Vrije Universiteit Amsterdam

When the crop fails—

How African households respond to agricultural droughts

M.Sc. Spatial, Transport and Environmental Economics (STREEM)

Master thesis

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Abstract:
This Master thesis aims at studying household behavior in the wake of agricultural droughts in Africa. Its unique methodological contribution lies in its departure from the traditional reliance on climate data. Instead, it develops a new approach and uses a satellite-based vegetation index to gain information about agricultural droughts. Relating drought to a wide range of individual and household characteristics from the "Demographic and Health Surveys" (DHS), the study examines different shock-coping strategies taken by drought-affected individuals. The strategies under examination include consumption cutbacks, asset sales, changes in human capital investment, labor reallocation, and migration. The findings reveal that agricultural droughts have the potential to severely affect African households, e.g., in the form of adverse health outcomes, reduced assets, movement out of agriculture, and migration. Yet, it reveals a sharp bifurcation in the effects, with the main sufferers oftentimes being uneducated and/or female individuals. Finally, the study achieves to a huge temporal and spatial scope by covering about 1 million individuals in 28 African countries over the period 1999-2015.

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"Because of this the land dries up, and all who live in it waste away;
the beasts on the field, the birds in the sky and the fish in the sea are swept away."

–Hosea 4:3

Contents

1 Introduction

'End hunger, achieve food security and improved nutrition and promote sustainable agriculture' is the second goal of the United Nations' "Sustainable Development Goals" (SDGs). The fact that the world is far from achieving this goal has been demonstrated by the numerous droughts that hit the African continent in recent years and drove millions of people into acute famine. As an example, the 2011 drought in eastern Africa caused a severe food crisis, resulting in tens of thousands of deaths from malnutrition and threatening the livelihoods of millions of people (Nicholson et al. 2018).

Agriculture remains an important backbone of many African economies, with up to 90% of the population in some sub-Saharan countries being engaged in farming activities (Sesmero et al. 2018). At the same time, a large part of African agriculture is rain-fed and hence sensitive to prevailing climatic conditions. Since agricultural technologies are often lacking, crop yields tend to be lower and less stable than in many developed countries (Petersen 2018). As an example, while improvements in agricultural technologies such as irrigation, pesticides and fertilizers have enabled the United States (US) to achieve corn yields of 10 t/ha today, Ethiopia is still falling far behind, reaching yields of only 3.5 t/ha (Petersen 2018).

Agriculture-dependent economies are particularly vulnerable to fluctuations in farming conditions and crop failures, as a functioning agriculture is essential for the provision of food, income, stability, and resilience of rural livelihoods (Petersen 2018). Given the widespread and frequent nature of droughts and their potentially severe consequences on local populations and economies, it is critical to understand the specific impacts that droughts have on individuals' behavior and well-being. Only once we understand the implications of agricultural shocks for affected households will we be able to design appropriate support measures and to avoid the collapse of agriculture-dependent livelihoods (Di Falco et al. 2012).

This thesis aims at studying household behavior in the wake of agricultural droughts on the African continent. To this end, we draw on a rich dataset on vegetation conditions and household outcomes in 28 African countries over the period 1999-2015. Exploiting information about the occurrence of agricultural droughts, we study how vegetational droughts relate to individual and household characteristics. To cope with shocks, individuals can generally employ a variety of strategies, including drawing on savings and social safety nets, reducing food consumption, selling assets, reallocating labor, or migrating. The richness of our data allows us to examine these strategies in more detail; precisely, we study whether consumption cutbacks, the sale of assets, labor supply responses, adjustments in human capital investment, or migration are significant coping strategies of drought-affected individuals. In answering these questions, we are particularly interested in heterogeneity in shock-coping behavior. This interest is based on a key finding of the empirical literature that heterogeneous households react to shocks differently (see, e.g., Acosta et al. 2021; Bengtsson 2010; Emerick 2018; Janzen and Carter 2019). While wealthier and more educated individuals are likely to have more opportunities to mitigate the effects of droughts, enabling them to withstand transitory shocks without making use of detrimental coping strategies, coping options for the more disadvantaged stratum of a population are often limited. We therefore hypothesize that the effects of agricultural droughts are particularly pronounced for the already disadvantaged individuals of a population, and examine this issue by allowing the effect of agricultural droughts to depend on their educational attainment and gender.[1]

For the empirical analysis, we capture agricultural productivity shocks by exploiting the "Normalized Difference Vegetation Index" (NDVI), one of the most commonly used vegetation indices to monitor and predict crop yields based on remote sensing data (Petersen 2018). Information on a wide range of household characteristics is retrieved from the "Demographic and Health Surveys" (DHS) Program, which has a long history in collecting survey data in Africa and other parts of the world. The resulting repeated cross-sectional dataset covers about 1 million individuals in 28 countries over the period 1999-2015.

The contribution of this study is twofold. First, the empirical analysis adds to a better understanding of individual shock-coping behavior and the implications of agricultural droughts in Africa. In light of global warming and its projected increase in the severity and frequency of extreme weather events such as droughts and heat waves, this knowledge is particularly valuable in developing appropriate support measures and fostering household resilience. The second contribution of the study is a more methodological one. While the existing literature predominantly captures agricultural productivity shocks through variation in climate variables such as precipitation, temperature or weather indices, this study moves beyond the reliance on weather data and instead uses a satellite-based vegetation index as a more direct measure of prevailing agricultural conditions. This is particularly useful for studies in the African context where the poor distribution of weather stations limits the reliability of weather-based indices. Moreover, NDVI-derived drought indicators not only capture climate-induced crop failures but also shocks that are caused by other factors, such as insects or diseases. The importance of considering such factors has been demonstrated by the numerous outbreaks of locust plagues in East Africa which have threatened food security and livelihoods in the area in recent decades. With global warming considered a major contributor to these plagues, the associated risks to food security are likely to exacerbate in the future (IPCC 2022; Peng et al. 2020; Salih et al. 2020). To the best of our knowledge, this study is the first to use NDVI to analyze the implications of agricultural productivity shocks on affected households. In contrast to many other studies that examine household shock-coping behavior on a small temporal and spatial scale (by focusing, for example, on one country over a period of a few years), this study covers 28 countries on the African continent over 15 years. The broad temporal and spatial scope of our analysis allows us to identify general relationships and to increase internal and external validity.

[1] Due to likely endogeneity in a person's wealth status we do not study heterogeneity along the wealth dimension, an issue that will be discussed later in this paper.

To summarize the findings of this paper, agricultural droughts have the potential to severely affect African households. The results reveal however a sharp bifurcation in the effects of agricultural droughts, with the uneducated, female and potentially otherwise disadvantaged often being the main victims of shocks to agriculture. For example, we find that primarily children of uneducated mothers lose weight in the course of agricultural droughts. However, this dichotomy does not hold uniformly throughout the analysis: When looking at the health outcomes of adults, mainly the *educated* lose weight while the *uneducated* tend to escape unscathed. In addition, we find asset sale to be a coping strategy used primarily by male individuals. Looking at the effect of drought on school dropout, we find evidence that drought is associated with an increase in the human capital investment of parents into their children. Finally, agricultural droughts are accompanied by a sizeable movement out of agriculture that comprises all individuals alike. Yet, while uneducated individuals largely move into unemployment, educated (and especially male) individuals appear successful in shifting labor to alternative employment activities. Our empirical analysis further suggests that labor reallocation is at least partly associated with migration.

The rest of the paper is organized as follows. Section 2 provides an overview of the literature that studies the impact of agricultural shocks on households in agrarian contexts and the different coping strategies adopted. The section that follows highlights the substantive and methodological contributions achieved by this study. Section 4 describes the data used in the empirical analysis, followed by a discussion of the estimation framework and identification strategy in section 5. Results from the empirical analysis are presented in section 6. Further analyses and robustness checks are provided in section 7, and section 8 follows with a discussion of the results in the light of climate change. Section 9 concludes.

2 Background and literature review

Many households in low-income countries face a wide range of risks in their daily lives, among them droughts, floods, and extreme heat. The academic literature studying the relationship between climatic shocks and agricultural livelihoods consistently reports detrimental effects on affected households or whole economies. For instance, Dell et al. (2012) find temperature shocks to negatively affect economic outcomes in poor countries, among others due to a reduction in agricultural output and income. Similarly, poor rainfall conditions have been linked to low economic growth in African countries (Barrios et al. 2010; Miguel et al. 2004). Climate-induced poor agricultural conditions that lead to rising food prices have the potential to negatively affect households in Africa (Bellemare 2015; Raleigh et al. 2015). To mitigate the negative effects of such shocks, individuals generally have two options. First, they may employ *ex ante* strategies to mitigate risks, among them precautionary savings and the diversification of income sources (Acosta et al. 2021). Second, they may use *ex post* strategies to cope with shocks after their occurrence. Common *ex post* strategies studied in the literature include the sale of assets (Berloffa and Modena 2013; Janzen and Carter

2019), consumption cutbacks (Janzen and Carter 2019), or adjustments in labor supply (Berloffa and Modena 2013; Cameron and Worswick 2003; Emerick 2018). Empirical evidence is provided for all of the above strategies, but the observed behaviors do not apply equally to all households. Instead, a key finding of the empirical literature is that heterogeneous households react to shocks differently (Janzen and Carter 2019). Understanding which households resort to which shock-coping strategy is critical in designing appropriate and targeted support measures, like social safety nets and microinsurance schemes.

The occurrence of drastic consumption cuts (voluntary or otherwise) and reduced health outcomes in response to agricultural productivity shocks is reported in a number of studies. Droughts are shown to significantly reduce the nutritional intake of Indian households (Carpena 2019) and to reduce the body weight of women but not of men in Zimbabwe (Hoddinott 2006). Bengtsson (2010) reports the body weight of agriculturally-dependent individuals in Tanzania to respond negatively to weather-induced income shocks, with the effect being strongest for female children. The finding that children are the main sufferers from bad agricultural conditions is supported by a substantial body of research (Davenport et al. 2017; Grace et al. 2015; Jensen 2000; Yamano et al. 2005). For instance, warmer and drier conditions are found to have negative effects on the health of children and new-borns in Africa (Davenport et al. 2017; Grace et al. 2015), and Yamano et al. (2005) reports crop yield failures to lead to child growth faltering in Ethiopia. The finding of negative health impacts on children raises additional concerns, given that inadequate food intake during childhood has long-lasting and impairing effects on health and productivity during adulthood, potentially resulting in a form of intergenerational poverty transmission (Davenport et al. 2017).

As regards the sale of assets as a shock-coping strategy, the academic literature largely focuses on productive assets such as livestock. While livestock is reported to be an important asset to cope with transitory shocks by a number of studies (Acosta et al. 2021; Janzen and Carter 2019), other studies find only limited evidence on the use of livestock as a buffering mechanism (Fafchamps and Lund 2003; Kazianga and Udry 2006). One of the rare studies examining the sale of both liquid assets (like jewelry) and livestock reports livestock sales to be the primary coping strategy and finds only little evidence for the use of liquid assets as buffer mechanism (Kinsey et al. 1998).

Both a restriction of food consumption and the sale of assets are likely to have detrimental long-term economic repercussions by impairing permanent agricultural productivity (Janzen and Carter 2019). In an effort to avoid one of these detrimental coping strategies, individuals may adjust their labor supply in response to agricultural droughts and seek alternative employment opportunities. Labor market responses have been extensively studied in the empirical literature, at least since Kochar's contribution to examining labor reallocation as a strategy to smooth consumption after idiosyncratic shocks (Kochar 1999). As an example, labor reallocation is found to be an important mechanism for Indonesian households to achieve consumption smoothing in the wake of crop losses (Cameron and Worswick 2003). Similarly, Emerick (2018) reports a decline in the agricultural labor share following abnormally wet growing seasons in India, with the movement out of agriculture being particularly pronounced for better-off and more educated individuals. In contrast, Acosta et al. (2021) find that labor supply adjustments is a coping strategy primarily among poor farmers, while non-poor farmers are more likely to run down assets and to draw on savings. Households facing deteriorating agricultural conditions in India appear to respond by reallocating labor to off-farm employment, particularly so in areas with a more developed manufacturing sector (Blakeslee et al. 2020) or with flexible labor regulation environments (Colmer 2021).

In addition to labor supply responses, it is possible that adults react to shocks by adjusting their human capital investment into their children. Yet, the relationship between (climate-induced) wage changes and human capital investment is theoretically ambiguous: While lower wages decrease the opportunity cost of schooling, they provide fewer incentives to invest into human capital formation (Shah and Steinberg 2017). Indeed, Shah and Steinberg (2017) report positive rainfall shocks to be associated with children dropping out of school and taking up employment, while Maccini and Yang (2009) find educational attainment to increase with higher rainfall.

Finally, the literature studying migration as a strategy to cope with environmental shocks is rapidly expanding (see, e.g., Baez et al. 2017; Gray and Mueller 2012; Kleemans and Magruder 2018; Marchiori et al. 2012). However, evidence on climate-induced human mobility is mixed. While, on the one hand, deteriorating economic and living conditions may provide an incentive to temporarily or permanently leave one's familiar living environment (Marchiori et al. 2012), they may on the other hand undermine the budgetary resources needed to migrate (Carleton and Hsiang 2016; Cattaneo and Peri 2016). Evidence for a positive relationship between agricultural shocks and migration is provided, for instance, by Feng et al. (2010) who report crop yield reductions in Mexico to induce emigration to the US. Mixed evidence is provided by Gray and Mueller (2012) who find labor migration by men to increase but marriage-related migration by women to decrease in response to droughts in Ethiopia.

3 Contribution of the study

The present study contributes to the literature in two important ways. First, by analyzing household behavior in the wake of agricultural droughts, the study adds to the knowledge on the implications of agricultural productivity shocks for individuals on the African continent. Given that many African households are heavily reliant on (rain-fed) agriculture for their everyday lives, poor farming conditions and crop yield failures have the potential to severely impair their living conditions. Yet, evidence on the concrete implications of agricultural droughts and the shock-coping strategies adopted by individuals of heterogeneous predispositions is mixed and requires further empirical scrutiny. While most of the empirical literature focuses on household responses within a certain area or time period, the present study performs its analysis within a broad geographic and temporal framework, allowing us to identify general relationships and to increase internal and external validity. In addition, thanks to the variety of questions asked in the DHS surveys we are able to look at a wide range of household responses, including health outcomes, asset ownership, schooling, labor supply responses, and migration. Given that these outcomes are all interrelated, considering them in conjunction with each other adds to a better understanding of the factors that influence the concrete shock-coping behavior adopted and the ultimate effect that agricultural droughts have on individual well-being. Consequently, the results of this analysis help identify the most vulnerable individuals in a population and design appropriate and well-targeted support measures.

The second contribution of this study is more a methodological one. The academic literature studying the relationship between agricultural productivity shocks and socio-economic outcomes largely exploits climatic variables, such as rainfall, temperature or drought indices, to proxy for shocks in agriculture. Exploiting climatic variables as proxies for vegetation conditions seems particularly justified in low-income countries where the connection between climate and crop yields is very close. Yet, a major drawback in the use of climate-based indicators to assess the impact of droughts is the need to interpolate climate data between weather stations. Given the sparse distribution of weather stations in many parts of Africa, interpolation over wide areas increases the risk of measurement error and limits the reliability of weather-based indices (Auffhammer 2018; Kourouma et al. 2021; Vrieling et al. 2013).[2] Moreover, while these indices allow to study the implications of shocks that are caused by climatic factors they are unable to capture shocks that are caused by factors unrelated to weather, such as insects or diseases. Given that insect infestations such as locust plagues have become more frequent in recent decades and have been robustly linked to global warming, considering such factors is highly relevant and is likely to become even more important in future (IPCC 2022; Peng et al. 2020; Salih et al. 2020).

The present study addresses the weaknesses of climate-based drought indicators and employs a novel approach to measuring prevailing agricultural conditions. Precisely, it exploits one of the most commonly used vegetation indices based on remote sensing, the "Normalized Difference Vegetation Index" (NDVI), to proxy for agricultural droughts and associated deviations in crop yields from the norm. The idea behind this approach is that, by measuring greenness of the underlying surfaces, NDVI describes the healthiness of vegetation at any given time and location and in turn should be correlated with agricultural yields (Turvey and Mclaurin 2012). Since initial studies in the 1980s and 1990s, remote sensing has become a standard tool in monitoring and predicting crop yields (Petersen 2018). Applications of vegetation indices include early warning systems (Funk and Brown 2006) and index-based

[2] One consequence of classical measurement error in independent variables is that it biases the estimates of the effect towards zero (Auffhammer 2018).

insurance schemes (Chantarat et al. 2013; Tadesse et al. 2014; Turvey and Mclaurin 2012). While NDVI values per se are not necessarily indicative of droughts, deviations in NDVI from its long-term mean have a higher predictive power and have been employed in a number of studies (Eze et al. 2022; Kourouma et al. 2021; Legesse and Suryabhagavan 2014). As shown by Petersen (2018), anomalies in vegetation indices perform well in predicting crop yield (failures) in Africa, even without the use of crop masks or special tuning for location and climate. While NDVI has been used for monitoring the health of crops in Africa (Klisch and Atzberger 2016; Petersen 2018; Tadesse et al. 2014), it has rarely been used to relate variation in crop yields to socio-economic outcomes and to study the impact of agricultural droughts on affected households.

Before closing this section, a brief comparison of the two approaches is in order. Given the high correlation of vegetation indices with rainfall (Kourouma et al. 2021; Martiny et al. 2006; Richard and Poccard 1998), both approaches lead to reliable indicators of agricultural droughts. Still, a caveat is in order when interpreting the results from both approaches equally. While the studies using weather-based indices give insights about the impact of climate-induced shocks, their findings do not necessarily imply that the effects operate through the channel of agricultural productivity shocks, as they could similarly likely run through other mechanisms. For instance, there is growing evidence of a strong link between higher temperatures and elevated levels of aggression and an increased propensity for violent behavior (Baysan et al. 2019; Ranson 2014). On the other hand, the strategy followed in this study yields insights about the impact of agricultural productivity shocks, but it does not necessarily allow to draw conclusions about the concrete causes of these shocks. Although crop failures may well be caused by adverse weather shocks, other factors unrelated to climatic conditions, like land conversion, insects, or diseases, could also play a role (Kourouma et al. 2021).

4 Data

4.1 Vegetation condition data

To retrieve information about vegetation conditions during the year and to derive an indicator of agricultural droughts, the present study exploits remote sensing data from optical sensors onboard satellites. This analysis, often referred to as "land surface phenology," uses time series of vegetation indices to study spatiotemporal patterns in the vegetated land surface (Vrieling et al. 2013). The original data was created by the National Aeronautics and Space Administration (NASA) using so-called "AVHRR" instruments on board of "NOAA" satellites.[3] The AVHRR's detectors study the extent to which visible (0.4-0.7 μm) and near-infrared (0.7-1.1 μm) lights are reflected by the earth's surface. While healthy vegetation reflects most of the near-infrared light (NIR) but strongly absorbs visible light (RED) for use

[3] "AVHRR" stands for Advanced Very High Resolution Radiometer and "NOAA" for National Oceanic and Atmospheric Administration, respectively.

in photosynthesis, surfaces of sparse or no vegetation reflect similar amounts of near-infrared and visible light (Weier and Herring 2000). The NDVI exploits these differences in reflected wavelengths and is formulated as follows:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

Figure 1 compares NDVI values resulting from dense and/or health vegetation (left) versus sparse or unhealthy vegetation (right). In general, if vegetation is healthy, the reflection in near-infrared wavelengths greatly exceeds the reflection in visible wavelengths and the NDVI takes on a value close to +1. If, on the other hand, vegetation is sparse and reflects the prevalence of grassland, tundra, or desert, the difference between the reflection is small and NDVI takes on values close to zero (Weier and Herring 2000). Negative values of NDVI correspond to surfaces covered by water, such as lakes, rivers, or the ocean.

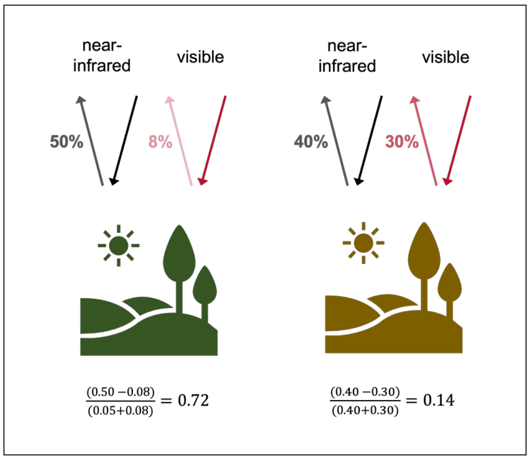


Figure 1: Reflected radiation by different types of vegetation (following Weier and Herring 2000)

For the analysis of vegetation conditions, we use geo-referenced NDVI data for the African continent over the period 1982-2015. The NDVI data is highly disaggregated both in terms of space (cells of size 0.08 x 0.08 degrees, corresponding to a length of approximately 9.25 km) and time (twice per month). The NDVI index can be used to establish the 'normal' vegetation conditions in a given region at a given time of the year, such that variations relative to the norm can interpreted as unusual occurrences such as agricultural droughts.

4.2 Household data

To study socio-economic outcomes, we use data collected through the DHS program in 28 African countries over the period 1999-2015. The DHS program releases its datasets separately for men, women, children, and household attributes of each country and survey wave, so we need to merge them to obtain one joint dataset. Due to partially inconsistent coding of the unique identifier variables in the datasets, we had to remove all observations with missing or incorrectly coded identifiers. This is inevitable because matching individuals with their corresponding coordinates required the unique identifiers in both datasets to be identical. Moreover, we had to exclude all observations before 1999 because households have only been georeferenced from 1999 onward. Our final dataset comprises almost one million observations over the study period and area, including men, women, and children aged 0-99 years. In that sense, there is scope for a future extension of the study, as a manual correction of the coding inconsistencies would certainly achieve a considerable expansion of the dataset and increase the significance of the results.[4] The time and effort involved in manually improving the inconsistencies however made it impossible for us to do so already for this study. The distribution of households across the study area is shown in figure 2.[5]

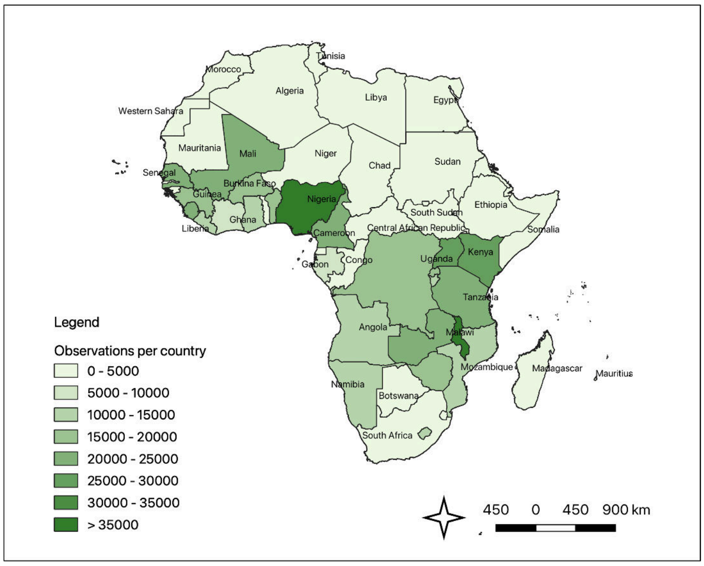


Figure 2: Location of DHS survey households

The DHS dataset contains information about the location of households at the time of the interview and about a wide range of their members' characteristics, including health indicators (e.g., height, weight), asset ownership (e.g., television, cars, bikes, animals, agricultural land), occupation, and educational attainment.

In DHS surveys, the original coordinates of interviewed households are 'geomasked' to conceal their precise locations, i.e., the coordinates are displaced through a "Global Positioning System" (GPS) coordinate displacement process. The process displaces urban clusters a distance up to 2 kilometers and rural clusters a distance up to 5 kilometers, with a further, randomly-selected 1% of rural clusters displaced a distance up to 10 kilometers (Burgert et al. 2013). Therefore, when relating households with the NDVI data based on location and time, it is possible that households are matched with negative NDVI values (e.g., because household locations are displaced on top of adjacent water bodies). These household locations are then transitioned through a searching algorithm until a non-negative NDVI value is found.[6]

[4]Theoretically, the dataset could be enlarged by up to approximately 700,000 additional observations.

[5]It should be noted however that not all countries are included every year; instead, each country is included in only 1-9 survey waves over the study period. See table A.1 for a full list of countries and the years they are included in the dataset.

[6]This work was done by Nam Bui, then working as a research fellow at the University of Auckland.

5 Estimation framework

5.1 Theory

In light of the severe consequences that agricultural productivity shocks can have on individuals, a number of studies has investigated household behavior in the wake of such shocks. However, there are opposing theoretical perspectives on how households of different predispositions react to shocks. In this section, we first provide an overview of the theoretical background on households' shock-coping behavior and then present the hypotheses to be subjected to empirical testing.

One of the earliest economic concepts to explain optimal behavior of utility-maximizing individuals is that risk-averse individuals have a desire to smooth consumption. The theoretical framework explaining the model of consumption smoothing is the expected utility model, in which the utility of a risk-averse individual is increasing but concave in consumption. Reflecting the principle of diminishing marginal utility, concavity in consumption has as a result that it is optimal for an individual to reduce consumption in states of high income and to increase it in states of low income. For the poor and credit-constrained people, this implies that they have to build up their asset stock during good times so that they can draw their stock down during times of crises in order to uphold consumption at its usual level (Carter and Lybbert 2012; Deaton 1991; Lee and Sawada 2010).[7]

A showcase example to illustrate consumption smoothing in real life is the purchase of insurance. While insurance can be a great method to reduce uncertainty about future consumption and has become standard in many high-income countries, it is often not available to people in developing countries. In many low-income settings, people must resort to other strategies to achieve consumption smoothing. For the management of shocks, it is thereby relevant whether the shocks are idiosyncratic or common shocks, i.e., whether they affect only single individuals or a whole community. In the case of idiosyncratic shocks, the community often plays a crucial role by supporting those affected, for example, through inter-household transfers or food sharing (Kazianga and Udry 2006). Yet, when shocks are common to the whole community, these support mechanisms may not be available anymore. While drawing on savings or taking out a loan can still be a way to achieve stable consumption for the better-off in a population, these mechanisms are often intangible for the poor and credit-constrained (Kazianga and Udry 2006). To the extent that households own assets (whether in the form of livestock, grain storage, or domestic appliances), consumption smoothing may still be achieved by selling these assets. Yet, a substantial literature reports consumption smoothing mechanisms to be only partially effective in low-income settings, potentially resulting in drastic consumption cutbacks and negative health effects (Kazianga and Udry

[7]Despite solid theoretical foundations, the consumption smoothing hypothesis has not always withstood empirical scrutiny—instead, there is evidence that individuals around a critical asset level may seek to protect their productive assets in order to avoid falling into a poverty trap, even if this comes at the cost of reduced consumption (Carter and Lybbert 2012; Janzen and Carter 2019).

2006; Maccini and Yang 2009). In our empirical analysis, we study how successful individuals are in maintaining consumption standards in the wake of agricultural droughts. As agricultural droughts are common shocks that affect the whole community, inter-household transfers and food sharing are likely to play only a minor role in keeping harm away from the most disadvantaged members of a population.

As mentioned earlier, one way to achieve consumption smoothing is through the sale of assets. Asset sale may be a particularly important means for liquidity-constrained individuals for whom the inability to borrow provides a precautionary motive to accumulate assets during good times and deplete them during bad times (Deaton 1991).[8] In our empirical analysis, we examine whether households respond to agricultural shocks by selling their assets, and we again test for heterogeneity in responses depending on individual predispositions.[9]

When drought-related income losses or rising food prices put parents in financial distress, they may respond by withdrawing their children from school. On the one hand, this could be simply because they can no longer afford the school fees; on the other hand, they might want their children to enter the labor market. In both cases, taking children out of school may be effective in mitigating financial distress in the short-term; a reduction in the human capital formation of children however is likely to have negative long-run consequences by impairing their future employment opportunities. Yet, the relationship between agricultural conditions and educational attainment is theoretically ambiguous, as it could just as well be that poor agricultural conditions lead to *more* school attendance. This prediction can be justified by an opportunity cost argument, according to which a drop in agricultural income lowers the opportunity cost of schooling and may therefore increase parents' human capital investment into their children (Shah and Steinberg 2017). Increased investment into the human capital formation of children in response to worsening environmental conditions may also be observed if parents want to prepare them for future employment outside the agricultural sector (Blakeslee et al. 2020). To test which of the theoretical perspectives best mirrors the behavior of drought-hit households, we enlarge our empirical analysis by studying responses in the form of school dropout in the wake of agricultural shocks.

Another way to mitigate the negative effects of drought-induced income losses is to adjust labor supply. If income flows from agricultural activities fail to materialize, households may seek other sources of income and take up off-farm employment activities. Reallocating labor away from agriculture into sectors that are less dependent on environmental conditions is particularly important when agricultural droughts are perceived as recurring or persistent events that threaten the viability of agricultural activities over the long run (Blakeslee et al. 2020). In our empirical analysis we therefore examine whether households respond to

[8] Note that, when income is very low and just enough to survive, wealth accumulation may be an infeasible strategy for these households even during comparably good times.

[9] We focus on not-living assets and exclude the ownership of animals as any observed decline in livestock is not necessarily attributable to the sale of livestock. On the contrary, it is likely that agricultural droughts lead to a decline in livestock numbers as animals die from malnutrition.

agricultural shocks through labor reallocation.

Finally, and related to adjustments in the labor supply, individuals may respond to agricultural shocks by migrating to areas with better environmental conditions or alternative employment opportunities (Blakeslee et al. 2020). In a final step of our empirical analysis, we therefore test whether human mobility is a margin of adjustment to worsening agricultural conditions. We thereby have to take a slight detour as we are not able to 'trace' individuals that have migrated away from the study area. Nevertheless, we are able to make statements about (temporary) migration based on the following reasoning: While regions with favorable agricultural conditions are more likely to *attract* migrants, drought-stricken regions are less likely to *attract* migrants (for work reasons or other). We therefore test whether there is a negative relationship between the occurrence of a drought in a location and the probability that an individual currently lives in this drought-hit location even though this is not their usual place of residence.

5.2 Independent variables

For our empirical analysis, we use NDVI data of high temporal and spatial resolution to derive an indicator of agricultural droughts. As is common practice in vegetation-based drought assessment, we thereby exploit the "Vegetation Condition Index." The VCI relates current NDVI at a location to the maximum and minimum NDVI values ever observed at that location for the same time of year:

$$VCI_{i,t} = \frac{ndvi_{i,t} - \overline{min\_ndvi_i}}{\overline{max\_ndvi_i} - \overline{min\_ndvi_i}} * 100$$

where $ndvi_{i,t}$ is the NDVI at location i at recording time t; $\overline{max\_ndvi_i}$ and $\overline{min\_ndvi_i}$ are the corresponding long-term maxima and minima of NDVI at location i for that time of the year. As first proposed by Kogan (1995) and since then widely adopted by other scholars (e.g., Liou and Mulualem 2019; Measho et al. 2019; Winkler et al. 2017), we define a drought as severe or extreme if VCI is below 20%.[10]

Since our NDVI values are only a snapshot of time, they might also capture droughts that last only for a short period of time. Yet, short-lived droughts probably don't have serious effects on individuals, whereas droughts that last over a longer period are likely to have a stronger impact. We therefore combine current and lagged NDVI in a location to construct an indicator of prolonged droughts. Precisely, we construct 4 different dummy indicators, $drought1m$, $drought2m$, $drought3m$, and $drought6m$ that turn 1 if drought conditions at a location have consistently been severe during the preceding 1, 2, 3, and 6 months, respectively.[11]

[10] No drought conditions prevail for VCI above 35%; VCI in the range 20-35% indicates moderate drought and VCI below 10% indicates extreme drought.

[11] Given the bimonthly nature of the NDVI data this implies that we use current NDVI and NDVI lagged by up to 2, 4, 6, and 12 recording dates respectively to construct the indicators. See table A.2 for summary statistics of the different drought indicators.

5.3 Dependent variables

For the analysis of household behavior in the wake of agricultural droughts, we draw on household- and individual-level data from the DHS program. The DHS dataset contains a wide range of personal characteristics, including health indicators, asset ownership, occupation, and educational attainment.

To assess consumption smoothing, we follow Hoddinott (2006) and rely on a respondent's health status as captured by the Body Mass Index (BMI). The BMI is a function of an individual's weight in relation to their height (specified in kg/m^2), such that variation in the BMI reflects changes in nutritional intake and/or energy-consuming activities. With normal weight ranging from 18.5 to 24.9, individuals are defined as thin if their BMI is below 18.5 and as overweight if their BMI is 25 or higher (Croft et al. 2018). Due to its right-skewed distribution, we logarithmize BMI such that our first dependent variable is $ln(BMI)$.

Household responses in the form of asset sales are analyzed by constructing an index for asset ownership. The variable *n_assets* represents the sum of all 'mobile' assets collected in the DHS survey. The full list of assets included in the index is: watches, radios, televisions, bicycles, motorcycles, cars.[12]

To analyze whether agricultural droughts lead to a reallocation of labor from agricultural to non-agricultural employment, we construct a dummy indicator *agri* that takes on the value 1 if the respondent is working in agriculture, and 0 otherwise. In a similar vein, we construct indicators of working in alternative sectors such as services, professional/managerial, or sales.

Adjustments in human capital investment are captured through changes in schooling attainment since the previous school year. Precisely, we exploit the DHS survey's questions on a child's school attendance and define an indicator *dropout* that takes on the value 1 if a child indicates to have dropped out of school since the previous school year, and 0 otherwise.

To analyze human mobility as a response to drought we make use of the DHS surveys' differentiation between a respondent's current (de facto) place of residence and their usual (de jure) place of residence. Our final dependent variable *not_dejure* then takes on the value 1 if a respondent's de facto place of residence is not the same as their de jure place of residence, and 0 otherwise.

5.4 Identification strategy

Having discussed the dependent and independent variables, we now turn to the identification strategy that enables us to estimate a causal effect of agricultural droughts. First, causal estimation requires the independent variables to be exogenous. In the case of our main independent variables this is plausibly the case: Droughts are highly dependent on conditions of the ambient environment (among them climatic variables like precipitation, temperature,

[12] Our focus on mobile assets is rooted in the assumption that immobile assets such as refrigerators and electricity are less likely to be sold (at least in the short run). See table A.3 for summary statistics of the assets included in the index. We acknowledge the fact that these assets are neither equally valuable nor equally likely to be sold in the event of a drought. We nevertheless restrict ourselves to a simple additive index, a simplification that could be sophisticated in future studies.

and soil moisture, but also other factors like locust plagues, plant pests, and other diseases) which themselves are mostly beyond human influence and therefore plausibly exogenous.[13]
The DHS program collects its household data by choosing a random sample of individuals at each successive survey wave over time. Consequently, the DHS dataset represents a repeated (pooled) cross-section. Under the assumption that the observations are independent but not identically distributed, the model can be estimated with a simple Ordinary Least Squares (OLS) estimator on the pooled cross-sections (Wooldridge 2010).
One disadvantage of pooled cross-sections compared to panel data is that individuals are not followed over time, making it impossible to control for unobserved characteristics of individuals through the inclusion of individual fixed effects. As is common practice in pooled cross-sections, all specifications control for aggregate time trends. Due to the broad geographic scope of our study area, we include country-by-year dummies that capture trends that are particular to certain countries. The inclusion of country-by-year dummies allows the intercept to differ across time and space, reflecting the fact that a population in a certain location may have different distributions at different points in time (Wooldridge 2012).
To further mitigate the threat of omitted variable bias (OVB), all specifications include covariates that are potentially correlated with our dependent variables and the impact of agricultural droughts. For example, all specifications include variables of the respondent's age and sex to control for the fact that adults generally have a higher body weight than teenagers and females have a higher BMI on average than males. The dummy indicator *sex* takes on the value 1 for male individuals and 0 for female individuals.
As we are interested in heterogeneity in the effect of agricultural droughts depending on individual/household-level predispositions, we interact our drought indicator with a dummy indicator of *uneducated* individuals which takes on the value 1 if a respondent has no or only incomplete primary education, and 0 if they have complete primary education or higher. Analyzing heterogeneity along the dimension of education is based on the reasoning that an individual's level of educational attainment is plausibly predetermined and unlikely to be influenced by current drought. Even though agricultural droughts are likely to have particularly severe impacts on poor and rural households, we refrain from analyzing differential effects of drought along the dimension of wealth or the type of place of residence. This is due to the fact that we do not observe households over time and cannot directly trace changes in a household's wealth and location of residence. As a consequence, these household characteristics are not necessarily predetermined and could instead also reflect an outcome of agricultural droughts—including them as covariates in a regression would therefore result in what Angrist and Pischke (2009) call "bad controls." In that light, an individual's

[13] We acknowledge the possibility that human activities, such as land management practices and land conversion, can contribute to variation in vegetation cover and associated NDVI values. Given the generally high correlation between NDVI and climatic variables however (Kourouma et al. 2021; Martiny et al. 2006; Richard and Poccard 1998; Vrieling et al. 2011), we do not consider this point a major threat to causal estimation.

educational level is plausibly more exogenous than their wealth and place of residence and improves the identification of causal effects.[14] Moreover, we interact *drought* with a dummy for an individual's gender to test for a potential gender bias in the effect of agricultural droughts.

Throughout all specifications, we use standard errors that are clustered at the country-vegetation-zone-year level. Clustered standard errors are not only robust to heteroskedasticity in the data but also account for spatial and temporal correlation in the error term. This is particularly necessary in our case where spatial and temporal dependence in agricultural droughts is likely to be present; using 'normal' robust standard errors would ignore the dependence between observations and lead to estimates with artificially high statistically significance. Using clustered standard errors relaxes the assumption of independent observations and increases the likelihood of obtaining reliable inference (Sesmero et al. 2018). As is common practice, we cluster at the level at which agricultural droughts occur. In our case, it seems appropriate to create clusters for each combination of countries, vegetation zones, and years. To this end, we exploit the division of African regions into vegetation zones as first presented by F. White (1983) and depicted in figure A.1.

One remaining threat to the identification of causal effects is that the composition of a population at a location may change as a consequence of agricultural droughts. If there is a dynamic relationship between the occurrence of droughts and the composition of the local population (e.g., because 'able' individuals move away and only the 'unable' and poor stay behind), there could be a correlation between agricultural droughts and bad outcomes that would bias the estimates towards more negative effects. To address this issue, we run additional specifications in our robustness analyses of section 7 where we only consider droughts that occur for the first time after a drought-free period of 5 years. This way, we only look at those events that hit a place relatively 'unexpectedly.' As a consequence, it is unlikely that people were able to prepare for this event through *ex ante* measures, allowing us to focus on *ex post* coping strategies.

5.5 Specifications and testable hypotheses

To study the effect of agricultural droughts on household outcomes, we estimate the following base specification 1:

$$outcome_{i,t} = \alpha + \beta drought_{i,t} + \mathbf{X}\gamma + \delta_{c,y} + \epsilon_{i,t} \tag{1}$$

where $outcome_{i,t}$ is one of the dependent variables at location i at time t, and $drought_{i,t}$ is one of the dummy indicators of agricultural droughts. $\mathbf{X}$ is a vector of control variables, $\delta_{c,y}$ are country-by-year (c and y) dummies, and $\epsilon_{i,t}$ represents the idiosyncratic error term.

[14]Uneducated individuals are often also more disadvantaged along other dimensions (primarily professional opportunities), leading to a correlation between educational attainment and wealth, location of residence, and occupational status (the Pearson's correlation coefficients between *uneducated* and *poor*/ *rural*/ *agri* are $\rho = 0.26$/ $\rho = 0.3$/ $\rho = 0.19$, respectively).

In the first specification, we study consumption smoothing behavior in the wake of agricultural shocks. To this end, we use $ln(BMI)$ as dependent variable and estimate model 1 as pooled OLS. The coefficient of interest β captures the effect of drought on a person's log BMI. As agricultural droughts are likely to cause negative shocks to food production, we anticipate that the effect of drought on dietary intake will be negative. Our first hypothesis to be tested is therefore:

Hypothesis 1: *If households are not completely successful in consumption smoothing, we should observe a decline in their BMI, i.e., $\beta < 0$ in the specification with $ln(BMI)$ als dependent variable.*

The second specification uses *n_assets* as dependent variable and tests whether households respond to agricultural shocks by selling their assets. Again, the coefficient of interest, β, captures the effect of drought, this time on an individual's asset ownership. The second hypothesis to be tested is:

Hypothesis 2: *If individuals use the sale of assets as a mechanism to cope with agricultural droughts, we will observe a decline in their stock of household items, i.e., $\beta < 0$ in the specification with n_assets as dependent variable.*

As the relationship between agricultural droughts and school attendance is theoretically ambiguous, we examine which of the channels (droughts putting parents into financial distress and forcing them to take their children out of school vs. droughts reducing the opportunity costs of schooling and increasing school attendance rates) dominate. We do so by estimating specification 1 as Linear Probability Model (LPM) with *dropout* as dependent variable and hypothesize the following:

Hypothesis 3: *If the channel of financial distress dominates, we expect an increase in children's school dropout, i.e., $\beta > 0$ in the specification with dropout as dependent variable. If the opportunity cost channel dominates, we expect a decrease in school dropout, i.e., $\beta < 0$.*

We next study whether individuals adjust to agricultural droughts by shifting labor away from agriculture to employment outside the agricultural sector. In examining the outflow of workers from the agricultural sector, we use *agri* as our dependent variable and estimate specification 1 as LPM. In a similar vein, dummy indicators for employment in alternative sectors serve as dependent variables to study which sectors gain and lose workforce as a response to worsening agricultural conditions. Our third hypothesis to be tested is:

Hypothesis 4: *If the occurrence of an agricultural drought leads to a reallocation of labor away from the agricultural sector we expect $\beta < 0$ in the specification with agri as dependent variable.*

Finally, we examine whether agricultural droughts affect human mobility and estimate model 1 als LPM using *not_dejure* as dependent variable. Since drought-affected areas are less likely to *attract* the in-migration of individuals, we assume that an individual will *not* move (for work reasons or other) to a location that is currently experiencing a prolonged drought. Our fifth and final hypothesis is:

Hypothesis 5: *If households respond to agricultural droughts by migrating to more 'favorable' conditions, we expect a negative relationship between agricultural droughts and the probability that a respondent is living in a drought-afflicted place even though this is not their usual place of residence, i.e., $\beta < 0$ in the specification with not_dejure as dependent variable.*

To study heterogeneity in the impact of agricultural droughts, we interact our drought indicator *drought* with variables that are deemed to be influential to impact of drought. As mentioned above, these variables include an individual's educational attainment and gender.[15]

6 Results

6.1 Descriptive analysis

Before presenting the main estimation results, we start with a descriptive analysis of the spatial patterns and temporal trends in agricultural conditions and in household outcomes.

6.1.1 Mean NDVI values and agricultural droughts

The descriptive analysis starts with an inspection of the variation in NDVI over time and space. Figure 3 shows how the mean decadal NDVI values during the 1990s (left), 2000s (middle) and 2010s (right) have changed compared to the 1980s. The maps suggest an increase in 'wetness' during the 1990s compared to the 1980s for many parts of Africa. This observation most likely reflects the recovery from a continent-wide shift to more arid conditions that occurred during the 1980s decade (Dai et al. 2004; Nicholson et al. 2018; Vrieling et al. 2011). As indicated by the two maps on the right, the positive trend in mean NDVI observed for the 1990s later reversed, with widespread negative changes in mean NDVI during the 2000s and 2010s compared to the 1980s. This negative trend can possibly be explained by two severe drought events that hit the African continent in the last decades. First, the 2011 drought in eastern Africa caused a severe food crisis and putting 750,000 people at risk of death (Gebremeskel Haile et al. 2019; United Nations 2012). Shortly after, one of the strongest observed El Niño events hit large parts of southern and eastern Africa in 2015, leading to an intense drought and bringing millions of people into acute famine (Blamey et al. 2018; IPCC 2022; Wolski et al. 2021). A caveat is in order when looking at the results from the 2010s decade: Because the NDVI data stops after 2015, the 2010s

[15] As the educational level is a direct consequence of school dropout, we refrain from including educational attainment as a regressor in the specifications with *dropout* as dependent variable.

figure only captures the first portion of the decade and does not reflect how NDVI evolved afterwards. Recent estimates suggest that drought frequency in East Africa has doubled from once every 6 to once every 3 years since 2005 (Gebremeskel Haile et al. 2019; ILO 2022).

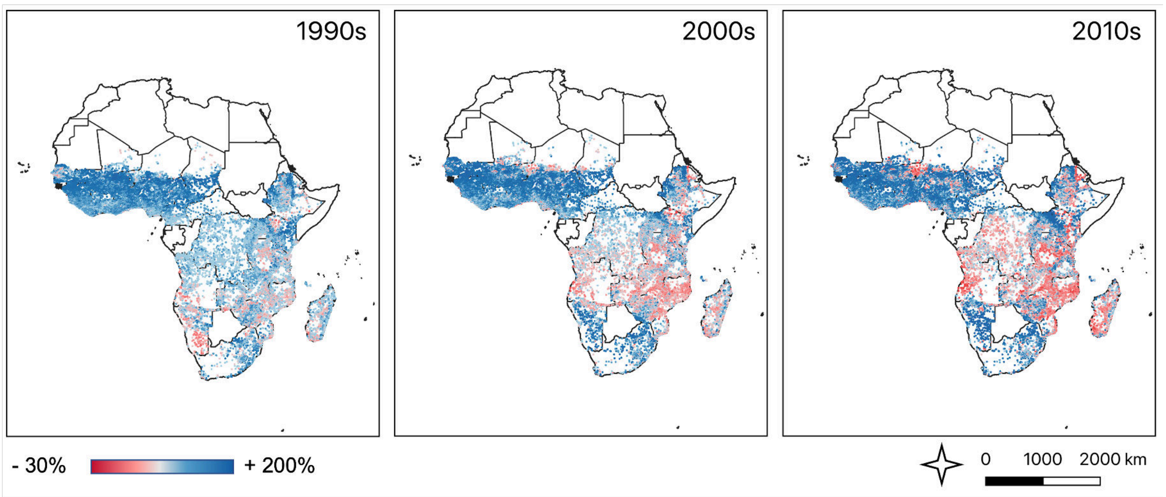


Figure 3: Mean NDVI values during 1990s, 2000s, 2010s compared to the 1980s

6.1.2 Start and end of growing seasons

Given the study's novel approach to using NDVI as an indicator of agricultural conditions, we want to devote somewhat more space to the possibilities of NDVI to study variation in vegetation conditions. In addition to using NDVI to derive indicators of unusual events, NDVI time series data can be post-processed to provide information on the timing and length of growing seasons. To do so, we follow the approach of Vrieling et al. (2013) and exploit the variable threshold method as first presented by M. A. White et al. (1997). This method determines per year and per pixel the maximum and minimum NDVI values and takes as threshold the average value between the both. For each location, the first NDVI value in a year that crosses the threshold in upward direction is marked as the start of growing season (SOS) and the last NDVI value in a year that crosses the threshold in downward direction is marked as the end of growing season (EOS), respectively. Although SOS and EOS may vary slightly from year to year, we can determine the month in which a growing season typically begins or ends, respectively. These average start and end months are shown in figure 4 and largely in line with Vrieling et al. (2013).[16] In the robustness checks of our empirical analysis, we use this information to examine whether droughts that occur inside or outside a growing season have differential impacts.

[16]Note however that figure 4 does not differentiate between first and second seasons of a year. This is because our algorithm to determine SOS and EOS slightly differs from that by Vrieling et al. (2013).

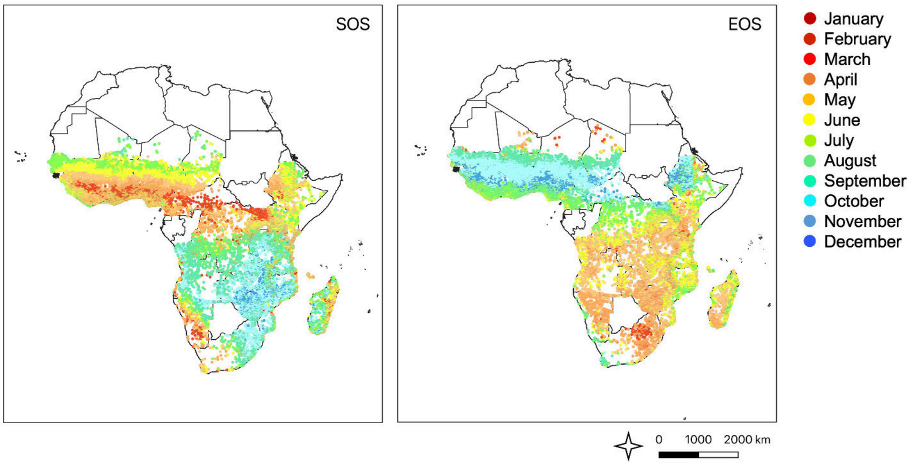


Figure 4: Month in which a growing season begins (left) and ends (right) on average

6.1.3 Household characteristics

Summary statistics for individual and household characteristics are provided in table 1, with column (1) showing the outcomes for the total population and columns (2) and (3) differentiating between uneducated and educated individuals, respectively. As defined in section 5, individuals are referred to as *uneducated* if they have incomplete primary education or lower, and as *educated* for higher educational levels. As shown in Panel A, uneducated individuals are on average about 1 year older than educated individuals. This observation seems surprising, given that most studies generally report a positive correlation between educational attainment and life expectancy (Bulled and Sosis 2010; Hummer and Hernandez 2013; Turan 2020). On the other hand, uneducated individuals have a BMI that is on average 1.43 points lower and, accordingly, they are significantly more likely to be thin (as indicated by a BMI below 18.5). As regards their occupational status and place of residence, Panel B shows that uneducated individuals are significantly more likely to work in agriculture (either self-employed or as employee) and to live in rural areas. Finally, Panel C compares uneducated and educated individuals with respect to their asset ownership and wealth. Consistent with the observation that uneducated own fewer assets on average, they are more likely to be classified as *poor*, as defined by their membership to one of the two lowest quintiles of the DHS wealth index.[17] As shown in column (4), all differences in means between educated and uneducated individuals are statistically significant at the 1% level.

[17] The DHS wealth index is a composite measure of a household's living standard based on a their ownership of selected assets, housing attributes, and types of access to water and sanitation, and is particularly useful when measures of income and expenditures are absent (Rutsein and Johnson 2004). The wealth quintiles are based on the distribution of national population, with each individual being assigned the wealth index score of their household.

Table 1: Mean household outcomes, differentiated by educational attainment

	All (1)	Uneducated (2)	Educated (3)	Difference in means (4)
Panel A. Demographics and health status				
Age (years)	23.66	24.07	23.12	0.95***
	(0.015)	(0.020)	(0.021)	(0.03)
BMI (kg/m^2)	22.76	22.14	23.56	-1.42***
	(0.007)	(0.008)	(0.011)	(0.014)
Thin (BMI < 18.5)	10.4%	12.1%	8.1%	4.0 p.p.***
	(0.001)	(0.001)	(0.001)	(0.001)
Panel B. Occupation and place of residence				
Working in agriculture	34.1%	43.5%	21.9%	21.6 p.p.***
	(0.001)	(0.001)	(0.001)	(0.001)
Rural	66.3%	78.2%	50.7%	27.5 p.p.***
	(0.001)	(0.001)	(0.001)	(0.001)
Panel C. Asset ownership and wealth				
Assets (number)	1.71	1.47	2.01	-0.54***
	(0.001)	(0.002)	(0.002)	(0.003)
Poor	39.2%	52.8%	21.9%	30.9 p.p.***
	(0.001)	(0.001)	(0.001)	(0.001)
Total	965,398	546,490	418,908	

The total number of observations differs for different variables. The figures in the last row show the maximum available observations. Differences in means are statistically significant at * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$, respectively.

6.2 Main results

6.2.1 Health outcomes

We start our main empirical analysis by estimating specification 1 using $ln(BMI)$ as dependent variable. Confirming our expectation that prolonged droughts have a stronger impact than short-lived droughts, we find no statistically significant effect of $drought1m$ on the body weight of individuals, while both $drought2m$ and $drought3m$ enter the regression with a negative sign and are statistically significant at the 5% level, see Panel A of table A.4. Focusing on the effect of $drought3m$, column (1) of table 2 indicates that a drought that has lasted for the past 3 months reduces the BMI of an average individual by 1.9%.[18] The finding of reduced health outcomes in the wake of agricultural shocks is supportive of hypothesis 1 and confirmed by a number of studies (Carpena 2019; Hoddinott 2006; Janzen and Carter 2019). As regards the other covariates, all coefficients enter with the expected sign and are of high statistical significance. The average BMI of uneducated individuals is 6.6% lower than that of educated individuals, and male individuals have a lower BMI on average than female individuals.

We next study heterogeneity in the effect of agricultural droughts along the dimension of gender and educational attainment. As shown in column (2), interacting $drought3m$ with our dummy for uneducated individuals yields a negative coefficient on stand-alone drought and a positive coefficient on the interaction term. This suggest that it is mainly individuals

[18]In log-lin regressions, the effect can be calculated as $exp(-0.019) - 1 = -0.0188 = -1.9\%$.

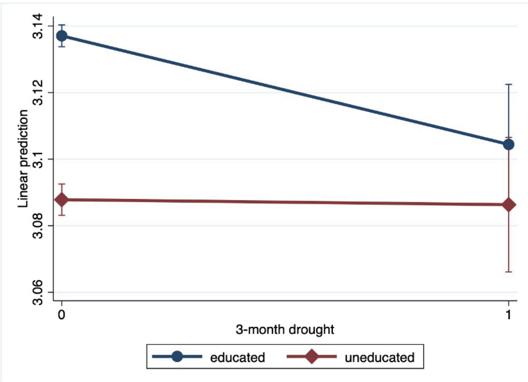
Table 2: Pooled OLS—consumption cutbacks

Sample:	Adults			Children		
Dependent variable:	ln(BMI)	ln(BMI)	ln(BMI)	BMI sd	BMI sd	BMI sd
	(1)	(2)	(3)	(4)	(5)	(6)
drought3m	-0.019**	-0.033***	-0.016*	-0.083	0.019	-0.081
	(0.009)	(0.009)	(0.008)	(0.062)	(0.084)	(0.074)
drought3m#uneducated		0.027**			-0.181**	
		(0.008)			(0.083)	
drought3m#sex			-0.034			-0.005
			(0.020)			(0.059)
uneducated	-0.066***	-0.066***	-0.066***	-0.135***	-0.133***	-0.135***
	(0.003)	(0.003)	(0.003)	(0.031)	(0.031)	(0.031)
age	0.005***	0.005***	0.005***	0.083***	0.083***	0.083***
	(0.000)	(0.000)	(0.000)	(0.015)	(0.015)	(0.015)
sex	-0.102***	-0.102***	-0.102***	0.027**	0.027**	0.027**
	(0.007)	(0.007)	(0.007)	(0.012)	(0.012)	(0.012)
N	381004	381004	381004	93837	93837	93837
adj. R^2	0.132	0.132	0.132	0.052	0.052	0.052

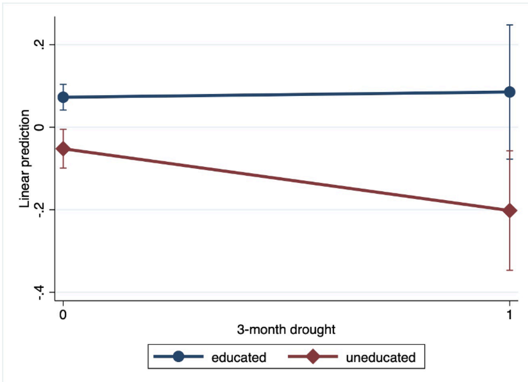
The 'adults' sample of columns (1)-(3) comprises all individuals at the age of 15 years or higher, while the 'children' sample of columns (4)-(6) includes children below the age of 5 years. All specifications include country-by-year dummies. Standard errors are clustered on the country-vegetation-zone-year level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

with complete primary education or higher that lose body weight in the course of a 3-month drought. Indeed, the effect of *drought3m* on uneducated individuals is not significantly different from zero, indicating that uneducated individuals appear rather unaffected in terms of their BMI. This finding seems surprising given that uneducated individuals presumably have fewer options to cope with droughts (e.g., they have a more than 30 percentage points higher probability of being *poor* compared to educated individuals, see table 1). Moreover, their average BMI is significantly lower than that of educated people, so a further reduction in their BMI could lead to severe health problems. One possible explanation for the insignificant effect of drought on the BMI of uneducated individuals could be that the uneducated resort to consumption cutbacks only when they have no other choice, whereas people with higher levels of education are more willing to accept temporary consumption restrictions without risking adverse health effects. Another explanation could be that uneducated individuals change the composition of their diet in times of food scarcity. For example, they might limit their consumption of relatively expensive fruits and vegetables and instead mainly eat relatively inexpensive high-calorie foods such as corn and rice. As a result, we would not necessarily observe an (immediate) weight loss even though this change in dietary intake is likely to be associated with malnutritrion. As the DHS questionnaires do not ask about the composition of an individual's diet, we are not able to empirically test this explanation however. Finally, if aid programs are in place that specifically target uneducated and/or poor people but exclude comparably better-off people from aid deliveries, we may observe weight losses only among educated people. However, this explanation would still leave open why the opposite effect is observed among children.

Interacting $drought3m$ with a dummy for an individual's gender, see column (3), yields negative coefficients on both stand-alone drought and the interaction term, but the effect is statistically significant only in the former case. We therefore fail to detect a significant gender bias in the effect and conclude that both women and men lose body weight in the course of a 3-month drought. This is in contrast to some studies, according to which BMI decreases mainly in women (see, e.g., Bengtsson 2010; Hoddinott 2006).
One common finding of the literature is that it is particularly children who suffer from crop failures (Davenport et al. 2017; Grace et al. 2015). To test this assertion, we run additional specifications where we analyze the impact of agricultural drought on the health status of children below the age of 5 years, and show the results in columns (4), (5), and (6). When recording anthropometry measures for young children, the DHS program reports measures as differences from a reference population of the same age and sex. Consequently, we use BMI expressed in units of standard deviations from the reference population to capture a child's health status. As shown in column (4), the coefficient on $drought3m$ enters with a negative sign but is just outside the range of conventional statistical significance. Interacting $drought3m$ with the same dummies as before reveals however significant heterogeneity in the effect of agricultural droughts. As shown in column (5), children of uneducated mothers appear to be the main sufferers from agricultural droughts: They experience a sizeable and significant reduction in their BMI by 0.18 units of standard deviation, while children of educated mothers remain rather unaffected by agricultural droughts in terms of body weight. Again, we fail to uncover a significant gender bias in the effect of drought on the BMI of children, see column (6).



(a) $ln(BMI)$



(b) $BMIsd$

Figure 5: Heterogeneous effect of drought, by educational attainment

To summarize the results from this section, agricultural droughts have a significant impact on the body weight of individuals in Africa. Although we don't find evidence for a gender bias in the effect of drought, there appears to be significant heterogeneity depending on an individual's educational attainment. Figure 5 plots the average marginal effects (AMEs) of $drought3m$ on $ln(BMI)$ from the analysis on the adult sample and $BMIsd$ from the analysis on the children sample, respectively. The 95% confidence intervals are represented by the vertical spikes. As discussed before, the left subfigure indicates that it is mainly educated adults who limit their food consumption and lose weight, whereas uneducated individuals do not react to droughts by cutting back on consumption. This finding is fundamentally different when looking at children, as depicted in the right subfigure: Now, children of uneducated mothers lose weight as a result of drought, whereas children of educated mothers are hardly affected.

6.2.2 Sale of assets

We proceed our empirical analysis with analyzing the sale of assets as a strategy of African households to cope with agricultural shocks. To this end, we estimate specification 1 with *n_assets* as dependent variable. In the first 3 estimations, we again iterate between $drought1m$, $drought2m$, and $drought3m$ as main independent variables. While the effect of a 1-month drought is positive but outside the range of conventional statistical significance, longer-lasting droughts enter the regression with a negative sign, see Panel B of table A.4. Focusing on the effects of $drought3m$, the results in column (1) of table 3 suggest that a 3-month drought is associated with a slight but statistically insignificant reduction in the asset holdings of an average individual.

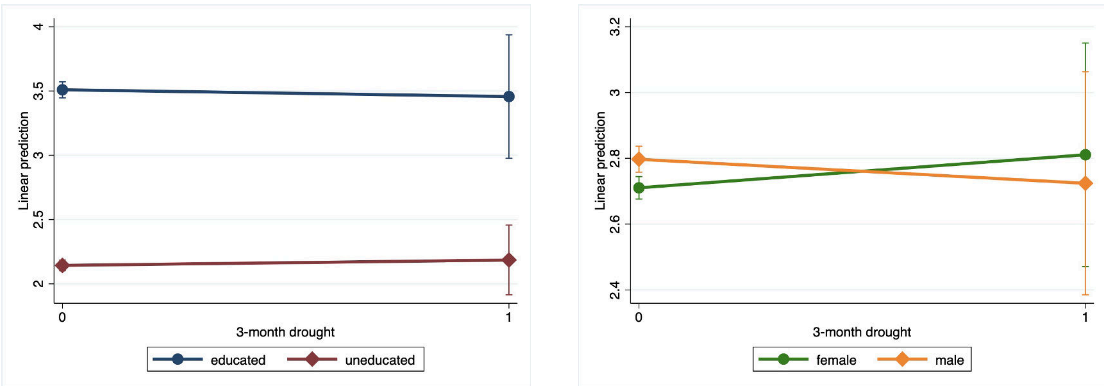
Table 3: Pooled OLS—asset sales

Dependent variable:	# Assets (1)	# Assets (2)	# Assets (3)
drought3month	-0.069	-0.105	-0.048
	(0.069)	(0.092)	(0.065)
drought3month#uneducated		0.068	
		(0.079)	
drought3month#sex			-0.069*
			(0.039)
uneducated	-0.653***	-0.653***	-0.653***
	(0.022)	(0.022)	(0.022)
age	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)
sex	0.035***	0.035***	0.036***
	(0.007)	(0.007)	(0.007)
N	965398	965398	965398
adj. R^2	0.198	0.198	0.198

All specifications include country-by-year dummies. Standard errors are clustered on the country-vegetation-zone-year level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

To study heterogeneity in the impact of drought, we again interact $drought3m$ with a dummy for educational attainment and gender and present the results in columns (2) and (3), respectively. As shown in column (2), the coefficients on both stand-alone drought and drought interacted with *uneducated* are statistically insignificant, delivering no evidence for (differential) effects of agricultural droughts on asset ownership. Interacting $drought3m$ with *sex* however reveals substantial heterogeneity in the effect of drought on asset ownership depending on an individual's gender: As shown in column (3), the effect of a 3-month drought on the asset stock of males is negative and statistically significant at the 10% level. Given that the average number of assets owned by a male individual amounts to 1.8 only, a reduction of 0.12 assets represents a sizeable decline of almost 7%. In contrast, the effect on stand-alone drought is outside the range of statistical significance, indicating that asset sale is a coping strategy used by males only. In that regard, our results are supportive of hypothesis 2, but only with respect to male individuals. This finding complements the literature, which reports asset sale to be an important buffering mechanism in many settings but generally focuses on livestock and does not differentiate between differential effects on males and females (Acosta et al. 2021; Janzen and Carter 2019).

As regards the interpretation of the other covariates, uneducated individuals own fewer assets on average than their educated fellows and males own more assets than females, with the difference in both cases being statistically significant at the 1% level. The coefficient on *age* is small throughout all specifications and economically not sizable. On the one hand, this could indicate that there is no significant accumulation in wealth over lifetime; on the other hand, this could be due to the fact that many items are jointly owned by a household and thus belong equally to older and younger household members.



(a) n_assets **(b)** n_assets

Figure 6: Heterogeneous effect of drought, by education (left) and gender (right)

In summary, the results of this section yield suggestive evidence that asset sale may indeed be used as a measure to cope with droughts, but that it is not taken equally by all individuals. Figure 6 plots the AMEs of $drought3m$ on n_assets, this time differentiated by education (left subfigure) and gender (right subfigure), and with the 95% confidence intervals again represented by the vertical spikes. While we fail to uncover heterogeneity in the effect along educational attainment, asset sale appears to be a margin of adjustment among male individuals only. One potential explanation for the revealed gender bias is that male individuals own more assets on average than females or generally have more 'control' over household assets, and may therefore be the ones who decide to sell some of them in the wake of a drought.

6.2.3 School dropout

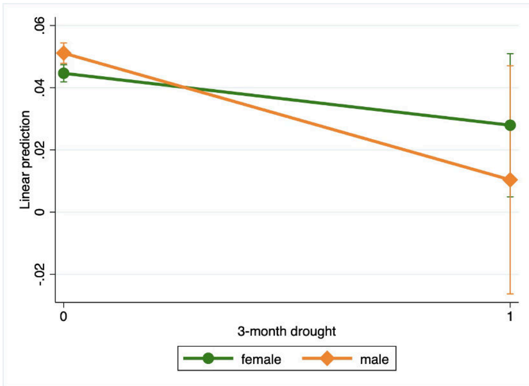
We now turn to the analysis of the relationship between agricultural droughts and children's school attendance. Theoretically, the relationship is ambiguous: On the one hand, droughts may put parents into financial distress and force them to reduce their human capital investment into their children. If this holds true, we should expect a negative relationship between droughts and school attendance. On the other hand, poor farming conditions reduce the need for children helping out in agriculture and may consequently lead to an increase in their school attendance. Moreover, lower income streams from agricultural activities reduce the opportunity cost of schooling, incentivizing parents to increase the human capital investment into their children. In the latter two cases, a positive relationship between drought and school attendance is expected.

Table 4: LPM—School dropout

Dependent variable:	Dropout (1)	Dropout (2)
drought3m	-0.023**	-0.016
	(0.010)	(0.012)
drought3m#sex		-0.025
		(0.023)
age	-0.002***	-0.002***
	(0.000)	(0.000)
sex	0.005**	0.005**
	(0.002)	(0.002)
N	131540	131540
adj. R^2	0.019	0.019

All specifications include country-by-year dummies. Standard errors are clustered on the country-vegetation-zone-year level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Figure 7: Heterogeneous effect of drought, by gender



$dropout = 1$

We test whether droughts lead to a decrease or increase in school attendance by estimating specification 1 with *dropout* as dependent variable. The dummy indicator *dropout* captures if a child reports in the survey to have dropped out of school since the previous school year. Again, the first 3 estimations iteratively use $drought1m$, $drought2m$, and $drought3m$ as main independent variable. As shown in Panel C of table A.4, the coefficient on $drought1m$ is positive but statistically insignificant, whereas both $drought2m$ and $drought3m$ enter the regressions with a negative sign and are statistically significant at the 5% level. This first finding suggests that parents respond to droughts by increasing their human capital investment into their children, providing suggestive evidence of a positive relationship between agricultural droughts and school attendance, a result that is in line with Shah and Steinberg (2017). Focusing on the effect of $drought3m$, column (1) of table 4 indicates that a 3-month drought reduces the probability that a child recently dropped out of school by 2.3 percentage points, with the effect being statistically significant at the 5% level.[19] Taking a stand on hypothesis 3, this finding suggests that the opportunity cost channel is the dominant factor in the decision on human capital investment in the wake of drought and is consistent with the results by Shah and Steinberg (2017). To interpret the sign of the other covariates, older individuals are slightly less likely to drop out of school whereas male individuals tend to be more likely to drop out of school.

In addition, we analyze whether there are differential effects with respect to a student's gender. As shown in column (2), we find tentative evidence that primarily the human capital investment into male children is increased in response to agricultural droughts, but the difference is not statistically significant at conventional levels. We plot the AMEs of $drought3m$ on $dropout$ in figure 7, with the effect being differentiated by gender and the 95% confidence intervals represented by the vertical spikes.

6.2.4 Labor reallocation

We next turn to the analysis of labor supply responses and study whether households reallocate labor away from agriculture and into non-agricultural employment in the wake of agricultural droughts. To this end, we estimate specification 1 with $agri$ as dependent variable. In a first step, we again iterate between droughts of different persistence as main independent variables, this time additionally estimating the model with $drought6m$ as independent variable. Including a 6-month drought as regressor is based on two assumptions: (1) labor reallocation oftentimes involves time-consuming processes such as job search, potentially making labor reallocation not a feasible margins of adjustment in the very short run, (2) leaving the agricultural sector and seeking alternative employment is likely to occur primarily when one has been suffering from a drought for an extended period of time and considers the viability of agriculture to be permanently threatened. As shown in Panel A of table A.5, drought enters the regression with a negative sign and is of high statistical significance in all but one specifications, indicating that agricultural droughts are indeed followed by a movement out of agriculture.[20] Interestingly and in line with expectation, the effects are of similar magnitude in the case of 1-month, 2-month, and 3-month drought, but considerably larger in the case of 6-month drought.

Although the finding of a movement out of agriculture is informative in itself, conclusions about the well-being of individuals can only be drawn if we know where labor flows after leaving the agricultural sector. For instance, an individual's well-being critically hinges on whether they move into unemployment or take up alternative employment. To gain a better understanding of where labor flows, we repeat our estimation with dummies for

[19]Since a respondent's educational attainment is a direct consequence of their decision to drop out of school, we do not study heterogeneity along the dimension of education and also refrain from including educational attainment as control variable in all regressions.

[20]The exception is the coefficient on 3-month drought which is just outside the range of statistical significance; the coefficients on 1-month, 2-month, and 6-month drought are statistically significant at the 1%, 5%, and 5% level, respectively.

alternative sectors as dependent variables. As an example, the dummy indicator *services* turns 1 if the respondent works in the services sector, and 0 otherwise. As the opportunities for alternative employment are likely to depend on the individual's level of education, we focus on analyzing heterogeneity in the effect of agricultural droughts along the dimension of educational attainment. Table 5 presents the results from the regressions with *drought3m* as main independent variable and summarizes which sectors lose or gain workforce as a result of agricultural shocks.[21]

Table 5: LPM—sectors that gain and lose workers after an agricultural drought

	Dependent variable: Working in the respective sector = 1			
	Agriculture	Unemployed	Household	Unskilled Manual
	(1)	(2)	(3)	(4)
drought3m	0.011	-0.020	-0.000	-0.000
	(0.033)	(0.023)	(0.004)	(0.007)
drought3m#uneducated	-0.096*	0.056*	0.003	-0.001
	(0.050)	(0.032)	(0.006)	(0.009)
uneducated	0.207***	-0.053***	-0.002**	-0.004**
	(0.015)	(0.012)	(0.001)	(0.001)
age	0.003***	-0.006***	-0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
sex	0.094***	-0.132***	-0.004***	0.018***
	(0.010)	(0.008)	(0.001)	(0.003)
N	885820	882982	882982	882982
adj. R^2	0.184	0.122	0.057	0.098
	Skilled Manual	Professional	Sales	Services
	(5)	(6)	(7)	(8)
drought3m	0.007	0.005	0.001	-0.004
	(0.020)	(0.008)	(0.011)	(0.011)
drought3m#uneducated	0.010	-0.012	0.027	0.009
	(0.021)	(0.011)	(0.031)	(0.006)
uneducated	-0.017***	-0.073***	-0.014**	-0.027***
	(0.002)	(0.003)	(0.005)	(0.002)
age	0.001***	0.001***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
sex	0.062***	0.021***	-0.064***	0.004
	(0.005)	(0.001)	(0.005)	(0.002)
N	882982	882982	882982	882982
adj. R^2	0.039	0.056	0.079	0.053

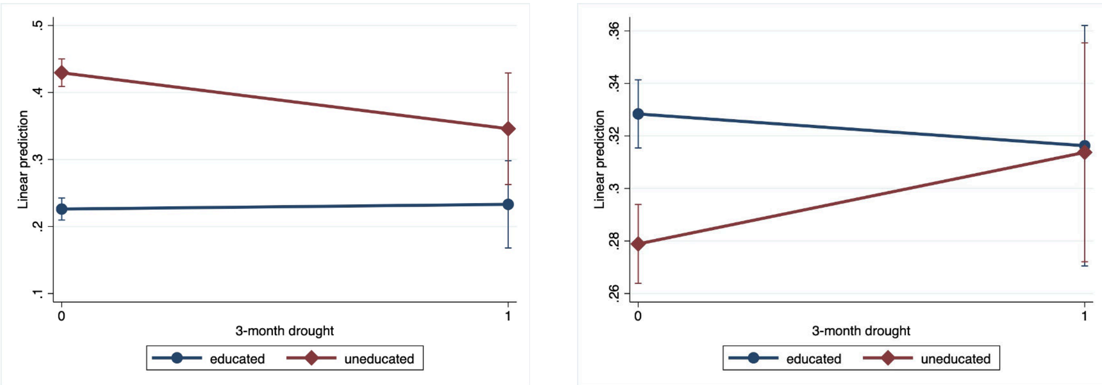
Household includes all people working in the household or running domestic activities and *Professional* reflects employment in professional, technical, and managerial activities.
All specifications include country-by-year dummies. Standard errors are clustered on the country-vegetation-zone-year level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

According to the results in column (1), a 3-month drought has no statistically significant effect on the probability of an average educated individual working in agriculture. This changes however when looking at uneducated individuals: The negative and statistically significant coefficient on the interaction term suggests that the probability of working in agriculture decreases by 8.5 percentage points for individuals with no or only incomplete

[21]For consistency reasons and because 6-month droughts are a very rare event (see table A.2), we continue to focus on *drought3m* instead of *drought6m*.

primary education. Hypothesis 4 is thus confirmed for the case of uneducated individuals. Column (2) gives an indication of where the uneducated workforce flows after leaving agriculture. While for educated individuals no significant increase in the probability of being unemployed can be detected, the positive and statistically significant coefficient on the interaction term suggests that the movement of agriculture among uneducated is mirrored to a large extent by an increase in unemployment. Interestingly, all other sectors experience only small and statistically insignificant in- or outflows of labor, suggesting that they play only a subordinate role in mitigating the effects of drought.

To give an interpretation of the other covariates in columns (1) and (2), uneducated and/or male individuals are significantly more likely to work in agriculture compared to their educated and/or female fellows and the effect of *sex* is positive but small and economically not sizeable. Interestingly, uneducated and/or male individuals are significantly *less* likely to be unemployed. This can probably be explained by the fact that these people often work on their own farm and are therefore not in an employment relationship with an external employer.



(a) $agri = 1$ **(b)** $unemployed = 1$

Figure 8: Heterogeneous effect of drought, by educational attainment

To summarize this section, figure 8 plots the AMEs of $drought3m$ on $agri$ (left subfigure) and $unemployed$ (right subfigure), differentiated by educational attainment and with the 95% confidence intervals again represented by the vertical spikes. As indicated by the left subfigure, agricultural droughts are followed by a significant movement out of agriculture among the uneducated only. The right subfigure highlights the substantial heterogeneity in the effect of drought on unemployment. For the uneducated, the exodus from agriculture is largely reflected by an increase in unemployment, suggesting that these individuals are rather unsuccessful in taking up alternative employment opportunities. These results are consistent with the literature that confirms the outflow from agriculture and emphasizes the importance of education for subsequent opportunities in the labor market (Emerick 2018).

6.2.5 *Migration*

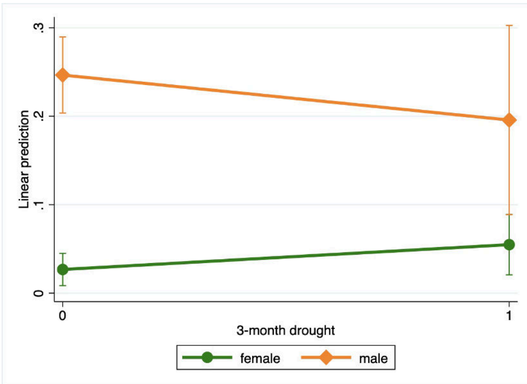
In a final step of our empirical analysis, we consider migration as a strategy to cope with agricultural droughts. As discussed before, we expect individuals to *not* move to drought-affected areas. We therefore expect a negative relationship between the occurrence of drought in a location and the probability that, for work reasons or other, a respondent is currently living in this place even though it is not their usual place of residence. To test this assumption, we estimate specification 1 with *not_dejure* as dependent variable. Again iterating between droughts of different persistence yields coefficients on drought that are positive but statistically insignificant throughout all specifications, see Panel B of table A.5. For our analysis of heterogeneity in the effect of drought, we focus on *drought3m* as main independent variable and present the regression results in table 6.

Table 6: LPM—Migration

Dependent var.:	Not de jure (1)	Not de jure (2)
drought3m	0.005	0.027
	(0.005)	(0.017)
drought3m#sex		-0.072
		(0.070)
uneducated	-0.028***	-0.028***
	(0.005)	(0.005)
age	0.004***	0.004***
	(0.001)	(0.001)
sex	0.237***	0.238***
	(0.033)	(0.033)
N	965398	965398
adj. R^2	0.335	0.335

All specifications include country-by-year dummies. Standard errors are clustered on the country-vegetation-zone-year level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Figure 9: Heterogeneous effect of drought, by gender



$not\_dejure = 1$

As already mentioned, the coefficient on *drought3m* in column (1) is small and statistically insignificant, indicating that a 3-month drought does not lead to a (temporary) change of residence of the average individual. In column (2), the coefficients on both stand-alone *drought3m* and *drought3m* interacted with *sex* are still statistically insignificant, but the coefficient on the interaction term has the expected negative sign. For males, an agricultural drought seems to reduce the probability that the respondent is currently living in a drought-hit place even though it is not their usual place of residence. This finding is consistent with the literature, which typically finds that primarily men migrate to take up employment in areas with better employment opportunities (see, e.g, Gray and Mueller 2012). We thus find tentative evidence that hypothesis 5 holds for men but not for women. Analyzing heterogeneity in the effect of drought along the educational dimension provides no evidence for differential effects between uneducated and educated individuals (results unreported).

As regards the other covariates, they are all statistically significant and in line with expectation. In comparison to educated individuals, uneducated individuals are significantly less likely to be living in a place other than their usual place of residence, and males are more likely than females to not be living in their usual place of residence.

In summary, the results from this section provide suggestive evidence that human mobility of men may occur after the occurrence of an agricultural drought. Even though we can't follow individuals over time and space and don't know the reasons for their moving, the results are in line with the literature that predominantly finds men to move to take up employment in areas with better job opportunities (Gray and Mueller 2012). The AMEs resulting from the regression of $drought6m$ on not_dejure are shown in the right subfigure of figure 9, with the effect being differentiated by gender and the 95% confidence intervals represented by the vertical spikes.

6.3 Summary and implications of the results

With the results from the empirical analysis at hand, we are able to consider them in a larger context. Our analysis has shown that agricultural droughts in Africa have the potential to severely affect individuals. Yet, it also has revealed significant heterogeneity in the effect of agricultural droughts.

First, individuals appear to respond to agricultural droughts by cutting back on consumption and experiencing subsequent weight losses. For adult individuals, consumption cutbacks are primarily observed among the educated, while the opposite holds true when looking at children below the age of 5 years. Now, it is the children of uneducated mothers who experience the strongest reduction in weight due to the occurrence of droughts. Second, we find tentative evidence that asset sale may used as a strategy to cope with drought, but that this strategy is used by men only. Regarding the analysis of school dropout, we've found evidence that the opportunity cost channel is dominating the relationship between droughts and schooling attendance: Droughts appear to reduce the likelihood of children dropping out of school, leading to a positive relationship between agricultural droughts and school attendance.

The next step of our analysis has shown that agricultural droughts are accompanied by a sizeable movement out of agriculture, this time comprising uneducated and educated individuals alike. While for uneducated individuals the flow of labor mostly goes into unemployment, educated individuals are generally not forced into unemployment and appear successful in shifting their labor to alternative employment activities. Finally, we find tentative evidence that migration is used as a margin of adjustment to agricultural drought among male individuals. These findings suggest that relocation may at least partly occur for reasons of alternative employment opportunities in more favorable locations.

In light of the detrimental consequences that agricultural droughts can have on individuals (e.g., by leading to an increase in unemployment among uneducated adults and to severe weight losses among children of uneducated mothers), it is the logical next step to ask how these adverse impacts can be mitigated. While the reallocation of labor to sectors that are less sensitive to conditions in the ambient environment is one strategy to reduce vulnerability to future shocks, the preceding analysis has also shown that opportunities for labor reallocation are often only available to certain segments of the population (e.g., educated individuals). Based on the findings of our analysis, the first obvious recommendation is to increase investment in the human capital formation of individuals (and primarily female ones) so as to increase their opportunities in the labor market. In that regard, the observation of a positive relationship between droughts and school attendance is hopeful. However, it would be naive to let things take their course, assuming that the level of education for everyone will improve over time and that resilience will automatically increase as a result. Moreover, although the results from our analysis suggest that education is a determinant of vulnerability, it would be premature to conclude that the effect of education on vulnerability is necessarily *causal*. As argued by Hsiang et al. (2013), one would need to exogeneously alter the hypothesized determinant of vulnerability to provide evidence of a causal relationship.

Once the most vulnerable members of a society have been reliably identified, measures can be developed that specifically target these individuals. Measures that can be taken in the short term include social safety nets and social protection programs. Studying how harmful behavioral responses like consumption cutbacks and asset sales can be mitigated, Janzen and Carter (2019) show that microinsurance schemes are able to reduce the reliance on both forms of costly coping strategies in times of crises. Similarly, Hidrobo et al. (2018) find that social protection programs have a positive impact on food security and asset formation in the developing world, both through an improvement in the quality of nutritional intake and an increase in asset holdings. Similarly, food aid programs are found to offset the negative health effects of harvest failures on Ethiopian children (Yamano et al. 2005). In addition to expanding social safety nets, there are other ways to reduce household vulnerability to agricultural shocks. A common finding of the literature is that rural households often experience the greatest decline in assets and body weight as a result of agricultural droughts. This could be addressed by improving access to markets, for example through improved transportation and communication infrastructure (Bonuedi et al. 2022).

7 Further analyses and robustness checks

The results presented above suggest that agricultural droughts have serious and wide-ranging impacts on households in Africa. In this section, we bolster our the robustness of our results with a series of further analysis.

7.1 Effect of drought during and outside a growing season

The preceding analysis has exploited NDVI to construct an indicator of agricultural droughts. To verify that the effect of drought indeed runs through the channel of shocks to agriculture, we examine whether droughts that occur inside or outside a growing period have differential effects. To this end, we first determine for each location the typical start and end of a growing season, following the procedure described in section 6.1. We then construct a dummy indicator *duringseason* that takes on the value 1 if a drought occurs during the typical time of a growing season, and 0 otherwise, and interact our drought indicators with *duringseason*. The results from these interacted regressions are shown in table B.1.

For the first two analyses (consumption cutbacks and asset sale), the effect of a drought outside a growing season exceeds that of a drought inside a growing season. These results can be explained logically: Since food availability is likely to be relatively scarce outside a growing season but relatively abundant inside a growing season, it makes sense that a drought will have a greater impact on nutritional intake in times of scarcity. Indeed, column (1) suggests that consumption cutbacks and associated weight losses occur only for droughts outside the growing season (and statistically significantly so at the 1% level), whereas droughts inside a growing season have no significant effect on an individual's body weight.[22] Similarly, asset sale appears to be a margin of adjustment primarily outside the growing season, even though the effects in column (2) are neither statistically significant for drought inside nor outside a growing season. Analyzing school dropout in column (3), both droughts inside and outside the growing season are associated with a significant reduction in the probability of school dropout and are not statistically significantly different from each other.

Turning to the analysis of labor reallocation and migration, the above observation reverses and the effect of drought inside a growing season exceeds the effect of drought outside a growing season. As indicated by column (4) of table B.1, droughts inside a growing season have a stronger negative effect on the probability of working in agriculture, even though the effects are not statistically significant in either case. This finding is in line with intuition: Individuals are likely to be engaged in agriculture primarily when natural resources for food production are abundant, while they are more likely to be engaged in other occupations outside the growing season. It therefore makes sense that a drought has a greater impact on agricultural employment when it occurs inside a growing season. Interestingly, column (5) suggests that unemployment mainly increases for droughts outside a growing season (even though not statistically significantly so), while droughts inside a growing season have even a slightly negative effect on the probability of being unemployed. This finding could potentially be explained by generally more employment opportunities in times of relative abundance. Finally, we fail to detect a significant effect of drought outside the growing season on the mobility of an average individual, see column (6). The negative and statistically significant effect on the interaction term however suggests that human mobility increases in the course of droughts inside a growing season. This is in accordance with our earlier assumption that periods of relative abundance may be associated with generally higher job availability (and that pursuing these jobs may require people to move, e.g., to urban areas with larger labor markets).

[22] The negative coefficient on stand-alone *drought3m* is fully offset by the positive coefficient on the interaction term, making the joint effect statistically indistinguishable from 0.

7.2 Effect of a first drought in 5 years

As discussed in section 5, one threat to the identification of causal effects is that the composition of a population at a location may change as a result of agricultural droughts. One potential reason for this could be that the 'able' individuals move away and only 'unable' and poor stay behind. The out-migration of comparably better-off individuals might then partly explain the bad outcomes observed in the aftermath of agricultural droughts. To test whether this issue threatens our identification of causal affects, we run additional specifications where we only consider droughts that occur for the first time since a drought-free period of 5 years. To this end, we construct a dummy $firstdrought3m$ that takes on the value 1 if there currently is a 3-month drought but there was *no other* 3-month drought in this location during the past 5 years.[23] Under the assumption that these droughts occur relatively unexpectedly, people are not able to prepare for this event through *ex ante* measures, allowing us to focus on *ex post* coping strategies.

The estimation results from these regressions are presented in table B.2. Comparing column (1) with the corresponding regression results of the main analysis shows that the effect of a first-time drought on $ln(BMI)$ is even stronger: While $drought3m$ led to a significant reduction in the BMI of an average individual by 1.9%, the decline in BMI now amounts to 2.4% when considering the effect of $firstdrought3m$ (with the effect being statistically significant at the 10% level). The same holds true for the analysis of asset sale, as depicted in column (2): $firstdrought3m$ is associated with a reduction in the asset stock of the average individual amounts by 0.13 assets, compared to 0.07 assets in the case of $drought3m$ (although the effects are not statistically significant in either case). As shown in column (3), restricting the sample to male individuals only reinforces this finding, as it makes the negative effect of $firstdrought3m$ stronger and statistically significant at the 10% level. Similarly, the effect of $firstdrought3m$ exceeds that of $drought3m$ when analyzing school dropout: The effect is negative and statistically significant in both cases, but larger in size and of higher statistical significance in the case of $firstdrought3m$, see column (4).

Interestingly, the story changes for the final two analyses. While $drought3m$ and $drought6m$ were both associated with a decline in the probability of working in agriculture (although statistically significantly so only in the latter case), the effect of a first 3-month drought since 5 years is small and statistically insignificant, as shown in column (5). This supports our previous assumption that adjustments in labor supply are done primarily when droughts are perceived to be prolonged or recurring and threaten the viability of agriculture over the long term. Only small differences in the effects of $drought3m$ and $firstdrought3m$ can be detected for the analysis of drought-induced human mobility. As the effect of $firstdrought3m$ on the place of residence of the average individual is outside the range of statistical significance,

[23]This implies that we must trace NDVI values in a location back by up to 120 lags. For a location to be designated drought-free for the past five years, drought conditions must not have occurred for 6 consecutive lags within the past 120 lags. Due to the high computational effort involved, we limit ourselves to going back 'only' 5 years. We leave it to future studies to extend the analysis to a longer historical period.

we again interact $firstdrought3m$ and sex and report the results in column (6). As in the main analysis, the coefficient on the interaction has a negative sign and can be interpreted as suggestive evidence that a first drought in 5 years reduces the probability that a man is currently living in a drought-hit place even though it is not their usual place of residence. However, the effect is still outside the range of statistical significance and is also smaller in magnitude than in the main analysis.

Together, these findings are reassuring for the validity of our identification strategy. If droughts were associated with a fundamental change in the composition of a local population (e.g., because better-off individuals move away), we would expect the effect of a first-time drought to be *lower* than that of a 'normal' drought. Instead, we make the opposite observation: Droughts that occur for the first time in 5 years have stronger effects on a local population than recurring droughts. This finding provides initial evidence that adaptation is occurring—however, as recurring droughts continue to have negative impacts on people, adaptation does not appear to be sufficient to fully offset the negative impacts of drought, an issue that will be discussed in the next section.

8 Discussion of the results in light of climate change

The results from the preceding analysis have highlighted the serious consequences that agricultural droughts can have for (especially uneducated and disadvantaged) households in Africa. In light of the anticipated consequences of global warming—among them a rise in global mean surface temperature and sea levels, as well as an increased frequency and severity of extreme weather events—climate change is likely to exacerbate this situation (IPCC 2022). Of great concern is the projected shift towards a drier climate in many African regions, which is likely to be accompanied by more frequent and severe droughts (Gizaw and Gan 2017).[24] Even if changes in exposure to global warming occur uniformly across space, it is likely that marginal damages from climatic changes exhibit nonlinearities, for instance due to differences in a population's initial climate or in their vulnerability to these changes (Hsiang et al. 2019). Vulnerability to climate change—defined as a function of exposure, sensitivity, and adaptive capacity (IPCC 2007)—is thereby likely to be particularly high among smallholder farmers in developing countries. First, rain-fed agriculture remains the dominant source of food production in many parts of Africa, making crop yields highly dependent on prevailing weather conditions. Given the high dependence on agriculture, crop yield failures have the potential to lead to famines, death, government instability, and war (Petersen 2018). According to the "Intergovernmental Panel on Climate Change" (IPCC), increasing weather extremes have already exposed millions of people in Africa to acute food insecurity and malnutrition, and climate change will likely exacerbate these food security risks in the future (IPCC 2022). Second, the capacity to adapt to climate change is typically

[24] The recent trend towards a drier climate and associated deteriorations in vegetation conditions in many regions of Africa has also been observed in our descriptive analysis of mean NDVI trends in section 6.1.

considered to be low in low-income countries; as a consequence, it is the poor countries of the world that are likely to suffer the bulk of damages from climate change (IPCC 2007; Mendelsohn et al. 2006).

However climate change manifests itself exactly, of critical importance will be whether and to what extent households are able to adapt to repeated or persistent changes in their ambient environment. If populations learn from previous climatic events and do precautionary investments, damages from and vulnerability to future events may decrease over time (Hsiang et al. 2019). While Neo-Malthusians support an environmentally deterministic opinion that aggravating resource scarcity and deteriorating living conditions will increase competition for scarce resources and have the potential to create political and social instability (Homer-Dixon 1999), they are contradicted by the so-called Cornucopians, among them neoclassical economists, who share an optimistic view and claim that functioning institutions and efficient markets will provide incentives to adapt to climate change by conserving or substituting scarce resources and by driving technological innovation (Lomborg 2001). As noted above, low-income countries whose economies are largely based on agricultural production typically have a low capacity to adapt to worsening environmental conditions, due in part to a lack of financial means and education to use advanced technologies (Petersen 2018).

Section 2 provided an overview of the literature studying the implications of agricultural shocks. This literature predominantly focuses on short-term variability in climatic conditions like rainfall or temperature (what we typically term 'weather') to proxy for shocks in agriculture. This is due in large part to the empirical challenges associated with studying the effects of long-term changes: first, gradual climatic changes are likely accompanied by unobserved confounders that make the identification of causal effects difficult; second, long-run changes in climate are typically correlated over space, requiring the comparisons of large and distant spatial units that are likely to differ in aspects other than climate or the environment (Blakeslee et al. 2020). As a consequence, while this literature yields valuable insights into the adaptive capacity of households to high-variability (weather) shocks, it does not allow statements to be made about the implications of long-term climate change.

The rare literature studying adaptation to long-term changes in climatic conditions focuses on labor reallocation (Blakeslee et al. 2020; Colmer 2021), income diversification (Wuepper et al. 2018), and migration (Cattaneo et al. 2019). As pointed out by Blakeslee et al. (2020), agriculture-dependent households experiencing worsening environmental conditions generally have two margins of adjustment: First, they may adjust to changing conditions by adopting new agricultural technologies; second, they may shift labor to off-farm employment (Blakeslee et al. 2020). While the authors find little evidence of agricultural adaptation to loss of groundwater access in rural India, households appear to be able to maintain their overall income levels through labor reallocation. These conclusions are closely in line with Colmer (2021) who finds that labor reallocation is an important margin of adjustment for managing agricultural productivity shocks in India, particularly so in flexible labor regulation environments that provide non-agricultural sectors a high capacity to absorb workers. Di Falco et al. (2012) study the role of adaptation for the impact of climate change on agriculture and find that adaptation can be enhanced through institutional support such as extension services and access to credit and information for farmers (Di Falco et al. 2012). Less optimistic are the findings by Prediger et al. (2014) who show that long-term exposure to resource scarcity is positively associated with antisocial behavior among pastoralists in Namibia. Overall, evidence for adaptation is mixed. While some authors provide evidence for adaptation and decreasing vulnerability to climatic changes after past exposure, others fail to uncover adaptation processes, and some even find the effect of adverse climatic conditions to intensify with past exposure. According to the IPCC (2014), future adaptation will need to be dramatic if it is to offset the potentially large adverse effect of future climate on agriculturally-dependent households. Indeed, the results of our empirical analysis provided suggestive evidence that some adaptation is occurring (see section 7), but that adaptation is insufficient to fully mitigate the adverse effects of recurring droughts.

9 Conclusion and outlook for future research

Exploiting NDVI data and an extensive set of household characteristics, we have analyzed how agricultural droughts affect individuals in Africa. In light of the frequent and oftentimes severe droughts that afflict the African continent, understanding the impacts of drought is essential for the development of appropriate adaptation measures. Focusing on a wide range of possible coping strategies, including consumption cutbacks, asset sales, labor reallocation, changes in human capital investment, and migration, the results of our empirical analysis have shown that agricultural droughts have the potential to severely affect African households. Yet, they have also revealed a sharp bifurcation in the effects of agricultural droughts, with the uneducated, female and otherwise potentially disadvantaged often being the main sufferers from shocks in agriculture. For example, we found that primarily children of uneducated mothers lose weight in the course of agricultural droughts. However, this dichotomy does not hold uniformly throughout the analysis: When looking at the health outcomes of *adults*, mainly the educated lose weight while the uneducated tend to escape unscathed. In addition, asset sale appears to be a coping strategy used mainly by male individuals. Looking at the effect of drought on school dropout, we found evidence that drought *increases* rather than *decreases* the human capital investment of parents into their children. Finally, agricultural droughts are accompanied by a sizeable movement out of agriculture, this time comprising all individuals alike. While uneducated individuals largely move into unemployment, educated (and especially male) individuals succeed in shifting labor to alternative employment activities. Our empirical analysis further suggests that labor reallocation is at least partly associated with migration.

In addition to the substantive contribution of our study to increasing the knowledge about the implications of agricultural droughts, our study has made an important methodological contribution. To the best of our knowledge, the present study is the first to exploit the vegetation index NDVI to gain information about agricultural conditions and to analyze how changes in the local resource base available for food production relate to individual and household characteristics.

While the richness of our data allowed us to examine a wide range of household outcomes, the cross-sectional nature of our dataset did not come without limitations. For example, it did not allow us to track individuals over time. Conducting a similar analysis with panel data would therefore help answering questions where we have reached our limits. For example, it would be interesting to investigate how individuals evolve over time, why migration occurs, and whether the composition of a population changes over time. As discussed in section 4, a further limitation of the present study involves the restriction to observations in the DHS datasets that have correctly coded unique identifier codes. A fruitful extension of this study would be to enlarge the DHS dataset by those observations that we had to remove due to missing or incorrectly coded unique identifiers. Correcting the coding inconsistencies would add many observations to the dataset and increase the statistical significance of the results.

The importance of a better understanding of the impact of droughts in agriculture is demonstrated by the devastating droughts that hit large parts of Africa in recent years, driving millions of people into poverty, hunger and migration. Climate change with its predicted (and already occurring) increase in the frequency and severity of droughts—whether due to heat waves, lack of rain, or an increase in insect infestations—will most likely exacerbate this situation. Our analysis has revealed the detrimental effects that agricultural droughts can have on individuals in Africa and has disentangled the different strategies used by heterogeneous people. In this sense, the results are also of practical relevance in that they can contribute to the development of appropriate and targeted support measures.

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Appendix A—Summary statistics and additional figures

Table A.1: Countries included in the DHS surveys of this analysis

Country	Frequency (1)	Percent (2)	Years (3)
Angola	20,407	2.11	2011, 2015
Burkina Faso	45,470	4.71	2003, 2010
Benin	30,938	3.20	2010-12
Burundi	11,589	1.20	2010-11
Congo Democratic Republic	33,607	3.48	2007, 2013-14
Cote d'Ivoire	13,405	1.39	2011-12
Cameroon	38,729	4.01	2004, 2011
Ghana	30,066	3.11	2003, 2008, 2014
Guinea	14,519	1.50	2012
Kenya	62,148	6.44	2003, 2008-09, 2014
Comoros	5,437	0.56	2012
Liberia	29,323	3.04	2006-2009, 2013
Lesotho	25,956	2.69	2004-05, 2009-10, 2014
Mali	38,979	4.04	2001, 1006, 2012
Malawi	88,629	9.18	2000, 2004-05, 2010, 2015
Mozambique	28,865	2.99	2011, 2015
Nigeria	118,538	12.28	2003, 2008, 2010, 2013
Namibia	24,148	2.50	2000, 2006-07, 2013
Rwanda	29,909	3.10	2000, 2005, 2010-11, 2014-15
Sierra Leone	38,148	3.95	2008, 2013
Senegal	56,511	5.85	2005, 2008-13, 2015
Swaziland	1,115	0.12	2006-07
Chad	8,679	0.90	2014-15
Togo	5,497	0.57	2013-14
Tanzania	55,196	5.72	2007-2012, 2015
Uganda	30,784	3.19	2000, 2006, 2009-11
Zambia	32,489	3.37	2007, 2013-14
Zimbabwe	46,361	4.80	1999, 2005-06, 2010-11, 2015
Total	965,442	100.00	

Column (3) shows the years in which the countries are included in the DHS survey waves.

Table A.2: Summary statistics of the different drought indicators

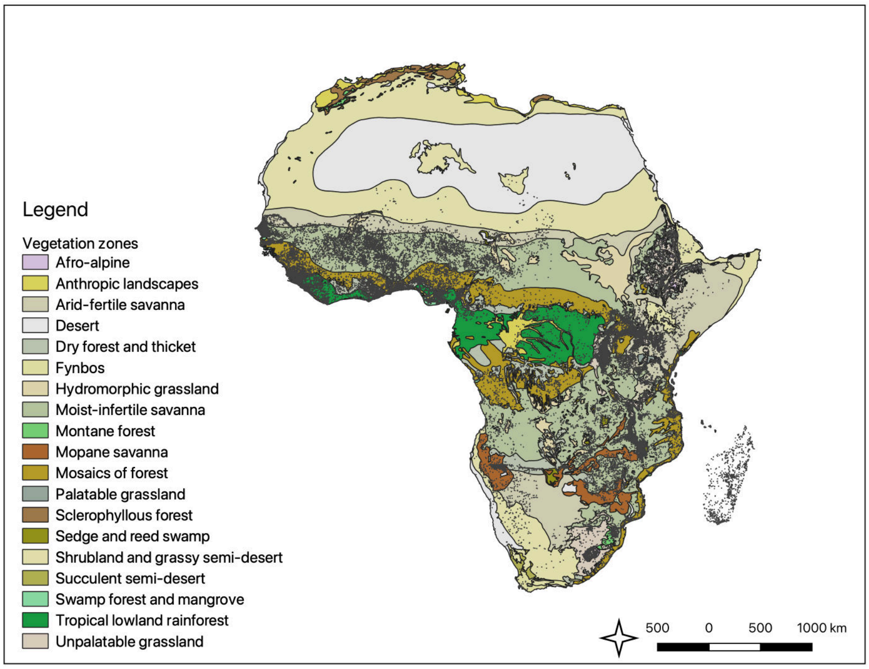
Drought indicator	Frequency (1)	Percent (2)
drought1m	770,428	1.72
drought2m	232,187	0.52
drought3m	87,468	0.20
drought6m	7,742	0.02
Total	1,097,825	2.46

The table summarizes how often the VCI was below 20% at the time of record and was already so during the past 1, 2, 3, or 6 months. The total number of observations is 44,807,405 over the period 1982-2015.

Table A.3: Summary statistics of the different assets included in *n_assets*

Type of asset	Frequency (1)	Total (2)	Percent (3)
radio	621,705	953,081	65.23
television	272,499	952,633	28.60
bicycle	318,888	952,355	33.48
motorcycle/scooter	146,541	952,264	15.39
car/truck	58,248	952,077	6.12
watch	230,579	611,711	37.69

The table summarizes how often the assets contained in the index *n_assets* are owned by the DHS households.



Data retrieved from African Marine Atlas (2022) and based on F. White (1983).

Figure A.1: White's Vegetation Map of Africa.

Table A.4: Comparison of the effects of *drought1m*, *drought2m*, and *drought3m*

Panel A. Dependent variable: ln(BMI)			
	(1)	(2)	(3)
drought1m	0.003		
	(0.004)		
drought2m		-0.013**	
		(0.006)	
drought3m			-0.019**
			(0.009)
uneducated	-0.066***	-0.066***	-0.066***
	(0.003)	(0.003)	(0.003)
age	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)
sex	-0.102***	-0.102***	-0.102***
	(0.007)	(0.007)	(0.007)
N	381004	381004	381004
adj. R^2	0.132	0.132	0.132
Panel B. Dependent variable: # Assets			
	(1)	(2)	(3)
drought1m	0.044		
	(0.040)		
drought2m		-0.044	
		(0.064)	
drought3m			-0.069
			(0.069)
uneducated	-0.653***	-0.653***	-0.653***
	(0.022)	(0.022)	(0.022)
age	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)
sex	0.035***	0.035***	0.035***
	(0.007)	(0.007)	(0.007)
N	965398	965398	965398
adj. R^2	0.198	0.198	0.198
Panel C. Dependent variable: Dropout			
	(1)	(2)	(3)
drought1m	0.002		
	(0.004)		
drought2m		-0.017**	
		(0.008)	
drought3m			-0.023**
			(0.010)
age	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)
sex	0.005**	0.005**	0.005**
	(0.002)	(0.002)	(0.002)
N	131540	131540	131540
adj. R^2	0.019	0.019	0.019

All specifications include country-by-year dummies. Standard errors are clustered on the country-vegetation-zone-year level and shown in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Table A.5: Comparison of the effects of *drought1m*, *drought2m*, *drought3m*, and *drought6m*

Panel A. Dependent variable: Agriculture				
	(1)	(2)	(3)	(4)
drought1m	-0.049***			
	(0.013)			
drought2m		-0.044**		
		(0.020)		
drought3m			-0.039	
			(0.028)	
drought6m				-0.155**
				(0.051)
uneducated	0.207***	0.207***	0.207***	0.207***
	(0.015)	(0.015)	(0.015)	(0.015)
age	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
sex	0.094***	0.094***	0.094***	0.094***
	(0.010)	(0.010)	(0.010)	(0.010)
N	885820	885820	885820	885820
adj. R^2	0.184	0.184	0.184	0.184

Panel B. Dependent variable: Not de jure				
	(1)	(2)	(3)	(4)
drought1m	0.003			
	(0.002)			
drought2m		0.004		
		(0.004)		
drought3m			0.005	
			(0.005)	
drought6m				0.003
				(0.004)
uneducated	-0.028***	-0.028***	-0.028***	-0.028***
	(0.005)	(0.005)	(0.005)	(0.005)
age	0.004***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
sex	0.237***	0.237***	0.237***	0.237***
	(0.033)	(0.033)	(0.033)	(0.033)
N	965398	965398	965398	965398
adj. R^2	0.335	0.335	0.335	0.335

All specifications include country-by-year dummies. Standard errors are clustered on the country-vegetation-zone-year level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Appendix B—Robustness analyses

Table B.1: Effect of a drought inside or outside a growing season

Dependent variable:	ln(BMI)	# Assets	Dropout
	(1)	(2)	(3)
drought3m	-0.031**	-0.143	-0.023*
	(0.010)	(0.099)	(0.013)
drought3m#duringseason	0.042**	0.194	0.001
	(0.016)	(0.142)	(0.011)
duringseason	-0.005	-0.053**	0.002
	(0.003)	(0.024)	(0.002)
uneducated	-0.066***	-0.654***	
	(0.003)	(0.022)	
age	0.005***	0.002***	-0.002***
	(0.000)	(0.000)	(0.000)
sex	-0.102***	0.035***	0.005**
	(0.007)	(0.007)	(0.002)
N	381004	965398	131540
adj. R^2	0.133	0.198	0.019
Dependent variable:	Agriculture	Unemployed	Not de jure
	(4)	(5)	(6)
drought3m	-0.012	0.030	0.009
	(0.030)	(0.021)	(0.006)
drought3m#duringseason	-0.055	-0.076**	-0.012*
	(0.033)	(0.038)	(0.007)
duringseason	0.051***	-0.018**	0.002
	(0.011)	(0.007)	(0.003)
uneducated	0.208***	-0.053***	-0.028***
	(0.015)	(0.012)	(0.005)
age	0.003***	-0.006***	0.004***
	(0.000)	(0.000)	(0.001)
sex	0.095***	-0.132***	0.237***
	(0.010)	(0.008)	(0.033)
N	885820	882982	965398
adj. R^2	0.186	0.122	0.335

All specifications include country-by-year dummies. Standard errors are clustered on the country-vegetation-zone-year level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Table B.2: Effect of a first drought in 5 years

Sample:	Full	Full	Males	Full	Full	Full
Dependent variable:	ln(BMI)	# Assets	# Assets	Dropout	Agriculture	Not de jure
	(1)	(2)	(3)	(4)	(5)	(6)
firstdrought3m	-0.024*	-0.129	-0.192*	-0.031**	0.013	0.016
	(0.013)	(0.088)	(0.113)	(0.010)	(0.029)	(0.025)
firstdrought3m#sex						-0.029
						(0.094)
uneducated	-0.066***	-0.652***	-0.640***		0.207***	-0.028***
	(0.003)	(0.022)	(0.024)		(0.015)	(0.005)
age	0.005***	0.002***	0.003***	-0.002***	0.003***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
sex	-0.102***	0.035***		0.005**	0.095***	0.238***
	(0.007)	(0.007)		(0.002)	(0.010)	(0.033)
N	380535	962590	281378	131146	883228	962590
adj. R^2	0.132	0.198	0.209	0.019	0.184	0.335

All specifications include country-by-year dummies. Standard errors are clustered on the country-vegetation-zone-year level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Declaration of Academic Honesty

Hereby, I declare that I have composed the presented paper independently on my own and without any other resources than the ones indicated. All thoughts taken directly or indirectly from external sources are properly denoted as such.
This paper has neither been previously submitted to another authority nor has it been published yet.

Amsterdam, June 23, 2022

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