# Climate Anomalies and International Migration: A Disaggregated Analysis for West Africa*

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**Abstract**

West Africa is vulnerable to negative impacts of climate change and a potential channel of adjustment is migration. Using novel geo-referenced and high-frequency data, we investigate the extent to which soil moisture anomalies have an impact on international migration within the region and directed to Europe. Our findings show that drier soil conditions decrease rather than increase the probability to migrate. A standard deviation decrease in soil moisture leads to a 2 percentage points drop in the probability to migrate, which is equivalent to a decrease of about 25% in the number of migrants. This effect is concentrated during the crop-growing season, suggesting that the decrease in migration is mainly driven by financial constraints. The effect is only seen for areas that are in the middle of the income distribution, with no impact on the poorest or richest areas of a country.

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# 1 Introduction

In the coming decades, hundreds of millions of people are expected to be exposed to the impacts of climate change. Extreme weather events, such as heatwaves and droughts, could increasingly become the norm. This trend is expected to have serious impacts on agricultural production (IPCC, 2014) and, by implication, to disproportionately affect poor economies where agriculture continues to be the main source of employment, livelihood, and income (see e.g., Barrios *et al.*, 2010). In light of a large influx of asylum applicants and a strong shift in the political landscape in favor of a reduction of immigration in recent years, European policymakers are concerned that the changing climate can exacerbate migration pressures (EC, 2020).[1]

In fact, when faced with worsening conditions, an important channel of adjustment for people may be international migration (see e.g., Black *et al.*, 2011a; Cattaneo *et al.*, 2019). While the effects of extreme weather events might increase the desire to migrate, they may simultaneously decrease the ability to migrate due to lower income or more severe liquidity constraints where the dependency on the agriculture sector is relatively strong (Cai, 2020; Black *et al.*, 2011b). It is therefore unclear how migration will change as a result of climate change, and the current literature using country-level, decadal data finds contradicting results. For instance, Beine and Parsons (2017) find zero impacts for poor countries, but a decrease in migration among middle-income countries. Cattaneo and Peri (2016) find the opposite, with higher temperatures in middle-income economies increasing migration rates, while decreasing migration in poor countries.[2]

In this paper, we analyze the impact of slow-onset climate anomalies on international migration, using data that are disaggregated in both time and space for West Africa, in order to contribute to the existing literature in three ways.[3] First, the high level of spatial

[1]According to Eurostat data, nearly one million people arrived from Sub-Saharan Africa alone between 2010 and 2017 (Connor, 2018).

[2]This does not only hold for studies examining slow onset events but also studies concerned with natural disasters (Cattaneo *et al.*, 2019).

[3]Slow-onset events are considered ones that take a longer period to develop such as warming, droughts, and land degradation, as compared to fast-onset events like floods, storms, and hurricanes that happen quite quickly.

and temporal granularity in our data (monthly information at the 55 x 55km sub-national cell level) allows for a more precise estimate of the association between climate anomalies and international migration by exploiting climate anomalies occurring over a short period of time and comparing changes within cells. Second, we are arguably better able to link the migration impacts of climate change to the channel of agricultural production by using deviations in soil moisture from the historic mean as a measure of climate anomalies. Combining temperature and precipitation in one single measure allows us to describe agricultural droughts more accurately at a fine temporal and spatial scale.

Third, we are the first to use a new migration dataset that is collected by the International Organization for Migration (IOM) during the process of migration in West Africa and captures migration both regionally and to Europe.[4] Commonly used census data may miss a large portion of migrants if measured at the origin (due to entire families migrating and not being captured in the data) or destination (due to lower response rates from undocumented migrants).[5] These data enable us to directly relate, for the first time, sub-national variation in climate anomalies with migration directed to Europe. Understanding this relationship is of particular interest to European policymakers who have increasingly focused their migration policy on West Africa, where a large share of asylum applicants are stemming from.[6]

Our identification strategy relies on soil moisture deviations from the month-and-cell-specific long-run average calculated using different time periods and the cell-specific crop growing season. We use cell fixed effects in our regression analyses. In doing so, we are comparing differences over time in these deviations from the long-term average across cells. We analyze the impact of soil moisture anomalies on the probability to migrate and the total number of migrants from a cell. The empirical strategy follows the seminal work of Harari and la Ferrara (2018), which studies the impact of worsening climatic conditions

[4]IOM FMS data have been used so far only to study self-selection of refugees (Aksoy and Poutvaara, 2019).

[5]Also, survey data on intentions as used in Abu *et al.* (2014) may misrepresent migration events if people that want to migrate are not able to.

[6]More than fifty percent of arrivals by sea to Italy in 2017 and 2018 are from individuals originating from West and Central Africa (Abdel Jelil *et al.*, 2018).

on the probability that conflict occurs at the cell level. Besides the outcome variable, we deviate from their work by using both a finer geographical and temporal disaggregation.

Following existing theoretical work (e.g., Cattaneo *et al.*, 2019), we explore agricultural production as a key mechanism through which weather shocks affect migration. Significantly lower soil moisture signals a drought which leads to lower crop production and therefore decreased income. This could lead to higher migration if affected individuals choose to seek opportunities to earn income elsewhere. It may also lead to lower migration if households that otherwise might have sent a migrant abroad now have reduced income and can no longer cover the cost of migration. Migration may also decrease if drought leads to liquidity constraints as households may no longer be able to borrow against their future harvest to cover the cost of migration for someone in the household.

Our results reveal a statistically significant positive relationship between soil moisture from the cell long-run mean and international migration. When distinguishing between positive and negative soil moisture anomalies, we find that drier soil conditions have a strong negative impact on the probability to migrate and on the number of migrants. Compared with normal soil moisture conditions, drier soil conditions by more than one standard deviation decrease the probability to migrate by 2 percentage points and lead to about 25% fewer migrants originating from the cell. This effect is only seen during the growing season, highlighting the relevance of favorable soil moisture conditions for agricultural yields. In contrast to previous literature, we also look at the impacts of positive weather shocks, and find suggestive evidence that wetter soil conditions (improving weather conditions) are related to a higher probability to migrate and a higher total number of migrants at the cell level. These findings may be explained by a general migration desire of many West African farmers, who are only able to realize their migration plans when agricultural yields are large enough to help cover the associated costs.

Consistent with this interpretation, our results show that migration responses to climate anomalies depend on the poverty level of the affected areas. In particular, with the high level of granularity of the data at hand, we find no effect of climate events for areas at the extremes of the income distribution, but a decrease in international migration as a result of drier weather conditions for areas in the middle of the income distribution. This finding suggests that financial constraints indeed offset the positive impact of climate anomalies on migration desires, corroborating the conclusion of previous studies that the impact of climatic change first of all affects individuals' financial constraints. Importantly, however, this does not imply that poor economies are excluded from the consequences of climate anomalies in terms of international migration. Indeed, there are sufficiently prosperous areas within poor economies where climate anomalies reduce emigration. This means that farming families in West Africa who, under normal circumstances, could afford international migration tend to be no longer able to finance the move as a result of climate anomalies.

These findings highlight how dire the consequences of climate change are for vulnerable populations like many farming households in West Africa. Not only are their agricultural yields negatively affected, they are also not able to revert to migration as a coping mechanism due to an even more severe lack of monetary resources. It seems therefore very important that additional adaptation policy actions are taken that protect livelihoods in order to support the well-being of those adversely affected by the shocks.

This paper is structured as follows. The next section presents the literature review and the background on international migration and climate conditions in West Africa. Section 3 describes the data sources that we use in the empirical analysis and provides descriptive statistics. Section 4 outlines the identification strategy. Section 5 presents the results and Section 6 concludes.

# 2 Background

## 2.1 Literature Review

A growing body of literature has investigated the impact of climate change on internal and international migration, mostly focusing on slow-onset events (see, e.g., Beine and Jeusette, 2019; Cattaneo *et al.*, 2019). The empirical evidence has shown contradicting heterogeneous impacts of climate change on migration across countries.

Several studies rely on cross-country comparisons and emphasize agriculture as the leading factor through which climate change relates to international migration. On the one hand, some studies find that rainfall variability (Coniglio and Pesce, 2015) and rising temperatures (Backhaus *et al.*, 2015) increase migration from agriculture-dependent countries to OECD countries (Cai *et al.*, 2016). By focusing on migration to OECD countries, which makes up only 43% of migration for non-OECD countries and only 27% for Sub-Saharan Africa[7], these studies provide an incomplete view of the relationship between migration and climate change that fails to capture the role of intra-regional migration.

On the other hand, Beine and Parsons (2015), using a decade panel of bilateral migration flows with a broader set of destination countries, show that climate anomalies have neither a direct impact on internal nor on international migration. Cattaneo and Peri (2016) and Beine and Parsons (2017) aim to explain the lack of statistical significance with effect heterogeneity across country income levels and report results that differ from one another. Cattaneo and Peri (2016) show that increasing temperatures are associated with significantly higher emigration rates in middle-income countries and lower migration rates in low-income countries. Beine and Parsons (2017) find a negative impact of temperature anomalies on international migration for middle income countries, and no impact for poor countries. The authors argue that anomalies eliminate scale effects and capture deviations in weather from the norm.[8] Yet, as discussed by Bertoli *et al.* (2020), these analyses conducted at the country level could be influenced by other time-varying, country-specific factors occurring during the period that might happen to be correlated with weather events. This is particularly true of studies using temperature over time, which has followed a steady increasing pattern.

The majority of studies using sub-national level data focus on internal migration. For instance, Henderson *et al.* (2017) estimate the impact of long-run soil moisture changes

[7] Calculated using data from UNPD on migration stocks for 2019.

[8] They calculate climatic anomalies as deviations from the countries' precipitation and temperature long-run average, divided by the corresponding standard deviation. The paper shows that not controlling for the long-run volatility of climatic conditions can lead to results with the opposite sign.

on within-district urbanization using census data for a panel of African countries. The findings suggest that unfavorable climatic conditions lead to greater urban population growth. However, the effects are confined to districts that can absorb the potential excess of labor. The only study focusing on international migration using data at the sub-national level for West Africa is Bertoli *et al.* (2020).[9] The study exploits the Standardized Precipitation Evapotranspiration Index (SPEI) and finds that deviations in the index exert a heterogeneous effect across countries on the intentions to move locally. While migration intentions could be a predictor of migration outcomes (see, e.g., Docquier *et al.*, 2014; Bertoli and Ruyssen, 2018), worsening climate conditions have most likely a larger impact on the financial possibilities to migrate, rather than on the desire to move (Beine and Parsons, 2017). Additionally, Docquier *et al.* (2014) find a much lower correlation between migration intentions and migration outcomes for the less educated (which is most aligned with the sample of potential migrants that are affected through the agricultural production mechanism). In this study, we build on Bertoli *et al.* (2020) and use a soil moisture index to measure weather anomalies and their impact on migration behavior, at an even finer spatial granularity. This paper also relates to literature that looks at migration costs and the role of budget restrictions and wealth on migration (McKenzie and Rapoport (2007); Angelucci (2015); Dustmann and Okatenko (2014); Bazzi (2017)). While these studies use household level data and for the most part focus on a single country, we similarly find that it is the middle of the income distribution whose migration decision is affected by financial constraints. One main difference is that these studies look at decreases in costs or decreases in financial constraints, while in this research we examine the impacts of events that can lower income and increase financial constraints, finding that these decrease migration among the middle-income cells.

[9] Other studies that use sub-national level data include Bazzi (2017), who combines census and survey data at the village level for Indonesia and finds that positive rainfall shocks are associated with higher migration in villages with a greater number of small landholders. Mastrorillo *et al.* (2016) focus on inter-district migration in South Africa and find that increasing temperatures as well as positive and negative rainfall shocks increase migration of the disadvantaged population. Studies using individual level data for Indonesia (Bohra-Mishra *et al.*, 2014), Pakistan (Mueller *et al.*, 2014), and Mexico (Jessoe *et al.*, 2018) find that heat stress is associated with an increase in long-term international migration outcomes (mostly from rural areas). However, these studies differ from ours because they focus only on one country.

## 2.2 Migration and Climate in West Africa

About 2.5% of Sub-Saharan Africans live abroad and this share has remained almost constant since the 1960s (European Commission, 2020). In West and Central Africa, migration patterns are characterized by international movements which mainly occur within the region given the free-movement regulations established by the Economic Community of West African States (ECOWAS) and strong networks among ethnic groups (IOM, 2020). In 2017, 70% of Sub-Saharan African migrants remained within the region (European Commission, 2020). These intra-regional flows are mostly due to seasonal or permanent labor mobility along established migration corridors such as Burkina Faso-Ivory Coast and Sierra Leone-Guinea. Intra-regional migrants tend to be low-skilled and their occupations are related to trade or agriculture (Devillard *et al.*, 2015). The main direction of the flows is from north to south, particularly from Sahel West African countries towards the coast, which is richer in minerals and plantations.

Additional relevant flows include migration to Europe, e.g., along the West Mediterranean and Central Mediterranean routes. From 2008 to 2016 the number of first residence permits from the EU to West African citizens increased from 93 thousand to 101 thousand.[10] The main three sending countries were Nigeria, Senegal, and The Gambia. The number of first-time asylum claims saw huge increases during the same time period. From 2010 to 2015, the number of registered asylum claims increased from 18 to 121 thousand (mainly driven by an increase in claims from Nigeria). However, first-time asylum claims have much higher irregularity, with a sudden drop to 61 thousand in 2019.[11]

Climate conditions in Western Africa are tied to the West African monsoon, which starts in May over the Guinean Coast, reaches the Sahel in August, and retreats in October. This period concentrates over 70% of the annual precipitation in the region (Sultan and Gaetani, 2016). Therefore, the climate is subject to the high variability of the monsoon which can differ year-to-year. For this region, climate change could lead to the coexistence of longer dry spells and periods with extreme precipitation intensity

[10] Estimated using data on first residence permits for West African citizens with a duration of 12 or more months issued by the EU-28 excluding permits granted for humanitarian reasons (Eurostat, 2020).

[11] The figures include first-time asylum claims of West African citizens to the EU-28 (Eurostat, 2020).

(Sylla *et al.*, 2016).

In Sub-Saharan Africa, agriculture is sensitive to climate with 95% of crops being rainfed (IPCC, 2019). An increasing degree of unpredictability in rainfall patterns poses a water-scarcity threat for the agricultural sector increasing its vulnerability (UNCCD, 2016). More than half of the total labor force is employed in agriculture in Sub-Saharan Africa, and smallholder farms constitute approximately 80% of all farms, directly employing around 175 million people (OECD-FAO, 2016). Therefore, a large part of the population in Sub-Saharan Africa is at risk of experiencing negative income shocks due to extreme weather events.

Reports from the Food and Agriculture Organization from the United Nations (FAO) provide a summary of the main weather events that caused stress to the region during 2018-2019. In the beginning of 2018, the food security situation in the Sahel was alarming given the poor performance of the 2017 rainy season. Compared to the past five years, Chad, Mauritania, Senegal, Burkina Faso, Mali, and Niger expected agricultural production deficits (FAO, 2018). However, the rainy season in 2018 had an overall positive outcome. In certain countries, e.g., Burkina Faso and Nigeria, above-average rainfall was registered leading to an increase in agricultural production (FAO, 2019). The outcome of the rainy season in 2019 was negative in several countries along the coast of West Africa due to a poor and erratic distribution of rainfall. Rainfall deficits were registered compared to the long-term average in The Gambia, Mauritania, and Senegal, which affected seed germination and crop growth. By September 2019, crop production estimates were 17% lower than the five-year average (FAO, 2020). Table A1 presents a summary of the main weather events for the region.

# 3 Data

We use high-frequency, geo-referenced data from different sources to build a database covering 17 West and Central African countries during 2018 and 2019. The countries included in the sample are Benin, Burkina Faso, Cameroon, Chad, Ivory Coast, The

Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone, and Togo.

*Migration data.* The data to measure migration outcomes come from the Flow Monitoring Surveys conducted by the IOM in Western and Central Africa in 2018 and 2019. The IOM established Flow Monitoring Points (FMP) in areas of significant transit in the region. The FMPs are located in strategic places such as border crossing posts, bus stations, rest areas, police stations, and reception centers to quantify migration flows, trends, and routes. The surveys collect data on a sample of people in transit at each FMP to provide a better understanding of inter- and intra-regional migration patterns.[12]

The data currently cover the period January 2018 to December 2019 and report information on 118,000 individuals. One of the most attractive features of the data is that it provides high-frequency migration data as the surveys are conducted daily. The surveys collect information on the region of origin at a small aggregate level, i.e., village or city, the intended final destination, trip characteristics (e.g., transportation means, number of people traveling together, and difficulties faced during trip), demographic characteristics, planned length of stay at the destination country, and reason for the journey. Each person is only interviewed once along the route.[13]

We identify migrants based on the planned length of stay at destination and the reason for the journey (economic, family reunification, or displacement due to conflict or natural disasters). Thus, we exclude from the sample individuals who report they are traveling for business, to attend a family or religious event, for tourism, and those who plan to return within the week (about 21 thousand individuals). We exclude individuals who departed from regions outside West and Central Africa (9 thousand). We also exclude return migrants (9 thousand), individuals for whom the information on the village of departure (14 thousand) or the country of destination (6 thousand) is missing, and internal migrants (11 thousand). Our final sample consists of 45,789 international migrants.[14]

[12]As of 2018, the IOM had about 35 FMPs in place (see Figure 1).

[13]The first question of the survey filters out migrants who previously answered the questionnaire. Migrants are asked whether they had already participated in the survey and the country where they were surveyed.

[14]Of those included in the sample, 88% report the main reason to migrate as being "Economic" with

To compute the number of migrants per cell, we geo-coded the place of departure at the individual level using the centroid of the village where migrants first departed from. We then aggregate observations at the monthly level based on the survey date. Figure 1 illustrates both the location of the IOM monitoring points (red) and the centroids of the villages where migrants originate from (green). For cells with no international migrants, we use gridded population data to distinguish cells with insufficient population numbers from those with sufficient population and no migration. As a reference, we take the smallest population size of cells where we observe at least one migrant, which is about 200 people. Thus, we assume that total migration equals zero for the specific cell and month if the cell has a minimum population of 200 and we do not observe a migrant originating from the cell, and we exclude cells with a population below 200. Most of the cells excluded from the analysis are located in the Sahel region, where the number of inhabitants is too small.

To confirm the quality of the data, we aggregate the number of international migrants into two destinations: within and outside Africa to the national level and compare the data with other official databases. In Table 1, we show the comparison between the aggregate IOM data and UNPD international migrant stocks. In general, the table shows that the proportion of intra-regional migrants and migrants outside Africa is similar when comparing both databases. The largest differences are found in countries without FMPs in place.

Our data cover two years. Thus, we capture a set of short-run responses to soil moisture anomalies which may differ from the long-run responses to climate change. However, little is known about how the affected population reacts right after the shock to weather shocks that potentially affect agricultural yields. Even if our estimates do not capture long-run effects, they are informative about the immediate response of the affected population.

It is challenging to use the data for measuring internal migration given the location of FMPs and their function of capturing international migration flows. While international migration is not the only mechanism through which individuals can adapt to weather

another 7% citing family reunification and 3% access to services.

shocks, previous evidence shows that rural-to-urban migration matters if urban areas can absorb the excess of labor (Henderson *et al.*, 2017). In West Africa, limited employment opportunities in urban areas have led to important seasonal and circular rural-to-rural international migration in the region (FAO, 2017).

*Climate data.* Soil moisture is an important determinant for plant growth and, together with precipitation and evotranspiration, is a basic component of the hydrological cycle. Thus, our climate measure is based on the Soil Moisture Anomalies index (SMA) at the cell-by-month level. The SMA index is standardized and determines the start and duration of potential meteorological and agricultural droughts. Meteorological droughts are periods with a precipitation deficit compared to the long-run average or due to increased evapo-transpiration caused by higher temperatures. Agricultural droughts occur after a meteorological drought, when the deficit in soil moisture limits the water availability for crops and affects crop growth and yield (EDO, 2019). The SMA index represents the deviation of current conditions from the usual water availability in the soil, and captures the spatial extension of droughts as well as their severity and duration. Higher values of the index correspond to higher soil moisture. Values smaller than $-1$ translate to drought conditions.

We calculate the SMA index following the methodology of the Copernicus European Drought Observatory technical description (EDO, 2019).[15] For each cell, the SMA is calculated as $SMA = (SMI_t - \overline{SMI})/\sigma_{\overline{SMI}}$, where $SMI_t$ is the soil moisture index for the month at time t. $\overline{SMI}$ is the SMI long-run average and $\sigma_{\overline{SMI}}$ the standard deviation, both are calculated using the first year the data are available to the last available full year (i.e, 1948 to 2017 for the index in 2018).

We calculate the soil moisture index (SMI) using the CPC Soil Moisture data (NOAA ESRL PSD, 2020) which provides monthly means from 1948/01 to 2019/12 at a grid size of .5x.5 degrees. The SMI is calculated as $SMI = 1 - \left(\frac{1}{1+(\frac{\theta}{\theta_{50}})^6}\right)$. $\theta$ represents soil moisture at time $t$ and $\theta_{50}$ is the mean between the wilting point and the field capacity.[16]

[15] We deviate from their methodology by using monthly averages instead of a 10-day anomaly.

[16] The wilting point refers to the minimum amount of water in the soil a plant requires not to wilt. The field capacity is the amount of water that stays in the soil after excess water has drained.

We obtain the wilting point and field capacity data from the Global Gridded Surfaces of Selected Soil Characteristics database (Global Soil Data Task Group, 2000) available at a 5 arc minutes resolution.

For the regressions, we calculate the average SMA index for different time periods. We calculate the SMA at time $t = t - 1$ and estimate a running average of the past two to the past twelve months. To avoid extreme outliers we recode the highest and lowest .05% of the SMA index values as missing. Based on this average measure, we build a categorical variable that takes the value 1 if the SMA ranged between -1 and 1, i.e., if soil moisture conditions are normal; 2 if the SMA is below -1, i.e., if soil moisture is drier than the long-run average; and 3 if the SMA is above 1, i.e., if soil moisture is wetter than normal. Finally, following Bertoli *et al.* (2020) we calculate the share of months during which the SMA index varied by more than one standard deviations. We estimate the soil moisture indicators for the months that belong to the cell-specific crop-growing season.

*Crop calendar data.* To identify the months during which climatic conditions affected agricultural production the most, we retrieve crop calendar data from MICRA 2000 (Portmann *et al.*, 2010). These data are available at a grid size of .5x.5 degrees and provide information on the total cultivated area of rainfed and irrigated crops as well as their respective crop-growing season. The data include the crop calendar for 26 irrigated and rainfed crops including major food crops and regionally relevant crops. For this analysis, we identify the most important rainfed crop based on the largest harvested area by cell (e.g., Cassava, Maize, or Sorghum). We create a binary variable indicating if a certain month of the year is part of the crop-growing season of a specific cell. In some cells, we identified perennial crops (e.g., cocoa and coffee), which means that the crop-growing season spans the whole year.

*Population data.* We further complement our database using spatial population data provided by WorldPop for 2018 (WorldPop, 2018). The data are available at 30 arc minute resolution. The data provide an estimate of the number of people per cell (see A3).

*Poverty data.* We proxy poverty at the cell level using data on infant mortality rates (IMR). The data are taken from the Global Subnational Infant Mortality Rates, V2 2015

(CIESIN, 2018). The IMR represents the number of children who died before their first birthday for every 1,000 live births. The data consist of a grid at a spatial resolution of 30 arc seconds. We calculate the average child mortality for each cell in our grid (see Figure A4) and use it as a proxy for poverty since other measures such as GDP per capita are not available at the sub-national level.

We report descriptive statistics in Table 2. The first two columns report the mean and standard deviation for the full sample, columns III and IV for the sub-sample of cells with crops, and the last two columns for the sample of cells that have at least one migrant. For the empirical analysis, we restrict the sample to cells with rainfed crops because we expect the effect of soil moisture anomalies to operate through decreases in agricultural yields. Most of the excluded cells are located in the Sahara desert. Besides the extreme climatic conditions of the area (lack of vegetation and rainfall), the population is mostly nomadic and may exhibit different mobility patterns than in other regions.

On average, 8% of observations (cell-by-month) have at least one migrant and have about one migrant per month. The mean SMA index is -0.081 indicating weather conditions through 2018 and 2019 that have been slightly less favorable than compared to the historical mean. FMPs are found in only 1% of the observations. However, 27% of observations are located within a 200 km radius of an FMP.

The growing season indicator shows that about 35% of observations occur during the crop-growing season, which usually spans from May to October. The average population per cell is about 165 thousand inhabitants and the average child mortality rate is 63 (defined as the number of children who die before their first birthday for every 1,000 live births).[17] The descriptive statistics for the sample of cells with crops and for the group of cells with at least one migrant are similar. The main difference observed is that these cells have a larger number of inhabitants and, accordingly, have more migrants per cell.

To show the sources of variation in our data, we plot the number of international migrants and the SMA index for 2018 and 2019 at the cell level. First, Figure 2 shows that international migrants mainly originate from the northern region and from the coastal

[17]The average mortality rate in OECD countries for 2017 was 3.8 (OECD, 2017).

hinterland of West Africa. Comparing international migration in 2018 and 2019, we observe similar areas of origin, except for Nigeria where a large decrease in the number of international migrants can be observed.

Figure 3 plots the average SMA index for 2018 and 2019. The upper figures present the average SMA index from January to December for 2018 and 2019, respectively. The lower figures present the average SMA index from January to December, but restricted to growing-season months of the respective cells (for the subset of cells with rainfed crops). The figure shows a similar pattern as discussed in Section 2. In general, soil moisture in 2018 was slightly above average, while 2019 was a drier year. For this year, the SMA index reveals drier conditions in northeastern Nigeria, Cameroon and to a lesser extent in Senegal, The Gambia, and Guinea-Bissau.

In Figure A1 and A2, we highlight the advantage of focusing on small geographical units over aggregating the data at the country level. The figures show a close-up of the countries located close to the Gulf of Guinea. Figure A1 plots the average SMA index for March and August in 2018, which correspond to the months before the arrival and retreat of the seasonal monsoon, and the average SMA index in 2018. Panel A, B, and C illustrate the average SMA at the cell level and Panel D, E, F the average SMA at the country level. At the cell level, the maps show important regional differences. For example, North-East Nigeria faced severe drought conditions; but in the rest of the country, soil moisture was above average. When calculating the SMA at the country level, the maps show these extremes net out and soil moisture conditions for the country appear close to normal. Similarly, Figure A2 plots total migration for March and August 2018 as well as the total number of migrants in 2018. The figure shows that by aggregating the data, we loose regional variation in sending areas.

# 4 Empirical strategy

The empirical analysis uses a panel data approach. We construct a database where variables are defined for each raster grid of size .5x.5 degrees of longitude. The unit of observation is the cell-by-month level. To estimate the impact of climate anomalies on international migration, we exploit soil moisture deviations from the long-run mean. We implement a panel data approach that controls for time-invariant cell, month, and country-by-year fixed effects and estimate the following model:

$$Mig_{c,i,m,t} = \alpha + \beta_1 SMA_{c,m,t} + \beta_2 \mathbf{X}_{c,t} + \delta_c + \lambda_m + \mu_{i,t} + \epsilon_{c,i,m,t} \tag{1}$$

The dependent variable $Mig_{c,i,m,t}$ is an indicator of out-migration from cell $c$, located in country $i$, measured at month $m$ during year $t$. We measure migration using (i) a binary variable indicating whether the cell has at least one migrant and (ii) the total number of migrants from the cell at time $m, t$. We estimate a cell fixed effects linear probability model for the binary dependent variable.[18] To account for the count nature and high number of zeros of the continuous dependent variable, we estimate cell fixed effects Negative Binomial regressions. For the total number of migrants, the standard deviation (7.96) is much larger than the mean, which justifies our choice of model. The Negative Binomial model fits the distribution of the dependent variable and allows for overdispersion. Poisson-type models are frequently used by studies looking at migration flows (see, e.g., Mastrorillo *et al.*, 2016; Belot and Ederveen, 2012) given that simply transforming the dependent variable to logarithms and estimating a linear model would lead to misleading elasticities because heteorskedasticity is ignored (Silva and Tenreyro, 2006).[19]

The variable of interest, $SMA$ refers to the Soil Moisture Anomalies Index (SMA). We exploit three main definitions of our variable of interest: (i) the continuous SMA index to estimate the relationship between soil moisture and migration; (ii) a categorical variable indicating if the cell experienced normal, drier, or wetter soil conditions to estimate

[18] Alternatively, we estimate regressions using a Logit model when focusing on the probability to migrate: In Table 4 in the robustness section, we report these results.

[19] Estimates of Negative Binomial Fixed Effects models may suffer from the "incidental parameters" problem. However, the estimator has good properties (see, e.g., Guimaraes, 2008) and has been used in recent studies (see, e.g., Michalopoulos and Papaioannou, 2016; Aghion *et al.*, 2013; Bloom *et al.*, 2013). To address concerns about the strong distributional assumptions of the model, we also estimate all regressions using a PPML model, and obtain similar results. We report PPML estimates of the main specification in Table 5 in the robustness section. The remaining results are available upon request.

the impact of positive and negative shocks; and (iii) the share of months (during the past twelve months) during which the SMA index deviated by more than one standard deviation to measure the intensity of negative shocks, following Bertoli *et al.* (2020).

Most of the literature has focused on temperature or rainfall measures. Yet, plant growth is a function of both rainfall and temperature. The advantage of using an index is that it incorporates the interaction of both measures to identify extreme events. For example, the impact of below average rainfall on agricultural yields could be further exacerbated by above average temperatures (Bertoli *et al.*, 2020).

$\beta_1$ is the coefficient of interest and captures the causal effect of local soil moisture anomalies on international migration. Identification of the effect that climate anomalies have on international migration comes from soil moisture deviations from the cell-specific long-run mean. The main assumption behind our approach is that conditional on the set of fixed effects and control variables, soil moisture anomalies are orthogonal to unobserved determinants of migration at the cell level.

$\mathbf{X}$ is a vector of time-varying cell-specific variables to control for the presence and distance to a Flow Monitoring Point (FMPs). We control for the number of FMPs in the cell to take into account a higher (lower) probability of registering migrants who originate from the cell after the opening (closing) of a monitoring point. To control for cells that do not have an FMP, but are located close to one, we control for the presence of an FMP in a 200 km radius.[20]

$\delta_c$ captures unobserved cell-level time-invariant characteristics such as geographical features which may facilitate or hinder migration from the region, e.g., location of the cell and terrain characteristics. $\lambda_m$ corresponds to monthly fixed effects which capture migration seasonal effects, e.g., higher intra-regional migration during the harvesting season. $\mu_{i,t}$ controls for country-by-year fixed effects to rule out yearly common shocks at the country level. To define the country fixed effects, we assign cells that are shared among more than one country to the country with the largest cell's area. $\epsilon_{c,i,t}$ is the error term. The standard errors are clustered at the cell level.

[20]The results remain unchanged if we control for the distance from a cell to the closest FMP.

The main threats to our identification strategy are threefold. First, unobservable factors affecting migration at the cell level could be correlated with climate anomalies. Changes in climatic conditions are exogenous and in principle randomly assigned by nature (see e.g. Henderson *et al.*, 2017). Dell *et al.* (2014) finds that an equation that controls for climate indicators and other variables that could be influenced by these indicators e.g., socio-political environment, probability of conflict, among others, would not capture the total net effect of climate anomalies on migration. Thus, following Dell *et al.* (2014) and Cattaneo and Peri (2016) we remain parsimonious in our specification by including only fixed effects as controls to identify the total net effect of climate on international migration.

Second, given the specific location of FMPs to capture international migration flows in West Africa, it could be possible that the migration data are not representative of the overall population of migrants in the region. In the robustness section we exclude all cells located within a 200 km radius of an FMP to show that migrants originating from these cells are not driving the results. Additionally, as shown in the previous section when comparing the IOM data with official statistics, the data appears to align better in countries with at least one FMP. Therefore, given that lack of an FMP in a country could lead to underestimates of migration for the country, in the robustness section we conduct the analysis restricting the sample to the countries with at least one FMP.

Finally, we measure the number of international migrants at the cell level using self-reported information on the destination country, while migrants are on-transit. Our measure of international migration could reflect "intentions to migrate", if the individual is not able to complete the journey. In the robustness section, we estimate our model using an alternative measure of international migration taking into account individuals who were surveyed in a different country than their country of origin. Even if migrants have not reached their final destination, they have at least crossed one border and are considered international migrants.

# 5 Results

This section reports our findings, starting with the main findings in sub-section 5.1. We present the relationship between the continuous SMA index and international migration, but then we present results for a categorical variable that distinguishes drier, normal, and wetter soil conditions. We use this categorical definition for the rest of the paper in order to investigate the effect of anomalies on international migration and to be able to distinguish between negative and positive events. The findings suggest that drier conditions are associated with a decrease in the probability to migrate and in the total number of migrants. Wetter conditions, on the other hand, seem to be positively associated with migration, though the relationship is not consistently significant. When we differentiate between migration to Europe and within the region, the results remain unchanged. Sub-section 5.2 shows heterogeneous effects by poverty quintile. We find that the effect is driven by cells in the middle of the distribution. For cells at the extremes, we find no significant effects. Sub-section 5.3 shows possible channels that explain our results. We find that the effects are concentrated in areas with crops, during the growing season, and with little access to irrigation systems. Finally, sub-section 5.4 shows that our results are robust to a number of alternative specifications.

## 5.1 Main Results

***A. Soil Moisture and International Migration***

To identify the effect of soil moisture anomalies on international migration, as a first step, we estimate the impact of the average SMA index calculated at different time intervals ranging from the past month to the past twelve months on i) the probability to migrate and ii) the total number of migrants from a cell. The sample consists of cells with rainfed crops and the SMA index is calculated during growing season months

The estimated coefficients and respective confidence intervals are plotted in Figure 4. The upper figure plots the results using the probability to migrate as the dependent variable. The coefficients show that increases in soil moisture, i.e., improving weather conditions in a cell – due to more rainfall or less extreme temperatures – increase the probability to migrate. All coefficients are positive and statistically significant except for when the SMA is calculated over the past 12 months. Similar results are found in the lower panel, which provides the estimates using the total number of migrants as the dependent variable.

Better weather conditions at the cell level are correlated with more outflow of international migrants, and conversely that would mean that worsening weather conditions are associated with a decrease in migration. On average, a one standard deviation increase in the SMA index leads to an increase in the probability to migrate by 1.5 percentage points and in the total number of migrants by 25%. This suggests that favorable climate conditions lead to higher agricultural yields allowing individuals to afford the costs of migration.

In general, we observe that including additional months to calculate the average SMA index reduces the variation of the indicator, i.e., extreme months are attenuated leading to point estimates that are closer to zero and to larger standard errors. This illustrates the implications of using coarse levels of aggregation. The results for the full sample are similar, but the size of the effect is smaller (see Tables A2 and A3 in the Appendix.).

***B. Positive and Negative Shocks***

While the previous subsection demonstrates a positive correlation between higher soil moisture and migration, the mechanism for this relationship remains unclear. To explore the mechanism, we differentiate between positive and negative soil moisture shocks for the baseline results. We use a categorical variable that indicates if soil moisture conditions are normal, wetter (SMA index$>1$), or drier (SMA index$<-1$) than the long-run mean. Given the aridity of the area, wetter conditions are usually considered as positive shocks. We report the coefficients and respective confidence intervals in Figure 5. The estimates are interpreted with respect to the baseline category: normal conditions. The upper panel presents the results focusing on the probability to migrate as the dependent variable and the lower panel on the total number of migrants.

The figure shows that drier and wetter soil moisture conditions trigger migration responses in different directions. Compared to normal soil conditions, increases in soil moisture are associated with a higher probability to migrate. All the estimated coefficients are positive; however, they are only statistically significant in some specifications. When focusing on the total number of migrants, we observe positive coefficients for the average SMA in the past month to the past seven months. Yet, by including additional months to the average, the coefficients drop to zero and are not statistically significant.

Compared with normal conditions, a decrease in soil moisture is associated with a decrease in the probability to migrate ranging between 1.5 to 3.5 percentage points and with a decrease in the number of migrants ranging between 20 to 30%. Taking the unconditional mean at the cell-by-year level, our estimates would translate to a decrease in the number of international migrants by 3.2.[21] The relationship holds across all specifications using the average SMA index in different time periods. Our results suggest that even if negative shocks broaden the income gap between the affected area and potential destinations, this does not necessarily spur international migration in the region. These results are in line with previous evidence suggesting that hotter and drier climate reduce the ability of rural populations to migrate (Cattaneo and Peri, 2016)[22], and they contradict previous evidence showing that decreases in rainfall and increases in temperature spur international migration in Sub-Saharan Africa (Marchiori *et al.*, 2012; Barrios *et al.*, 2006).

A possible explanation for our results is that Sub-Saharan Africa is more affected by drier conditions given the rural nature of the countries and rare investments in irrigation, which makes the region highly dependent on seasonal rainfall. The lack of rainfall has a direct impact on agricultural production which inhibits the possibility to migrate in order to mitigate the shock. While climate stress can increase the incentives to move as shown by Bertoli *et al.* (2020), we show that it can also limit the capacity of moving. In sub-section 5.3, we further investigate if the decrease in migration after a shock is mainly observed in agricultural areas.

[21] There are, on average, 13 migrants by cell at the yearly level.

[22] The study finds that a 1% increase in temperature would lead to a decrease in the emigration rate of poor countries by 22%.

### *C. Migration to Europe*

We further investigate whether climate shocks have a different impact by destination region. We calculate total migration from the cell to all destinations within the region i.e., to another African country, and total migration to European countries.[23] The estimates presented in Figure 6 are interpreted with respect to the baseline category: normal conditions. The upper panel presents the results focusing on the probability to migrate as the dependent variable and the lower panel on the total number of migrants. The black points show the results using total migration in transit to Europe and the gray points total migration to other countries within the region.

The results show that negative soil moisture shocks decrease the probability to migrate and the number of migrants for both intra-regional migration and migration to European countries. While Beine and Parsons (2017) find that natural disasters, in general, deter migration from low-income countries to neighboring countries, but spur migration to former colonial powers, we find that negative shocks decrease international migration to all destinations. The latter finding is of particular relevance in light of concerns in Europe about rising influx of West African asylum applicants. It does not support the view that climate change increases migration pressures in the European Union. When looking at climate anomalies in West Africa, the opposite, in fact, seems to be the case.

## 5.2 Heterogeneous Effects

In this section, we build on the previous results and estimate heterogeneous responses to soil moisture deviations. We start by analyzing how positive and negative soil moisture shocks affect the probability to migrate and total migration by poverty quintile. To proxy poverty at the cell level, we use raster data on child mortality. In the absence of gridded poverty data, child mortality is a good proxy because it correlates with poverty-related metrics such as income, education, and health status (see, e.g., Barbier, 2015; Barbier and Hochard, 2018a,b). We classify the cells into poverty quintiles and interact this variable

[23] In our sample of international migrants 71.7% migrate to another country within the region, 27.9% to a European country, and only 0.4% to other international destinations.

with the categorical indicator if the cell registered normal, drier, or wetter conditions during the crop-growing season.

Figure 7 plots the estimated coefficients and respective standard errors for wetter and drier soil conditions focusing on the probability to migrate and Figure 8 focusing on total migration. The coefficients are interpreted with respect to the reference category: normal soil conditions in the cell.

Both figures show a similar pattern. For the richest quintiles (first and second), we do not observe significant differences in the probability to migrate or in the number of migrants for cells that experienced drier or wetter soil conditions. At the top of the distribution, the population might not depend on weather conditions to afford the costs of migration. For the third and fourth quintiles, we observe that wetter soil conditions (positive shocks) lead to an increase in migration and drier soil conditions (negative shocks) to a decrease in migration. We argue that the population in these quintiles depends on their agricultural yields to be able to afford the costs of migration. Decreases in soil moisture have a direct impact on agricultural yields, hindering the possibility to move. For the fifth quintile, the estimated coefficients are not significantly different from zero. At the bottom of the distribution, people are so poor they cannot afford the costs of international migration even before the shock, thus we find no significant differences.

Our results are related to previous literature on migration and inequality which shows that an inverse U-shaped relationship between migration and wealth exists (McKenzie and Rapoport, 2007). At the top of the income distribution, people could afford to migrate but lack the incentives to do so, while people at the bottom of the distribution cannot afford to migrate. Those who are in the middle of the distribution have both the means and the incentives to migrate. If their liquidity is directly affected after a negative weather shock, this will limit their capacity to migrate. Figure A5 in the Appendix plots the correlation between the number of migrants and the infant mortality rate, and shows that indeed an inverse U-shaped relationship exists and that most international migrants originate from the middle of the distribution.

In contrast to the findings in Cattaneo and Peri (2016) and Beine and Parsons (2017), our results present a more complex setting where responses are heterogeneous within countries. Drier soil conditions have a direct impact on income, potentially through the reduction of agricultural yields. After a shock, the affected population in the middle of the income distribution may not be able to afford to cover the costs of migration such as transportation or housing (Bryan *et al.*, 2014).

## 5.3 Channels: Agricultural Shocks

In this section, we focus on negative soil moisture shocks to further support our argument that the decrease in international migration mainly operates through a reduction of agricultural yields. We analyze the impact of soil moisture decreases focusing on the intensity of the drought. For this, we construct a continuous variable indicating the share of months – during the past twelve months – in which the SMA index registered values lower than a standard deviation of the local long-term average. Table 3 shows the results focusing on the probability to migrate (Panel A) and on total migration (Panel B).

Columns I and II show the results calculating the share of months during the past 12 months in which the SMA index scored values lower than -1 for all months and only for growing season months, respectively. The estimates in both columns are negative and significant when focusing on total migration as the dependent variable, but the size of the effect is larger when including only growing season months.

In columns III and IV, we conduct placebo tests. In column III, we define the share of months using only non-growing season months. In column IV, we restrict the sample to cells that experienced shocks exclusively during the non-growing season. In general, the estimated coefficients are close to zero and not statistically significant.

Finally, in columns V and VI we show the estimations of the sub-sample of cells without and with irrigated land, respectively. For this, we restrict the sample to cells where the average coverage of irrigated land is higher (lower) than the mean.[24] The results show no significant impact of an increase in the share of very dry months cells with irrigated land, but a negative and significant impact in cells with no irrigation systems in place.

[24]On average, a cell has about 5% of crop land which is irrigated.

Taken together, these findings show that the main channel through which weather anomalies have an impact on migration is likely through the reduction of agricultural production. The decrease in international migration can be explained by shocks that occur during the growing season and in areas that highly depend on seasonal rainfall for crop production. Finally, to show that our results are not driven by long-term trends, we identify i) cells that experienced no droughts during the growing season in the past 5 years, ii) cells that experienced one drought, iii) cells that experienced two or more droughts. We find that the impacts do not vary significantly across areas that experienced more or less droughts in the past. These results focusing on the probability to migrate are reported in Figure A6 in the Appendix.[25]

## 5.4 Robustness Checks

We conduct several robustness tests using our categorical measure of the SMA index which identifies drier and wetter conditions during the crop-growing season and report the results focusing on the probability to migrate in Table 4 and on the total number of migrants in Table 5. We estimate the results for each average SMA measure, but report only the results using the average SMA during the previous month, and the previous three, six, nine and twelve months.

A first concern is that migrants are surveyed in their origin country while in transit; therefore, the dependent variable could be capturing intentions to migrate instead of actual international migration. We restrict the sample to migrants who were surveyed in a different country rather than their country of origin (see Figure A7). While many of these migrants have not reached their final destination country, they have crossed at least one border and their outcomes reflect actual international migration and not intentions. The results reported in Panel A are robust to the alternative measure of international migration.

A second concern is that FMPs are located in strategic places and thus they register a very specific type of migrant, e.g., individuals who reside close to the FMPs. Although

[25]The remaining results are available upon request.

Figure 1 shows that migrants originate from different villages, we estimate the model excluding all cells in a 200 km buffer of a monitoring point. The results remain similar in magnitude and statistical significance. An opposite concern is that the data is not representative of migration patterns in countries where there is no FMP because only a selected group of migrants is captured. In Panel C, we restrict the sample to the countries with an FMP in place i.e., Burkina Faso, Chad, Guinea, Mali, Niger, Nigeria, and Senegal. The results remain robust.

As previously mentioned, migration patterns in Nigeria have been affected by conflict, which led to the internal displacement of over 2 million people and to an increase in the number of asylum claims in Europe. However, migration flows for this region started to decrease in 2016. Figure 2 shows a large decrease in the number of migrants originating from Nigeria. Thus, we conduct the regressions excluding all cells located in Nigeria and report the results in Panel D. The coefficients remain similar in magnitude and are significant in all columns.

An additional concern is that cells that contain borders are assigned to the country with the largest overlapping area. As our definition of the dependent variables is calculated at the cell level, in some cases, we could be capturing migration from two different countries. To show that this is not driving our results, we estimate the regressions excluding all cells that contain a border and report the results in Panel E. The results remain robust in all columns.

In Panel F, we show that the results are not driven by our choice of grid size by conducting the analysis at a different aggregation level. For this, we construct a database at a grid size of 1x1 degrees (4 times larger than our baseline grid) and calculate all the variables using this aggregation level. The estimated coefficients are negative and remain statistically significant.

In Panel G, we report estimates using alternative models. For the binary dependent variable, we estimate a logit model and report the marginal effects. For the continuous variable, we report the estimates of a PPML model – traditionally used by the literature looking at migration flows. In both models, the point estimates and statistical significance remain robust.

Finally, In Panel H we estimate the linear probability model taking into account spatial correlation in terms of distance and time. We estimate Spatial HAC standard errors as suggested by Conley (2008) taking into account a distance of 200 km and a temporal correlation of 12 months. The standard errors are similar to those estimated in our baseline specification.[26]

# 6 Conclusion

In this paper, we provide evidence on the effect of climate anomalies on international migration using spatially disaggregated data that allows us to better associate weather events to the populations affected and their responses. Our empirical strategy relies on within-cell deviations from the month-and-cell-specific long-run average conditions to identify the effect. We also use soil moisture as a measure of droughts, which allows us to more directly isolate agricultural production as a mechanism. Finally, we use a new source of data for migration that systematically captures data during the process of migration, which helps to address some of the biases associated with typical census data, migration intention data or other survey data collected at origin or destination.

We find that drier soil conditions decrease the probability to migrate and the number of migrants at the cell level. Our results suggest that, compared to normal soil moisture conditions, drier conditions are associated with a 20 to 30% decrease in the total number of migrants. This translates to a decrease of 3.2 migrants by cell and month. We find no substantial differences in the size of the effect when focusing on intra-regional migration or migration to European countries. Finally, our results show that migration responses to climate anomalies depend on the poverty level of the affected areas, showing substantial sources of heterogeneity within countries. While we find no effect of soil moisture anomalies for areas at the extremes of the income distribution, we find a decrease in international

[26]The results are also robust to increasing the distance and temporal threshold. These results are available upon request. For the estimations, we use the code by Fetzer (2014) which accounts for spatial correlation with high-dimension fixed effects, an extension of Hsiang (2010).

migration for areas in the middle of the income distribution.

Taken together, our results show that even if climate anomalies increase the incentives to move (Bertoli *et al.*, 2020), they can also limit the capacity of moving, especially among the middle class in poor economies. These findings challenge the idea that the population is forced to move in order to adapt to weather shocks and instead present a scenario where the population is trapped because they cannot afford the costs of migration (Black *et al.*, 2011b; Bryan *et al.*, 2014; Cai *et al.*, 2016; Gazeaud *et al.*, 2019). Our results further support previous findings stating that climate change can increase inequality by widening the gap between the rich and the poor (Burzyńskia *et al.*, 2019). For policymakers, our results indicate that to avoid climate-related humanitarian crises, preventive measures are needed to address the impacts of climate change, such as local-disaster reduction systems and risk diversification (see e.g., Premand and Stoeffler, 2020a,b), i.e., improving the provision of irrigation systems, as well as supporting sustainable development for more resilient rural and urban communities.

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# Figures

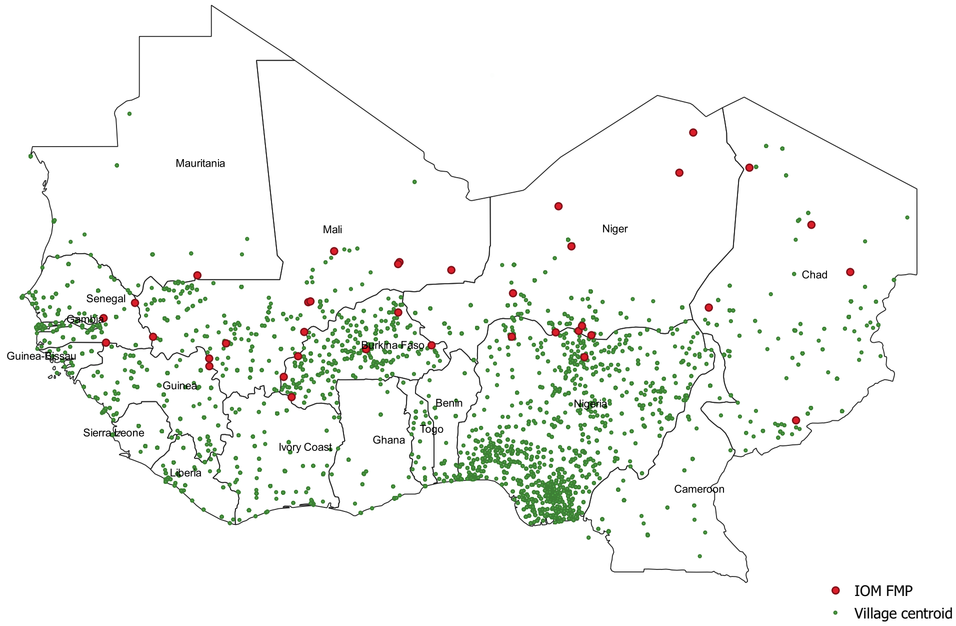


**Figure 1:** Location of FMPs and Villages of Origin
*Source:* Authors' analysis using data from IOM (2019).
*Notes: – The red dots indicate the exact location of the FMPs established by the IOM to monitor migration flows. The green dots indicate the centroid of all origin-villages of migrants.*

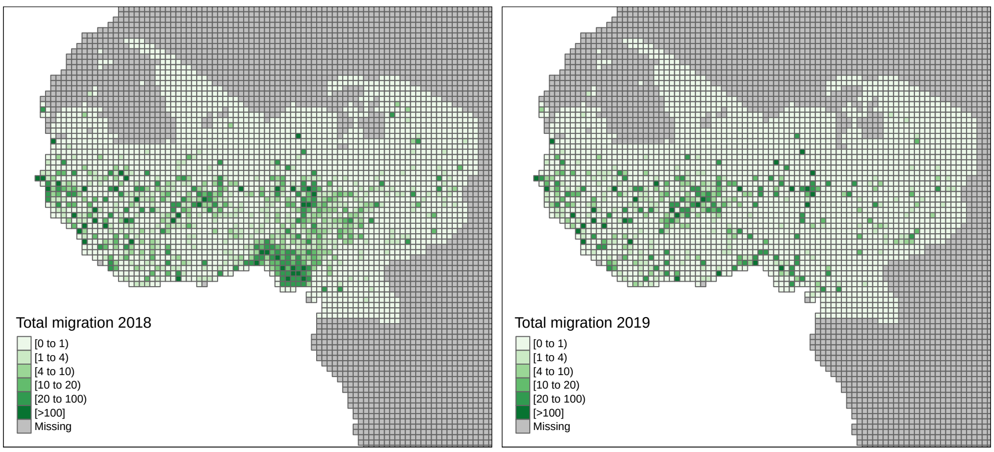


**Figure 2:** Total Number of Migrants by Cell and Year
*Source:* Authors' analysis using data from IOM (2019).

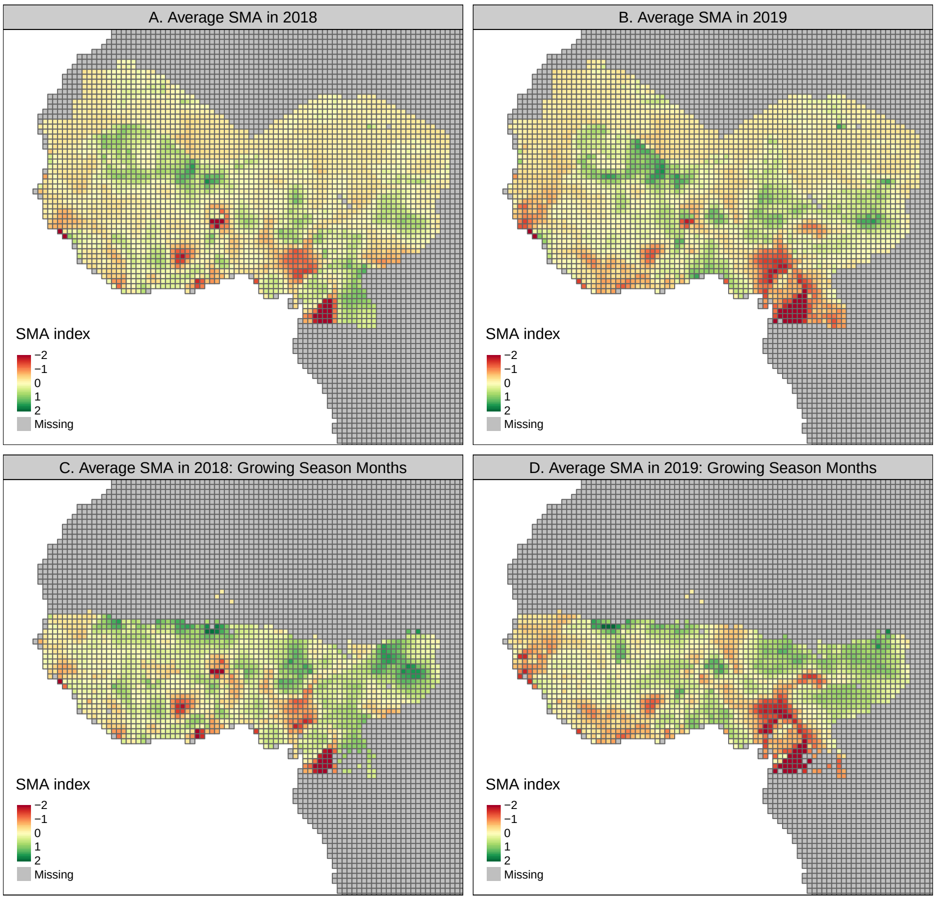


**Figure 3:** Average SMA Index for 2018 and 2019

*Source:* Authors' analysis using data from NOAA ESRL PSD (2020); EDO (2019).

*Notes: – Figures A and B illustrate the average SMA index by cell for 2018 and 2019, respectively. Figures C and D illustrate the average SMA index calculated for the specific crop growing season of the cell in 2018 and 2019, respectively.*

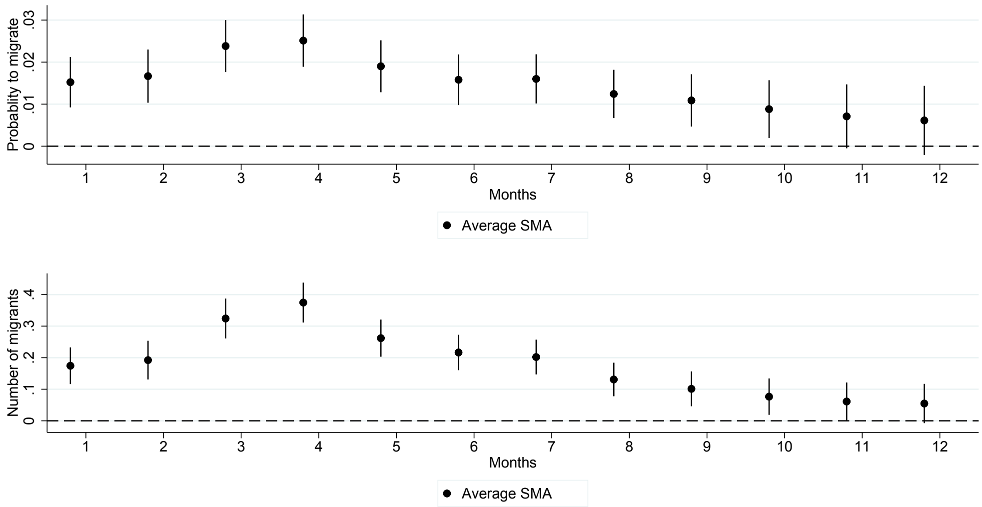


**Figure 4:** Effect of SMA index on International Migration

*Notes: – The figure presents the results of regression models including as the main variable of interest the average SMA index. The index is calculated using growing season months and different time spans ranging from the past month to the past twelve months. For the upper figure, the dependent variable is the probability to migrate. For the lower figure, the dependent variable is the total number of migrants. The regressions include the full set of control variables and fixed effects as presented in Equation (1). – Confidence intervals are calculated at the 95% level and the standard errors are clustered at the cell level.*

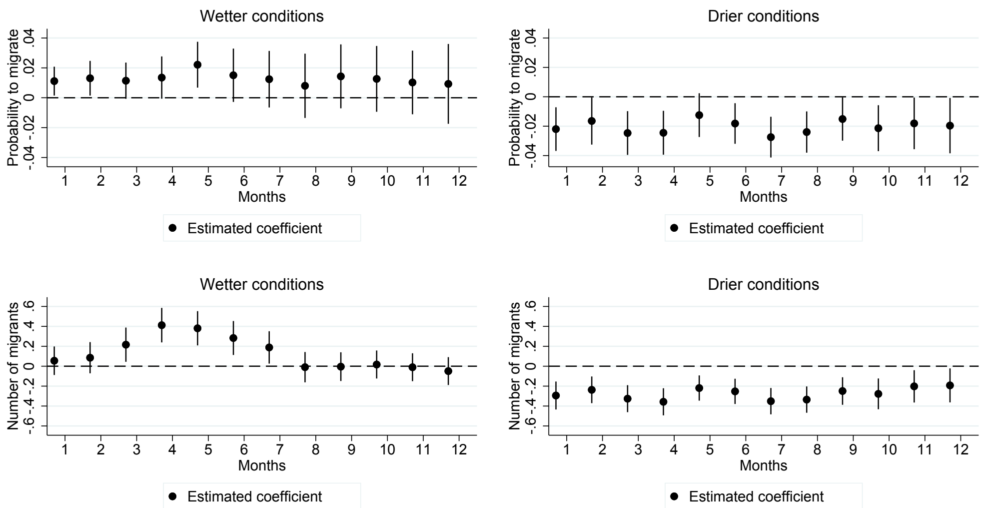


**Figure 5:** Effect of Positive and Negative Soil Moisture Shocks on International Migration

*Notes: – The figure presents the results of regression models including as the main variable of interest a categorical indicator based on the SMA index calculated during growing season months. Drier conditions are SMA index values lower than -1, wetter conditions are SMA values higher than 1. The reference category is "normal conditions" which occur when the SMA index scores between -1 and 1. The dependent variable is the probability to migrate for the upper figures and the number of migrants for the lower figures. The regressions include the full set of control variables and fixed effects as presented in Equation (1). – Confidence intervals are calculated at the 95% level and the standard errors are clustered at the cell level.*

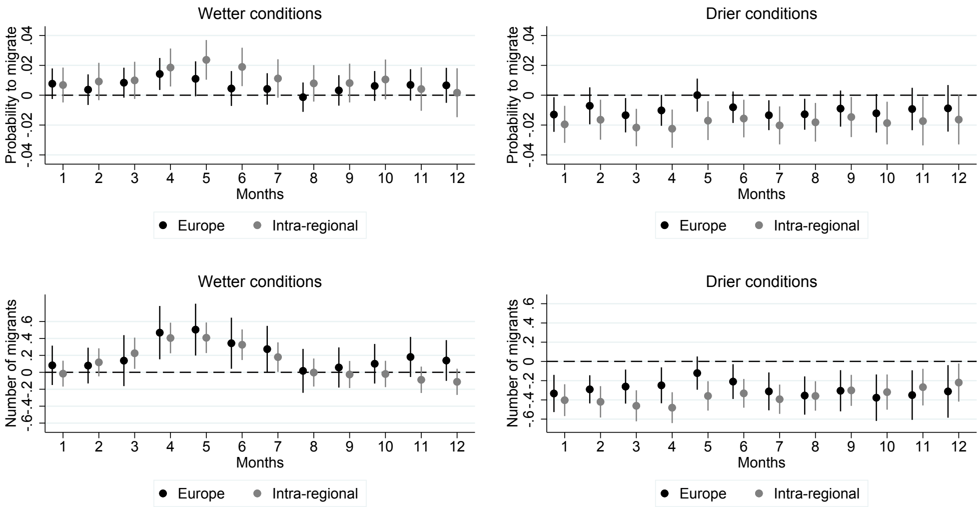


**Figure 6:** Effect of Positive and Negative Soil Moisture Shocks by Destination

*Notes: – The figure presents the results of regression models including as the main variable of interest a categorical indicator based on the SMA index calculated during growing season months. Drier conditions are SMA index values lower than -1, wetter conditions are SMA values higher than 1. The reference category is "normal conditions" which occur when the SMA index scores between -1 and 1. The dependent variable is the probability to migrate for the upper figures and the number of migrants for the lower figures. The regressions include the full set of control variables and fixed effects as presented in Equation (1). – Confidence intervals are calculated at the 95% level and the standard errors are clustered at the cell level.*

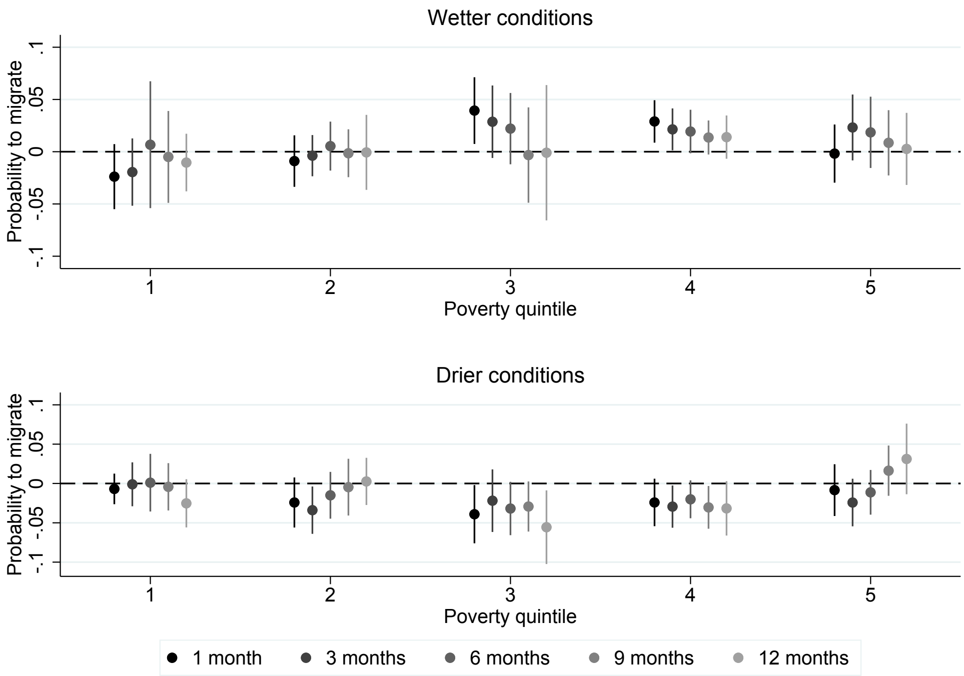


**Figure 7:** Effect of Soil Moisture Shocks on Probablity to Migrate by Poverty Quintile

*Notes: – The figure presents the results of regression models including as the main variable of interest a categorical indicator based on the SMA index calculated during growing season months. Drier conditions are SMA index values lower than -1, wetter conditions are SMA values higher than 1. The reference category is "normal conditions" which occur when the SMA index scores between -1 and 1. The regressions include the full set of control variables and fixed effects as presented in Equation (1). – Confidence intervals are calculated at the 95% level and the standard errors are clustered at the cell level.*

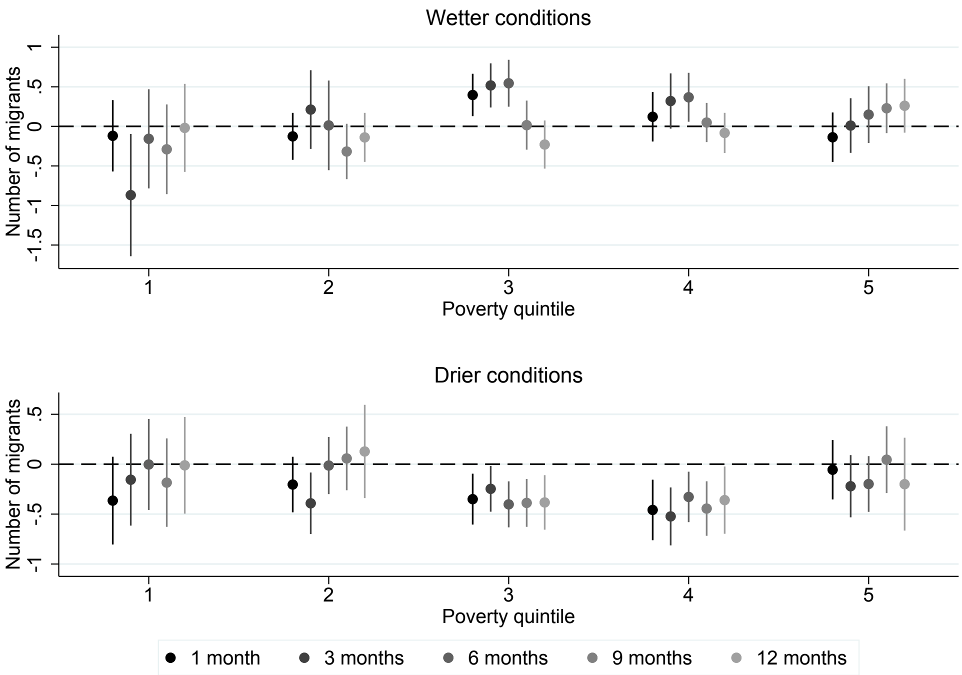


**Figure 8:** Effect of Soil Moisture Shocks on Number of Migrants by Poverty Quintile

*Notes: – The figure presents the results of regression models including as the main variable of interest a categorical indicator based on the SMA index calculated during growing season months. Drier conditions are SMA index values lower than -1, wetter conditions are SMA values higher than 1. The reference category is "normal conditions" which occur when the SMA index scores between -1 and 1. The regressions include the full set of control variables and fixed effects as presented in Equation (1). – Confidence intervals are calculated at the 95% level and the standard errors are clustered at the cell level.*

# Tables

## Table 1: Comparison of International Migration Within an Outside Africa: FMP vs UN Stocks

| | UN Stocks | | | IOM FMPs | | | |
|---|---|---|---|---|---|---|---|
| | Within in % | Outside in % | Total | Within in % | Outside in % | Total | Δ Outside (IOM-UN)[b] |
| Benin | 94.71 | 5.29 | 666,357 | 91.60 | 8.40 | 238 | 3.11 |
| Burkina Faso[a] | 97.99 | 2.01 | 1,581,083 | 92.41 | 7.59 | 3,704 | 5.58 |
| Cameroon | 35.35 | 64.65 | 383,029 | 85.43 | 14.57 | 357 | −50.08 |
| Chad[a] | 89.85 | 10.15 | 206,400 | 92.56 | 7.44 | 766 | −2.71 |
| Côte d'Ivoire | 81.84 | 18.16 | 1,114,003 | 62.61 | 37.39 | 1,471 | 19.23 |
| The Gambia | 17.39 | 82.61 | 118,483 | 47.89 | 52.11 | 1,324 | −30.50 |
| Ghana | 49.34 | 50.66 | 970,625 | 90.07 | 9.93 | 292 | −40.73 |
| Guinea[a] | 77.95 | 22.05 | 530,963 | 78.20 | 21.80 | 17,384 | −0.25 |
| Guinea-Bissau | 56.72 | 43.28 | 103,587 | 69.80 | 30.20 | 255 | −13.08 |
| Liberia | 48.05 | 51.95 | 219,338 | 57.52 | 42.48 | 226 | −9.47 |
| Mali[a] | 90.10 | 9.90 | 1,264,700 | 59.31 | 40.69 | 5,036 | 30.79 |
| Mauritania | 73.67 | 26.33 | 128,506 | 96.47 | 3.53 | 482 | −22.80 |
| Niger[a] | 94.40 | 5.60 | 401,653 | 98.85 | 1.15 | 4,801 | −4.45 |
| Nigeria[a] | 43.83 | 56.17 | 1,438,331 | 38.63 | 61.37 | 6,782 | 5.20 |
| Senegal[a] | 44.61 | 55.39 | 642,654 | 57.83 | 42.17 | 1,992 | −13.22 |
| Sierra Leone | 30.45 | 69.55 | 187,102 | 62.74 | 37.26 | 475 | −32.29 |
| Togo | 86.29 | 13.71 | 543,277 | 87.25 | 12.75 | 204 | −0.96 |
| Total | 71.87 | 28.13 | 10,500,091 | 71.68 | 28.32 | 45,789 | 0.19 |

*Notes: – [a] At least one FMP in the country. – The stocks data were obtained from the UNPD International Migrant Stock Data (UNPD, 2019). We use the stock of international migrants in all destinations to calculate the number of international migrants within Africa and outside Africa by origin country. – [b] Reports the difference between the percentage of migrants residing outside Africa for the IOM and UN data (column V minus column II).*

## Table 2: Descriptive Statistics

| | **All cells** | | **Cells with crops** | | **Cells with a migrant** | |
|---|---|---|---|---|---|---|
| | Mean | S.D. | Mean | S.D. | Mean | S.D. |
| **Dependent variables** | | | | | | |
| At least one migrant | 0.081 | 0.272 | 0.122 | 0.327 | 0.285 | 0.451 |
| Number of migrants | 0.719 | 7.996 | 1.087 | 9.902 | 2.539 | 15.010 |
| **Independent variables** | | | | | | |
| SMA index | −0.081 | 0.732 | −0.071 | 0.836 | −0.080 | 0.779 |
| *Num. of FMPs* | | | | | | |
| No FMP in cell | 0.991 | 0.097 | 0.987 | 0.112 | 0.974 | 0.158 |
| One FMP in cell | 0.009 | 0.094 | 0.012 | 0.109 | 0.024 | 0.153 |
| Two FMP in cell | 0.000 | 0.022 | 0.001 | 0.027 | 0.002 | 0.042 |
| FMP in 200km radius | 0.265 | 0.442 | 0.305 | 0.460 | 0.352 | 0.478 |
| Growing season | 0.348 | 0.476 | 0.538 | 0.499 | 0.522 | 0.500 |
| Population (in thousands) | 165.312 | 470.121 | 252.579 | 564.878 | 452.678 | 803.984 |
| Child mortality rate | 62.938 | 21.257 | 70.244 | 18.499 | 70.502 | 17.065 |
| Observations | 60,528 | | 39,126 | | 16,754 | |

*Notes: – The table reports the mean and standard deviation for the full sample, the sample of cells with rainfed crops, and for the sample of cells where at least one migrant is observed. The values are calculated at the cell-by-month level.*

**Table 3:** INTENSITY OF NEGATIVE SOIL MOISTURE SHOCKS AND IMPACT ON INTERNATIONAL MIGRATION

| | I | II | III | IV | V | VI |
|---|---|---|---|---|---|---|
| | **All months** | **Growing months** | **Non-growing months** | **No crop cells** | **No irrigation cells** | **Irrigation cells** |
| **A. Probability to migrate** | | | | | | |
| Intensity >1sd[a] | −0.025 | −0.035* | −0.013 | −0.034 | −0.033 | −0.112 |
| | (0.018) | (0.021) | (0.037) | (0.031) | (0.021) | (0.145) |
| Observations | 39,126 | 39,126 | 39,126 | 21,375 | 36,129 | 2,997 |
| **B. Total migration** | | | | | | |
| Intensity >1sd[a] | −0.335** | −0.734*** | −0.001 | −5.137 | −0.824*** | −0.170 |
| | (0.131) | (0.195) | (0.221) | (3.359) | (0.206) | (0.944) |
| Observations | 16,754 | 16,754 | 16,754 | 543 | 15,125 | 1,629 |
| Cell FE | yes | yes | yes | yes | yes | yes |
| Month FE | yes | yes | yes | yes | yes | yes |
| Country-by-year FE | yes | yes | yes | yes | yes | yes |

*Notes: – Results are obtained from a linear probability model for Panel A and from a negative binomial model for Panel B. – [a]Refers to the share of months that the SMA index registered values smaller than −1 during the past 12 months. – Standard errors in parenthesis (clustered at the cell level). – *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.*

**Table 4:** EFFECT OF POSITIVE AND NEGATIVE SOIL MOISTURE SHOCKS ON THE PROBABILITY TO MIGRATE: ROBUSTNESS CHECKS

| | 1 month | 3 months | 6 months | 9 months | 12 months |
|---|---|---|---|---|---|
| **A. On the move** | | | | | |
| *SMA Ref:. Normal conditions* | | | | | |
| Drier than normal | $-0.011^{*}$ | $-0.023^{***}$ | $-0.015^{***}$ | $-0.007$ | $-0.009$ |
| | (0.006) | (0.006) | (0.005) | (0.005) | (0.006) |
| Wetter than normal | $-0.006$ | $-0.002$ | 0.005 | 0.003 | 0.005 |
| | (0.005) | (0.004) | (0.005) | (0.004) | (0.005) |
| Observations | 21,087 | 26,441 | 34,368 | 39,117 | 39,126 |
| **B. No FMP in a 200 km buffer** | | | | | |
| *SMA Ref:. Normal conditions* | | | | | |
| Drier than normal | $-0.021^{***}$ | $-0.017^{**}$ | $-0.018^{***}$ | $-0.013^{*}$ | $-0.019^{**}$ |
| | (0.008) | (0.007) | (0.007) | (0.007) | (0.010) |
| Wetter than normal | $0.014^{*}$ | 0.007 | 0.009 | 0.008 | 0.005 |
| | (0.007) | (0.007) | (0.008) | (0.007) | (0.008) |
| Observations | 15,274 | 19,024 | 24,280 | 27,194 | 27,202 |
| **C. Only countries with an FMP** | | | | | |
| *SMA Ref:. Normal conditions* | | | | | |
| Drier than normal | $-0.041^{**}$ | $-0.042^{**}$ | $-0.032^{**}$ | $-0.029^{**}$ | $-0.033$ |
| | (0.017) | (0.017) | (0.014) | (0.015) | (0.021) |
| Wetter than normal | $0.025^{***}$ | $0.026^{***}$ | $0.023^{**}$ | 0.007 | 0.008 |
| | (0.009) | (0.009) | (0.009) | (0.008) | (0.010) |
| Observations | 11,151 | 15,121 | 21,043 | 24,729 | 24,737 |
| **D. Excluding Nigeria** | | | | | |
| *SMA Ref:. Normal conditions* | | | | | |
| Drier than normal | $-0.018^{**}$ | $-0.031^{***}$ | $-0.024^{***}$ | $-0.018^{**}$ | $-0.017^{*}$ |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.010) |
| Wetter than normal | 0.001 | 0.008 | $0.011^{*}$ | 0.000 | $-0.003$ |
| | (0.006) | (0.006) | (0.006) | (0.007) | (0.010) |
| Observations | 17,659 | 21,934 | 28,273 | 32,016 | 32,019 |
| **E. Excluding cells with a border** | | | | | |
| *SMA Ref:. Normal conditions* | | | | | |
| Drier than normal | $-0.024^{***}$ | $-0.023^{***}$ | $-0.018^{**}$ | $-0.021^{**}$ | $-0.022^{**}$ |
| | (0.009) | (0.009) | (0.008) | (0.008) | (0.011) |
| Wetter than normal | $0.015^{**}$ | $0.017^{**}$ | $0.014^{*}$ | 0.002 | 0.008 |
| | (0.007) | (0.008) | (0.008) | (0.008) | (0.009) |
| Observations | 16,008 | 19,910 | 25,691 | 29,168 | 29,173 |
| **F. Grid size 1x1** | | | | | |
| *SMA Ref:. Normal conditions* | | | | | |
| Drier than normal | $-0.087^{***}$ | $-0.088^{***}$ | $-0.038^{*}$ | $-0.008$ | $-0.017$ |
| | (0.020) | (0.019) | (0.019) | (0.021) | (0.025) |
| Wetter than normal | 0.021 | 0.028 | $0.038^{*}$ | 0.019 | $-0.028$ |
| | (0.019) | (0.020) | (0.020) | (0.018) | (0.023) |
| Observations | 5,340 | 6,672 | 8,657 | 9,843 | 9,845 |
| **G. Logit model** | | | | | |
| *SMA Ref:. Normal conditions* | | | | | |
| Drier than normal | $-0.062^{*}$ | $-0.077^{***}$ | $-0.059^{***}$ | $-0.050^{**}$ | $-0.075^{***}$ |
| | (0.032) | (0.024) | (0.018) | (0.023) | (0.028) |
| Wetter than normal | 0.036 | $0.054^{*}$ | $0.050^{**}$ | 0.019 | 0.015 |
| | (0.023) | (0.030) | (0.023) | (0.023) | (0.026) |
| Observations | 7,215 | 9,801 | 14,059 | 16,414 | 16,418 |
| **H. Spatial correlation** | | | | | |
| *SMA Ref:. Normal conditions* | | | | | |
| Drier than normal | $-0.022^{**}$ | $-0.025^{***}$ | $-0.018^{**}$ | $-0.015^{*}$ | $-0.020^{*}$ |
| | (0.009) | (0.008) | (0.008) | (0.009) | (0.010) |
| Wetter than normal | $0.013^{*}$ | $0.017^{**}$ | $0.017^{**}$ | 0.006 | 0.005 |
| | (0.007) | (0.007) | (0.007) | (0.008) | (0.010) |
| Observations | 21,087 | 26,441 | 34,368 | 39,117 | 39,126 |

*Notes: – Results are obtained from a linear probability model. – The categorical variable indicating drier, normal, and wetter soil moisture conditions is constructed using the average SMA index during the growing season of the cell during the past 1, 3, 6, 9 and 12 months. – Drier conditions are SMA index values lower than $-1$, wetter conditions are SMA values higher than 1. The reference category is "normal conditions" which occur when the SMA index scores between $-1$ and 1. – Standard errors in parentheses (clustered at the cell level). – *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.*

**Table 5:** Effect of Positive and Negative Soil Moisture Shocks on Total Migration: Robustness Checks

| | 1 month | 3 months | 6 months | 9 months | 12 months |
|---|---|---|---|---|---|
| **A. On the move** | | | | | |
| *SMA Ref:. Normal conditions* | | | | | |
| Drier than normal | $-0.297^{***}$ | $-0.361^{***}$ | $-0.209^{***}$ | $-0.110$ | $-0.074$ |
| | (0.073) | (0.073) | (0.072) | (0.078) | (0.097) |
| Wetter than normal | 0.036 | 0.004 | 0.097 | 0.031 | 0.003 |
| | (0.092) | (0.112) | (0.117) | (0.098) | (0.094) |
| Observations | 5,352 | 6,676 | 8,772 | 10,099 | 10,099 |
| **B. No FMP in a 200 km buffer** | | | | | |
| *SMA Ref:. Normal conditions* | | | | | |
| Drier than normal | $-0.322^{***}$ | $-0.210^{***}$ | $-0.222^{***}$ | $-0.199^{**}$ | $-0.261^{**}$ |
| | (0.076) | (0.073) | (0.076) | (0.083) | (0.106) |
| Wetter than normal | 0.109 | 0.083 | $0.288^{**}$ | 0.063 | 0.020 |
| | (0.090) | (0.123) | (0.131) | (0.111) | (0.111) |
| Observations | 5,321 | 6,757 | 9,129 | 10,471 | 10,475 |
| **C. Only countries with an FMP** | | | | | |
| *SMA Ref:. Normal conditions* | | | | | |
| Drier than normal | $-0.328^{***}$ | $-0.364^{***}$ | $-0.345^{***}$ | $-0.353^{***}$ | $-0.255^{**}$ |
| | (0.102) | (0.092) | (0.084) | (0.093) | (0.115) |
| Wetter than normal | 0.129 | $0.349^{***}$ | $0.368^{***}$ | 0.015 | $-0.015$ |
| | (0.086) | (0.095) | (0.091) | (0.077) | (0.075) |
| Observations | 4,978 | 7,177 | 10,977 | 13,069 | 13,073 |
| **D. Excluding Nigeria** | | | | | |
| *SMA Ref:. Normal conditions* | | | | | |
| Drier than normal | $-0.265^{***}$ | $-0.552^{***}$ | $-0.330^{***}$ | $-0.305^{***}$ | $-0.177^{*}$ |
| | (0.090) | (0.093) | (0.081) | (0.085) | (0.101) |
| Wetter than normal | 0.052 | $0.264^{**}$ | $0.232^{**}$ | $-0.108$ | $-0.184^{**}$ |
| | (0.085) | (0.104) | (0.099) | (0.082) | (0.079) |
| Observations | 5,144 | 6,868 | 9,715 | 11,296 | 11,296 |
| **E. Excluding cells with a border** | | | | | |
| *SMA Ref:. Normal conditions* | | | | | |
| Drier than normal | $-0.308^{***}$ | $-0.303^{***}$ | $-0.260^{***}$ | $-0.286^{***}$ | $-0.164$ |
| | (0.078) | (0.074) | (0.072) | (0.080) | (0.101) |
| Wetter than normal | 0.053 | $0.265^{***}$ | $0.321^{***}$ | $-0.047$ | $-0.010$ |
| | (0.080) | (0.099) | (0.098) | (0.086) | (0.083) |
| Observations | 6,000 | 7,920 | 11,122 | 12,859 | 12,861 |
| **F. Grid size 1x1** | | | | | |
| *SMA Ref:. Normal conditions* | | | | | |
| Drier than normal | $-0.339^{***}$ | $-0.473^{***}$ | $-0.294^{***}$ | $-0.093$ | $-0.220^{**}$ |
| | (0.077) | (0.079) | (0.074) | (0.076) | (0.092) |
| Wetter than normal | 0.138 | $0.408^{***}$ | $0.181^{*}$ | 0.085 | $-0.064$ |
| | (0.093) | (0.089) | (0.096) | (0.082) | (0.089) |
| Observations | 3,503 | 4,546 | 6,116 | 7,042 | 7,044 |
| **G. PPML model** | | | | | |
| *SMA Ref:. Normal conditions* | | | | | |
| Drier than normal | $-0.386^{***}$ | $-0.335^{***}$ | $-0.199^{**}$ | $-0.186^{*}$ | $-0.030$ |
| | (0.092) | (0.082) | (0.096) | (0.104) | (0.096) |
| Wetter than normal | 0.030 | $0.357^{***}$ | $0.337^{***}$ | $-0.287^{**}$ | $-0.149$ |
| | (0.078) | (0.108) | (0.104) | (0.139) | (0.123) |
| Observations | 7,490 | 10,014 | 14,335 | 16,738 | 16,742 |

*Notes: – Results are obtained from a negative binomial model. – The categorical variable indicating drier, normal, and wetter soil moisture conditions is constructed using the average SMA index during the growing season of the cell during the past 1, 3, 6, 9 and 12 months. Drier conditions are SMA index values lower than* $-1$*, wetter conditions are SMA values higher than 1. The reference category is "normal conditions" which occur when the SMA index scores between* $-1$ *and* $1$*. – Standard errors in parenthesis (clustered at the cell level). – **** $p < 0.01$*; *** $p < 0.05$*; ** $p < 0.1$.

# Appendix

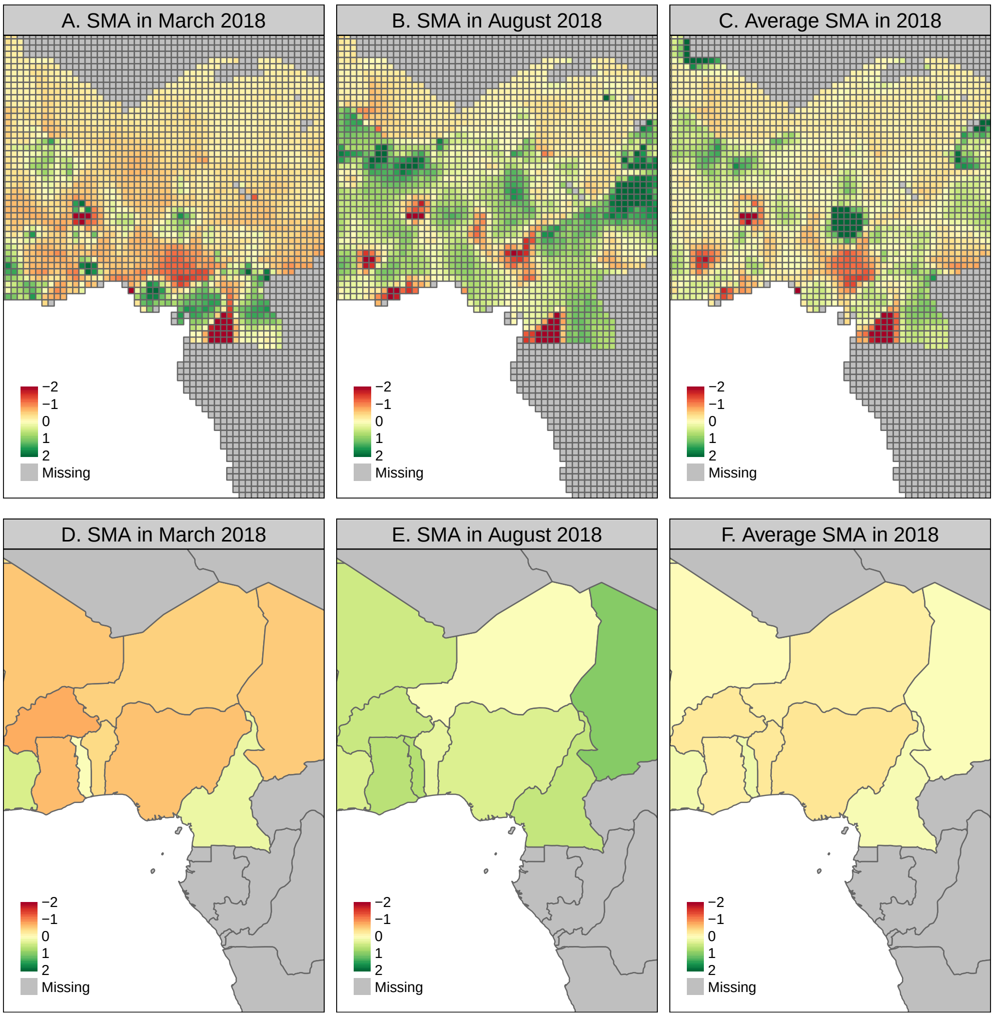


**Figure A1:** SMA Index: March, August, and Yearly Average at the Grid and Country Level for 2018

*Source:* Authors' analysis using data from NOAA ESRL PSD (2020); EDO (2019).

*Notes: – Upper panel: Figures A and B illustrate the average SMA index by cell for March and August 2018. Figure C illustrates the average SMA index in 2018. Lower panel: Figures D and E illustrate the average SMA index at the country level for March and August 2018. Figure F illustrates the average SMA index at the country level for 2018.*

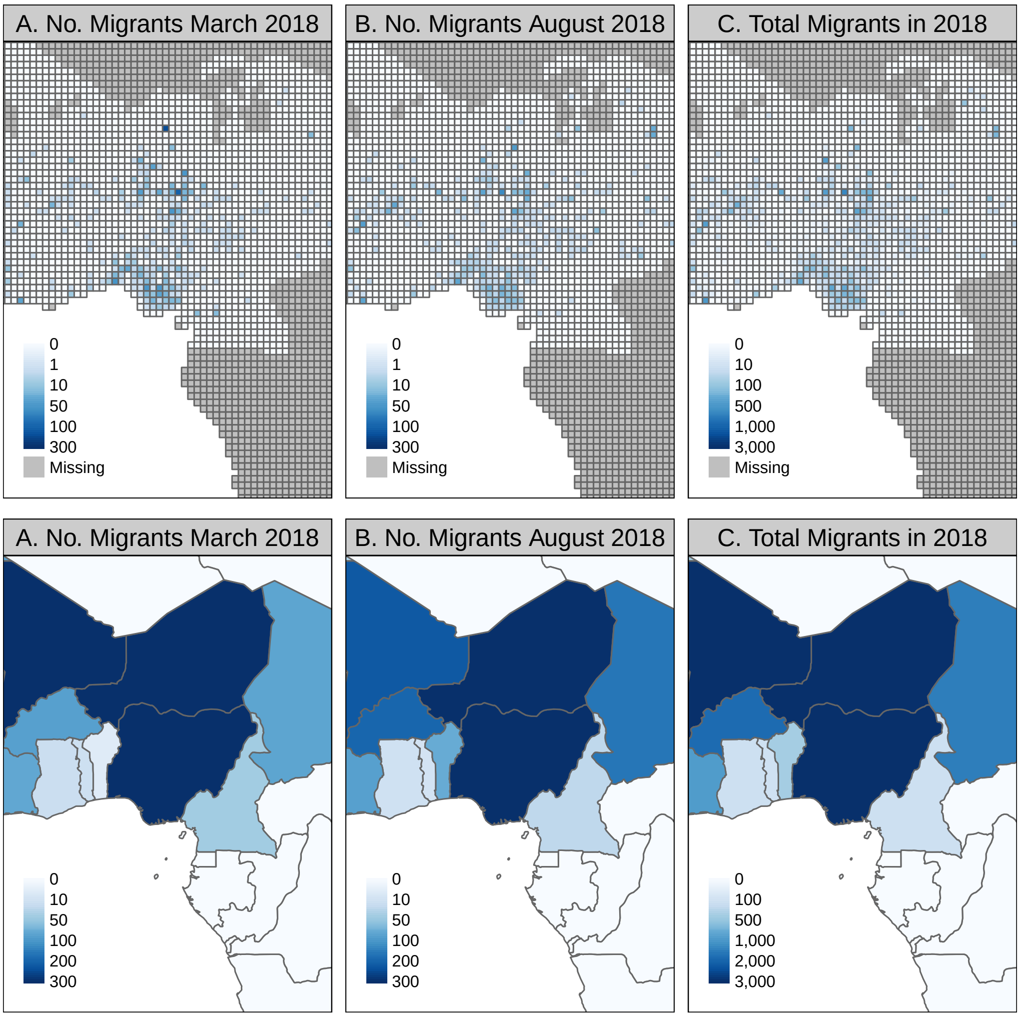


**Figure A2:** Migration: March, August, and Yearly Average at the Grid and Country Level for 2018

*Source:* Authors' analysis using data from NOAA ESRL PSD (2020); EDO (2019).

*Notes: – Upper panel: Figures A and B illustrate the total migration by cell for March and August 2018. Figure C illustrates total migration in 2018. Lower panel: Figures D and E illustrate total migration at the country level for March and August 2018. Figure F illustrates total migration at the country level for 2018.*

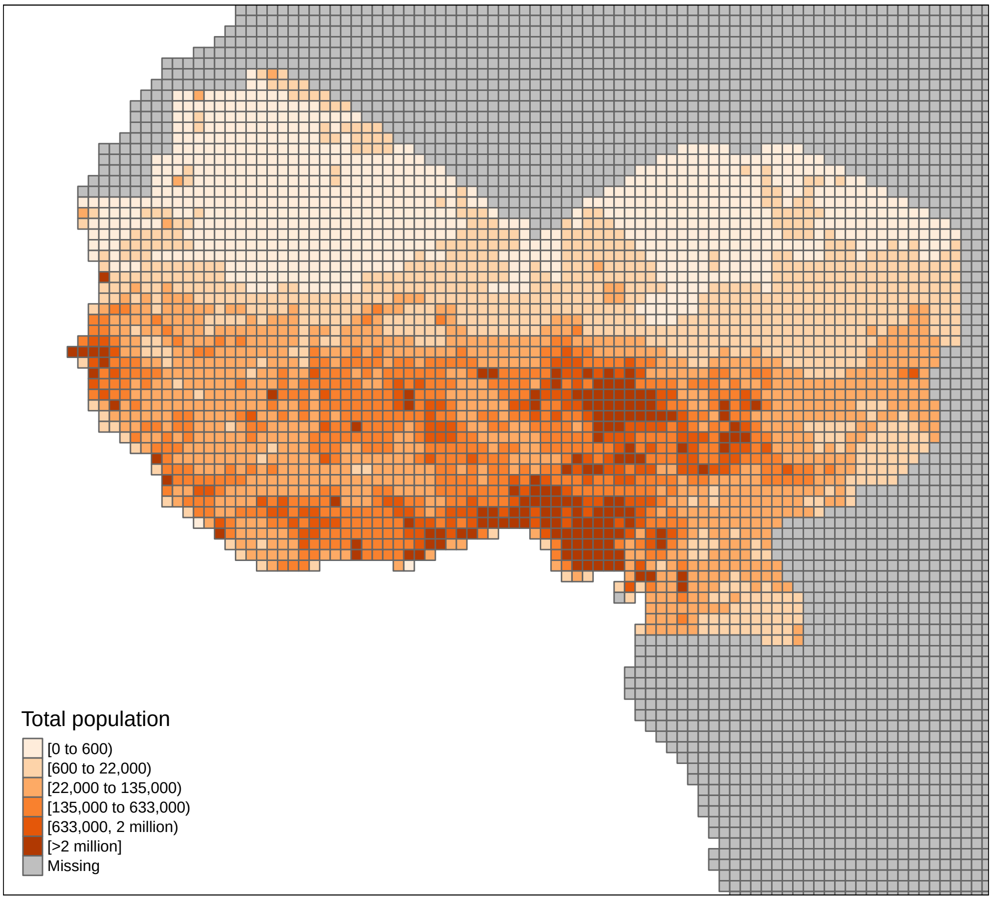


**Figure A3:** Total Population in 2018

*Source:* Authors' analysis using data from WorldPop (2018).

*Notes: – The figure shows the sum of the total population at the cell level for 2018 using a grid size of 0.5x0.5 degrees.*

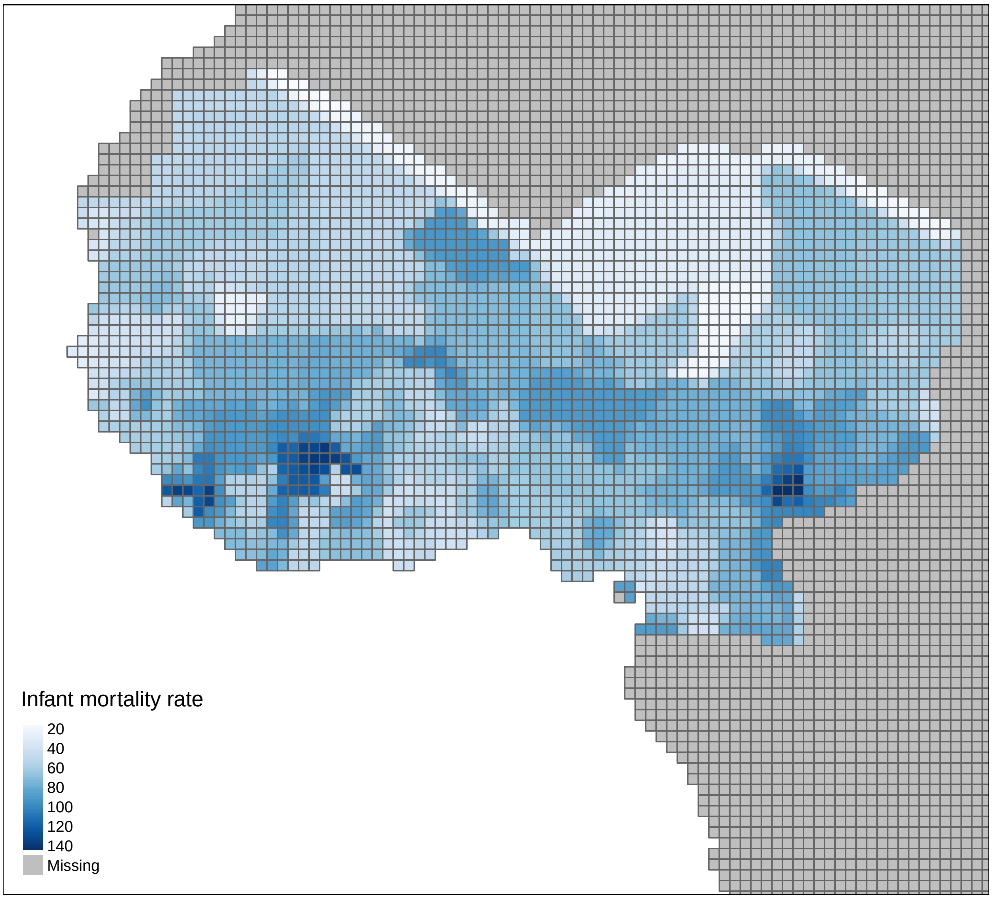


**Figure A4:** Infant Mortality Rate in 2015

*Source:* Authors' analysis using data from CIESIN (2018).

*Notes: – The figure shows the average infant mortality rate at the cell level for 2015 using a grid size of 0.5x0.5 degrees.*

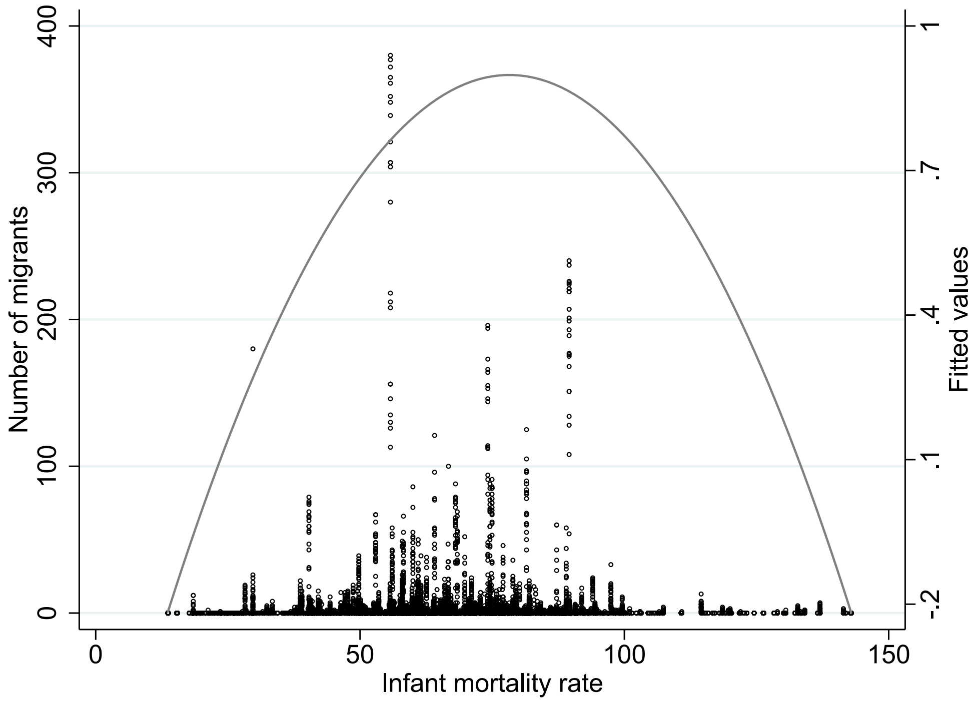


**Figure A5:** Number of migrants and Infant Mortality Rate
*Source:* Authors' analysis using data from IOM (2019) and CIESIN (2018).
*Notes: – The continuous line depicts an overlaid quadratic fitted prediction of the scatterplot.*

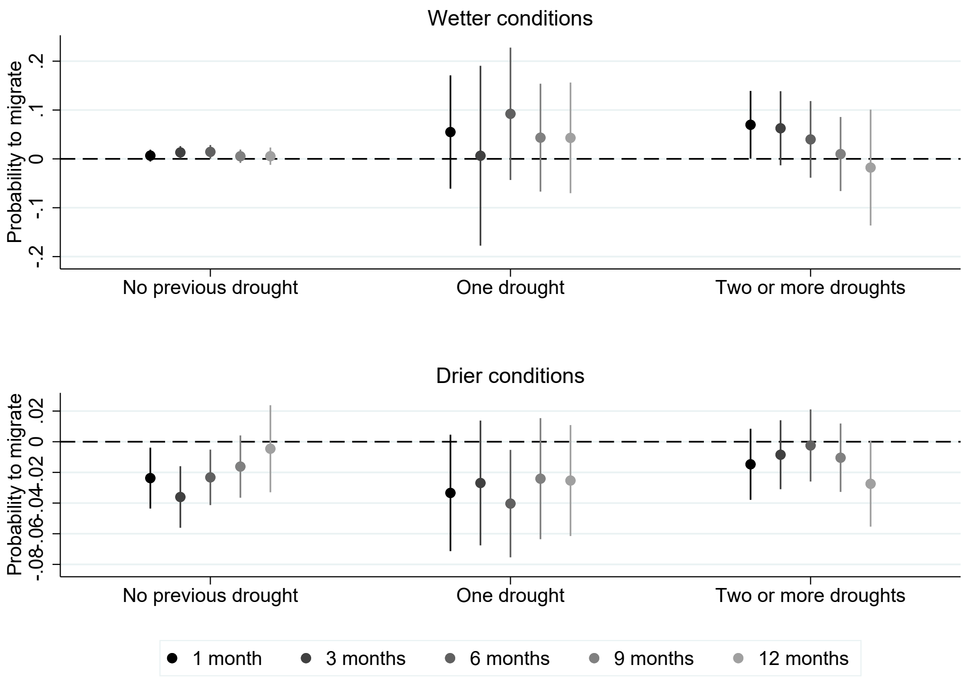


**Figure A6:** Effect of Soil Moisture Shocks on Probablity to Migrate by Number of Droughts in the Past 5 Years

*Notes: – The figure presents the results of regression models including as the main variable of interest a categorical indicator based on the SMA index calculated during growing season months. Drier conditions are SMA index values lower than -1, wetter conditions are SMA values higher than 1. The reference category is "normal conditions" which occur when the SMA index scores between -1 and 1. We interact this variable with an indicator if cells experienced i) no droughts in the past 5 years, ii) one drought, or iii) two or more droughts. The regressions include the full set of control variables and fixed effects as presented in Equation (1). – Confidence intervals are calculated at the 95% level and the standard errors are clustered at the cell level.*

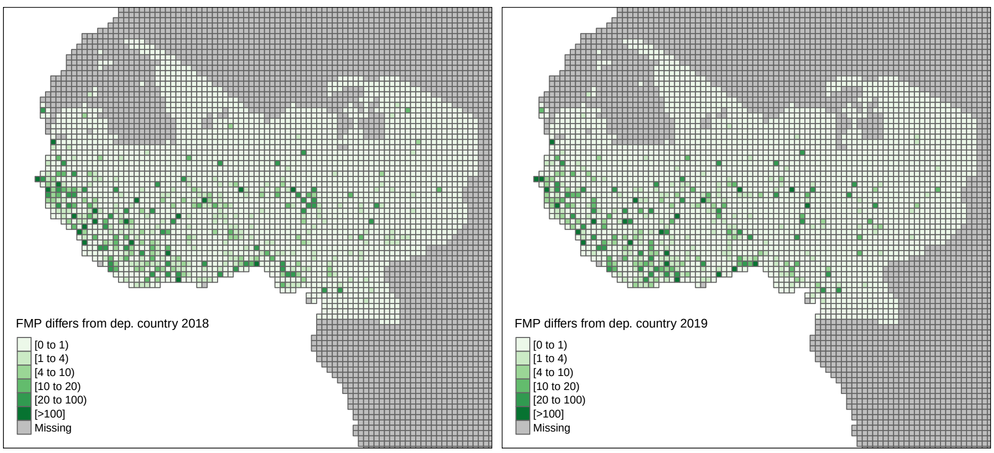


**Figure A7:** International migration in West and Central Africa: On the Move

*Source:* Authors' analysis using data from IOM (2019).

*Notes: – Figure A and B show the total number of international migrants who were surveyed in a different country than their country of origin for 2018 and 2019, respectively. The sample includes individuals who have at least crossed one international border.*

**Table A1:** Summary of Main Weather Events in West Africa

| Year | Outcome of rainy season | Agricultural output |
|---|---|---|
| 2017 | Negative | Alarming food security situation in Chad, Mauritania, Senegal. |
| 2018 | Positive | Burkina Faso, Nigeria register above average rainfall and increase agricultural production. |
| 2019 | Negative | Crop production estimates 17% lower for Gambia, Mauritania, Senegal. |

*Notes: – Based on reports by the Food and Agriculture Organization (FAO, 2018, 2019, 2020)*

**Table A2:** Effect of SMA Index on Probability to Migrate

| | 1 month | 3 months | 6 months | 9 months | 12 months |
|---|---|---|---|---|---|
| SMA index | 0.014*** | 0.017*** | 0.014*** | 0.010*** | 0.007 |
| | (0.002) | (0.002) | (0.003) | (0.003) | (0.004) |
| *Num. of FMPs Ref:. No FMP* | | | | | |
| One FMP in cell | 0.210*** | 0.210*** | 0.210*** | 0.211*** | 0.211*** |
| | (0.061) | (0.060) | (0.061) | (0.061) | (0.061) |
| Two FMP in cell | 0.376*** | 0.375*** | 0.378*** | 0.379*** | 0.380*** |
| | (0.128) | (0.127) | (0.130) | (0.130) | (0.130) |
| FMP in 200km radius | 0.036*** | 0.036*** | 0.038*** | 0.039*** | 0.039*** |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| Constant | 0.059*** | 0.058*** | 0.056*** | 0.057*** | 0.057*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Cell FE | yes | yes | yes | yes | yes |
| Month FE | yes | yes | yes | yes | yes |
| Country-by-year FE | yes | yes | yes | yes | yes |
| Observations | 61,729 | 61,729 | 61,729 | 61,729 | 61,729 |
| $R^2$ | 0.539 | 0.539 | 0.539 | 0.538 | 0.538 |

*Notes: – Results are obtained from a linear probability model. – The table presents the results of regression models including as the main variable of interest the average SMA index. The index is calculated for different time spans ranging from the past month to the past twelve months. – Standard errors in parentheses (clustered at the cell level). – *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.*

## Table A3: Effect of SMA Index on Total Migration

| | 1 month | 3 months | 6 months | 9 months | 12 months |
|---|---|---|---|---|---|
| SMA index | 0.226*** | 0.289*** | 0.264*** | 0.130*** | 0.069* |
| | (0.021) | (0.024) | (0.029) | (0.034) | (0.040) |
| *Num. of FMPs Ref:. No FMP* | | | | | |
| One FMP in cell | 0.251** | 0.248** | 0.249** | 0.258** | 0.260** |
| | (0.112) | (0.113) | (0.113) | (0.112) | (0.112) |
| Two FMP in cell | 0.157 | 0.089 | 0.117 | 0.228 | 0.272 |
| | (0.351) | (0.356) | (0.353) | (0.346) | (0.344) |
| FMP in 200km radius | 0.217*** | 0.226*** | 0.243*** | 0.239*** | 0.232*** |
| | (0.073) | (0.073) | (0.073) | (0.073) | (0.073) |
| Constant | 1.010 | 1.037 | 0.858 | 1.252 | 1.427 |
| | (1.005) | (1.032) | (0.943) | (1.255) | (1.431) |
| Cell FE | yes | yes | yes | yes | yes |
| Month FE | yes | yes | yes | yes | yes |
| Country-by-year FE | yes | yes | yes | yes | yes |
| Observations | 17,519 | 17,519 | 17,519 | 17,519 | 17,519 |

*Notes: – Results are obtained from a negative binomial model. – The table presents the results of regression models including as the main variable of interest the average SMA index. The index is calculated for different time spans ranging from the past month to the past twelve months. – Standard errors in parentheses (clustered at the cell level). – *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.*