.110	0.124	-0.077	0.425**	-0.016
	(0.400)	(0.025)	(0.033)	(0.020)	(0.023)	(0.115)	(0.073)	(0.153)	(0.092)	(0.169)	(0.068)
Obs.	1,332	3,279	3,279	3,279	3,279	1,257	3,279	3,279	3,279	3,279	3,279
Obs. per round	444	1,093	1,093	1,093	1,093	419	1,093	1,093	1,093	1,093	1,093
Child, Year and Region FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Robust standard errors (clustered at child level) in parentheses *** p< 0.01, ** p<0.05, * p<0.1

Table A.7: Impact of Drought on Children's Outcomes in Rural Areas.

	Educational Outcomes	Living Conditions			Health		Time	Allocation			
	Enrollment	Grade Completion	Relative Grade	Food Security	Well Being	Stunting	Paid work	Domestic tasks	Chores	Education	Sleep
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Drought	-1.096**	-0.027*	-0.052***	0.071***	-0.074***	0.109	0.081*	0.136	-0.152**	-0.295**	0.007
*Rural	(0.449)	(0.016)	(0.018)	(0.016)	(0.020)	(0.077)	(0.046)	(0.089)	(0.073)	(0.120)	(0.055)
Age	2.122	0.563***	-	-0.130*	0.035	0.794	0.084	-0.032	0.169	0.845	-0.589**
	(1.415)	(0.168)		(0.077)	(0.087)	(0.623)	(0.159)	(0.477)	(0.331)	(0.657)	(0.251)
Age sq.	-0.167***	-0.032***	-	0.003	0.002	-0.010	0.013	-0.006	-0.011	-0.063***	0.028***
	(0.047)	(0.005)		(0.003)	(0.003)	(0.015)	(0.009)	(0.016)	(0.012)	(0.022)	(0.009)
HAZ (t-1)	0.556***	0.029**	0.039***	0.017*	-0.007	0.090*	0.012	0.123**	-0.086**	0.062	0.034
	(0.193)	(0.012)	(0.015)	(0.010)	(0.012)	(0.046)	(0.026)	(0.053)	(0.041)	(0.075)	(0.033)
Hhd. Male	-0.632	-0.019	-0.029	-0.001	0.019	0.058	-0.050	0.130	-0.216**	-0.447**	0.109
	(0.444)	(0.031)	(0.041)	(0.029)	(0.030)	(0.155)	(0.060)	(0.139)	(0.106)	(0.193)	(0.092)
Hhd. Age	0.001	0.001	0.003	0.001	0.002	0.014	-0.001	0.001	-0.005	0.010	0.000
	(0.026)	(0.002)	(0.003)	(0.002)	(0.002)	(0.011)	(0.002)	(0.007)	(0.008)	(0.011)	(0.005)
Father Edu	0.185**	0.012*	0.005	-0.021***	0.004	-0.027	0.005	-0.016	-0.005	-0.012	-0.001
	(0.093)	(0.007)	(0.007)	(0.004)	(0.005)	(0.026)	(0.009)	(0.025)	(0.017)	(0.039)	(0.015)
Mother Edu	-0.121	0.025*	0.030*	-0.019	0.002	0.014	-0.009	-0.041	0.087*	-0.053	-0.043
	(0.193)	(0.015)	(0.016)	(0.012)	(0.012)	(0.039)	(0.019)	(0.046)	(0.050)	(0.077)	(0.033)
Parental Shock	-0.058	-0.028*	-0.029	0.044***	-0.035**	0.038	0.015	0.238***	-0.085	-0.080	0.042
	(0.253)	(0.016)	(0.020)	(0.013)	(0.015)	(0.066)	(0.041)	(0.075)	(0.055)	(0.103)	(0.044)
Hhd. Size	0.268**	0.010	0.015	-0.011	0.019**	0.030	-0.038*	-0.005	-0.095***	0.174***	-0.024
	(0.132)	(0.008)	(0.011)	(0.007)	(0.008)	(0.038)	(0.021)	(0.041)	(0.031)	(0.055)	(0.025)
No. children <6	-0.364	-0.019	-0.000	0.039***	-0.031**	0.020	-0.004	-0.038	0.076	-0.284***	0.003
	(0.234)	(0.017)	(0.020)	(0.013)	(0.014)	(0.062)	(0.026)	(0.073)	(0.052)	(0.103)	(0.044)
No. children	-0.097	-0.005	-0.006	0.022**	-0.010	0.035	0.039**	-0.022	0.043	-0.180**	0.004
6-18	(0.146)	(0.012)	(0.014)	(0.009)	(0.010)	(0.048)	(0.018)	(0.050)	(0.037)	(0.070)	(0.032)
Wealth index (t-1)	-1.180	-0.043	-0.034	0.082	0.068	0.243	-0.146	0.785*	0.506	-0.204	-0.493*
	(1.447)	(0.088)	(0.115)	(0.079)	(0.088)	(0.404)	(0.175)	(0.475)	(0.330)	(0.649)	(0.261)
PSNP	1.418***	-0.012	-0.020	0.009	-0.050**	-0.242**	-0.105	0.139	-0.065	0.387**	-0.021
	(0.405)	(0.025)	(0.033)	(0.021)	(0.023)	(0.116)	(0.073)	(0.152)	(0.092)	(0.168)	(0.068)
Obs.	1,332	3,279	3,279	3,279	3,279	1,257	3,279	3,279	3,279	3,279	3,279
Obs. per round	444	1,093	1,093	1,093	1,093	419	1,093	1,093	1,093	1,093	1,093
Child, Year and Region FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Robust standard errors (clustered at child level) in parentheses *** p< 0.01, ** p<0.05, * p<0.1

Table A.8: Impact of Drought Frequency on Children's Outcomes.

	Educational Outcomes	Living Conditions			Health		Time	Allocation			
	Enrollment	Grade Completion	Relative Grade	Food Security	Well Being	Stunting	Paid work	Domestic tasks	Chores	Education	Sleep
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
No.	0.791***	-0.038***	-0.074***	0.030***	0.020	0.115**	0.031	0.142**	-0.209***	-0.115	0.020
of Droughts	(0.287)	(0.010)	(0.016)	(0.011)	(0.014)	(0.056)	(0.025)	(0.061)	(0.045)	(0.076)	(0.040)
Age	2.080	0.550***	-	-0.127	0.030	0.849	0.085	-0.042	0.186	0.848	-0.593**
	(1.395)	(0.169)		(0.078)	(0.088)	(0.617)	(0.159)	(0.478)	(0.332)	(0.660)	(0.252)
Age sq.	-0.167***	-0.032***	-	0.003	0.002	-0.010	0.013	-0.007	-0.011	-0.063***	0.028***
	(0.048)	(0.005)		(0.003)	(0.003)	(0.015)	(0.009)	(0.016)	(0.012)	(0.022)	(0.009)
HAZ (t-1)	0.547***	0.033***	0.040***	0.017*	-0.007	0.108**	0.011	0.118**	-0.079*	0.069	0.032
	(0.186)	(0.012)	(0.015)	(0.010)	(0.012)	(0.049)	(0.026)	(0.053)	(0.042)	(0.076)	(0.033)
Hhd. Male	-0.737	-0.013	-0.020	-0.000	0.005	0.072	-0.047	0.116	-0.190*	-0.460**	0.106
	(0.486)	(0.031)	(0.040)	(0.029)	(0.030)	(0.154)	(0.061)	(0.141)	(0.105)	(0.195)	(0.091)
Hhd. Age	0.004	0.001	0.003	0.001	0.002	0.010	-0.001	0.000	-0.005	0.010	0.000
	(0.028)	(0.002)	(0.003)	(0.002)	(0.002)	(0.011)	(0.002)	(0.007)	(0.008)	(0.011)	(0.005)
Father Edu	0.166*	0.013*	0.005	-0.021***	0.003	-0.026	0.005	-0.017	-0.004	-0.011	-0.001
	(0.087)	(0.007)	(0.007)	(0.004)	(0.005)	(0.026)	(0.009)	(0.025)	(0.017)	(0.039)	(0.015)
Mother Edu	-0.191	0.026*	0.027	-0.016	0.001	0.014	-0.007	-0.035	0.079	-0.062	-0.042
	(0.207)	(0.015)	(0.017)	(0.012)	(0.012)	(0.038)	(0.019)	(0.047)	(0.050)	(0.078)	(0.033)
Parental Shock	-0.085	-0.030*	-0.031	0.046***	-0.039**	0.037	0.019	0.246***	-0.094*	-0.099	0.043
	(0.249)	(0.016)	(0.019)	(0.013)	(0.016)	(0.065)	(0.041)	(0.075)	(0.054)	(0.103)	(0.044)
Hhd. Siz	0.279**	0.011	0.016	-0.011	0.018**	0.029	-0.039*	-0.009	-0.090***	0.178***	-0.025
	(0.132)	(0.008)	(0.011)	(0.007)	(0.008)	(0.038)	(0.021)	(0.041)	(0.032)	(0.056)	(0.025)
No. children <6	-0.408*	-0.022	-0.005	0.041***	-0.029**	0.036	-0.003	-0.030	0.064	-0.289***	0.004
	(0.222)	(0.017)	(0.020)	(0.013)	(0.014)	(0.061)	(0.026)	(0.073)	(0.052)	(0.104)	(0.044)
No. children	-0.100	-0.006	-0.007	0.022**	-0.008	0.037	0.038**	-0.022	0.041	-0.177**	0.004
6-18	(0.146)	(0.012)	(0.014)	(0.009)	(0.010)	(0.048)	(0.018)	(0.050)	(0.037)	(0.070)	(0.032)
Rural	-11.730***	-0.064	0.005	-0.451***	-0.021	-1.694***	0.105	0.768	-0.973**	-2.048***	0.367
	(1.191)	(0.109)	(0.269)	(0.120)	(0.052)	(0.303)	(0.099)	(0.674)	(0.401)	(0.664)	(0.464)
Wealth index (t-1)	-0.986	-0.069	-0.037	0.047	0.109	0.304	-0.171	0.791*	0.478	-0.143	-0.482*
	(1.453)	(0.089)	(0.114)	(0.078)	(0.088)	(0.404)	(0.175)	(0.476)	(0.328)	(0.647)	(0.259)
PSNP	1.401***	-0.012	-0.032	0.010	-0.038*	-0.228**	-0.105	0.158	-0.099	0.393**	-0.018
	(0.399)	(0.025)	(0.033)	(0.021)	(0.023)	(0.114)	(0.074)	(0.153)	(0.092)	(0.170)	(0.068)
Obs.	1,332	3,279	3,279	3,279	3,279	1,257	3,279	3,279	3,279	3,279	3,279
Obs. per round	444	1,093	1,093	1,093	1,093	419	1,093	1,093	1,093	1,093	1,093
Child, Year and Region FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Robust standard errors (clustered at child level) in parentheses *** p< 0.01, ** p<0.05, * p<0.1

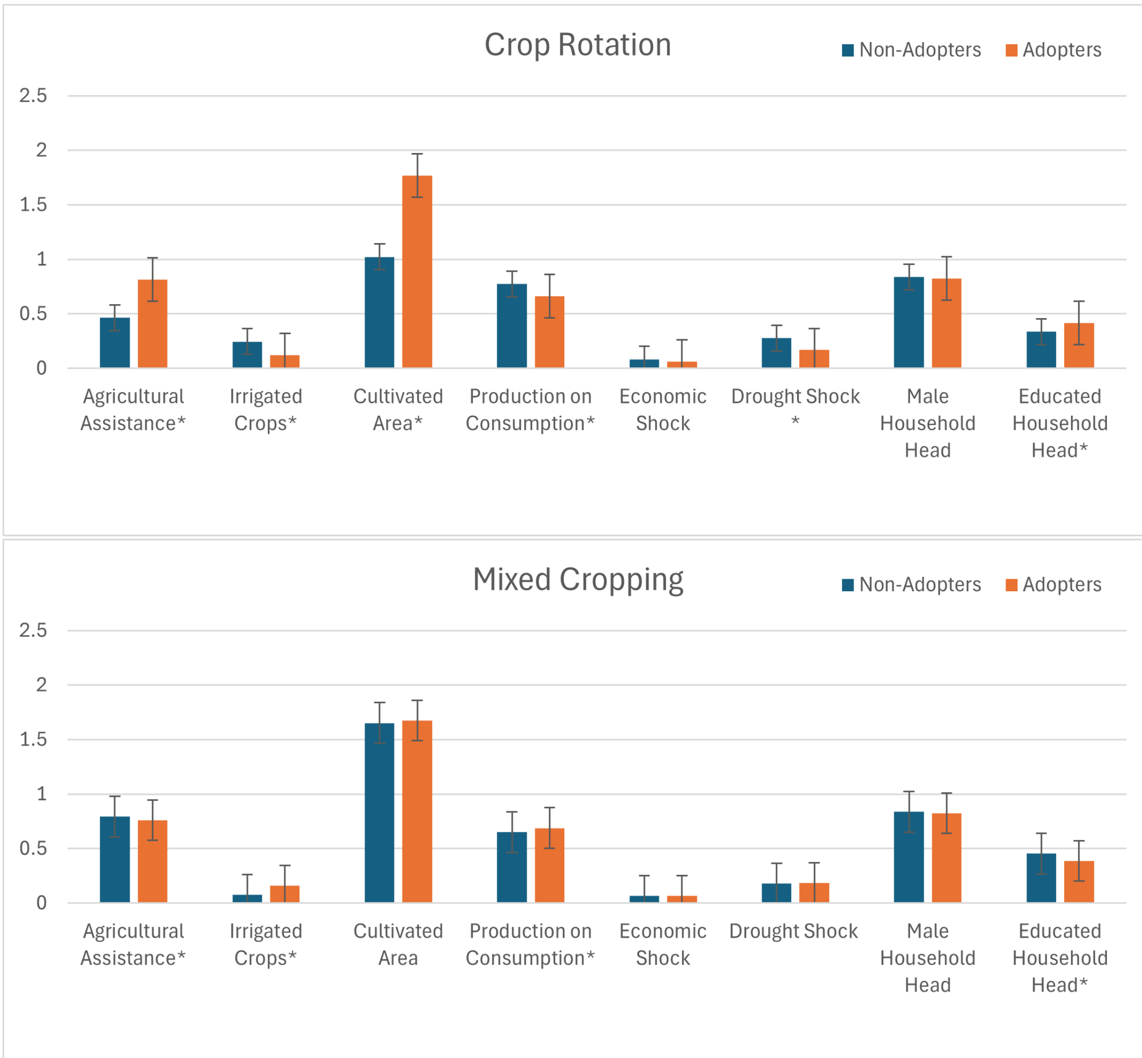
Table A.9: Impact of Drought on Children's Education using self-reported drought.

	Educational Outcomes	Living Conditions			Health		Time	Allocation			
	Enrollment	Grade Completion	Relative Grade	Food Security	Well Being	Stunting	Paid work	Domestic tasks	Chores	Education	Sleep
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Drought	-0.408*	0.012	0.028	0.096***	-0.049***	-0.036	-0.015	0.101	0.044	-0.168	-0.057
(self-reported)	(0.232)	(0.017)	(0.020)	(0.014)	(0.016)	(0.064)	(0.041)	(0.096)	(0.065)	(0.127)	(0.051)
Age	1.966	0.571***	-	-0.087	0.016	0.855	0.084	0.005	0.179	0.782	-0.609**
	(1.362)	(0.167)		(0.078)	(0.088)	(0.613)	(0.160)	(0.474)	(0.330)	(0.660)	(0.252)
Age sq.	-0.176***	-0.032***	-	0.002	0.002	-0.009	0.013	-0.007	-0.011	-0.062***	0.028***
	(0.050)	(0.005)		(0.003)	(0.003)	(0.015)	(0.009)	(0.016)	(0.012)	(0.022)	(0.009)
HAZ (t-1)	0.599***	0.028**	0.037**	0.012	-0.004	0.116**	0.012	0.115**	-0.086**	0.076	0.036
	(0.183)	(0.012)	(0.015)	(0.010)	(0.012)	(0.048)	(0.026)	(0.053)	(0.042)	(0.077)	(0.033)
Hhd. Male	-0.684	-0.025	-0.036	0.004	0.010	0.081	-0.039	0.145	-0.238**	-0.482**	0.112
	(0.457)	(0.031)	(0.041)	(0.028)	(0.030)	(0.155)	(0.060)	(0.139)	(0.105)	(0.195)	(0.091)
Hhd. Age	0.010	0.001	0.003	0.001	0.002	0.012	-0.001	0.001	-0.006	0.009	0.000
	(0.029)	(0.002)	(0.003)	(0.002)	(0.002)	(0.011)	(0.002)	(0.007)	(0.008)	(0.011)	(0.005)
Father Edu	0.179**	0.011	0.004	-0.021***	0.004	-0.027	0.005	-0.017	-0.005	-0.011	-0.001
	(0.088)	(0.007)	(0.007)	(0.004)	(0.005)	(0.026)	(0.009)	(0.025)	(0.017)	(0.039)	(0.015)
Mother Edu	-0.156	0.024	0.029*	-0.017	0.000	0.013	-0.007	-0.038	0.084*	-0.059	-0.043
	(0.194)	(0.015)	(0.016)	(0.012)	(0.012)	(0.038)	(0.019)	(0.046)	(0.050)	(0.078)	(0.033)
Parental Shock	-0.079	-0.030*	-0.032	0.043***	-0.038**	0.043	0.020	0.244***	-0.097*	-0.095	0.045
	(0.249)	(0.016)	(0.019)	(0.013)	(0.015)	(0.065)	(0.041)	(0.075)	(0.055)	(0.103)	(0.044)
Hhd. Size	0.268**	0.009	0.014	-0.012*	0.020**	0.033	-0.037*	-0.008	-0.096***	0.179***	-0.023
	(0.134)	(0.008)	(0.011)	(0.007)	(0.008)	(0.038)	(0.021)	(0.041)	(0.031)	(0.055)	(0.025)
No. children <6	-0.392*	-0.018	0.000	0.040***	-0.031**	0.033	-0.005	-0.039	0.078	-0.283***	0.003
	(0.224)	(0.017)	(0.020)	(0.012)	(0.014)	(0.061)	(0.026)	(0.073)	(0.052)	(0.103)	(0.044)
No. children	-0.088	-0.005	0.005	0.023**	-0.009	0.037	0.037**	-0.024	0.046	-0.176**	0.003
6-18	(0.148)	(0.012)	(0.014)	(0.009)	(0.010)	(0.048)	(0.018)	(0.050)	(0.037)	(0.070)	(0.032)
Rural	-11.990***	-0.094	-0.040	-0.424***	-0.014	-1.679***	0.123	0.871	-1.104***	-2.141***	0.374
	(1.151)	(0.111)	(0.275)	(0.112)	(0.050)	(0.306)	(0.094)	(0.652)	(0.383)	(0.646)	(0.463)
Wealth index (t-1)	-1.027	-0.033	-0.007	0.059	0.093	0.191	-0.186	0.754	0.570*	-0.131	-0.501*
	(1.430)	(0.088)	(0.115)	(0.077)	(0.087)	(0.398)	(0.174)	(0.476)	(0.329)	(0.642)	(0.258)
PSNP	1.467***	-0.007	-0.015	0.009	-0.046**	-0.241**	-0.114	0.129	-0.045	0.412**	-0.026
	(0.395)	(0.025)	(0.033)	(0.020)	(0.023)	(0.114)	(0.073)	(0.152)	(0.092)	(0.168)	(0.068)
Obs.	1,332	3,279	3,279	3,279	3,279	1,257	3,279	3,279	3,279	3,279	3,279
Obs. per round	444	1,093	1,093	1,093	1,093	419	1,093	1,093	1,093	1,093	1,093
Child, Year and Region FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Robust standard errors (clustered at child level) in parentheses *** p< 0.01, ** p<0.05, * p<0.1

APPENDIX B

FIGURES



Note: The asterisk * denotes that differences are significant at 5%.

Figure A1: Determinants of SAP adoption.

Figure A2: Adaptation of FIES questions to Ethiopia Socioeconomic Survey questionnaire.

Questions (FIES)	Questions (ESS)
1. In the past twelve months, did you worry that your household would not have enough food?	1. In the past twelve months, did you worry that your household would not have enough food?
In the past twelve months:	In the past seven days:
2. Was there a time when you or others in your household were unable to eat healthy and nutritious food because of a lack of money or other resources?	2. Someone in the household had to rely on less preferred foods?
3. Was there a time when you or others in your household ate only a few kinds of foods because of a lack of money or other resources?	3. Limit the variety of foods eaten?
4. Was there a time when you or others in your household had to skip a meal because there was not enough money or other resources to get food?	4. Reduce number of meals eaten per day?
5. Was there a time when you or others in your household ate less than you thought you should because of a lack of money or other resources?	5. Limit portion size at mealtimes?
6. Was there a time when your household ran out of food because of a lack of money or other resources?	6. Have no food of any kind in your household?
7. Was there a time when you or others in your household were hungry but did not eat because there was not enough money or other resources for food?	7. Borrow food, or rely on help from a friend or relative?
8. Was there a time when you or others in your household went without eating for a whole day because of a lack of money or other resources?	8. Go a whole day and night without eating anything?

Figure A3: Adaptation of HFIAS questions to Ethiopia Socioeconomic Survey questionnaire.

Questions (HFIAS) - In the past <u>four weeks:</u>	**Questions (ESS) - In the past <u>seven days:</u>**
1. Did you worry that your household would not have enough food?	1. Did you worry that your household would not have enough food?
1a. 1 = Rarely (once or twice), 2 = Sometimes (3-10 times), 3 = Often (>10 times)	1a. No frequency questions.
2. Were you or any household member not able to eat the kinds of foods you preferred because of a lack of resources?	2. Someone in the household had to rely on less preferred foods?
2a. 1 = Rarely (once or twice), 2 = Sometimes (3-10 times), 3 = Often (>10 times)	2a. 0 – 7 days
3. Did you or any household member have to eat a limited variety of foods due to a lack of resources?	3. Limit the variety of foods eaten?
3a. 1 = Rarely (once or twice), 2 = Sometimes (3-10 times), 3 = Often (>10 times)	3a. 0 – 7 days
4. Did you or any household member have to eat some foods that you really did not want to eat because of a lack of resources to obtain other types of food?	4. No such question.
4a. 1 = Rarely (once or twice), 2 = Sometimes (3-10 times), 3 = Often (>10 times)	4a. No such question.
5. Did you or any household member have to eat a smaller meal than you felt you needed because there was not enough food?	5. Limit portion size at mealtimes?
5a. 1 = Rarely (once or twice), 2 = Sometimes (3-10 times), 3 = Often (>10 times)	5a. 0 – 7 days
6. Did you or any other household member have to eat fewer meals in a day because there was not enough food?	6. Reduce number of meals eaten per day?
6a. 1 = Rarely (once or twice), 2 = Sometimes (3-10 times), 3 = Often (>10 times)	6a. 0 – 7 days
7. Was there ever no food to eat of any kind in your household because of lack of resources to get food?	7. Have no food of any kind in your household?
7a. 1 = Rarely (once or twice), 2 = Sometimes (3-10 times), 3 = Often (>10 times)	7a. 0 – 7 days
8. Did you or any household member go to sleep at night hungry because there was not enough food?	8. No such question.
8a. 1 = Rarely (once or twice), 2 = Sometimes (3-10 times), 3 = Often (>10 times)	8a. No such question.
9. Did you or any household member go a whole day and night without eating anything because there was not enough food?	9. Go a whole day and night without eating anything?
9a. 1 = Rarely (once or twice), 2 = Sometimes (3-10 times), 3 = Often (>10 times)	9a. 0 – 7 days

Figure A4: Types of food included in determining HDDS score.

A.	Cereals
B.	Roots and tubers
C.	Vegetables
D.	Fruits
E.	Meat, poultry, offal
F.	Eggs
G.	Fish and seafood
H.	Pulses, legumes, nuts
I.	Milk and milk products
J.	Oil/fats
K.	Sugar/honey
L.	Miscellaneous

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