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Droughts and Malnutrition in Africa

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Droughts and Malnutrition in Africa

Abstract

How costly are droughts to individuals' nutrition in Africa? We measure severe droughts using a detailed satellite-based vegetation index observed bi-monthly for 0.08° grids between 1982 and 2015. Across 32 African countries, conditional on individual characteristics, timing relative to growing seasons, irrigation, climate, and country-year effects, we show that, unlike recurring droughts, a first-time exposure to a three-month severe drought reduces individuals' body mass index by 2.5%. Droughts are worse for underweight and uneducated individuals. The uneducated are more likely to become unemployed during first-time droughts, whereas both labor reallocation across occupations and migration mitigate the effect of recurring droughts.

JEL-Codes: Q540, I100, I240, O130, J600.

Keywords: drought, nutrition, body-mass index, education, labor reallocation.

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1 Introduction

Climate change is predicted to increase temperatures faster in Sub-Saharan African than globally, even if global warming is kept below 1.5°C. With further warming, Western and Southern Africa face the greatest risk of experiencing the strongest drying, an increase in the number of consecutive dry days, and more extreme droughts (IPCC, 2022b). The climate change literature has mostly focused on the hazard rate of droughts, but relatively less is known about the magnitude of the average impact of droughts on nutritional intake, which hampers an assessment of the socioeconomic impact of climate change and of droughts in particular (Carleton and Hsiang, 2016).¹ Most studies focus on individual countries, and find, e.g., for India, that droughts significantly reduce the nutritional intake of households (Carpena, 2019), and for Zimbabwe, that droughts reduce the body weight of women, but not of men (Hoddinott, 2006). A more substantial body of research provides further evidence that droughts during the in-utero or early childhood period can have long-lasting negative consequences (Dinkelman, 2017; Maccini and Yang, 2009).² The literature has in common that droughts are typically measured using rainfall and/or temperature data, which is justified in low-income countries where agriculture tends to be rain-fed so that the connection between climate and crop yields is very close. However, and especially in Africa, these data rely on relatively sparse weather gauges and thus on modeled interpolation to provide better spatial and temporal coverage. This approach limits the spatial resolution, may lead to measurement error, aggregation bias, and increases spatial- and autocorrelation, which may attenuate the estimated effects towards zero (Auffhammer, 2018).³

This paper contributes to our understanding of the impacts of droughts by using high-resolution, bi-monthly satellite data that tracks the greening of plants, with the aim of capturing drought spells more accurately, and by relating these to outcomes to georeferenced

¹ The socioeconomic impact translates the change in climate and extreme events into human and economic costs, which in turn informs the social cost of carbon and climate policies such as the optimal carbon tax (Carleton and Greenstone, 2022).

² Children in general suffer the most from bad agricultural conditions (Davenport et al., 2017; Grace et al., 2015; Yamano et al., 2005; Jensen, 2000)

³ Moreover, while these indices allow one to study the implications of shocks that are caused by climatic factors, they are unable to capture agricultural output shocks that are caused by factors less directly related to weather, such as insects or diseases that also threaten food security and livelihoods (IPCC, 2022a; Salih et al., 2020).

individuals across a broad sample of African countries.

We set the stage for our analysis by demonstrating an increase in the frequency and geographic spread of droughts across Africa during the past 15 years. We measure droughts using 34 years of satellite data since 1982 by identifying consecutive periods of severe anomalies in the phenology-based ‘Normalized Difference Vegetation Index’ (NDVI), one of the most commonly used vegetation indices for monitoring and predicting crop yields (Petersen, 2018).

Our core analysis employs the Demographic and Health Survey (DHS), which has been collecting survey data in Africa since 1985. The survey is a sub-nationally representative repeated cross-section with georeferenced locations. Between 1992 and 2015 we observe one to nine intermittent survey waves for each of the 32 included African countries, totaling 4 million individuals with information on their coordinates and covering 50,000 locations. Our main variable of interest is an adult’s body mass index (BMI), defined as an individual’s weight in relation to their height. We also consider an individual’s occupation, educational attainment, and migrant status.

We show that, during severe three-month droughts, adults’ BMI is reduced by 2.5% on average, which translates to one-seventh of a standard deviation of BMI, and that the proportion of affected individuals who are underweight increases from one in seven to one in five. The effect is driven by unanticipated ‘first-time’ droughts—events that people are less likely to have prepared themselves for in any way and we therefore consider to be exogenous shocks. Instead, more regularly ‘recurring’ droughts have a much noisier effect. This finding is robust to a broad set of control variables, including individual characteristics, timing relative to growing seasons, aridity, irrigation, long-run time-of-year average climate, and country-year fixed effects.

The DHS survey enables us to identify mitigating mechanisms, including labor market adjustment, migration, and education. Educated individuals appear unaffected in terms of occupation because they are less likely to work in agriculture directly. In contrast, uneducated individuals (i.e., incomplete or no primary education) lose agricultural employment and become unemployed in response to first-time droughts, whereas more regular droughts lead to a smaller increase in unemployment and instead to an occupational reallocation from agriculture towards sales. We also find that more people migrate away from rural to urban

areas during recurring droughts. Although we are unable to directly follow individuals over time, we gauge the average effect on migration by comparing the probability of an individual having a migrant status in drought-affected versus non-drought-affected areas.

Our paper contributes to several strands of the existing literature that examine the effects of droughts. Apart from the literature that looks at households in a few countries and the long-run effect on children, a related literature focuses on trade and infrastructure to reduce the local impact of droughts (Costinot et al., 2016; Burgess and Donaldson, 2010). Although we do not directly model infrastructure, we control for a nation’s ability to cope with droughts through country-year fixed effects.

A related literature estimates the effects of climate and weather shocks on a variety of outcomes (Dell et al., 2014), including agricultural yields (Hultgren et al., 2022), economic growth (e.g., Dell et al., 2012; Barrios et al., 2010), migration (Marchiori et al., 2012; Feng et al., 2010), conflict (Miguel et al., 2004), urbanization (Poelhekke, 2011; Barrios et al., 2006), and food prices (Bellemare, 2015). While these contributions tend to measure shocks by the variability of (annual) weather, we focus on the effects of consecutive bi-monthly periods of drought that are not necessarily captured by summary measures such as year-to-year changes in average temperature or the standard deviation of rainfall within a year.

We also contribute to the literature on the geophysics of droughts, which focuses on their location, frequency, and duration (e.g., Spinoni et al., 2014; Sheffield and Wood, 2008; New et al., 2006). Our contribution lies in the usage of NDVI data to construct a drought indicator instead of other common indices that are based on modeled and interpolated rainfall and temperature data, such as the Standardised Precipitation-Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010) and the Palmer Drought Severity Index (PDSI) (Dai, 2011; Palmer, 1965).

Finally, a related literature has used the NDVI for early warning systems (Funk and Brown, 2006), index-based insurance schemes (Turvey and McLaurin, 2012; Tadesse et al., 2014; Chantararat et al., 2013), crop monitoring (Tadesse et al., 2014; Klisch and Atzberger, 2016; Petersen, 2018), and agricultural productivity assessments during droughts (Kourouma et al., 2021; Legesse and Suryabagavan, 2014). To the best of our knowledge, this study is the first to use NDVI to analyze the implications of droughts for affected households. The

use of NDVI data has the additional advantage that, while being closely related to rainfall and temperature, it tracks plant growth through visible greening and is thus more directly linked to agricultural yields, so we can better understand the link between agricultural productivity shocks and health outcomes. For example, the effect of temperature shocks could also work through other channels, such as through elevated levels of aggression and an increased propensity for violent behavior (Baysan et al., 2019; Ranson, 2014).

2 Related literature on mechanisms

How can individuals cope with droughts, and why might the effects depend on education, labor market adjustments, and migration?

Droughts can be understood as shocks to agricultural productivity and thus to income, which are mitigated by irrigation in more developed countries (Schlenker et al., 2005). A large literature studies the responses of (poor) households to income shocks when formal financial and insurance markets are underdeveloped or unavailable. These include ex-ante measures such as precautionary savings, the diversification of income sources (e.g., Acosta et al., 2021; Carter and Lybbert, 2012; Deaton, 1991), and informal insurance (Kazianga and Udry, 2006); and ex-post strategies such as the sale of assets and consumption cutbacks (Janzen and Carter, 2019) or adjustments in labor supply (Emerick, 2018). Arguably, these strategies require a degree of sophistication and knowledge, suggesting that education may be beneficial in mitigating income shocks. Moreover, it is also likely that better educated individuals have higher incomes and are able to save more. While risk-sharing strategies like informal insurance and borrowing help absorb idiosyncratic shocks, they may be less effective when shocks are correlated over space and time—as is the case with droughts—such that detrimental coping strategies like consumption cutbacks may be the only options. Our empirical analysis examines the extent to which, on average, individuals manage to maintain their consumption during a drought, as captured by their BMI, with a focus on heterogeneity by education.

Droughts, when recurrent or more persistent, can threaten the longer-term viability of agriculture in an affected region, potentially leading to a process of structural transforma-

tion away from agriculture. Households facing deteriorating agricultural conditions in India respond by reallocating labor to off-farm employment, particularly in areas with a more developed manufacturing sector (Blakeslee et al., 2020; Emerick, 2018) or with more flexible labor markets (Colmer, 2021). Droughts may initially lead to higher unemployment and migration when less outside employment is available. Mostly men migrate away in response to droughts in rural Ethiopia (Gray and Mueller, 2012), and youth are more likely to migrate after droughts in Latin America (Baez et al., 2017). However, migration is costly and potentially less affordable to those with lower incomes, such as those without education. While labor reallocation and migration may not be feasible or attractive strategies for coping with unexpected or short droughts that are perceived as transitory shocks, they become more likely during prolonged or recurrent droughts that indicate a permanent change in agricultural viability.

3 Data

3.1 Measuring droughts using satellite data

We measure droughts based on vegetation conditions as captured by satellites. We use georeferenced GIMMS3g NDVI data for the African continent over the period 1982-2015 (Pinzon and Tucker, 2014).⁴ The NDVI data are highly disaggregated both in terms of space (grid cells of size 0.08×0.08 degrees, corresponding to a length of approximately 9.25km at the equator) and time (twice per month). The index is defined as the difference in visible versus near-infrared light that is reflected by the earth's surface.

Healthy vegetation reflects most of the near-infrared light but strongly absorbs visible light for use in photosynthesis (resulting in NDVI close to 1), while surfaces of sparse or no vegetation reflect similar amounts of near-infrared and visible light (resulting in NDVI close to 0) (Weier and Herring, 2000). The NDVI index tracks the vegetation conditions in a given region at a given time of the year, so variations relative to the norm can be interpreted as unusual occurrences (e.g., agricultural droughts).

⁴ The data is processed to correct for cloud cover and aerosoles. See the Online data Appendix for more details.

We first construct the ‘Vegetation Condition Index’ (VCI, see Kogan, 1995), which relates current NDVI at time t in a location i to its maximum ($\overline{max_ndvi_i}$) and minimum NDVI ($\overline{min_ndvi_i}$) values ever observed at that location for the same time of year:

$$VCI_{i,t} = \frac{ndvi_{i,t} - \overline{min_ndvi_i}}{\overline{max_ndvi_i} - \overline{min_ndvi_i}} * 100$$

As is standard in the remote sensing literature (e.g., Liou and Muluaalem, 2019; Measho et al., 2019; Winkler et al., 2017), we define drought conditions as severe or extreme if the VCI is below 20%.⁵

Finally, we define a dummy *drought* equal to 1 if at time t the VCI has been continuously below 20% during the past three months. We similarly define dummies for shorter and for longer droughts.⁶ In addition, we split the ‘all’ droughts dummy into ‘first-time’ droughts (which occur for the first time in five years in location i at time t) and ‘recurring’ droughts (which are those where one or more droughts happened in that same location before time t during the past five years).

3.2 Household data

To study socio-economic outcomes, we use data collected through the DHS program in 32 African countries over the period from 1992-2015. The DHS program includes data sets for men, women, and children. After merging, our final data set comprises information on about 4 million individuals over the study period and area.⁷ The DHS data set contains information about the location of households at the time of the interview and a wide range of household members’ characteristics, including health indicators (e.g., height, weight), occupation, place

⁵ No drought conditions prevail for VCI above 35%; VCI in the range 20-35% indicates moderate drought and VCI below 10% indicates extreme drought.

⁶ See Appendix Table OA2 for summary statistics of the different drought indicators. As expected, longer droughts are rarer than shorter droughts.

⁷ See Appendix Table OA3 for a full list of countries and years included in the data set.

of residence, and educational attainment.⁸

To measure nutrition we define the log of *BMI*. The BMI is a function of an individual’s weight in relation to their height (specified in kg/m^2), so variation in BMI reflects changes in nutritional intake and/or energy-consuming activities. While normal BMI ranges from 18.5 to 24.9, individuals are defined as underweight if their BMI is below 18.5 and as overweight if their BMI is 25 or higher (Croft et al., 2018).

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 for unemployment or working in alternative occupations, such as services, professional/managerial, or sales.

To analyze human mobility as a response to drought, we exploit an individual’s status as migrant or non-migrant. The dependent dummy indicator *migrant* takes on the value 1 if the respondent has a migrant status, and 0 otherwise.

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

We define standard control variables *age*, and dummies *male*, *uneducated*, and *uneducated head of household*. *Age* equals an individual’s age in years; *male* equals 1 if an individual is of male gender; *uneducated* equals 1 if an individual has incomplete primary or no education; and *uneducated head of household* equals 1 if an individual’s household head has incomplete primary or no education.

⁸ In surveys of the DHS program, the original coordinates of interviewed households are ‘geomasked’ to conceal their precise locations. The process displaces urban clusters a distance up to 2 kilometers and rural clusters a distance up to 5 kilometers. A further, randomly-selected 1% of rural clusters was displaced a distance up to 10 kilometers (Burgert et al., 2013). However, our NDVI grids are about $9.25 \times 9.25 \text{km}$, so households are not necessarily matched to grids other than their true grid, and spatial correlation in droughts ensures that neighboring grids are similar. This random process introduces measurement error and attenuation bias, but does not invalidate our estimates: its impact is negligible in practice (Michler et al., 2022). Some households are matched to grids with missing NDVI values, such as on top of water bodies. We drop these from the sample.

3.3 Other data

We control for a number of potentially relevant factors. Data on vegetation zones in Africa are based on White (1983) and taken from the African Marine Atlas. To control for an area’s aridity, we exploit the ‘Global Aridity Index’ (Global-AI) of the Global Aridity Index and Potential Evapo-Transpiration Database (Zomer and Trabucco, 2022) to define the variable *aridity index*. The irrigation potential of a given location is taken from the FAO’s Global Information System on Water and Agriculture, AQUASTAT (Siebert et al., 2013), which captures the percentage of the area that is suitable for irrigation, *irrigation %*.⁹

Given that the effect of drought likely depends on whether it occurs inside or outside a growing season, we define growing seasons following the variable threshold method described in Vrieling et al. (2013). This method determines per year and per grid the maximum and minimum NDVI values and takes the average of both as the threshold. In each location, the first NDVI value in a year that crosses the threshold in an upward direction is marked as the start of growing season (SOS), and the last NDVI value in a year that crosses the threshold in a downward direction is marked as the end of growing season (EOS).¹⁰

Based on SOS and EOS, we then construct a dummy indicator *surveyed during growing season* that equals 1 if the interview takes place during a growing season, and 0 otherwise. Moreover, we use the variable threshold method to define whether there are one or two *growing seasons per year*.

We further construct the *long-run time-of-year average NDVI* observed at each location and time of the year across the full 1982-2015 period. Finally, we calculate the *number of past drought periods* that occurred in the same location during the past 5 years (measured as the total of half-month periods with severe drought, and excluding the current three-month drought spell).

We merge all control variables through household geographic coordinates. Summary statistics are provided in the Online Appendix Table OA1.

⁹ See the Global Map of Irrigation, version 5, layer ‘gmia.v5_aei_pct_cellarea’.

¹⁰ An application of this method to our data is shown in the Online Data Appendix.

4 Empirical Strategy

4.1 Baseline specification

The DHS program collects household data by choosing a random sample of individuals at each successive survey wave over time that is representative at the subnational level. Consequently, the DHS data set represents a repeated (pooled) cross-section. We therefore start with a basic cross-sectional regression setup:

$$Outcome_{i,t} = \alpha + \beta Drought_{i,t} + \mathbf{X}\gamma + \delta_{c,y} + \epsilon_{i,t} \quad (1)$$

in which t is the day of interview, $Outcome_{i,t}$ is one of the dependent variables of individual 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, and $\epsilon_{i,t}$ represents the idiosyncratic error term. $\delta_{c,y}$ are country-by-year-of-interview (c and y) dummies that capture a country's institutions, level of development, and overall state of the economy, and thus its ability to cope with droughts in a given year.

To study heterogeneity in the impact of agricultural droughts, we interact the drought indicator with an individual's educational attainment:

$$\begin{aligned} Outcome_{i,t} = & \alpha + \beta_0 Drought_{i,t} + \beta_1 Drought_{i,t} * Uneducated_{i,t} \\ & + \beta_2 Uneducated_{i,t} + \mathbf{X}\gamma + \delta_{c,y} + \epsilon_{i,t} \end{aligned} \quad (2)$$

For the analysis of migration, we also interact *Drought* with an indicator of the location's remoteness. Using a location's urbanity as a proxy of expected job opportunities, we add an interaction of our drought indicator with a dummy indicator *rural*, which equals 1 if the DHS program categorizes the area as rural. If anything, we expect drought to lead to migration from places with poor labor opportunities (i.e., rural areas) to places with better labor opportunities (i.e., urban areas).

We cluster standard errors at the level of country-vegetation-zone-year to account for

heteroskedasticity and spatially correlated errors within vegetation zones (White, 1983), since agriculture is more similar within than across vegetation zones.¹¹

In the BMI analysis, we estimate models (1) and (2) as pooled OLS. We also perform so-called ‘unconditional’ quantile regressions of (2) following the method of Firpo et al. (2009).¹² In the analysis of labor reallocation and migration, we estimate models (1) and (2) as linear probability models.

4.2 Identifying assumptions

Our identification rests on the unexpected nature of droughts. We focus on severe or extreme droughts, so we abstract from weather fluctuations that are a relatively predictable component of a location’s climate and annual cycle between wet and dry seasons. Moreover, our definition of drought requires that the VCI is below 20% for a prolonged consecutive period of time (3 months in our baseline), within which agriculture is not able to recover, which would be partially possible between shorter dry spells. However, some regions may be more drought-prone than others, even within this restricted definition.¹³ Therefore, we distinguish between droughts that occur for the first time in a five-year period preceding the interview, and recurring droughts that were preceded by at least one other drought in the past five years. We assume that first-time droughts are unexpected and could not have been anticipated. For example, anticipation could lead to more investment in irrigation or stockpiling of food, which would reduce the effect of droughts, even if their timing would be hard to predict.¹⁴ We further include the following grid-level variables to control for the local climate: *number of past drought periods, growing seasons per year, surveyed during growing season, irrigation %*, *aridity index*, and the *long-run time-of-year average NDVI*.

One limitation of the DHS data for our purposes is that individuals are not followed over time, making it impossible to control for unobserved time-invariant characteristics at

¹¹ Results are robust to clustering by country-year instead.

¹² See also Rios-Avila (2020).

¹³ 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 (Kourouma et al., 2021; Vrieling et al., 2011), we do not consider this a major threat to causal estimation.

¹⁴ Results are robust to choosing four, six, or ten years, see Online Appendix OA2.

the individual level. We may thus observe only those who have not been able to migrate. However, unexpected first-time droughts are less likely to cause immediate migration because people do not account for how long the drought will last. Individuals in our sample may also be survivors of severe droughts and the DHS surveys may not have taken place in areas hit by the most severe droughts, leading to potential underestimation of the effect. However, as shown in the Online Data Appendix, the frequency pattern of both three-month and six-month severe droughts is very similar for all 225,110 grids that cover Sub-Saharan Africa, compared to the 20,021 grids covered by the DHS. Furthermore, the probability that an individual is surveyed during a three-month drought is 0.38%, while the probability that a three-month drought occurs in any grid and any time period is 0.42%, which is very similar.

All specifications include covariates that are potentially correlated with our independent and dependent variables. We include the respondent’s age and gender to control for the fact that adults generally have a higher body weight than teenagers, and that females have a higher average BMI than males. We also control for education of the respondent and the education of the respondent’s household head. An individual’s level of educational attainment is plausibly predetermined and unlikely to be influenced by the current drought.

5 Results

5.1 Droughts over time and space

We start by tracking the occurrence of droughts over time and space. The top panel of Figure 1 shows the distribution of the coefficient of variation (annual standard deviation divided by the annual mean) of the VCI over time for a balanced panel of 20,021 grids, in which at least one household was ever sampled by the DHS, and a simple quadratic fit. It suggests that, from year to year, the coefficient of variation of the VCI had been decreasing until the mid-1990s, when it began to increase.¹⁵ In other words, during the years 2000-2015 Africa became dryer on average, and the spatial variation in dryness increased. This has

¹⁵ Figure OA1 (Online Appendix) shows that the pattern is both due to an increase and then decrease in the annual mean VCI, and due to a decrease and then increase in the annual standard deviation of VCI. In the Online Data Appendix we show that the pattern is very similar for all 225,110 grids that cover all of Sub-Saharan Africa.

translated into an increasing number of droughts spread across more locations, as shown in the bottom panel of Figure 1. By 2015, 7.2% of grids experienced at least one three-month drought, up from 0.8% in 2000. This drying pattern is also spatially visible in Figure 2, which illustrates 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, most likely reflecting the recovery from a continent-wide shift to more arid conditions that occurred during the 1980s (Nicholson et al., 2018; Vrieling et al., 2011). However, more and more areas were drying during the 2000s and the 2010s compared to the 1980s. This observation is consistent with one of the strongest observed El Niño events hitting large parts of Southern and Eastern Africa in 2015, leading to an intense drought (Blamey et al., 2018; IPCC, 2022a).

5.2 Droughts and malnutrition

Our main outcome of interest is the log of BMI. While the average BMI in our sample is 22.3, 13.6% of people have a BMI of below 18.5, which is considered underweight. Overall, the uneducated, the young, and males have lower BMIs.

The estimation results, presented in Table 1, provide strong evidence that three-month droughts negatively affect BMI. A drought during the time of interview is associated with a 2.3% reduction in BMI, relative to households unaffected at the time of interview, suggesting that coping mechanisms are imperfect in mitigating the effects of droughts (see Panel A, column 1).

Evaluated at the mean of 22.3, this average effect corresponds to one-seventh of a standard deviation (of 4.2) reduction in BMI. This translates to 1.3kg weight loss given that the average weight of affected individuals is 55.7kg. This matters most for those at risk of malnutrition: the proportion of affected individuals who are underweight is 18.2% (about one in five people), and would have been 14.6% without the drought (about one in seven people).

We always control for country-year fixed effects, individual controls (*uneducated*, *uneducated head of household*, *age*, and *male*), and grid-level controls (*aridity index*, *irrigation %*, *number of past drought periods*, *growing seasons per year*, *surveyed during growing season*,

and the *long-run time-of-year average NDVI*).¹⁶

Splitting all droughts into recurring and first-time droughts shows that the negative effect of droughts is driven by grids where a drought occurs for the first time in five years (column 3), while recurring droughts have a much noisier effect on average (column 2). This suggests that at least some people are better able to cope with drought if they live in areas where droughts are more common.

Columns 1 and 2 control for the number of months that the household's location has experienced severe droughts during the past five years, so the drought dummy captures the marginal effect of an additional drought taking place during the time of interview. However, these past droughts may have lingering effects: to capture these, we do not control for the number of past drought months in grids with current droughts in columns 4 and 5. The drought dummy then captures the combined effect of a current drought and any past droughts. Column 5 shows that recurring droughts indeed have a greater effect, but the coefficient is still not significant at standard confidence levels: the average effect of all droughts (column 4) is again driven by first-time droughts (column 6, which effectively repeats column 3).¹⁷

In Panel B, we estimate equation (2) to test for heterogeneity in the effect of droughts by adding to the regressions of columns 4-6 an interaction of drought with an indicator whether a person is uneducated. Although the uneducated have a lower baseline BMI, they do not appear to be significantly more affected by droughts on average. However, it may well be that those who were already among the most vulnerable groups are also the most affected by shocks. We investigate this issue by re-estimating the regressions where we evaluate the effect of droughts at the first decile of the (unconditional) distribution, following the quantile regression method of Firpo et al. (2009).¹⁸ The first decile of the distribution of BMI

¹⁶ These control variables are not reported in Table 1 for brevity, but we list all in Online Appendix OA2 (Table OA4). We find that successively including these controls does not affect the main variable of interest. In Table OA5 we show that the effect is driven by three-month droughts. Shorter droughts appear much less harmful. Longer droughts are also estimated to have little effect, but these are very rare in the sample (see also bottom panel of Figure 1 and Table OA2) such that the test suffers from low power.

¹⁷ Because droughts are rare events that are irregularly spaced with respect to the time of interview and of various duration, we do not separately control for each past drought in Table 1.

¹⁸ Online Appendix OA2.4 lists other deciles.

corresponds to a BMI of 18.1, which are those that are borderline underweight. Columns 10-12 show the results from these regressions: we now find evidence that uneducated individuals are more affected by first-time droughts. In the bottom row we report the marginal effects of a drought for the uneducated. Compared to the marginal effect for the educated in the first row of Panel B, the uneducated are much worse off during droughts, which is again driven by first-time droughts.

5.3 Mitigating mechanisms

Why are first-time droughts worse than recurring droughts? Households may update expectations and seek ways to at least partially alleviate the impact of future droughts in areas where they appear to be recurring. But this process takes time and is likely not possible during first-time droughts. Households may try to adapt via the labor market, both in terms of shifting employment away from agriculture and shifting employment to other locations. Therefore, we change the dependent variable to indicators of employment status, occupation, and migrant status.

5.3.1 Labor reallocation

We measure the labor market status of individuals who are three months into a severe drought spell, and estimate specification (2) with indicators of the current occupation and employment status as dependent variables. The results are shown in Table 2. We again differentiate between all, recurring, and first-time droughts in Panels A, B, and C, respectively.

Panel A, columns 1-3, shows the effect of all three-month droughts, with the marginal effects for the uneducated reported in the bottom row of each panel. Droughts are followed by a sizable and statistically significant exodus of uneducated people from agriculture and an almost equally large increase in unemployment. Unemployment typically leads to a sharp drop in income which, apart from the direct impact on agricultural yields and food availability, is an additional reason why droughts are associated with a significant decrease in BMI. Apart from a small decline in sales employment, the educated appear not to be affected in terms of occupation and employment status.

The picture changes when we distinguish between recurring droughts in Panel B and first-time droughts in Panel C. In the case of recurring droughts, uneducated individuals still leave agriculture (column 4), but appear able to find new jobs in sales (column 6) rather than becoming unemployed (column 5).¹⁹

Panel C shows that this does not happen during first-time droughts. Instead, uneducated workers become unemployed, explaining the worse effect of first-time droughts on BMI relative to recurring droughts. The effect is large: during a first-time drought the uneducated are 7% less likely to work in agriculture and 8.2% more likely to be unemployed.

In Online Appendix OA3, we show that the likelihood of working in occupations other than agriculture and sales does not change during droughts. Domestic work, unskilled and skilled manual jobs, professional/technical jobs, and jobs in services are unaffected. First, uneducated workers with an agricultural background may not have the necessary experience for these other jobs: they are generally less likely to work in these occupations (except ‘domestic’) than educated individuals. Second, sales may be the only other viable option when no other economic growth takes place locally to absorb labor (Blakeslee et al., 2020). Workers may also have migrated and found work elsewhere, which we look at next.

5.3.2 Migration

Labor reallocation may not be feasible locally if the place of residence is remote and offers only few alternative job opportunities. One option is then to migrate to find work elsewhere. We test this channel’s importance in Table 3, which reports the results of estimating specification (2) with *migrant* as dependent variable. In addition, we include an interaction between drought and *rural*: if migration occurs from rural areas with few job opportunities to urban areas with better job opportunities, we expect a negative interaction effect. The drought dummy then captures the effect of a local drought on the probability than an urban and educated individual is a migrant.

We find no significant differences in migration status between uneducated and educated individuals. In contrast, all specifications yield negative and statistically significant coeffi-

¹⁹ Although the interaction in column 5 is still significant, the marginal effect in the bottom row indicates that a recurring drought no longer significantly increases unemployment among uneducated.

coefficients on the interaction terms between *drought* and *rural*. The bottom row shows the marginal effect of a drought in rural areas.

In rural areas, individuals are 13% less likely to be a migrant when hit by a recurring drought, while the marginal effect is not significant when hit by a first-time drought²⁰ As indicated by the negative coefficient on *rural*, individuals living in rural areas are generally significantly less likely to be migrants, providing further evidence that migration goes from the countryside to cities.

5.4 Extension: School dropouts

It is possible that investment in human capital is also affected by droughts. Loss of income or rising food prices reduce the affordability of school fees and related costs while increasing the incentive for parents to let their children work and generate income, leading to lower enrollment and an increase in school dropouts. However, if droughts reduce labor demand in agriculture, then the lower short-run opportunity costs of going to school may increase school attendance. For example, Shah and Steinberg (2017) find that positive rainfall shocks lead to more school dropouts in India, and Hyland and Russ (2019) and Alderman et al. (2006) find that children exposed to drought in infancy receive fewer years of formal education. Furthermore, structural transformation away from agriculture and towards other occupations may require investment in human capital (Blakeslee et al., 2020).

Given the importance of education in mitigating the effect of droughts, we assess the relationship between agricultural droughts and human capital formation, as measured by individuals' school attendance. Theoretically, the relationship is ambiguous: droughts may put individuals into financial distress and force them to reduce the investment into their own or their children's education. In this case, we expect a positive relationship between droughts and school dropout rates. On the other hand, poor farming conditions and low income streams from agricultural activities reduce the opportunity cost of schooling, incentivizing households to increase their human capital investment. In this case, a negative relationship between drought and school dropout rates is expected. We test whether droughts lead to a

²⁰ The pattern is very similar when including a (insignificant) triple interaction (and all constituent terms) between drought, rural, and uneducated.

decrease or increase in school dropouts by estimating specification (2) with *dropout* as the dependent variable.²¹ The dummy indicator *dropout* captures if an individual has dropped out of school since the previous school year. However, we interact with the educational attainment of the *household head*.

The results for all, recurring, and first-time droughts are shown in Table 4 and indicate a strong bifurcation in the effect of drought on school dropout: While the uninteracted coefficient on drought remains negative and statistically significant throughout all specifications, the coefficient on drought interacted with *uneducated head of household* is positive and statistically significant for all and for first-time droughts. Nevertheless, the marginal effects in the bottom row show that first-time droughts reduce the probability of dropout if the household head is uneducated (-0.7%). The effect for educated head of households is however much stronger (-2.3%). The results imply that human capital investment increases in response to a drought, but mostly for individuals from more-educated families, whereas they hardly change for individuals from less educated families. This pattern is consistent with droughts reducing labor demand in agriculture, lowering the short-run opportunity costs of going to school. Educated heads of household may have more financial means to pay for schooling during droughts, further deepening inequality.

6 Concluding remarks

Seeking to gain a better understanding of the impact of droughts on individuals' nutrition, and thus indirectly of the potential consequences of climate change, this paper measures drought spells using a detailed satellite-based index that does not rely on modeled imputation, and combines it with a large georeferenced household survey data set for 32 Sub-Saharan African countries covering the period 1992-2015.

We find that the frequency and geographic spread of severe three-month droughts spells has increased since the early 2000s and that a drought spell reduces individuals' BMI by 2.5%. However, the effect is driven by first-time droughts, whereas recurring droughts have

²¹ As the educational level is a direct consequence of school dropout, we refrain from including educational attainment as a regressor in the specifications.

much less impact. Furthermore, individuals with little or no education appear to be impacted the most.

These results are consistent with two important mitigating mechanisms that reduce the impact of recurring droughts: labor reallocation and migration. First, educated individuals are affected less because they are less likely to work in agriculture directly. In contrast, uneducated individuals lose agricultural employment and become unemployed in response to first-time droughts, while recurring droughts lead to a smaller increase in unemployment and instead to an occupational reallocation from agriculture towards sales that limits the loss in income. Second, more people migrate away from rural to urban areas during recurring droughts.

Our findings have implications for policy choices. While investment in irrigation and water conservation would limit the impact of droughts most directly, stimulating a process of structural transformation away from agriculture in increasingly drought-prone areas would also limit the human impact of droughts.

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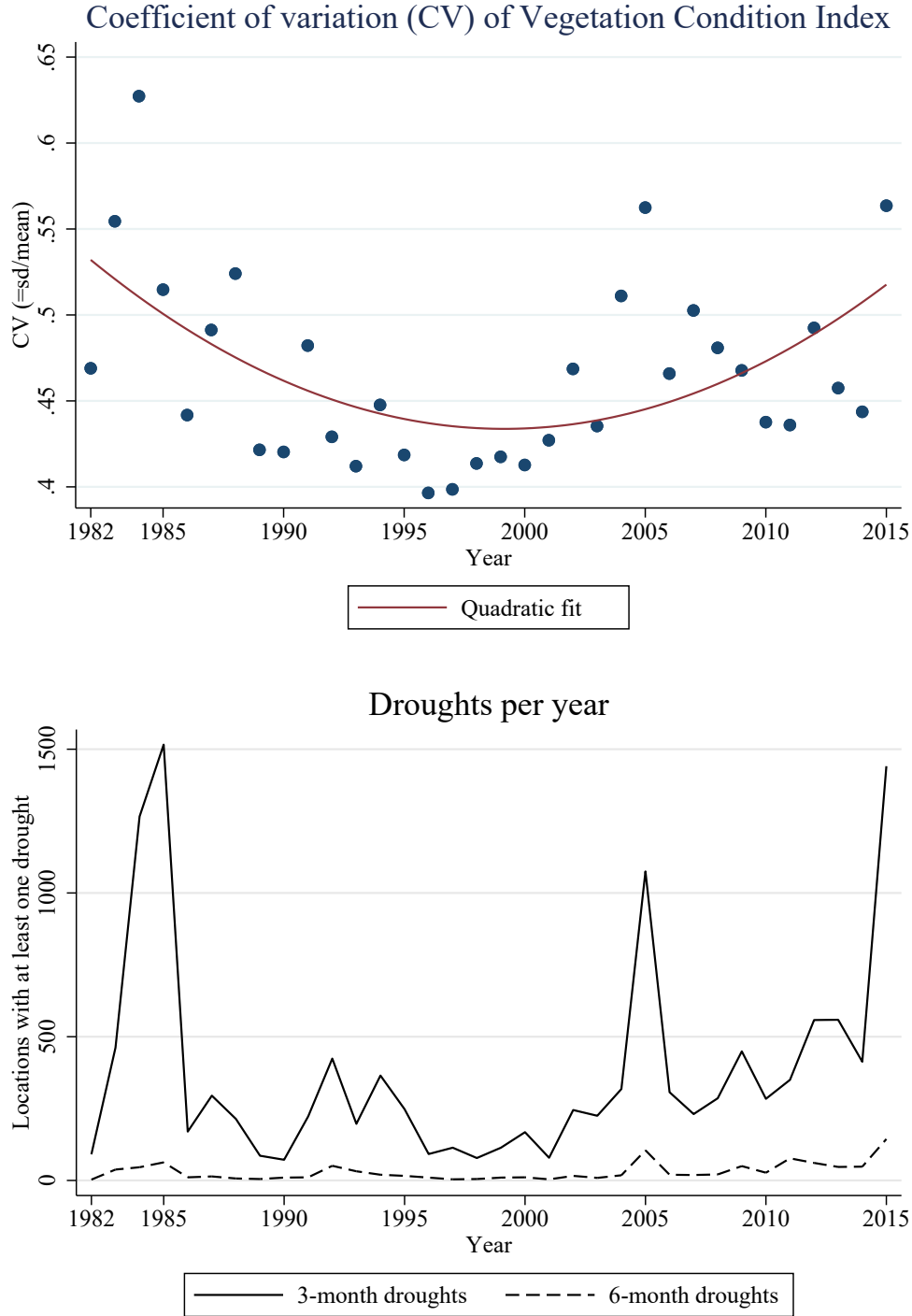
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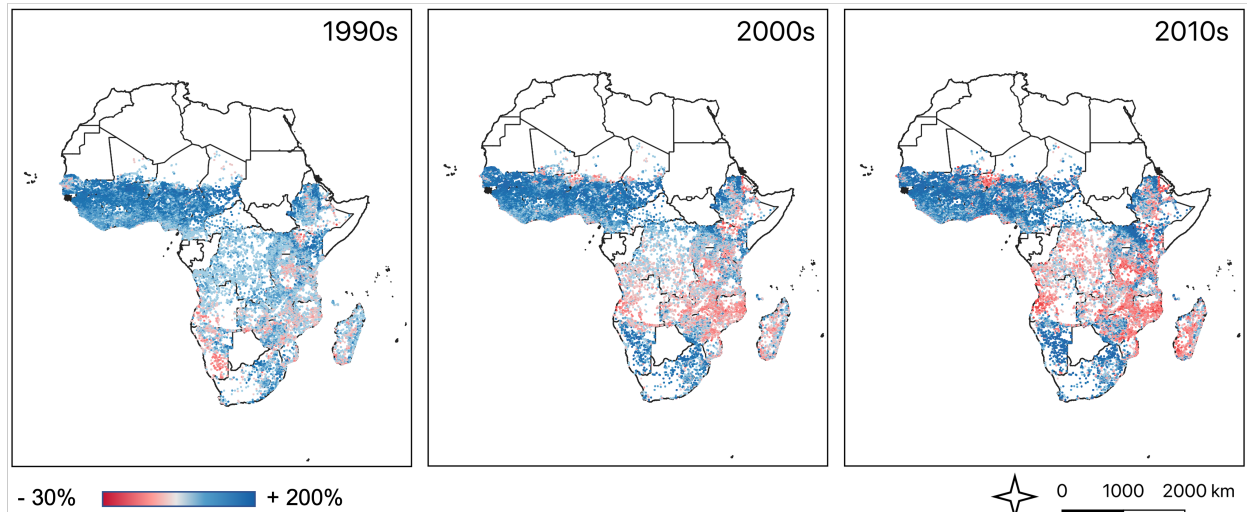
Tables and Figures

Figure 1: Vegetation index and droughts



Notes: Sample includes 20,021 distinct NDVI grids (of 0.08×0.08 degrees) in Africa within which at least one household was ever sampled in the DHS survey.

Figure 2: Mean NDVI values during 1990s, 2000s, 2010s compared to the 1980s



Notes: Sample includes 20,021 distinct NDVI grids (of 0.08×0.08 degrees) in Africa within which at least one household was ever sampled in the DHS survey.

Table 1: The effect of droughts on BMI

Dependent variable →	log BMI					
Panel A: average effect						
Droughts →	all	recurring	first	all	recurring	first
	[1]	[2]	[3]	[4]	[5]	[6]
Drought dummy	-0.023** (0.009)	-0.022 (0.020)	-0.023** (0.011)	-0.025*** (0.009)	-0.033 (0.020)	-0.023** (0.011)
Country × year fixed effects	✓	✓	✓	✓	✓	✓
Individual and grid controls	✓	✓	✓	✓	✓	✓
Control for past drought periods in treated grids	✓	✓	–	✗	✗	–
Observations	479,447	478,405	479,134	479,447	478,405	479,134
R-squared	0.195	0.195	0.195	0.195	0.195	0.195
Clusters	433	432	433	433	432	433
Grids (NDVI, 0.08°×0.08°)	15,629	15,596	15,615	15,629	15,596	15,615
Panel B: heterogeneous effects						
Droughts →	all	recurring	first	all	recurring	first
Method →	OLS			QR, 1st decile		
	[7]	[8]	[9]	[10]	[11]	[12]
Drought dummy	-0.023** (0.011)	-0.032 (0.024)	-0.021 (0.014)	-0.002 (0.009)	0.029 (0.022)	-0.009 (0.010)
Drought dummy * uneducated	-0.004 (0.013)	-0.002 (0.032)	-0.004 (0.014)	-0.051** (0.023)	-0.108* (0.066)	-0.034** (0.017)
Uneducated	-0.037*** (0.002)	-0.037*** (0.002)	-0.037*** (0.002)	-0.018*** (0.001)	-0.018*** (0.002)	-0.018*** (0.001)
Country × year fixed effects	✓	✓	✓	✓	✓	✓
Individual and grid controls	✓	✓	✓	✓	✓	✓
Observations	479,447	478,405	479,134	479,447	478,405	479,134
R-squared	0.195	0.195	0.195			
Marg. effect of drought if uneducated	-0.027** (0.012)	-0.034 (0.026)	-0.025** (0.011)	-0.053** (0.021)	-0.079 (0.056)	-0.044*** (0.016)

Notes: ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level. Standard errors are clustered on the country-vegetation-zone-year level and shown in parentheses (by means of bootstrapping in [10]-[12]). *Drought* equals 1 if the individual is interviewed during a 3-month consecutive drought period. *All* is the union of recurring and first-time droughts, where *recurring* droughts equal 1 if other droughts occurred before in the same grid during the past five years, while *first-time* droughts equal 1 if no droughts occurred during the past five years in the same grid. Columns [1] and [2] control for the number of past drought periods in treated grids during the previous 5 years, so the drought dummy captures the effect of an additional drought. Columns [4] and [5] (and also [7], [8], [10], and [11]) thus measure the average effect of droughts including any cumulative effects of past drought periods. *Uneducated* equals 1 if a person has incomplete primary or no education. *QR* is the ‘unconditional’ quantile regression method by Firpo et al. (2009).

Table 2: The effect of droughts on labor reallocation

Dependent variable →	Working in Agriculture	Unemployed	Working in Sales
Panel A: All droughts			
	[1]	[2]	[3]
Drought dummy	0.048 (0.031)	-0.039 (0.031)	-0.022** (0.011)
Drought dummy * uneducated	-0.133*** (0.037)	0.112*** (0.037)	0.044* (0.026)
Uneducated	0.171*** (0.008)	-0.057*** (0.008)	0.002 (0.003)
Observations	1,082,493	891,923	891,923
R-squared	0.234	0.176	0.083
Marg. effect of drought if uneducated	-0.085** (0.036)	0.073*** (0.027)	0.022 (0.023)
Panel B: Recurring droughts			
	[4]	[5]	[6]
Drought dummy	0.074* (0.041)	-0.036 (0.026)	-0.044*** (0.014)
Drought dummy * uneducated	-0.183*** (0.055)	0.094** (0.044)	0.109*** (0.035)
Uneducated	0.171*** (0.008)	-0.057*** (0.008)	0.002 (0.003)
Observations	1,079,929	889,693	889,693
R-squared	0.234	0.176	0.083
Marg. effect of drought if uneducated	-0.109** (0.052)	0.058 (0.040)	0.065** (0.030)
Panel C: First-time droughts			
	[7]	[8]	[9]
Drought dummy	0.033 (0.033)	-0.040 (0.045)	-0.011 (0.014)
Drought dummy * uneducated	-0.103*** (0.039)	0.122*** (0.045)	0.006 (0.022)
Uneducated	0.171*** (0.008)	-0.057*** (0.008)	0.002 (0.003)
Observations	1,080,986	890,667	890,667
R-squared	0.234	0.176	0.083
Marg. effect of drought if uneducated	-0.070* (0.036)	0.082** (0.033)	-0.005 (0.020)

Notes: ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level. Standard errors are clustered on the country-vegetation-zone-year level and shown in parentheses. All specifications include country×year fixed effects, additional individual controls, and grid-level controls. Panel A covers 17,248 grids and 526 clusters; Panel B covers 17,210 grids and 524 clusters; Panel C covers 17,225 grids and 526 clusters. See notes to Table 1 for variable definitions.

Table 3: The effect of droughts on migration

Dependent variable →	Migrant status		
	all	recurring	first-time
Droughts →	[1]	[2]	[3]
Drought dummy	0.098** (0.044)	0.085 (0.061)	0.104* (0.061)
Drought dummy * uneducated	0.002 (0.035)	0.031 (0.037)	-0.011 (0.041)
Drought dummy * rural	-0.156*** (0.055)	-0.215*** (0.083)	-0.130* (0.072)
Uneducated	0.000 (0.009)	0.000 (0.009)	0.000 (0.009)
Rural	-0.153*** (0.011)	-0.153*** (0.011)	-0.153*** (0.011)
Country × year fixed effects	✓	✓	✓
Individual and grid-level controls	✓	✓	✓
Observations	543,779	542,437	542,880
R-squared	0.112	0.111	0.111
Clusters	342	340	342
Grids (NDVI, 0.08°×0.08°)	11979	11953	11960
Marg. effect of drought if rural	-0.059** (0.028)	-0.131** (0.052)	-0.026 (0.025)

Notes: ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level. Standard errors are clustered on the country-vegetation-zone-year level and shown in parentheses. *Rural* equals 1 for individuals located in rural areas. See notes to Table 1 for other variable definitions.

Table 4: The effect of droughts on school dropout

Dependent variable → Droughts →	Dropout		
	all [1]	recurring [2]	first-time [3]
Drought dummy	-0.016*** (0.004)	-0.010** (0.004)	-0.023*** (0.006)
Drought dummy * uneducated head of household	0.014** (0.006)	0.015 (0.011)	0.016** (0.007)
Uneducated head of household	-0.004*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)
Country × year fixed effects	✓	✓	✓
Individual and grid-level controls	✓	✓	✓
Observations	624,908	623,303	623,488
R-squared	0.024	0.024	0.024
Clusters	232	230	232
Grids	9263	9246	9249
Marg. effect of drought if uneducated head of household	-0.002 (0.006)	0.005 (0.011)	-0.007** (0.003)

Notes: ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level. Standard errors are clustered on the country-vegetation-zone-year level and shown in parentheses. *Uneducated head of household* equals 1 if an individual's head of household has incomplete primary or no education. See notes to Table 1 for other variable definitions.

Online Appendix

“Droughts and malnutrition in Africa”

Nora Fingado and Steven Poelhekke

April 6, 2023

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OA1 Descriptive Statistics

OA1.1 Summary Statistics (Figure 2; Tables OA1, OA2, OA3)

Table OA1: Summary statistics

Variable	Description	Mean	Sdev	Min	Max
Panel A. Dependent variables					
lnBMI	log of BMI	3.09	0.17	2.49	4.09
BMI	body-mass index (weight/height ²)	22.23	4.18	12.02	59.90
Agri	= 1 if occupation is agriculture	0.37	0.48	0	1
Unemployed	= 1 if unemployed	0.30	0.46	0	1
Sales	= 1 if occupation is sales	0.14	0.34	0	1
Dropout	= 1 if school dropout	0.03	0.16	0	1
Domestic	= 1 if occupation is work at home	0.02	0.13	0	1
Unskilled manual	= 1 if occupation is unskilled manual	0.04	0.20	0	1
Skilled manual	= 1 if occupation is skilled manual	0.07	0.25	0	1
Professional	= 1 if occupation is professional/technical	0.04	0.20	0	1
Services	= 1 if occupation is in services	0.04	0.20	0	1
Panel B. Individual controls					
Uneducated	Dummy that equals 1 if an individual has incomplete primary or no education	0.60	0.49	0	1
Uneducated head of household	Dummy that equals 1 if an individual's head of household has incomplete primary or no education	0.56	0.50	0	1
Age	Individual's age in completed years	22.13	19.09	0	97
Male	Dummy that equals 1 if an individual is male	0.49	0.50	0	1
Panel C. Grid-level controls					
Number of past half-months where 3-month droughts=1, last 5 years	Number of past half-months where 3-month droughts=1, duration the last five years, excluding the current drought	0.25	1.57	0	66
Surveyed during growing season	Timing of the interview during or outside of an NDVI growing season	0.59	0.49	0	1
Aridity index	Inverse hyperbolic sine of the area's aridity index	0.60	0.33	0	1.83
Irrigation %	Inverse hyperbolic sine of the area's percentage equipped for irrigation	0.30	0.77	0	4.97
NDVI growing seasons per year	Number of NDVI growing seasons per year	1.25	0.43	1	2
Long-run time-of-year average NDVI	Long-run average NDVI during that time of the year	0.50	0.18	0.04	0.91

Notes: This table provides summary statistics. All grid-level control variables are observed for the total number of 4,080,169 DHS individuals. *Number of past 3-month droughts (in half-months), last 5 years:* this variable takes the value 6 if only one 3-month drought happened during the past five years.

Table OA2: Summary statistics of the drought indicators

Drought indicator D	Observations if D = 1	Observations	Percent
Panel A. All droughts			
Drought dummy, 1 month	92,552	4,080,169	2.27
Drought dummy, 2 months	29,183	4,080,169	0.72
Drought dummy, 3 months	15,392	4,080,169	0.38
Drought dummy, 6 months	1,738	4,080,169	0.04
Panel B. Recurring droughts			
Drought dummy, 1 month	70,718	4,058,335	1.74
Drought dummy, 2 months	16,492	4,067,478	0.41
Drought dummy, 3 months	6,158	4,070,935	0.15
Drought dummy, 6 months	248	4,078,679	0.01
Panel C. First-time droughts			
Drought dummy, 1 month	21,834	4,009,702	0.54
Drought dummy, 2 months	12,691	4,063,516	0.31
Drought dummy, 3 months	9,234	4,073,850	0.23
Drought dummy, 6 months	1,490	4,079,760	0.04

Notes: This table summarizes how often DHS individuals are affected by a general drought, recurring drought, and/or first-time drought, differentiated by drought duration.

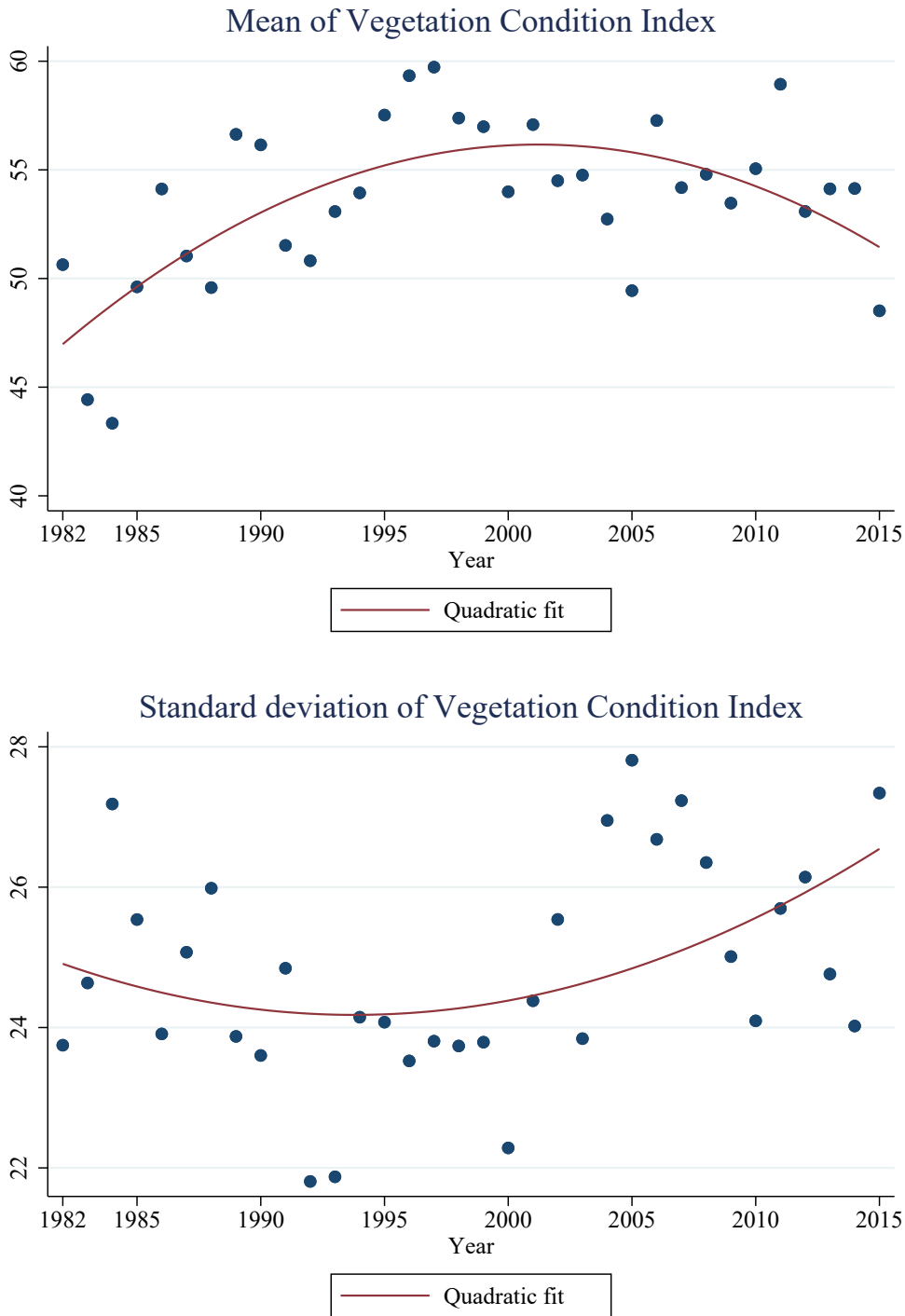
Table OA3: Summary statistics of the countries included in the analysis

Country	Observations	Percent	Survey years
Angola	88,895	2.18	2006-07, 2010-11, 2015
Burkina Faso	242,547	5.94	1992-93, 1998-99, 2003, 2010-11, 2014-15
Benin	145,828	3.57	1996, 2001, 2011-12
Burundi	42,201	1.03	2010-11
Congo Dem. Rep.	133,686	3.28	2007, 2013-14
Central African Rep.	28,050	0.69	1994-95
Cote d'Ivoire	87,687	2.15	1994, 2011-12
Cameroon	124,063	3.04	2004, 2011
Ethiopia	281,640	6.9	1992, 1997-98, 2003, 2008
Gabon	40,251	0.99	2012
Ghana	131,355	3.22	1993-94, 1998-99, 2008, 2014
Guinea	114,304	2.80	1999, 2005, 2012
Kenya	226,993	5.56	2003, 2008-09, 2014
Comoros	20,830	0.51	2012-13
Liberia	52,354	1.28	2006-07, 2011-12
Lesotho	122,489	3.00	2004-05, 2009-10, 2014
Madagascar	156,198	3.83	1997-98, 2008-09, 2011
Mali	122,345	3.00	2006, 2010, 2015
Malawi	191,832	4.70	2000, 2010, 2014
Mozambique	117,148	2.87	2009, 2011, 2015
Nigeria	259,475	6.36	2003, 2008, 2010, 2015
Namibia	114,616	2.81	2000, 2006-07, 2013
Rwanda	158,370	3.88	2005, 2010-11, 2014-15
Sierra Leone	116,441	2.85	2008, 2013
Senegal	222,222	5.45	1992-93, 1997, 2006-07, 2010-12, 2015
Swaziland	21,734	0.53	2006-07
Chad	99,620	2.44	2014-15
Togo	45,519	1.12	2013-14
Tanzania	154,418	3.78	1999, 2007-2010, 2015
Uganda	145,356	3.56	2000-01, 2006, 2011, 2014-15
Zambia	117,257	2.87	2007, 2013-14
Zimbabwe	154,445	3.79	1999, 2005-06, 2010-11, 2015
Total	4,080,169	100.00	

Notes: This table summarizes how often the countries are included in the DHS survey waves.

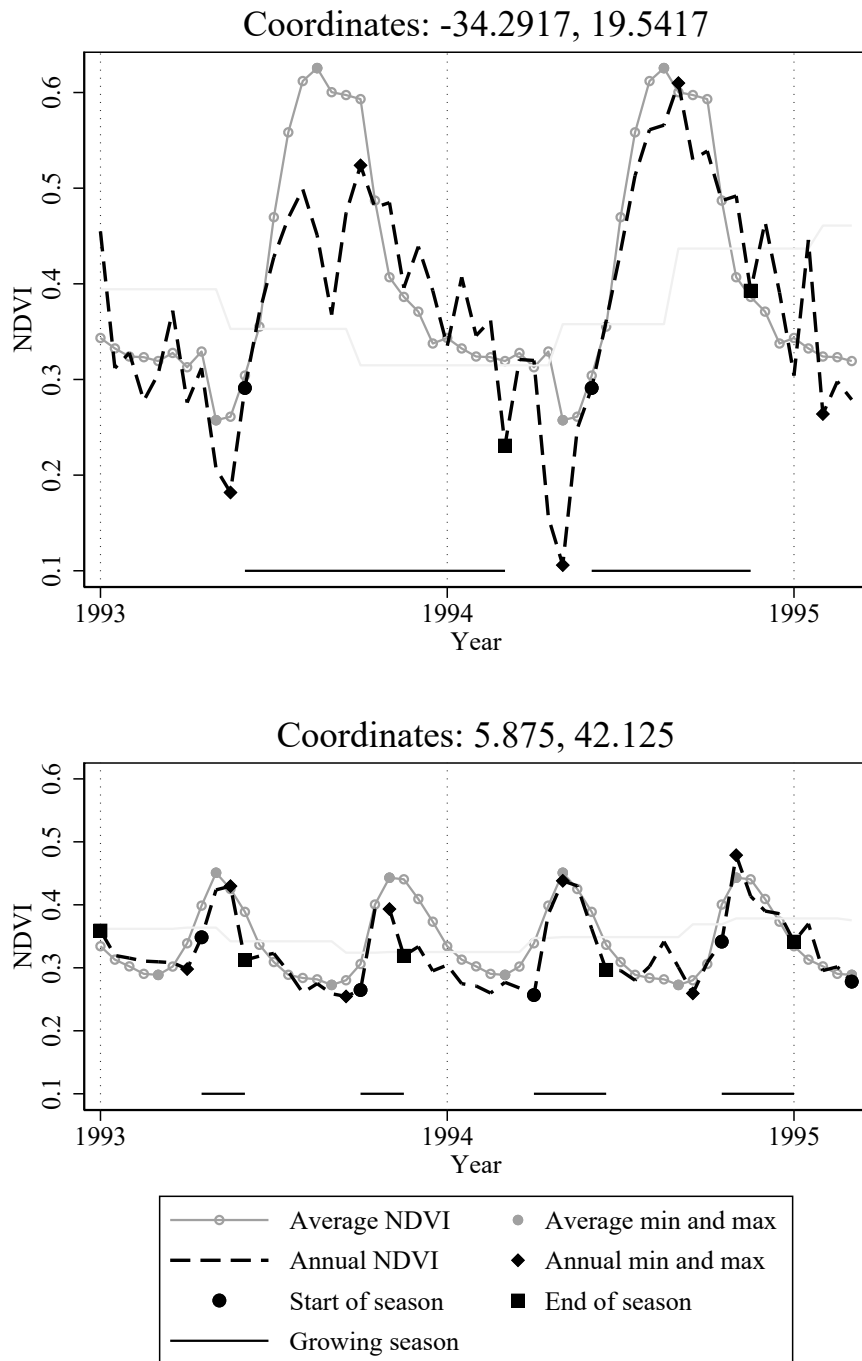
OA1.2 Additional figures (Figures OA1, OA2)

Figure OA1: Mean and s.d. of the vegetation index



Notes: Sample includes 20,021 distinct NDVI grids (of 0.08×0.08 degrees) in Africa within which at least one household was ever sampled in the DHS survey.

Figure OA2: Construction of growing season



Notes: Dashed black lines track the current NDVI. Solid gray lines are the average time-of-year NDVI across 1992-2015 for that location. Bullets and squares show the start and end dates of the current growing season(s), following the algorithm of Vrieling et al. (2013). The top panel shows a location with one season per year, and the bottom panel a location with two seasons per year. The annual maximum for a grid is the point where it has a) the highest value in a window ranging from three values before and three values after, and b) is higher than the average value of absolute maximum and minimum for that grid.

OA2 Robustness

OA2.1 Adding control variables sequentially (Table OA4)

Control variables are successively added in Table OA4. Column 5 in Table OA4 corresponds to column 4 in Table 1, and the full set of control variables is always included in all of the other tables. The table looks very similar when we change the dependent variables to first-time droughts. However, when changing the dependent variable to recurring droughts, we find that they are only significant (with 90% confidence) in specifications 1-3 of Table OA4 and not in specification 4-6 (not shown for reasons of brevity).

Table OA4: Adding control variables sequentially and alternative clustering

Dependent variable →	log BMI					
	Clustered by country × year × vegetation-zone					Clustered by country × year
	[1]	[2]	[3]	[4]	[5]	[6]
Drought dummy (all, 3 months)	-0.028*** (0.009)	-0.023*** (0.009)	-0.026*** (0.009)	-0.021** (0.009)	-0.025*** (0.009)	-0.025*** (0.009)
<i>Individual controls:</i>						
Uneducated		-0.042*** (0.002)	-0.042*** (0.002)	-0.039*** (0.002)	-0.037*** (0.002)	-0.037*** (0.002)
Uneducated head of household		-0.041*** (0.002)	-0.041*** (0.002)	-0.039*** (0.001)	-0.038*** (0.001)	-0.038*** (0.002)
Age		0.004*** (0.000)	0.004*** (0.000)	0.004*** (0.000)	0.004*** (0.000)	0.004*** (0.000)
Male		-0.093*** (0.006)	-0.093*** (0.006)	-0.094*** (0.006)	-0.093*** (0.006)	-0.093*** (0.009)
<i>Grid-level controls:</i>						
Number of past drought periods			-0.002*** (0.001)	-0.001* (0.001)	-0.002*** (0.001)	-0.002** (0.001)
Surveyed during growing season			-0.006** (0.002)	-0.006*** (0.002)	0.001 (0.002)	0.001 (0.002)
Aridity index				0.046*** (0.006)	0.068*** (0.008)	0.068*** (0.009)
Irrigation %				0.010*** (0.001)	0.009*** (0.001)	0.009*** (0.001)
NDVI growing seasons per year					0.010*** (0.002)	0.010*** (0.002)
Long-run time-of-year average NDVI					-0.079*** (0.011)	-0.079*** (0.012)
Country × year fixed effects	✓	✓	✓	✓	✓	✓
Observations	585,703	479,455	479,447	479,447	479,447	479,447
R-squared	0.089	0.188	0.188	0.192	0.195	0.195
Clusters	433	433	433	433	433	94
Grids (NDVI, 0.08×0.08 degrees)	15640	15630	15629	15629	15629	15629

Notes: ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level. *Droughts* are severe droughts lasting at least three consecutive months. Standard errors in parentheses and clustered as indicated. Sample: individuals aged 15 to 64.

OA2.2 Droughts of various length (Table OA5)

Table OA5: The effect of drought on BMI, by drought duration

Dependent variable → Droughts →	log BMI			
	all, 1 month	all, 2 months	all, 3 months	all, 6 months
	[1]	[2]	[3]	[4]
Drought dummy	-0.004 (0.004)	-0.015** (0.008)	-0.025*** (0.009)	0.005 (0.005)
Uneducated	-0.037*** (0.002)	-0.037*** (0.002)	-0.037*** (0.002)	-0.037*** (0.002)
Uneducated head of household	-0.038*** (0.001)	-0.038*** (0.001)	-0.038*** (0.001)	-0.038*** (0.001)
Age	0.004*** (0.000)	0.004*** (0.000)	0.004*** (0.000)	0.004*** (0.000)
Male	-0.093*** (0.006)	-0.093*** (0.006)	-0.093*** (0.006)	-0.093*** (0.006)
Country × year fixed effects	✓	✓	✓	✓
Grid-level controls	✓	✓	✓	✓
Observations	479,402	479,402	479,447	479,447
R-squared	0.195	0.195	0.195	0.195

Notes: ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level. Standard errors are clustered on the country-vegetation-zone-year level and shown in parentheses.

OA2.3 Changing the years within-which any previous drought occurred (Table OA6)

Table OA6: First-time droughts: Changing the years within-which any previous drought occurred

Dependent variable →	log BMI			
	4 years	5 years	6 years	10 years
Drought is the first in... →	[1]	[2]	[3]	[4]
Drought dummy (first-time)	-0.0230** (0.0105)	-0.0230** (0.0105)	-0.0228** (0.0106)	-0.0202* (0.0121)
Country × year fixed effects	✓	✓	✓	✓
Individual and grid-level controls	✓	✓	✓	✓
Observations	479,134	479,134	479,071	478,941
R-squared	0.1947	0.1947	0.1947	0.1948
Clusters	433	433	433	433
Grids (NDVI, 0.08×0.08 degrees)	15,615	15,615	15,610	15,606

Notes: ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level. *Droughts* are severe droughts lasting at least three consecutive months. Standard errors in parentheses and clustered by country-vegetation-zone-year.

OA2.4 Other quantiles of BMI (Table OA7)

This section extends Columns 10-12 of Table 1 (Panel B) to other quantiles. Table OA7 reports so-called ‘unconditional’ quantile regressions following the method by Firpo et al. (2009) (and implemented in Stata by Rios-Avila (2020)). Unconditional quantile regressions estimate the marginal effect of droughts (for the educated or the uneducated) at specific points of the distribution of log BMI. In contrast, conditional quantile regressions would capture the effect of droughts for levels of education across a distribution of BMI *within* a group of individuals with otherwise similar characteristics (other than drought and education). Unreported *conditional* quantile regressions, using the method by Machado and Santos Silva (2019), show similar marginal interaction effects except that they are of about half the magnitude.

Standard controls and fixed effects are always included. Coefficients highlighted in bold are significant marginal effects of significant interactions terms.

The table shows that individuals with above median BMI but different education are affected equally by droughts. Only for the first and second decile do we find that the uneducated are affected significantly more than the educated. These results are driven by first-time droughts.

Table OA7: Quantile regressions of the effect of droughts across the (unconditional) distribution of log BMI

Dependent variable →		log BMI								
Centile →		10%	20%	30%	40%	50%	60%	70%	80%	90%
Panel A: all droughts										
Drought dummy	[1]	-0.002 (0.009)	-0.004 (0.008)	0.000 (0.008)	-0.008 (0.008)	-0.021*** (0.008)	-0.031*** (0.010)	-0.033*** (0.012)	-0.040** (0.020)	-0.045 (0.038)
Drought dummy * uneducated		-0.051** (0.023)	-0.029** (0.014)	-0.021 (0.014)	-0.004 (0.013)	0.014 (0.011)	0.018* (0.011)	0.022* (0.012)	0.019 (0.018)	0.010 (0.035)
Uneducated		-0.018*** (0.001)	-0.019*** (0.001)	-0.022*** (0.001)	-0.025*** (0.001)	-0.030*** (0.002)	-0.035*** (0.002)	-0.044*** (0.002)	-0.058*** (0.003)	-0.077*** (0.004)
Marg. effect of drought if uneducated		-0.053** (0.021)	-0.034** (0.013)	-0.021 (0.014)	-0.012 (0.013)	-0.008 (0.010)	-0.013 (0.010)	-0.011 (0.010)	-0.021 (0.012)	-0.035 (0.018)
Panel B: recurring droughts										
Drought dummy	[1]	0.029 (0.022)	0.005 (0.022)	-0.000 (0.023)	-0.008 (0.022)	-0.036 (0.022)	-0.040 (0.026)	-0.062* (0.032)	-0.052 (0.038)	-0.078 (0.052)
Drought dummy * uneducated		-0.108* (0.066)	-0.055 (0.035)	-0.043 (0.031)	-0.023 (0.027)	0.020 (0.029)	0.029 (0.031)	0.048 (0.033)	0.041 (0.040)	0.043 (0.059)
Uneducated		-0.018*** (0.002)	-0.019*** (0.001)	-0.022*** (0.002)	-0.025*** (0.002)	-0.030*** (0.002)	-0.035*** (0.002)	-0.043*** (0.003)	-0.058*** (0.003)	-0.077*** (0.005)
Marg. effect of drought if uneducated		-0.079 (0.056)	-0.051* (0.027)	-0.044** (0.021)	-0.031 (0.020)	-0.016 (0.019)	-0.011 (0.021)	-0.015 (0.023)	-0.011 (0.031)	-0.034 (0.046)
Panel C: first-time droughts										
Drought dummy	[1]	-0.009 (0.010)	-0.006 (0.008)	0.000 (0.009)	-0.008 (0.009)	-0.018** (0.009)	-0.029*** (0.011)	-0.026* (0.014)	-0.039* (0.022)	-0.037 (0.044)
Drought dummy * uneducated		-0.034** (0.017)	-0.021* (0.012)	-0.013 (0.012)	0.003 (0.012)	0.013 (0.012)	0.015 (0.013)	0.016 (0.017)	0.014 (0.022)	0.002 (0.042)
Uneducated		-0.018*** (0.001)	-0.019*** (0.001)	-0.022*** (0.001)	-0.025*** (0.001)	-0.030*** (0.002)	-0.035*** (0.002)	-0.044*** (0.002)	-0.058*** (0.003)	-0.077*** (0.004)
Marg. effect of drought if uneducated		-0.044*** (0.016)	-0.028** (0.013)	-0.012 (0.014)	-0.005 (0.014)	-0.005 (0.011)	-0.014 (0.012)	-0.01 (0.012)	-0.025 (0.015)	-0.035 (0.021)

Notes: ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level. Standard controls and fixed effects always included. Bootstrapped standard errors in parentheses and clustered by country-vegetation-zone-year. Observations: 479,447 in Panel A; 478,405 in Panel B; 479,134 in Panel C. Coefficients highlighted in bold are significant marginal effects of significant interactions terms.

OA3 Droughts and other occupations (Table OA8)

Table OA8: The effect of drought on working in other sectors

Dependent variable →	Domestic	Unskilled manual	Skilled manual	Professional, technical	Services
Panel A: All droughts					
	[1]	[2]	[3]	[4]	[5]
Drought dummy	0.002 (0.005)	0.002 (0.005)	0.018 (0.026)	0.004 (0.009)	-0.006 (0.010)
Drought dummy * uneducated	-0.001 (0.007)	0.000 (0.007)	-0.019 (0.028)	-0.012 (0.013)	0.003 (0.007)
Uneducated	0.006*** (0.002)	0.001 (0.002)	-0.013*** (0.002)	-0.071*** (0.002)	-0.017*** (0.002)
Observations	891,923	891,923	891,923	891,923	891,923
R-squared	0.060	0.081	0.046	0.084	0.057
Panel B: Recurring droughts					
	[1]	[2]	[3]	[4]	[5]
Drought dummy	0.006 (0.011)	0.007 (0.008)	-0.011 (0.009)	-0.001 (0.016)	0.023 (0.015)
Drought dummy * uneducated	-0.004 (0.014)	0.002 (0.008)	0.004 (0.017)	-0.016 (0.019)	-0.021* (0.011)
Uneducated	0.006*** (0.002)	0.001 (0.002)	-0.013*** (0.002)	-0.071*** (0.002)	-0.017*** (0.002)
Observations	889,693	889,693	889,693	889,693	889,693
R-squared	0.060	0.081	0.046	0.084	0.057
Panel C: First-time droughts					
	[1]	[2]	[3]	[4]	[5]
Drought dummy	0.001 (0.005)	-0.001 (0.005)	0.031 (0.037)	0.007 (0.010)	-0.020* (0.011)
Drought dummy * uneducated	0.000 (0.007)	-0.002 (0.009)	-0.030 (0.038)	-0.010 (0.013)	0.014 (0.009)
Uneducated	0.006*** (0.002)	0.002 (0.002)	-0.013*** (0.002)	-0.071*** (0.002)	-0.017*** (0.002)
Observations	890,667	890,667	890,667	890,667	890,667
R-squared	0.060	0.081	0.046	0.084	0.057

Notes: ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level. Standard errors are clustered on the country-vegetation-zone-year level and shown in parentheses. Country × year fixed effects and individual and grid-level controls are always included.

OA4 Data appendix

OA4.1 NDVI (Figure OA3)

The original NDVI data was created by the National Aeronautics and Space Administration (NASA) using Advanced Very High Resolution Radiometer (AVHRR) instruments on board of Landsat satellites (Vermote et al., 2016; Masek et al., 2006).¹

We specifically use the Global Inventory Modeling and Mapping Studies (GIMMS) 3g version by Pinzon and Tucker (2014), which is based on the AVHRR/2 and AVHRR/3 instruments onboard NOAA-7 through NOAA-19 satellites.² Pinzon and Tucker (2014) process the raw data to correct for navigation errors, calibrate to oceans and deserts, and, using composite images, correct for atmospheric water vapor, non-volcanic aerosols, and cloud-cover. By using composite images, the raw data's daily frequency is reduced to a bi-monthly frequency.

The NDVI data is highly disaggregated both in terms of space (cells of size 0.08×0.08 degrees, corresponding to a length of approximately 9.25 km at the equator) and time (twice per month). The index is defined as the difference in wavelengths of light that is reflected by the earth's surface.

The index is defined as the difference in wavelengths of light that is reflected by the earth's surface:

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

where NIR is near-infrared light (0.7-1.1 μm) and RED is visible light (0.4-0.7 μm).

Figure OA3 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

¹ See also <https://www.usgs.gov/landsat-missions/landsat-normalized-difference-vegetation-index>.

² Currently available for download from <http://poles.tpdc.ac.cn/en/data/9775f2b4-7370-4e5e-a537-3482c9a83d88/>.

of NDVI correspond to surfaces covered by water, such as lakes, rivers, or the ocean.

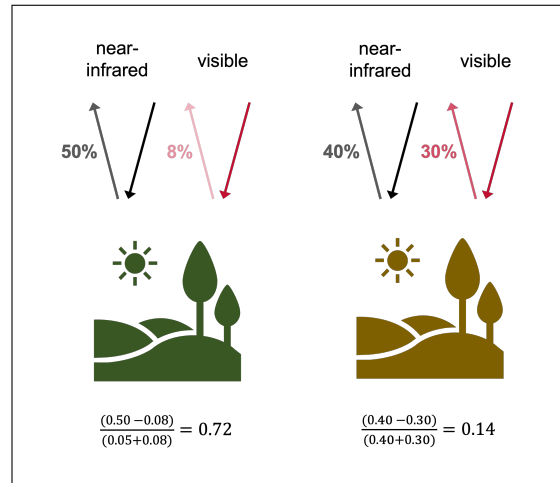
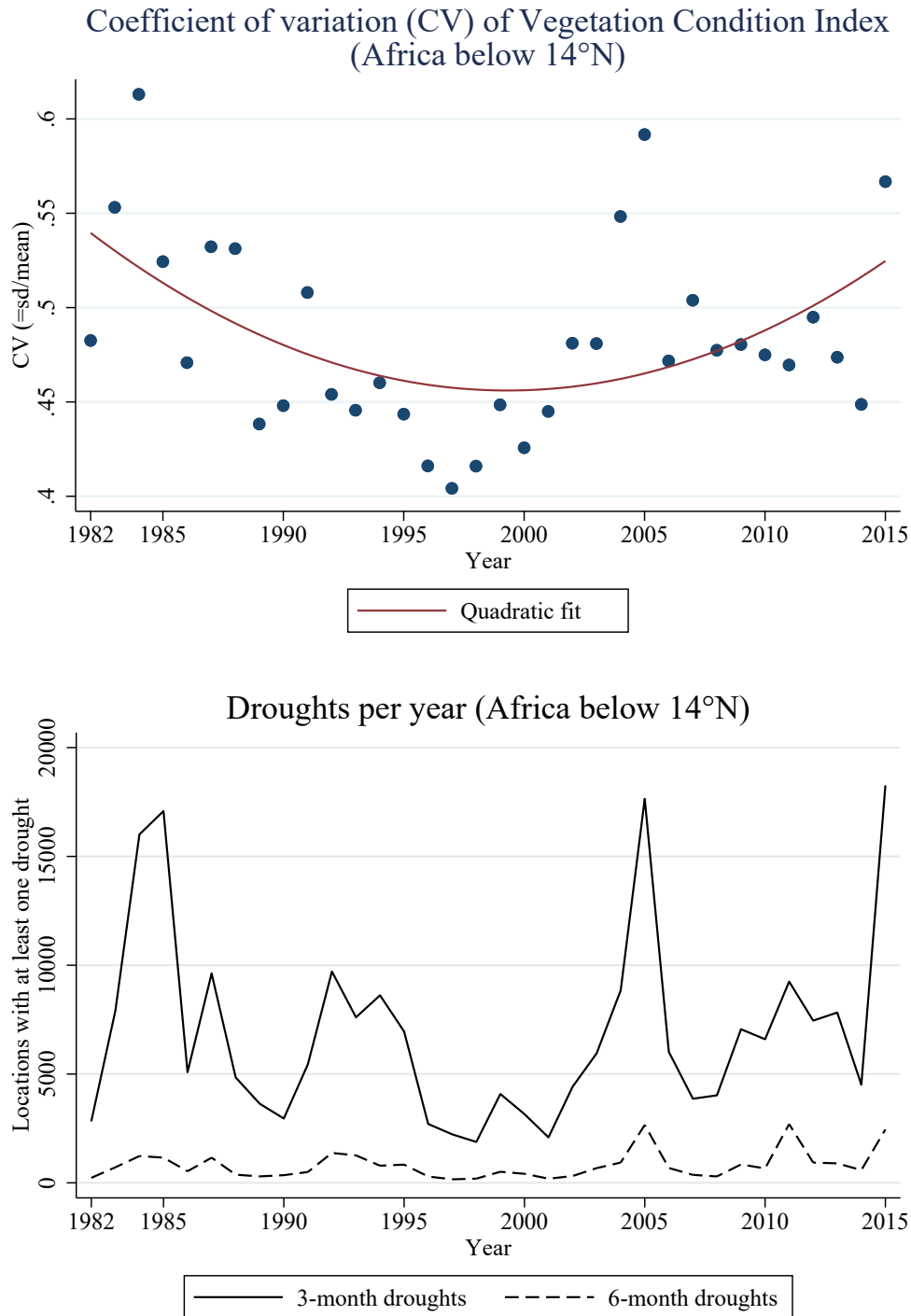


Figure OA3: Reflected radiation by different types of vegetation (following Weier and Herring, 2000)

OA4.2 Frequency of droughts in Africa below the 14°N parallel (Figures OA4, OA5)

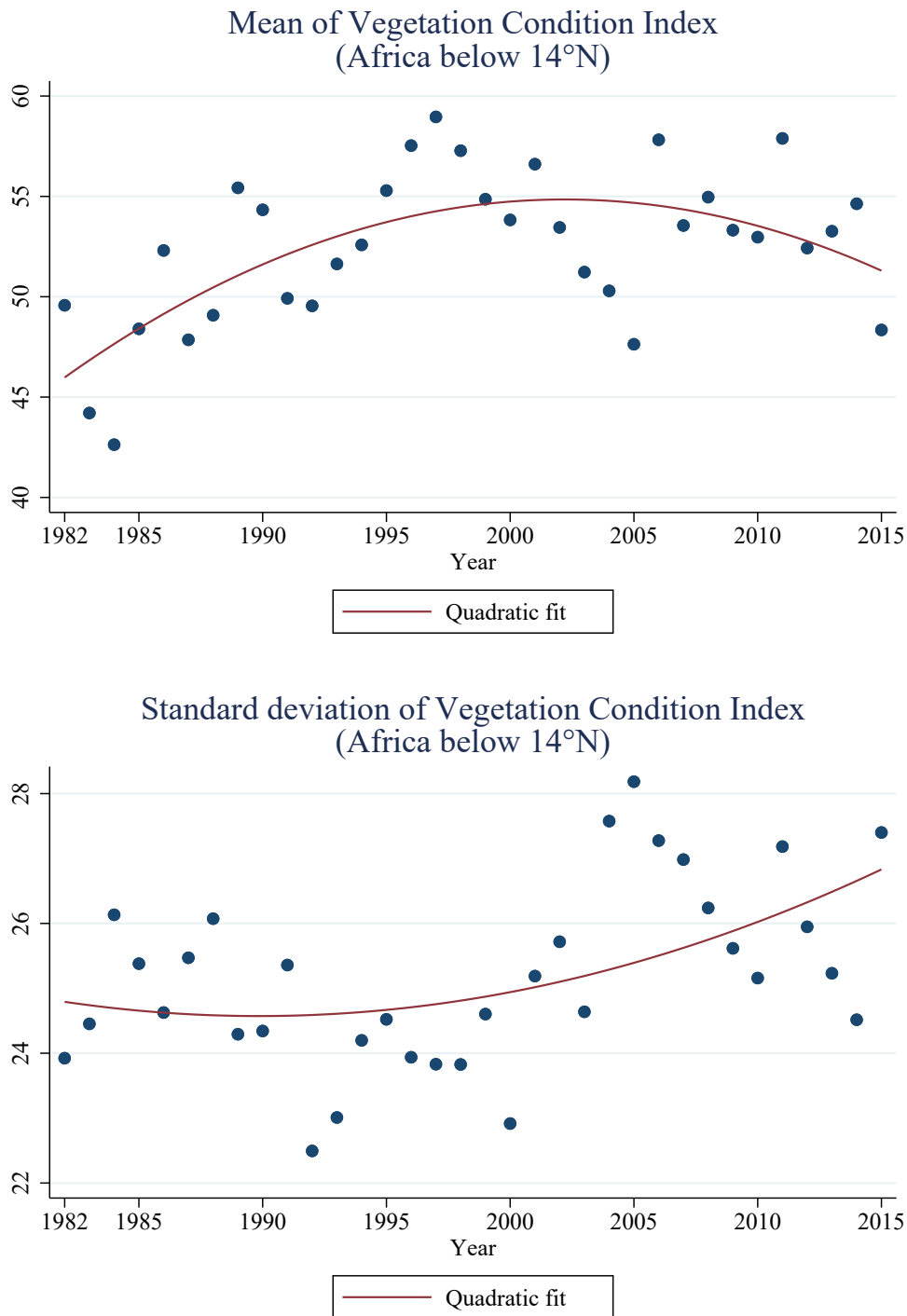
This subsection presents illustrations of the frequency of droughts over time in Sub-Saharan Africa (similar to Figures 1 and OA1). Rather than defining the region by using country borders, which would include countries such as Mali that also extend into the Sahara, we present results for all 225,110 NDVI grids that fall below the 14°N parallel. Of all surveyed DHS individuals, 95% are located below this parallel. The subsequent figures are very similar when choosing the 13°N or 15°N parallels.

Figure OA4: Vegetation index and droughts: Africa below 14°N



Notes: Sample includes 225,110 distinct NDVI grids (of 0.08×0.08 degrees) in Africa below 14°N latitude. 95% of individuals surveyed in the DHS live below this latitude.

Figure OA5: Mean and s.d. of the vegetation index: Africa below 14°N



Notes: Sample includes 225,110 distinct NDVI grids (of 0.08×0.08 degrees) in Africa below 14°N latitude. 95% of individuals surveyed in the DHS live below this latitude.

OA4.3 Country coverage of DHS survey (Figure OA6)

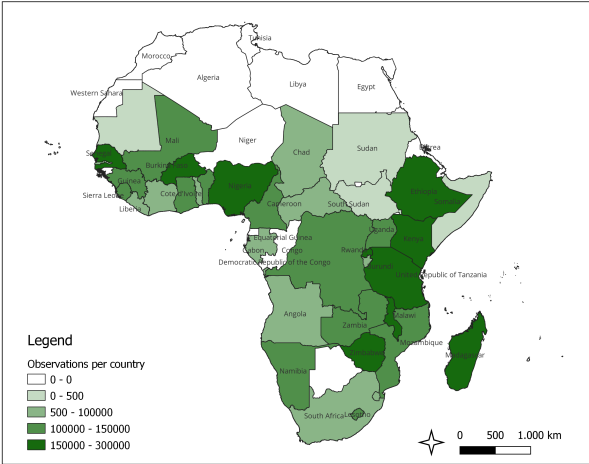


Figure OA6: Location of DHS survey households

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