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Nora Fingado, Steven Poelhekke

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Droughts and Malnutrition in Africa

Abstract

How costly are droughts to individuals' nutrition in Africa? Do people adapt to recurring droughts? We measure severe drought events using a detailed satellite-based index of greening observed bi-monthly on a relatively high-resolution 0.083° grid between 1982 and 2015, that captures persistent and severe deficits in soil moisture relative to grid- and time-of-year normal moisture. Across 32 African countries, conditional on individual characteristics, timing relative to growing seasons, irrigation, and local grid-level climate, we show that a severe three-month drought reduces adults' body mass index by 2.5%. Droughts are worse for underweight and uneducated individuals. In contrast, recurring severe droughts, that happen in locations that have seen droughts before, do not significantly affect adults. The effect is driven by unexpected first-time exposure to droughts. 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.

Nora Fingado
Free University Amsterdam
De Boelelaan 1105
The Netherlands - 1081 HV Amsterdam
nora.fingado@gmx.de

*Steven Poelhekke**
Free University Amsterdam
De Boelelaan 1105
The Netherlands – 1081 HV Amsterdam
steven.poelhekke@vu.nl
ORCID ID: 0000-0001-9256-7853

*corresponding author

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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, Northern, 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, 2023b).[1] 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 for adults, which hampers an assessment of the socioeconomic impact of climate change—and of droughts in particular (Carleton and Hsiang, 2016).[2] 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).[3] The economics literature has in common that droughts are typically measured using rainfall and/or temperature data, which is justified by agriculture tending to be rain-fed in low-income countries so that the connection between climate and crop yields is relatively 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. While these are available for long historical time periods, this approach limits the spatial resolution, may lead to measurement error, aggregation bias, and increases spatial- and autocorrelation,

[1] See Section "11.6 Droughts" therein, and projections on page 1,584. At the same time, the Sahara and middle Africa may experience *fewer* droughts, although precipitation and soil moisture scenarios contain more uncertainty than temperature scenarios.

[2] 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).

[3] Using the same DHS data as this study, Anttila-Hughes et al. (2021) find that heat during El Niño periods also adversely affects child nutrition. Children in general suffer the most from bad agricultural conditions (Davenport et al., 2017; Grace et al., 2015; Yamano et al., 2005; Jensen, 2000)

which may attenuate the estimated effects towards zero (Auffhammer, 2018).[4]

This paper contributes to our understanding of the impacts of droughts by using high-resolution (0.083°) gridded, bi-monthly satellite data that tracks the greening of plants, with the aim of capturing severe soil moisture drought spells more accurately, and by relating these to outcomes of georeferenced individuals across a broad sample of African countries. We measure droughts using 34 years of satellite data since 1982 by identifying consecutive 3-month 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 plant growth (Petersen, 2018).[5]

We set the stage for our analysis by demonstrating an increase in the frequency and geographic spread of severe droughts across Africa during the past 15 years. 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 (in which the NDVI is continuously far below normal in this period and grid location), adults' BMI is reduced by 2.5% on average, which translates to one-seventh of a standard deviation reduction in BMI. In other words, the proportion of affected individuals who are underweight increases from one in seven to one in

[4] The Intergovernmental Panel on Climate Change (IPCC) defines droughts as 'A period of abnormally dry weather long enough to cause a serious hydrological imbalance'. Droughts have more causes than lack of rainfall and include 'evapotranspiration induced by enhanced radiation, wind speed, or vapor pressure deficit (itself linked to temperature and relative humidity), as well as pre-conditioning (pre-event soil moisture; lake, snow, and/or groundwater storage)', which all affect soil moisture (Seneviratne et al., 2012, p.167). Also, rain and temperature alone 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, 2023a; Salih et al., 2020).

[5] A related alternative is the ESA CCI Soil Moisture climate data that uses radar backscatter rather than spectral bands (Gruber et al., 2019), which is available at a lower resolution of 0.25° from 1997 and coarser resolutions for earlier years, and is for example used in Proctor et al. (2022) (using a 0.5° resolution).

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 insignificant 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 fixed effects. In addition, we show that this pattern of results remains after controlling for various alternative spatial fixed effects, deforestation, and spatially and temporally coarser measures of rainfall deficits and temperature.

The DHS survey also enables us to identify mitigating mechanisms, including education, labor market adjustment, and migration. We show that educated individuals appear unaffected in terms of occupation because they are less likely to work in agriculture directly. In contrast, uneducated individuals (i.e., no education or incomplete primary education) lose agricultural employment and become unemployed in response to first-time droughts, whereas recurring droughts lead to a smaller increase in unemployment and instead to a process of 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 relate to the large literature that studies coping mechanisms in the face of adverse shocks (see next section), by focusing on an aggregate shock and by distinguishing between unexpected first-time droughts and more regular droughts, which may have distinct short- and long-run responses, respectively. However, in this paper we look at labor market and migration responses, but not at credit and insurance markets since the more aggregate nature of the drought shocks means that they are less likely to be individually insurable (see also next section).

This paper also relates 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, distinguishing between first-time and recurring droughts, and relating these to socio-economic outcomes.

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; Chantarat 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 Suryabhagavan, 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. While the spatial resolution of the NDVI data is much higher than typical meteorological spatial data, each grid cell covers an area large enough (about 86 km^2) that we can reasonably assume that individuals use of farming inputs or changes in farming practices (on the median farm that spans an area of 0.1 km^2) does not affect our measure of *severe* droughts directly. A further benefit of using satellite-based observational data is that 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, borrowing and off-farm employment help absorb idiosyncratic shocks as in Kochar (1999), they may be less effective when shocks are correlated over space and time (Costa et al., 2023)—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 transformation 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 the viability of agriculture.

3 Data

3.1 Measuring droughts using satellite data

We measure droughts based on vegetation conditions as captured by satellites, instead of using 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), with the aim of more accurately measuring local soil moisture droughts. We use georeferenced GIMMS3g NDVI data for the African continent over the period 1982-2015 (Pinzon and Tucker, 2014). The NDVI data are highly disaggregated both in terms of space (grid cells of size 0.083×0.083 degrees, corresponding to a length of approximately 9.26km at the equator) and time (twice per month).[6] 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).

[6] 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, and thus relative to what is normal in that location:

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

As is standard in the remote sensing literature (e.g., Liou and Mulualem, 2019; Measho et al., 2019; Winkler et al., 2017), we define drought conditions as severe or extreme if the VCI is below 20%.[7]

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.[8] 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). We also alternatively consider four, six, or ten years as the relevant window.

3.2 Individual and 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. We focus on those aged between 15 and 65 years of age.[9] After merging, our final data set comprises information on over 2 million individuals over the study period and area.[10]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 of residence, and

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

[8] See Appendix Table OA1 for summary statistics of the different drought indicators. As expected, longer droughts are rarer than shorter droughts.

[9] We choose 15 because labor force participation jumps from 0.04% at the age of 14 to 55% at the age of 15 and is 56% on average after that, decreasing again after the age of 50.

[10] See Appendix Table OA2 for a full list of countries and years included in the data set.

educational attainment. For health outcomes such as height and weight, most respondents are women that were physically present at the time of interview, but the survey also asked about occupations for male household members that were not at home.[11]

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.[12]

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.

[11] We use the coordinates of 'clusters' of households (typically census enumeration areas, see `https://dhsprogram.com/data/Guide-to-DHS-Statistics/Analyzing_DHS_Data.htm`) as provided by the DHS and use GIS software to match them to grid cells. 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. Points always stay within the country, within the DHS survey region, and within the second administrative layer area (Burgert et al., 2013). However, our NDVI grids are about 9.26×9.26km, 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). A few households are matched to grids with missing NDVI values, such as on top of water bodies. We drop these from the sample.

[12] We proxy migrant status by comparing the age of the individual with 'Time lived in current place of residence'.

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 %*.[13]

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).[14]Finally, for each location, we take the long-run average of the SOS and EOS over time and construct a dummy indicator *surveyed during growing season* that equals 1 if the interview takes place during the normal growing season, and 0 otherwise.[15] 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 during the past 5 years (measured as the total of half-month periods with severe drought).

We merge all control variables through household geographic coordinates. Summary statistics are provided in Table 1.

[13] See the Global Map of Irrigation, version 5, layer 'gmia_v5_aei_pct_cellarea'.

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

[15] By averaging the start and end months we avoid bias arising from droughts potentially affecting these dates.

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 sub-national level. Consequently, the DHS data set represents a repeated (pooled) cross-section of individuals that covers multiple areas and years. Our baseline regression equation is as follows:

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

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 individual, geographic and climatic 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.[16]

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

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

We focus on educational attainment as the main source of heterogeneity because it is predetermined, unlike income. 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. The rural dummy

[16] The full set of interactions also absorb the separate country dummies and year dummies. In robustness tests we allow for sub-national fixed effects.

is equal to zero for cities, but also for smaller towns.[17] 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., more 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.[18]

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).[19] 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 more common 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.[20] First, we define droughts relative to the normal cycle of seasonal NDVI in each grid, which accounts for spatial differences in climate that are stable over time, and in addition control for grid-level observed (time-of-year) climate and country-by-year fixed effects, thus comparing households in similar local climates. In robustness tests we additionally experiment with sub-national regional fixed effects. Second, we distinguish between droughts that occur for

[17] See variable v102 in `https://dhsprogram.com/pubs/pdf/DHSG4/Recode7_DHS_10Sep2018_DHSG4.pdf`

[18] Results are robust to clustering by country-year or two-way by country and year instead.

[19] See also Rios-Avila (2020).

[20] 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), and the fact that individual farms are small (with a median of 10 hectares $=0.1$ km^2) relative to the size of a grid cell of 86 km^2, we do not consider this a major threat to causal estimation. In the online appendix we also show that results are robust to controlling for deforestation. Household land ownership is only available for less than half of the observations, but does not change results when we add it to the baseline regressions.

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.[21] We further include the following grid-level variables to control for the local climate: *number of past drought periods*, *number of growing seasons per year*, *surveyed during growing season*, *irrigation %*, *aridity index*, and the *long-run time-of-year average NDVI*.[22] In the online appendix we additionally show tests where we control for various alternative spatial fixed effects, deforestation, and spatially and temporally coarser measures of rainfall deficits and temperature.

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 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

[21] Results are robust to choosing four, six, or ten years, see Online Appendix OA2. The cut-off of five years is the result of a trade-off: a longer period reduces the number of treatment events, also because the NDVI data does not go back further than 1982, and a shorter window makes it more likely that precautionary stockpiling is economical.

[22] Specifically, we control for the number of past drought periods in currently untreated grids during the past five years. This implies that the drought dummy of all and recurring droughts captures the combined effect of the current drought and potentially lingering effects of past droughts. Alternatively, we could control for past droughts in both currently untreated and treated grids, such that the drought dummy would capture the marginal effect of an additional drought. This by definition does not affect the estimate of first-time droughts, because in those grids no previous droughts took place (within a five-year window). 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.

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.

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.[23] In other words, during the years 2000-2015 Africa became dryer on average, and the spatial variation in dryness increased. This has 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, 2023a).

[23] 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.

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 and malnourished (WHO, 2005). Overall, the uneducated, the young, and males have lower BMIs.

The estimation results, presented in Table 2, provide strong evidence that three-month droughts negatively affect BMI. A drought during the time of interview is associated with a 2.5% reduction in BMI (column 1), relative to households unaffected at the time of interview, suggesting that coping mechanisms are imperfect in mitigating the effects of droughts.

We always control for country-by-year fixed effects, individual controls (*uneducated*, *uneducated head of household*, *age*, and *male*), and grid-level controls (*number of past drought periods*, *aridity index*, *irrigation %*, *growing seasons per year*, *surveyed during growing season*, and the *long-run time-of-year average NDVI*). These are not reported here for brevity, but in Online Appendix OA2.1 we successively include and report all variables.[24]

Splitting all droughts into recurring and first-time droughts shows that the negative effect of droughts is driven by cases where a drought occurs for the first time in five years in a grid (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. In contrast, when affected by a drought for the first time, BMI is significantly reduced. Evaluated at the mean of 22.3, the average effect of first-time droughts 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 18.3% (about one in five people), and would have been 14.8% without the drought (about one in seven people).

In Online Appendix OA2.1 we discuss and show that this pattern is robust to controlling for an index of precipitation, temperature, deforestation, is not different in more urban areas,

[24] 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 OA1) such that the test suffers from low power.

and to sub-national region and grid fixed effects.[25] [26]

Do the educated fare better during droughts? In columns 4-6, we test for heterogeneity in the effect of droughts by adding to the estimations an interaction of drought with an indicator whether a person is uneducated (equation 2). 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).[27] The first decile of the distribution of BMI corresponds to a BMI of 18.1, which are those that are borderline underweight. Columns 7-9 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 columns 7-9, the uneducated (who represent 73% of the bottom decile of BMI) 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.

[25] In Online Appendix Table OA2.3 we also show that the effect of first-time droughts is robust to choosing a window of 4, 6, or 10 years instead.

[26] Alternatively controlling for the number of past drought periods in both currently untreated and treated grids, such that the drought dummy captures the marginal effect of an additional drought, results in similar effect of all and recurring droughts: -0.023** (0.009) and -0.022 (0.020), respectively.

[27] Online Appendix OA2.4 lists other deciles.

5.3.1 Labor reallocation

We measure the labor market status of male and female individuals aged 15 to 65 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.[28] Descriptive statistics in Table 1 show that the most common occupation is agriculture (39%) and that the unemployment rate is 24%. The results are shown in Table 3. 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 and first-time droughts. In the case of recurring droughts (Panel B), uneducated individuals still leave agriculture (column 4), but appear able to find new jobs in sales (column 6) rather than becoming unemployed (column 5), pointing to a possible long-term response.[29]

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 10.4% less likely to work in agriculture and 8.1% more likely to be unemployed.

In Online Appendix Table OA8, we show that the likelihood of working in occupations other than agriculture and sales does not change during any type of drought. Domestic

[28] The sample contains more male individuals than Table 2, because those interviewed were asked about the occupation of male household members even if they were not present at the time of interview. All specifications include country-by-year fixed effects, the standard individual and grid-level controls, and in addition we control for urban status and population density of the grid (those surveyed) to account for the fact that it is easier to switch occupation in denser labor markets. Results however do not depend on their inclusion. Results are also robust to selecting only those of age 18 and above.

[29] 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 the uneducated.

work, unskilled and skilled manual jobs, and professional/technical jobs are unaffected.[30] Jobs in services, that may be related to sales, somewhat rise during recurring droughts only. 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' and 'unskilled manual') 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).

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 indirectly in Table 4, which reports the results of estimating specification (2) with *migrant* as dependent variable. Note that we observe individuals where they are during the interview. In the case of a migrant, this is their destination location, but not their origin. We thus estimate the effect of droughts in the destination location on the probability of observing any migrants in that location. In addition, we include an interaction between drought and *rural*, both referring to conditions at the place of destination: if migration occurs from rural areas with few job opportunities to more urban areas with better job opportunities, we expect a negative interaction effect. The drought dummy then captures the effect of a local destination 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 coefficients on the interaction terms between between *drought* and *rural* (again, both referring to the place where the individual is at the time of the interview). The bottom row shows the marginal effect of a drought in rural destination areas.

Individuals observed in rural areas that are hit by a recurring drought are 12.3% less likely to be a migrant, while the marginal effect is not significant when hit by a first-time

30 These categories are mutually exclusive, see also `https://dhsprogram.com/data/Guide-to-DHS-Statistics/Employment_and_Occupation.htm`. We do no analyze 'clerical' because it is very rare.

drought[31] The distinction between first-time and recurring droughts suggests that (costly) migration is rather a long-term response than a short-run response, as it only appears in the data when droughts happen more than once. As indicated by the negative coefficient on $rural$, individuals living in rural areas are generally significantly less likely to have migrated there, providing further evidence that migration takes place from the countryside to towns and cities.

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 soil moisture 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% on average. However, the effect is driven by first-time droughts, whereas recurring droughts do not have a significant 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 likely limits the loss in income. Second, more people migrate away from rural to more urban areas during recurring droughts. Other mechanisms such as the development of drought-resistant crops may also play a role in future adaptation.

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

Our findings have implications for policy. While investment in irrigation, genetically modified crops, and water conservation would prevent soil moisture droughts and limit their impact 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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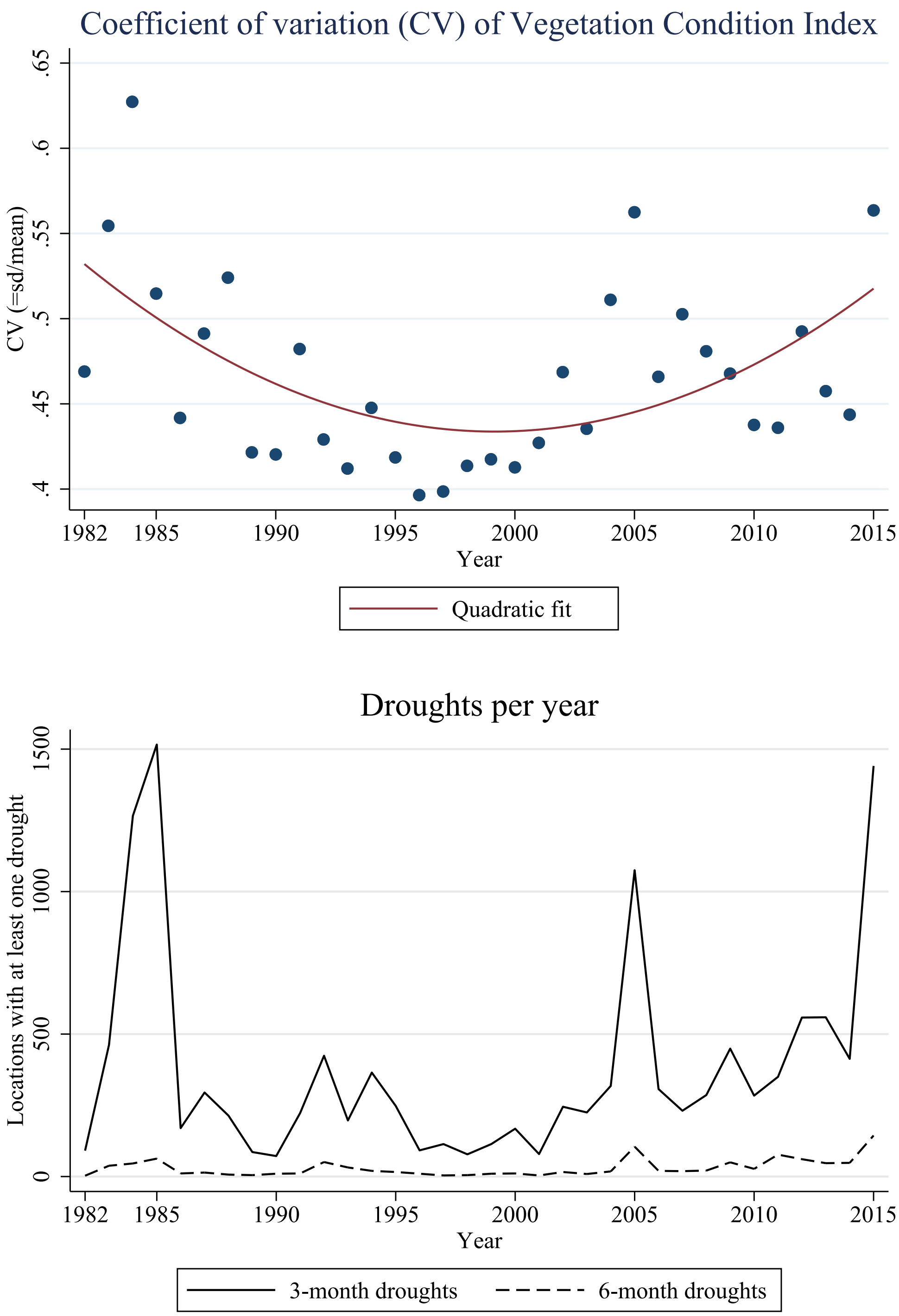
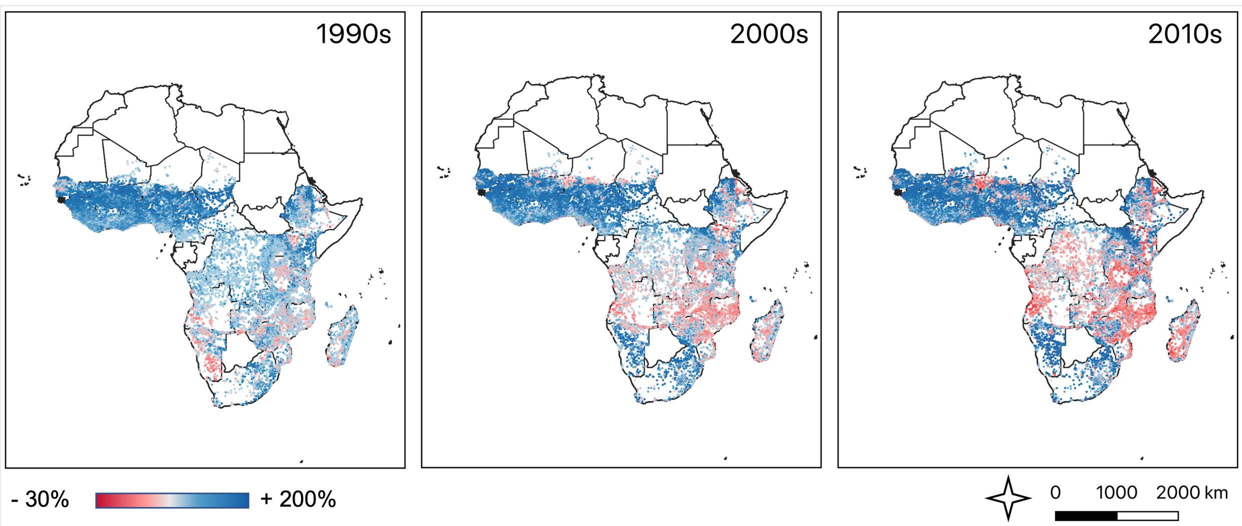
Tables and Figures

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 0.083×0.083 degrees) in Africa within which at least one household was ever sampled in the DHS survey.

Table 1: Summary statistics

Variable	Description	N	Mean	Sdev	Min	Max
Panel A. Dependent variables						
BMI	body-mass index (weight/height^2)	479,447	22.31	4.23	12.02	59.90
lnBMI	log of BMI	479,447	3.09	0.17	2.49	4.09
Agri	= 1 if occupation is agriculture	1,065,290	0.39	0.49	0.00	1.00
Unemployed	= 1 if unemployed	1,065,290	0.24	0.43	0.00	1.00
Sales	= 1 if occupation is sales	1,065,290	0.13	0.34	0.00	1.00
Domestic	= 1 if occupation is work at home	1,065,290	0.01	0.12	0.00	1.00
Unskilled manual	= 1 if occupation is unskilled manual	1,065,290	0.04	0.20	0.00	1.00
Skilled manual	= 1 if occupation is skilled manual	1,065,290	0.08	0.27	0.00	1.00
Professional	= 1 if occupation is professional/technical	1,065,290	0.05	0.22	0.00	1.00
Services	= 1 if occupation is in services	1,065,290	0.04	0.21	0.00	1.00
Migrant status	= 1 if age > 'Time lived in current place of residence'	501,120	0.54	0.50	0	1
Panel B. Drought dummies						
All droughts	= 1 if severe drought occurs in grid for at least 3 consecutive months	479,447	0.003	0.053	0	1
Recurring drought	= 1 if severe drought occurs for at least 3 consecutive months, where at least one other occurred in the same grid within the past 5 years	478,405	0.001	0.026	0	1
First-time drought	= 1 if severe drought occurs for at least 3 consecutive months, for the first time in grid in the past 5 years	479,134	0.002	0.047	0	1
Panel C. Individual controls						
Uneducated	Dummy that equals 1 if an individual has incomplete primary or no education	479,447	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	479,447	0.57	0.49	0	1
Age	Individual's age in completed years	479,447	29.71	9.86	15	64
Male	Dummy that equals 1 if an individual is male	479,447	0.15	0.35	0	1
Rural (destination)	=1 if individual is located outside of towns (inverse of 'urban')	479,447	0.66	0.47	0	1
Panel D. Grid-level controls						
Number of past half-months where 3-month droughts=1, last 5 years	Number of past half-months where 3-month drought=1, during the last five years, in grids with no current drought	479,447	0.20	1.10	0	35
Surveyed during growing season	Timing of the interview during or outside of an NDVI growing season	479,447	0.61	0.49	0	1
Aridity index	Inverse hyperbolic sine of the area's aridity index	479,447	0.60	0.32	0	1.83
Irrigation %	Inverse hyperbolic sine of the area's percentage equipped for irrigation	479,447	0.32	0.78	0	4.97
NDVI growing seasons per year	Number of NDVI growing seasons per year	479,447	1.26	0.44	1	2
Long-run time-of-year average NDVI	Long-run average NDVI during that time of the year	479,447	0.50	0.18	0.04	0.91

Notes: This table provides summary statistics for the sample of Table 2; statistics for occupations are for the sample of Table 3; statistics for migrant are for the sample of Table 4. *Number of past 3-month droughts (in half-months), last 5 years*: this variables takes the value 6 if only one 3-month drought happened during the past five years.

Table 2: The effect of droughts on BMI

Dependent variable →	log BMI								
Method →	OLS			OLS			Quantile Regression, 1st decile		
Droughts →	all	recur-ring	first-time	all	recur-ring	first-time	all	recur-ring	first-time
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Drought	-0.025***	-0.033	-0.023**	-0.023**	-0.032	-0.021	-0.002	0.029	-0.009
	(0.009)	(0.020)	(0.011)	(0.011)	(0.024)	(0.014)	(0.009)	(0.022)	(0.010)
Drought * uneducated				-0.004	-0.002	-0.004	-0.051**	-0.108*	-0.034**
				(0.013)	(0.032)	(0.014)	(0.023)	(0.066)	(0.017)
Uneducated				-0.037***	-0.037***	-0.037***	-0.018***	-0.018***	-0.018***
				(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Country × year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual & grid controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	479,447	478,405	479,134	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	433	432	433
Grids (0.083°×0.083°)	15,629	15,596	15,615	15,629	15,596	15,615	15,629	15,596	15,615
Marg. effect of drought if uneducated				-0.027**	-0.034	-0.025**	-0.053**	-0.079	-0.044***
				(0.012)	(0.026)	(0.011)	(0.021)	(0.056)	(0.016)

Notes: ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level. Sample: individuals aged 15-65 (15% is male). Standard errors are clustered on the country-vegetation-zone-year level and shown in parentheses (by means of bootstrapping in [7]-[9]). *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. *Uneducated* equals 1 if a person has no or incomplete primary education. *Quantile Regression* is the 'unconditional' quantile regression method by Firpo et al. (2009), first decile of the distribution of BMI. Individual and grid controls are the same variables as reported in Table OA3 column 5.

Table 3: The effect of droughts on labor reallocation

Dependent variable →	Works in Agriculture	Unemployed	Works in Sales
Panel A: All droughts			
	[1]	[2]	[3]
Drought	0.004	-0.029	-0.009
	(0.020)	(0.027)	(0.014)
Drought * uneducated	-0.133***	0.100***	0.045*
	(0.036)	(0.031)	(0.026)
	(0.036)	(0.037)	(0.026)
Uneducated	0.108***	-0.051***	0.024***
	(0.006)	(0.007)	(0.004)
Country×year FEs & controls	✓	✓	✓
Observations	1,065,290	1,065,290	1,065,290
R-squared	0.314	0.192	0.093
Marg. effect of drought if uneducated	-0.129***	0.072***	0.036*
	(0.036)	(0.025)	(0.019)
Panel B: Recurring droughts			
	[4]	[5]	[6]
Drought	0.009	-0.029	-0.030*
	(0.023)	(0.022)	(0.017)
Drought * uneducated	-0.179***	0.086**	0.106***
	(0.049)	(0.036)	(0.033)
Uneducated	0.108***	-0.051***	0.025***
	(0.006)	(0.007)	(0.004)
Country×year FEs & controls	✓	✓	✓
Observations	1,062,771	1,062,771	1,062,771
R-squared	0.313	0.192	0.093
Marg. effect of drought if uneducated	-0.171***	0.056	0.076***
	(0.057)	(0.036)	(0.026)
Panel C: First-time droughts			
	[7]	[8]	[9]
Drought	0.000	-0.028	0.003
	(0.026)	(0.040)	(0.016)
Drought * uneducated	-0.104***	0.109***	0.008
	(0.037)	(0.039)	(0.020)
Uneducated	0.108***	-0.051***	0.024***
	(0.006)	(0.007)	(0.004)
Country×year FEs & controls	✓	✓	✓
Observations	1,063,789	1,063,789	1,063,789
R-squared	0.313	0.192	0.093
Marg. effect of drought if uneducated	-0.104***	0.081***	0.010
	(0.034)	(0.030)	(0.015)

Notes: ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level. Sample: individuals aged 15-65 (44% is male). Standard errors are clustered on the country-vegetation-zone-year level and shown in parentheses. All specifications include country×year fixed effects and baseline individual and grid-level controls (of Table 2 columns 4-6 and the same variables as reported in Table OA3 column 5), and for urban status and log density. See notes to Table 2 for variable definitions.

Table 4: The effect of droughts on migration

Dependent variable →	Migrant status (at destination)		
Droughts →	all	recurring	first-time
	[1]	[2]	[3]
Drought (at destination)	0.117**	0.110	0.118**
	(0.048)	(0.068)	(0.059)
Drought (at destination) * uneducated	-0.005	0.022	-0.017
	(0.035)	(0.037)	(0.041)
Drought (at destination) * rural (destination)	-0.169***	-0.233***	-0.137*
	(0.061)	(0.088)	(0.074)
Uneducated	0.004	0.004	0.004
	(0.009)	(0.009)	(0.009)
Rural destination	-0.155***	-0.155***	-0.155***
	(0.012)	(0.012)	(0.012)
Country × year fixed effects	✓	✓	✓
Individual and grid-level controls	✓	✓	✓
Observations	501,120	499,778	500,221
R-squared	0.110	0.109	0.109
Clusters	336	334	335
Grids (0.083°×0.083°)	11,979	11,953	11,960
Marg. effect of drought in rural (destination)	-0.051*	-0.123**	-0.019
	(0.028)	(0.053)	(0.026)

Notes: ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level. Sample: individuals aged 0-95 (31% is male). 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 2 for other variable definitions. Sample: individuals aged 15-65 (31% is male). Individual and grid controls are the variables reported in Table OA3 column 5.

Online Appendix

"Droughts and malnutrition in Africa"

Nora Fingado and Steven Poelhekke

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OA1 Descriptive Statistics

OA1.1 Descriptive Statistics (Tables OA1, OA2)

Table OA1: 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.

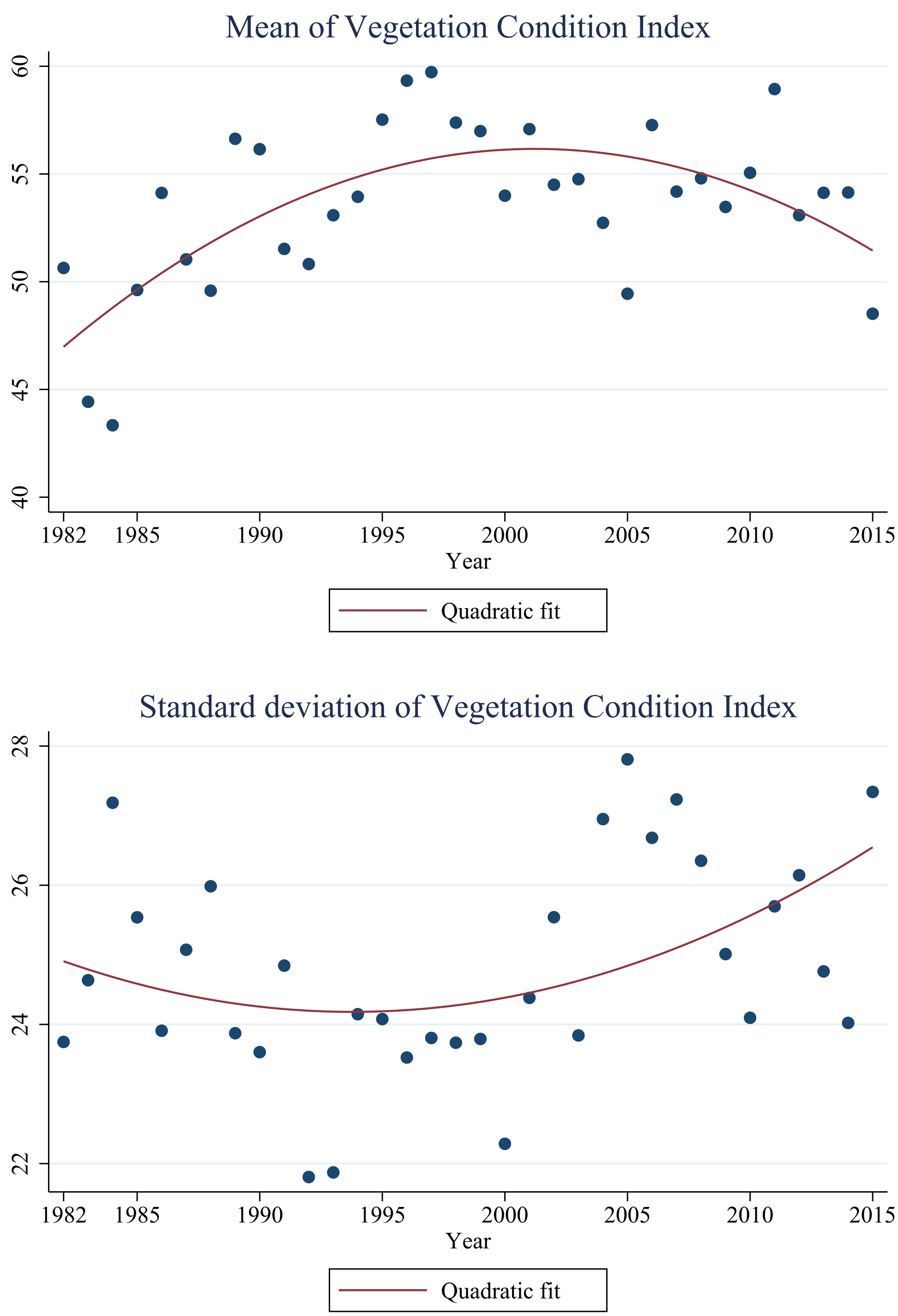
Table OA2: Summary statistics of the countries included in the analysis

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.

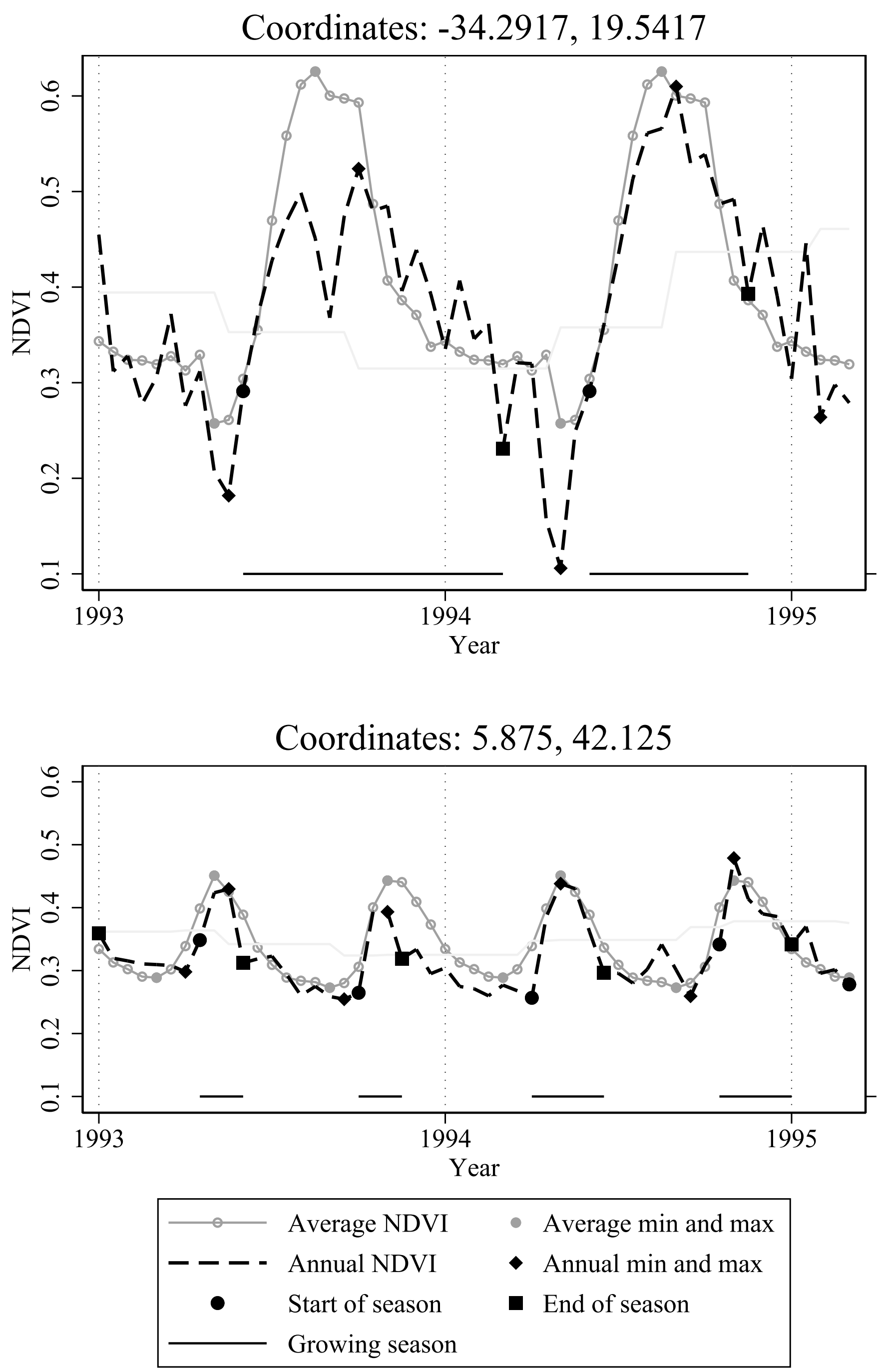
OA1.2 Additional figures (Figures OA1, OA2)

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



Notes: Sample includes 20,021 distinct NDVI grids (of 0.083×0.083 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 (Tables OA3 and OA4)

Control variables are successively added in Table OA3. Column 5 in Table OA3 corresponds to column 1 in Table 2 (our baseline specification), and the full set of control variables is always included in all subsequent columns of Tables OA3 and OA4. Column 6 changes the level of clustering to country-by-years, which does not visibly change the size of the standard errors. Clustering two-way by country and year in column 7 is also very similar. The table looks very similar when we change the dependent variables to first-time droughts (not shown for reasons of brevity). However, when changing the dependent variable to recurring droughts, we find that they are only significant (with 90% confidence) in estimations corresponding to 1-3 of Table OA3 and not in those corresponding to 4-7 (not shown for reasons of brevity).

Table OA4 adds to the baseline specification (which is repeated for ease of reference in column 1) further control variables and fixed effects. In general, the table shows that the main pattern observed in Table 2 is very stable across these additional specifications: all droughts reduce BMI on average (Panel A), while recurring droughts (Panel B) have a much noisier effect than first-time droughts (Panel C).

Column 2 adds the Standardized Precipitation Index (McKee et al., 1993) across the past three months relative to the day of interview (SPI3). We calculate this index using the R-package 'SPEI' and the 'GPCC Full Data Monthly Product Version 2022' (Schneider et al., 2022) of monthly precipitation for all years, at the highest available resolution of a 0.25° grid.[1] The index thus covers an area nine times as large (≈771 km^2) as the drought dummy, which may mask underlying heterogeneity. It is based on modeled and interpolated rainfall data: only 10% of grid-years have a weather gauge (in grids where a DHS household was ever sampled). SPI3 measures the cumulative 3-month rainfall deficit (or surplus) relative to what is normal for that time of year and location in standard deviations.[2] While it tracks

[1] Available at `https://opendata.dwd.de/climate_environment/GPCC/html/fulldata-monthly_v2022_doi_download.html`

[2] We also considered the 2-month and 6-month versions but these are less significant and do not change our results. See also Lloyd-Hughes and Saunders (2002) for a discussion of time windows and comparison to other indices.

meteorological rainfall deficits, it does not capture irrigation (either through infrastructure or natural stream flows) or evapotranspiration which also affect soil moisture (Herrmann et al., 2005; Winkler et al., 2017).[3] With these caveats in mind, we find that it is positively correlated to BMI, but does not visibly affect the severe drought dummy coefficient.[4]

Column 3 adds the average temperature during the three months leading up to the survey date, and the month-of-year average temperature, available at a 0.5° resolution.[5] These additionally control for the effects of evapotranspiration but only marginally attenuate the coefficient of the drought dummy.

Column 4 controls for deforestation, to address the possibility that the drought dummy captures a persistent drop in NDVI that may be caused by deforestation rather than droughts (Querin et al., 2016). We believe this to be unlikely, because the drought dummy is based on a 0.083° grid, such that for it to be capturing deforestation it would require a 86 km^2 area to be cleared in a very short period of time, since droughts are measured over a 3-month period. To test this formally, we create a 0.083° grid that matches the drought dummy grid, using the high-resolution 30×30 meters grid of forest cover and -loss by Hansen et al. (2013). The updated database includes Landsat imagery based tree cover in the year 2000 and annual pixel-level events of forest loss between 2000 and 2021.[6] Forest loss is a dummy defined as a change from a forest to non-forest state. Tree cover at the pixel level is defined between 0 and 100%, which we recode to a dummy if tree cover is $\geq$ 50%. We aggregate the pixels up to a 0.083° grid by counting the share of pixels in a grid cell that is equal to one, and match the resulting vector layer to DHS household locations. The data reveals that the median forest cover in grids with DHS households is only 0.08% (with a mean of 13.07%). Moreover, despite deforestation increasing over time, the largest single deforestation event cleared only 41% of forest in a household's grid during a full year, while the maximum annual

[3] The related Standardised Precipitation-Evapotranspiration Index also includes temperature, but requires rainfall and temperature to be observed on the same grid resolution and time period. Because our temperature data has a lower resolution we control for temperature separately in the next column.

[4] Note that the number of observations is slightly lower because the SPI cannot be calculated in areas without any observed historical rainfall, which are parts of desert and semi-desert vegetation zones.

[5] Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series data provided by the NOAA PSL, Boulder, Colorado, USA, from their website at https://psl.noaa.gov

[6] Version 1.9, available and visualized as .tif raster files at `https://storage.googleapis.com/earthenginepartners-hansen/GFC-2021-v1.9/download.html`. We use PostGIS software to process the very large raster data files and create a vector layer shapefile.

99th percentile is only 6% forest loss. Nevertheless, the result shows that deforestation correlates positively with BMI, possibly because it expands agricultural land, but it does not affect our main results (despite the smaller sample due to the shorter time span). While the greenness of land drops after deforestation in forested cells (Hamunyela et al., 2016), controlling for deforestation events does not explain away extreme events as captured by the extreme deviations in the VCI index that define our drought dummy.

In column 5 we include a household-level dummy for de facto urban status and its interaction with droughts.The urban dummy is equal to one for cities, but also for smaller towns.[7] Given that we find significant migration effects, this variable can also be an outcome of droughts and may thus be a 'bad control'. Urban individuals tend to have higher BMI, presumably due to higher income or better infrastructure and other urban benefits, and urbanity somewhat attenuates the effect of droughts. However, the insignificant interaction shows that the impact of droughts in towns and cities is not different from the impact on rural individuals.

In columns 6 and 7 we add sub-national fixed effects. At the household level, the DHS data is a repeated cross-section such that individual fixed effects are not possible. We measure droughts as extreme deviations of NDVI relative to the long-run time-of-year average of NDVI in that location, which is similar to measuring weather shocks relative to location fixed effects—that absorb long-run averages. In addition, we always control for a broad set of observed time-invariant grid effects (aridity, irrigation %, growing seasons, and long-run time-of-year average NDVI), and country, year and country-by-year fixed effects.[8] At the 0.083° grid level, where we measure droughts, only 34% of grids are surveyed more than once.[9] Adding sub-national fixed effects exploits variation within sub-national areas, but most variation will thus be from comparing individuals observed within the same area and year. With this in mind, in column 6 we add sub-national region fixed effects (and interactions with year dummies), using the borders of the second administrative layer. We fix

[7] See variable v102 in `https://dhsprogram.com/pubs/pdf/DHSG4/Recode7_DHS_10Sep2018_DHSG4.pdf`

[8] Country $\times$ year fixed effects absorb the separate country and year fixed effects.

[9] This number increases to 71% for 0.5° grids, but taking grid averages before adding fixed effects would trow away a lot of data and underlying heterogeneity such as sub-grid differences in droughts that may arise through different vegetation and elevation zones.

borders to the year 2000 to account for any mergers and splits of administrative regions.[10] These render most grid-level variables insignificant (except past droughts, aridity, irrigation % and long-run average NDVI), but we still find that severe droughts affect BMI negatively. Column 7 replaces region fixed effects by 0.5° fixed effects (and interactions with year dummies), where we split grids along country borders such that they are defined within countries. None of the grid-level variables is significant anymore, but we still find a negative effect of severe droughts on BMI.

[10] FAO, 'Sub-national boundaries of Africa (2000)', from `https://data.apps.fao.org/map/catalog/srv/eng/catalog.search#/home`

Table OA3: Adding control variables sequentially and alternative clustering

Dependent variable →	log BMI						
	Clustered by country × year × vegetation-zone					Clustered by country × year	Clustered by country & year
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Drought (all, 3 months)	-0.028***	-0.023***	-0.026***	-0.021**	-0.025***	-0.025***	-0.025***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
Individual controls:							
Uneducated		-0.042***	-0.042***	-0.039***	-0.037***	-0.037***	-0.037***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Uneducated head of household		-0.041***	-0.041***	-0.039***	-0.038***	-0.038***	-0.038***
		(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Age		0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male		-0.093***	-0.093***	-0.094***	-0.093***	-0.093***	-0.093***
		(0.006)	(0.006)	(0.006)	(0.006)	(0.009)	(0.012)
Grid-level controls:							
Number of past drought periods			-0.002***	-0.001*	-0.002***	-0.002**	-0.002*
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Surveyed during growing season			-0.006**	-0.006***	0.001	0.001	0.001
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Aridity index				0.046***	0.068***	0.068***	0.068***
				(0.006)	(0.008)	(0.009)	(0.011)
Irrigation %				0.010***	0.009***	0.009***	0.009***
				(0.001)	(0.001)	(0.001)	(0.002)
NDVI growing seasons per year					0.010***	0.010***	0.010***
					(0.002)	(0.002)	(0.003)
Long-run time-of-year average NDVI					-0.079***	-0.079***	-0.079***
					(0.011)	(0.012)	(0.012)
Country × year fixed effects	✓	✓	✓	✓	✓	✓	✓
Observations	585,703	479,455	479,447	479,447	479,447	479,447	479,447
R-squared	0.089	0.188	0.188	0.192	0.195	0.195	0.195
Clusters	433	433	433	433	433	94	31 & 23
Grids (0.083×0.083 degrees)	15640	15630	15629	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 65.

Table OA4: Additional control variables

Dependent variable →	log BMI						
Panel A: All droughts							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Drought	-0.025***	-0.025***	-0.021**	-0.024***	-0.017**	-0.013**	-0.013**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.005)	(0.006)
SPI3 precipitation index		0.000**	0.000**	0.000**	0.000***	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temperature, mean of previous 3 months			-0.001***	-0.001***	-0.001***	-0.000	0.001
			(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Temperature, month-of-year mean			-0.001***	-0.001**	-0.001**	-0.001*	-0.000
			(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Forest cover in year 2000				-0.012**	-0.001	0.002	0.000
				(0.005)	(0.005)	(0.008)	(0.005)
Annual forest loss				0.301**	0.218**	-0.009	0.046
				(0.134)	(0.099)	(0.108)	(0.125)
Urban					0.056***	0.050***	0.045***
					(0.002)	(0.002)	(0.002)
Drought * urban					0.014		
					(0.015)		
Fixed effects:							
Country (c), year (t), and $c \times t$	✓	✓	✓	✓	✓		
Country-region (r), year (t), and $r \times t$						✓	
Country-grid (0.5°, g), year (t), and $g \times t$							✓
Observations	479,447	478,307	478,307	415,626	415,626	415,621	415,599
R-squared	0.195	0.195	0.196	0.196	0.214	0.233	0.257
Panel B: Recurring droughts							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Drought	-0.033	-0.032	-0.028	-0.027	-0.018	-0.021	-0.008
	(0.020)	(0.020)	(0.020)	(0.020)	(0.018)	(0.017)	(0.022)
Drought * urban					0.020		
					(0.018)		
Same controls as in Panel A	✓	✓	✓	✓	✓	✓	✓
Observations	478,405	477,265	477,265	414,652	414,652	414,647	414,626
R-squared	0.195	0.195	0.196	0.196	0.213	0.233	0.257
Panel C: First-time droughts							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Drought	-0.023**	-0.023**	-0.019*	-0.023**	-0.017*	-0.011**	-0.014**
	(0.011)	(0.010)	(0.010)	(0.010)	(0.009)	(0.005)	(0.006)
Drought * urban					0.012		
					(0.017)		
Same controls as in Panel A	✓	✓	✓	✓	✓	✓	✓
Observations	479,134	477,994	477,994	415,313	415,313	415,308	415,286
R-squared	0.195	0.195	0.196	0.196	0.213	0.233	0.257

Notes: ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level. Standard controls of Table OA2.1, column [5], are always included. Panels B and C only show the main coefficients of interest for brevity but include the same variables as Panel A. *Droughts* are severe droughts lasting at least three consecutive months. SPI3 is the Standardized Precipitation Index across a 3 months period. *Forest cover in year 2000* and *Annual forest loss* are 0.083° (≈ 9 × 9km) grid averages of dummies defined at 30 × 30 meter pixels: =1 if at least 50% forest cover, and =1 if significant forest loss event occurred in that year, respectively. Standard errors in parentheses and clustered by country × year × vegetation-zone, and column [6] additionally clusters (two-way) by country-region and column [7] additionally by country-0.5° grid. Sample: individuals aged 15 to 65.

OA2.2 Droughts of various length (Table OA5)

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

Dependent variable →	log BMI			
Droughts →	all, 1 month	all, 2 months	all, 3 months	all, 6 months
	[1]	[2]	[3]	[4]
Drought	-0.004	-0.015**	-0.025***	0.005
	(0.004)	(0.008)	(0.009)	(0.005)
Uneducated	-0.037***	-0.037***	-0.037***	-0.037***
	(0.002)	(0.002)	(0.002)	(0.002)
Uneducated head of household	-0.038***	-0.038***	-0.038***	-0.038***
	(0.001)	(0.001)	(0.001)	(0.001)
Age	0.004***	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Male	-0.093***	-0.093***	-0.093***	-0.093***
	(0.006)	(0.006)	(0.006)	(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			
Drought is the first in... →	4 years	5 years	6 years	10 years
	[1]	[2]	[3]	[4]
Drought (first-time)	-0.0230**	-0.0230**	-0.0228**	-0.0202*
	(0.0105)	(0.0105)	(0.0106)	(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 (0.083×0.083 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 7-9 of Table 2 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	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Drought	-0.002	-0.004	0.000	-0.008	-0.021***	-0.031***	-0.033***	-0.040**	-0.045
	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)	(0.012)	(0.020)	(0.038)
Drought * uneducated	-0.051**	-0.029**	-0.021	-0.004	0.014	0.018*	0.022*	0.019	0.010
	(0.023)	(0.014)	(0.014)	(0.013)	(0.011)	(0.011)	(0.012)	(0.018)	(0.035)
Uneducated	-0.018***	-0.019***	-0.022***	-0.025***	-0.030***	-0.035***	-0.044***	-0.058***	-0.077***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Marg. effect of drought if uneducated	**-0.053****	**-0.034****	-0.021	-0.012	-0.008	-0.013	-0.011	-0.021	-0.035
	(0.021)	(0.013)	(0.014)	(0.013)	(0.010)	(0.010)	(0.010)	(0.012)	(0.018)
Panel B: recurring droughts	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Drought	0.029	0.005	-0.000	-0.008	-0.036	-0.040	-0.062*	-0.052	-0.078
	(0.022)	(0.022)	(0.023)	(0.022)	(0.022)	(0.026)	(0.032)	(0.038)	(0.052)
Drought * uneducated	-0.108*	-0.055	-0.043	-0.023	0.020	0.029	0.048	0.041	0.043
	(0.066)	(0.035)	(0.031)	(0.027)	(0.029)	(0.031)	(0.033)	(0.040)	(0.059)
Uneducated	-0.018***	-0.019***	-0.022***	-0.025***	-0.030***	-0.035***	-0.043***	-0.058***	-0.077***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)
Marg. effect of drought if uneducated	-0.079	-0.051*	-0.044**	-0.031	-0.016	-0.011	-0.015	-0.011	-0.034
	(0.056)	(0.027)	(0.021)	(0.020)	(0.019)	(0.021)	(0.023)	(0.031)	(0.046)
Panel C: first-time droughts	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Drought	-0.009	-0.006	0.000	-0.008	-0.018**	-0.029***	-0.026*	-0.039*	-0.037
	(0.010)	(0.008)	(0.009)	(0.009)	(0.009)	(0.011)	(0.014)	(0.022)	(0.044)
Drought * uneducated	-0.034**	-0.021*	-0.013	0.003	0.013	0.015	0.016	0.014	0.002
	(0.017)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.017)	(0.022)	(0.042)
Uneducated	-0.018***	-0.019***	-0.022***	-0.025***	-0.030***	-0.035***	-0.044***	-0.058***	-0.077***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Marg. effect of drought if uneducated	-0.044***	-0.028**	-0.012	-0.005	-0.005	-0.014	-0.01	-0.025	-0.035
	(0.016)	(0.013)	(0.014)	(0.014)	(0.011)	(0.012)	(0.012)	(0.015)	(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	0.004	0.006	0.022	0.008	-0.002
	(0.005)	(0.004)	(0.019)	(0.011)	(0.008)
Drought * uneducated	-0.000	0.001	-0.015	-0.012	0.003
	(0.006)	(0.008)	(0.023)	(0.017)	(0.008)
Uneducated	0.009***	0.007**	-0.001	-0.071***	-0.010***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Observations	1,065,290	1,065,290	1,065,290	1,065,290	1,065,290
R-squared	0.060	0.079	0.063	0.094	0.058
Panel B: Recurring droughts					
	[1]	[2]	[3]	[4]	[5]
Drought	0.006	0.006	0.013	0.012	0.024**
	(0.009)	(0.007)	(0.012)	(0.013)	(0.010)
Drought * uneducated	-0.000	0.011	-0.000	-0.022	-0.017
	(0.011)	(0.011)	(0.021)	(0.021)	(0.018)
Uneducated	0.009***	0.007**	-0.001	-0.071***	-0.010***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Observations	1,062,771	1,062,771	1,062,771	1,062,771	1,062,771
R-squared	0.060	0.079	0.063	0.093	0.058
Panel C: First-time droughts					
	[1]	[2]	[3]	[4]	[5]
Drought	0.002	0.006	0.027	0.006	-0.016*
	(0.005)	(0.006)	(0.027)	(0.012)	(0.009)
Drought * uneducated	-0.000	-0.005	-0.023	-0.006	0.014
	(0.007)	(0.009)	(0.029)	(0.016)	(0.009)
Uneducated	0.009***	0.007**	-0.001	-0.071***	-0.010***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Observations	1,063,789	1,063,789	1,063,789	1,063,789	1,063,789
R-squared	0.060	0.079	0.063	0.093	0.058

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. Sample: individuals aged 15-65.

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, from Landsat 4 onward (Vermote et al., 2016; Masek et al., 2006).[11]

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.[12] 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. While the raw AVHRR data has a resolution of 500m for spectral bands 3-5, the composite processed data has a resolution of 0.083 degrees, corresponding to a length of approximately 9.26 km at the equator.

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

[11] See also `https://www.usgs.gov/landsat-missions/landsat-normalized-difference-vegetation-index`.
[12] Currently available for download from `http://poles.tpdc.ac.cn/en/data/9775f2b4-7370-4e5e-a537-3482c9a83d88/`.

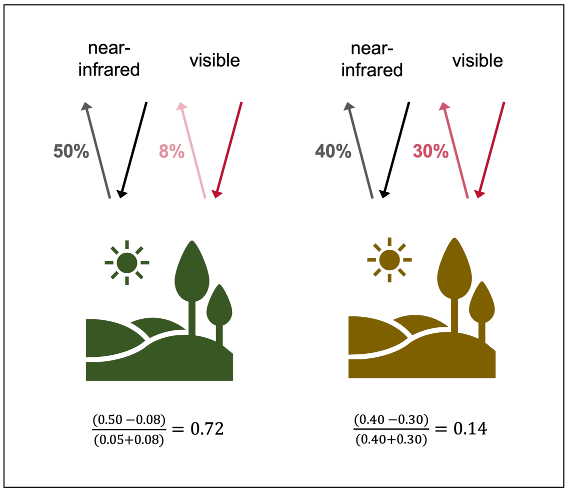
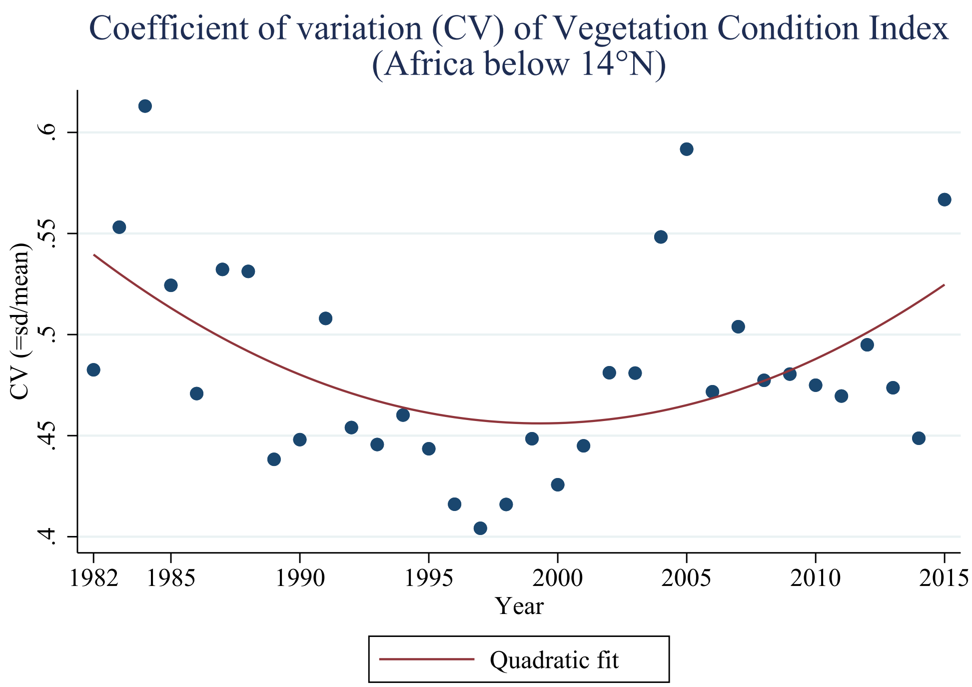


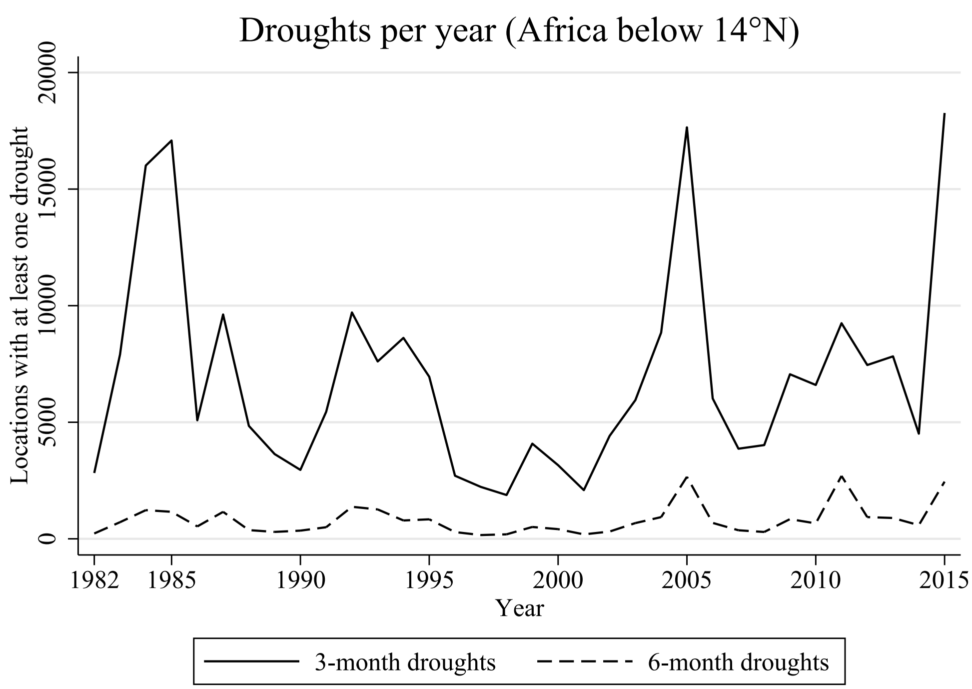
Figure OA3: Reflected radiation by different types of vegetation (following Weier and Herring, 2000)

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.

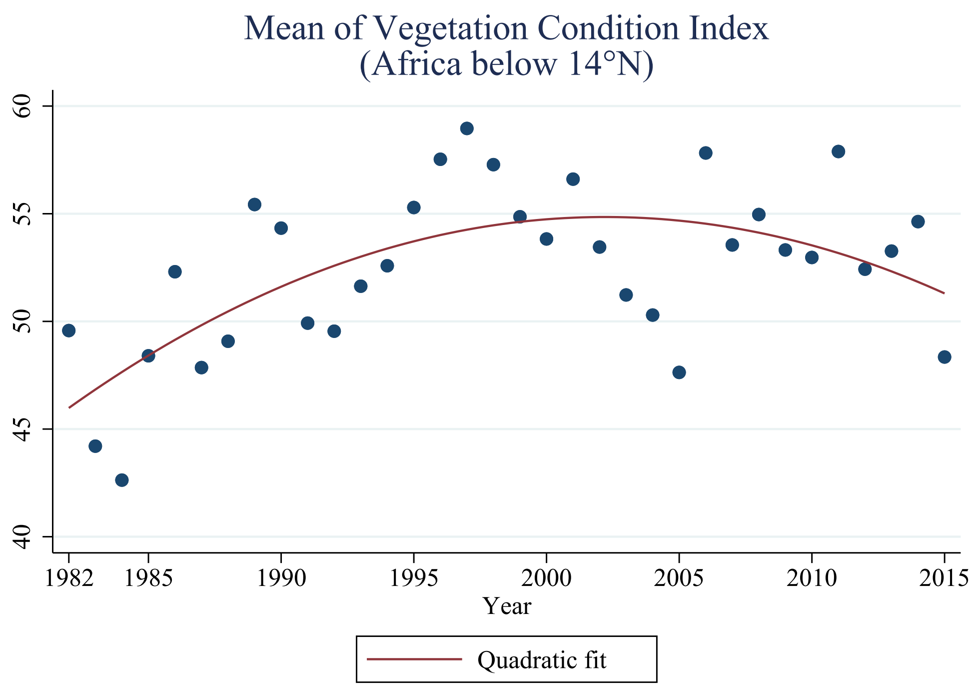
Figure OA4: Vegetation index and droughts: Africa below 14°N

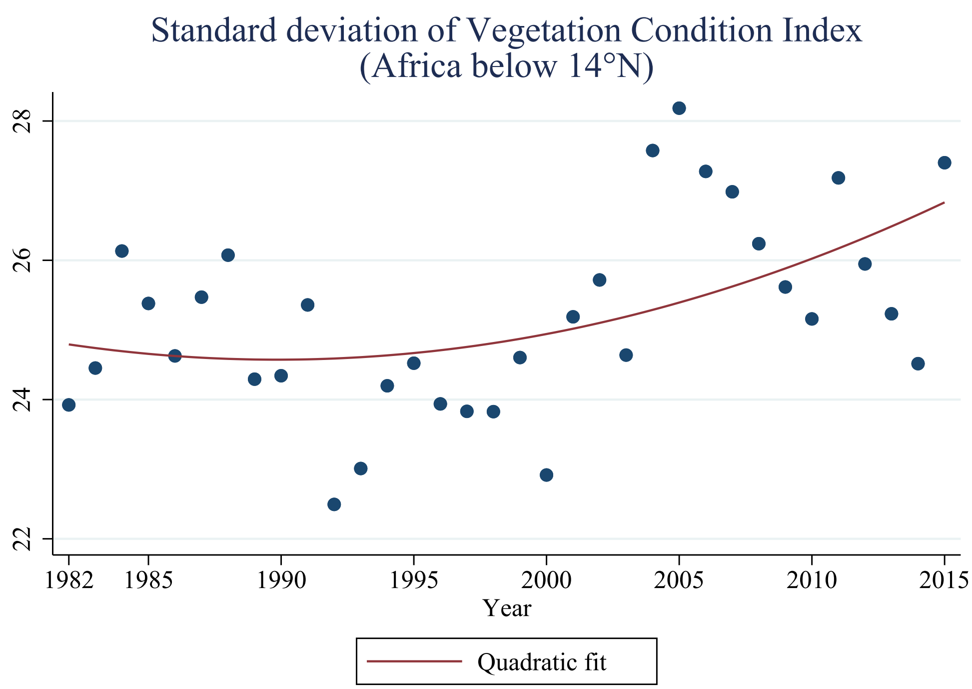




Notes: Sample includes 225,110 distinct NDVI grids (of 0.083×0.083 degrees) in Africa below 14°N latitude. 95% of individuals surveyed in the DHS live below this latitude.

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





Notes: Sample includes 225,110 distinct NDVI grids (of 0.083×0.083 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)

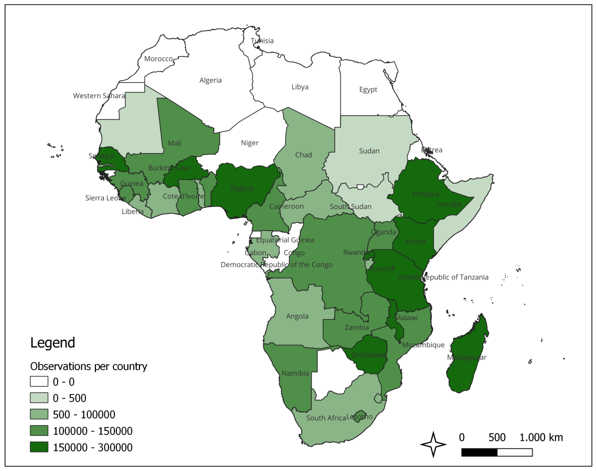


Figure OA6: Location of DHS survey households

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