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Labor Migration Responses to Drought-Induced Shocks in Tunisia

Esther Delesalle,
Minh-Phuong Le,
Mohamed Ali Marouani
and Federica Alfani

ECONOMIC RESEARCH FORUM
منتدى البحوث الاقتصادية

Forced to migrate in a warming world: Labor migration responses to drought-induced shocks in Tunisia

Esther Delesalle, Minh-Phuong Le, Mohamed Ali Marouani, Federica Alfani

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Abstract

This study investigates two key strategies for coping with drought in Tunisia: agricultural adaptation and migration, using panel data on net migration rates, agricultural production, and weather conditions at a detailed administrative level. Our results indicate that farmers expand irrigated land to cope with droughts. However, since this is not sufficient, migration becomes a prominent alternative strategy. Indeed, less favorable weather is associated with higher out-migration, particularly among males, less educated individuals, and informal or agricultural workers. Migration, however, is predominantly accessible to wealthier households due to its associated costs. Furthermore, we provide also strong evidence of climate-induced international migration, but primarily to neighboring countries.

1 Introduction

Climate change and drought in particular is threatening the livelihoods of billions of people worldwide and particularly those living from agriculture in climate change hotspots. There is a range of complementary and substitutable strategies for coping with climate shocks (Cattaneo et al.; 2019). Our objective in this paper is to contribute to the understanding of how households adapt to drought by examining simultaneously two key coping strategies: the modification of agricultural practices and migration.

To cope with climate risks, rural households can rely on formal insurance and credit mechanisms, provided that markets are sufficiently developed and accessible, which is often not the case in developing countries (Barnett and Mahul; 2007), and that the shocks they face are not prolonged. Alternatively, they can rely on informal mechanisms that can be categorized into two types of strategies: ex ante to reduce their magnitude, and ex post to protect their livelihoods. Among the ex-ante strategies aimed at mitigating the effects of climate shocks, farm households can adapt their agricultural practices. This could involve specializing in production techniques that are less dependent on rainfall, increasing the cultivation of irrigated crops, or favoring drought-resistant varieties (Bryan et al.; 2009). This is precisely the first focus of our paper: examining crop adaptation strategies in response to short-term climate variations in Tunisia.

Despite the potential of the aforementioned adaptations to mitigate the impact of climate shocks, households may be compelled to adopt alternative coping strategies, such as using their savings, liquidating assets, borrowing, or altering their household composition. They may also turn to migration, which can serve both as an ex-ante strategy to diversify income sources and protect against future risks, and as an ex-post strategy to compensate for losses already incurred. Migration, as an informal coping mechanism, will be the second focus of this article.

Characterized by a range of climates, spanning from a humid Mediterranean climate in the North to an arid Saharan climate in the South,[1] Tunisia has experienced several droughts in recent decades, including a particularly severe drought in the late 90's, between 1999 and 2002 and a more recent one since 2020. The majority of climatic projections[2] indicate that these climate events are expected to become more frequent in the future. By 2050, rainfall in Tunisia is expected to decrease significantly, by between 10% and 35%, and temperatures are expected to increase by between 1.9% and 2.9%. These climatic changes are highly likely to result in a drop in agricultural production, particularly in rain fed cereal production and olive production (Mougou; 2011). As the country is part of the water stress zone, with less than 500 m3 of water per inhabitant available annually and irrigation systems still underdeveloped (less than 7% of agricultural land according to Mansour (2014)), food security and the living conditions of rural populations dependent on farming activities can be easily threatened by present and future climatic hazards.

[1]Precipitation levels vary from 1400 mm/year in the North to less than 40 mm/year in the South (Feki.H et Cudennec.C; 2022).

[2]The median scenarios (Belghrissi.H; 2018; Ben Rached.S et al.; 2015) and the A2 greenhouse effect scenario(Paeth; 2009)

Both internal and international migration are common practices in Tunisia, and will be examined. Since the 1960s, internal migration has been characterized by a major rural exodus from the North-West and Centre-West towards the metropolis of Tunis and the Eastern coastal Centre (Gsir and Bounouh; 2017). More recently, short-term internal migration has mainly involved young rural women seeking seasonal work in urban areas (Zuccotti et al.; 2018). These internal displacements are mainly economic in nature and have been triggered by droughts. Although agriculture currently employs only 15% of the workforce, the country's climate, ranging from a Saharan environment in the south to a milder Mediterranean climate in the north, suggests differentiated climate shocks in the future and is likely to drive increased internal migration.

While the existing literature suggests that internal migration is more sensitive to climatic hazards, the decision to migrate abroad can also be affected. As Defrance et al. (2023) reminds us, the decision to migrate across borders is primarily influenced by two factors: resources and the migration network. Long-distance migration is expensive, and building a support network is crucial for migrants' integration before they can achieve financial independence. These two preconditions help to explain why environmental stressors such as drought do not necessarily lead to long-distance international migration, but rather to short-distance mobility. Indeed, the scarcity of resources during droughts decreases the ability of individuals to invest in long-distance migration. This phenomenon of liquidity constraint, also highlighted in Cattaneo and Peri (2016), would explain why poverty exerts a constraint on international migration. In the case of Tunisia, international migration, mainly to European countries and, to a lesser extent, other Arabic countries, is not an uncommon phenomenon and is mainly motivated by economic reasons and wage differentials (Fargues.P; 2005). Consequently, if droughts in Tunisia exacerbate this wage differential, they are likely to increase the number of international migrants, provided that household budget constraints are not too tight.

In this paper, we analyze two key strategies for coping with drought: on-farm adaptation and migration. On-farm adaptation is analyzed using a fractional multinomial logit model, where farmers choose between high-input rain-fed, low-input rain-fed, irrigated crops, and subsistence crops based on weather conditions. This approach enables the decomposition of climate's impact on production into two components: crop structure and within-crop productivity. Internal migration is modeled using a pseudo-gravity model that incorporates both climate push and pull factors. In contrast, our focus is on the effects of climate on the delegation[3] of origin when estimating international migration patterns.

Our analysis utilizes panel data on agricultural production, net migration rates and weather conditions at a detailed administrative level, covering all 265 delegations in Tunisia. The agricultural data span the period from 1999 to 2013, while migration data, drawn from the 2014 national census, cover the period from 2009 to 2014. We combine these datasets with temperature and precipitation data, also at the same administrative level, for the corresponding periods.

We show that, despite the expansion of irrigation, this coping strategy is insufficient to

[3]A Tunisian administrative unit equivalent to a district

mitigate the adverse effects of unfavorable weather conditions. As a result, households turn to migration as an alternative strategy. Our findings on internal migration are consistent with recent literature: increased droughts lead to higher rates of out-migration, particularly among males, less educated individuals, informal workers, and those dependent on agriculture. However, this strategy is primarily accessible to wealthier households, as migration incurs significant costs. Finally, we find strong evidence of climate-induced international migration, predominantly to neighboring countries.

The remainder of the paper is structured as follows. The next section reviews the relevant literature. The data and methodology are described in Sections 3 and 4. Section 5 presents our results. Finally, Section 6 concludes.

2 Literature review

As highlighted by Berlemann and Steinhardts' survey (2017) and Hoffmann et al.s' meta-analysis (2020), the majority of studies on climate and migration agree that adverse climate events significantly increase internal migration in low and middle income countries. For instance, using two waves of survey data from 200 households in four villages in northern Nigeria (1988 and 2008), Dillon et al. (2011) predict the effect of ex ante and ex post agricultural income risks, measured by temperature, on migration. They find a strong male migratory response to ex ante idiosyncratic risk and ex post covariate risk. Marchiori et al. (2012) provide a theoretical model combined with empirical data on rural-urban and international migration patterns in Sub-Saharan Africa from 1960 to 2000. They estimate a 5-million-person displacement due to weather anomalies. Mastrorillo et al. (2016) use a gravity model applied to census and climate data from South Africa (1997-2011) and find that positive temperature extremes and rainfall anomalies increase outmigration at the inter-district level. Dallmann and Millock (2017) construct bilateral migration flows from the Indian census and use the Standardized Precipitation Index (SPI) to measure rainfall deficits and surpluses. Their findings align with the literature: rainfall variation drives internal migration, with deficits increasing migration and surpluses having varying effects depending on the region. Using urbanization as a proxy for rural-urban migration, Henderson et al. (2017) find that drier conditions in rural, agriculture-dependent regions increase urbanization in Sub-Saharan Africa, as migration serves as an escape from negative agricultural shocks. Using a multi-country panel dataset of African countries, Di Falco et al. (2024) highlight the cumulative impact of prolonged drought on migration.

Using weather variables as instruments to estimate the effect of climate-driven agricultural yield changes on migration from Mexico to the U.S., Feng et al. (2010) find that declines in crop yields due to climate change significantly increase emigration from Mexico. Various papers using cross-country data and gravity models reach the same conclusion. Beine and Parsons (2015) show that natural disasters do not have a significant direct effect on international migration, but long-term climatic factors (e.g., temperature increases) indirectly affect migration by widening wage differentials between origin and destination countries. Cai et al. (2016) suggest that temperature increases (but not precipitation changes) significantly drive international migration in agriculture-dependent countries. Coniglio and Pesce (2015) suggest that climatic events in origin countries significantly increase migration to OECD countries, especially from regions with large agricultural sectors.

However, as mentioned above, the effect of weather anomalies varies greatly depending on the initial economic conditions of the household (Berlemann and Steinhardt 2017; Hoffmann et al. 2020). On one hand, negative climate shocks can increase migration as a coping strategy. On the other hand, these shocks might reduce the capacity of poorer households to migrate. Gray (2009) and Gray and Mueller (2012) use household surveys and discrete regression models to examine the effect of environmental changes on international and internal migration in Ethiopia and the Southern Ecuadorian Andes. Climate shocks often trigger internal migration, but effects vary significantly across countries. In the case of Ecuador, low rainfall reduces both internal and international migration due to financial constraints.

Kubik and Maurel (2016) study household survey data from Tanzania and find that negative weather shocks increase migration only for households with enough income to cover migration costs. Poorer households are less able to migrate, indicating that economic constraints play a crucial role. Peri and Sasahara (2019) use global fine-grain migration data to track rural-urban migration patterns in relation to temperature changes over the 1970-2000 period. They find evidence that rising temperatures reduce outmigration from rural areas in poor countries but increase rural-to-urban migration in middle-income countries. Rich countries show no significant migration response to temperature changes, likely due to advanced agricultural technologies. A recent paper by Defrance et al. (2023), using census data from Mali, suggests that the effect of droughts on the net migration rate, while positive, varies across localities and depends on household adaptation capabilities.

Studies on international migration suggest similar findings. Cattaneo and Peri (2016) extend the Roy-Borjas migration model and apply migration data from 115 countries (1960-2000) to predict migration in response to warming trends. They show that increasing temperatures reduce urbanization and international migration in poor countries due to liquidity constraints, but increase migration in middle-income countries, where agricultural income is still significant and migration is financially feasible. Falco et al. (2019), using a 2SLS approach to assess how climate shocks drive international migration, find that climate-related declines in agricultural productivity increase emigration, particularly from poor countries. The effects are weaker in middle-income countries, where agricultural sectors are less dominant but still significant.

3 Data

3.1 Measuring migration through the 2014 Tunisian population censuses

The migration analysis is based on the 2014 Tunisian exhaustive census, which collects basic dwelling and household characteristics. To measure internal migration, we use the actual delegation of residence of all individuals declaring to be living in another dwelling five years previously. By comparing the actual place of residence with the former place of residence and the year in which the individual moved, we are able to construct, for the period 2009-2014, the annual bilateral flows between the 264 delegations, which total 69,432 bilateral flows. Furthermore, the Tunisian census reports the typology of previous and current locations, which allows us to distinguish between rural and urban localities. This enables us to capture all movements from one administrative delegation to another, as well as all movements between rural and urban localities, including those within the same delegation. Although the geographical level of our analysis is relatively fine-grained in relation to the size of the country, it is important to note that this measure of internal migration does not allow us to capture movements within the same delegation, between two localities with the same typology. This may result in an underestimation of our migration variable and introduce a downward bias in our estimation.

Bilateral flows have an average of 0.09%, with a range of 0 to 20%. The variable exhibits a high degree of dispersion, with a standard deviation that is five times greater than the average. When expressed in terms of the number of migrants, this corresponds to an average of 4.2 migrants per flow, with values ranging from 0 to 3082 migrants.

For international migration, we follow the Defrance et al. (2023)'s approach and employ the emigration module to quantify this phenomenon. This entails requesting the head or other reference member of a household to enumerate the household members who have departed the country to reside abroad over the past five years. Based on the year of departure and the country of destination, we construct annual international flows for each delegation of origin.

The rate of international migration per delegation, defined in relation to the initial size of the delegation of origin, is approximately 0.03% on average. This is lower than the figures for internal migration. Expressed in numbers of migrants, this corresponds to an average of 6 international migrants per year, ranging from 0 to 467 migrants, when we consider all destination countries together.

Whether for internal or international migration, it is possible to construct migration sub-flows by cross-referencing the characteristics of individuals or delegations. For example, it might be of interest to compare the responses of men and women to climate hazards. To do this, we construct annual flows of bilateral delegations by counting men and women separately, which results in two data matrices that we will use in turn for heterogeneity analyses. When examining this dimension of heterogeneity, we no longer distinguish between rural and urban localities in order to avoid too many delegation flows with zero migration flows.

3.2 Measuring climate events

3.2.1 Standardised Precipitation-Evapotranspiration Index (SPEI)

This paper deploys the Standardised Precipitation-Evapotranspiration Index (SPEI) proposed by Vicente-Serrano et al. (2010) to measure drought episodes between 2009 and 2014. The SPEI inherits the calculation algorithm from its predecessor, the Standardised Precipitation Index (SPI). The SPI is a multi-scalar drought index that captures the deviation of observed precipitation from the climatological average over a given period. Therefore, this index allows for comparison over time and space. The main criticism of the SPI is its disregard for other variables that might influence water demand, especially temperature. Vicente-Serrano et al. (2010) addresses this criticism by incorporating temperature and potential evapotranspiration into the SPEI.

In this study, we use the Global SPEI base, version 2.9, provided by the Spanish National Research Council (CSIC)[4]. The dataset contains SPEI data on a global scale, with a spatial resolution of 0.5x0.5 degrees and a monthly temporal resolution, covering the period from January 1901 to December 2022. As suggested by the literature, we utilize a 12-month SPEI time scale. Our primary explanatory variable is the annual average of the SPEI. We also use the seasonal average of the SPEI, focusing solely on the agricultural season from October to May. In addition, to capture a dry year (season), we create a dummy variable which takes the value 1 if the annual (seasonal) average SPEI falls below -1. Figure 1 presents substantial within-country variation in SPEI during the period 2009-2014. The majority of drought episodes during this time occurred in the southern delegations.

3.2.2 Standardised Precipitation Index (SPI)

Despite its advancements, the index has a limitation in our context. The SPEI is computed at the 50-square-kilometer-cell level, whereas on the left-hand side, the bilateral flows are constructed at a much finer granularity (delegation level). As a result, using the SPEI diminishes the statistical power of the regression. For robustness check, we use the SPI computed at the 5-square-kilometer-cell level. The precipitation data are drawn from the European Centre for Medium-Range Weather Forecasts Reanalysis version 5 (ERA5). ERA5 provides hourly estimates of climate variable at the 0.05x0.05-degree level over the period from January 1940 to present. The precipitation data are standardised over the 1940-2014 period using the R package **SPEI** provided by Beguería et al. (2010)[5].

3.3 Spatial Production Allocation Model (SPAM)

To examine the most intuitive adaptation strategy - agricultural production, we collect aggregate data from the Spatial Production Allocation Model (SPAM) database. SPAM estimates agricultural production using crop production statistics, satellite-based cropland data, irrigated land, rural population density, etc. It provides data on harvested land,

[4]Source: `https://spei.csic.es/database.html`

[5]Source: `https://github.com/sbegueria/SPEI`

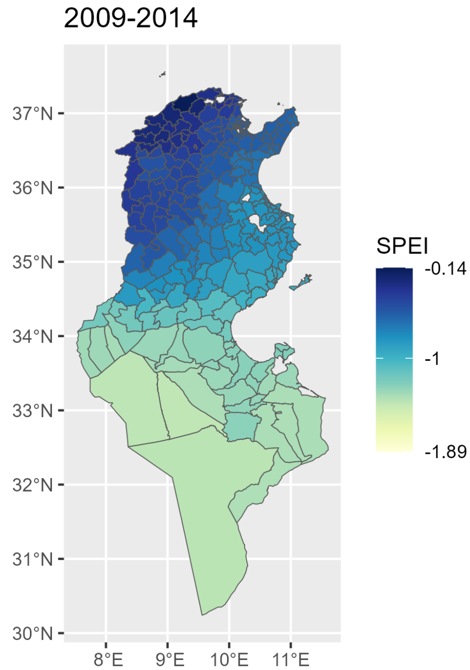
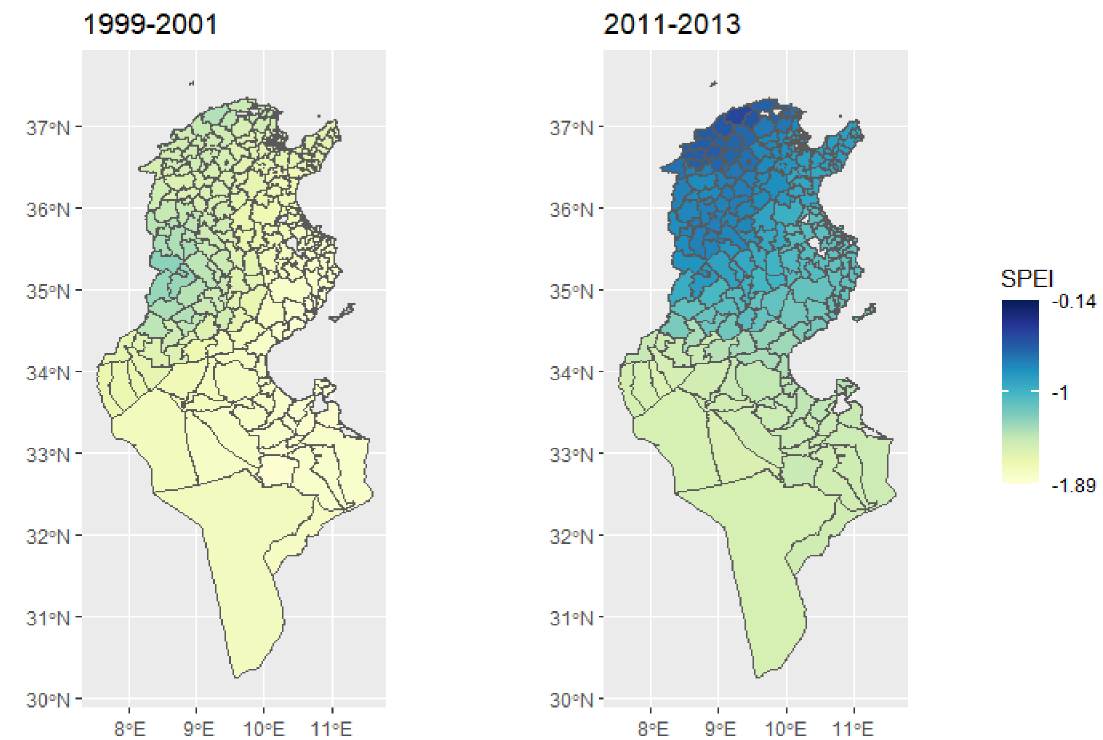
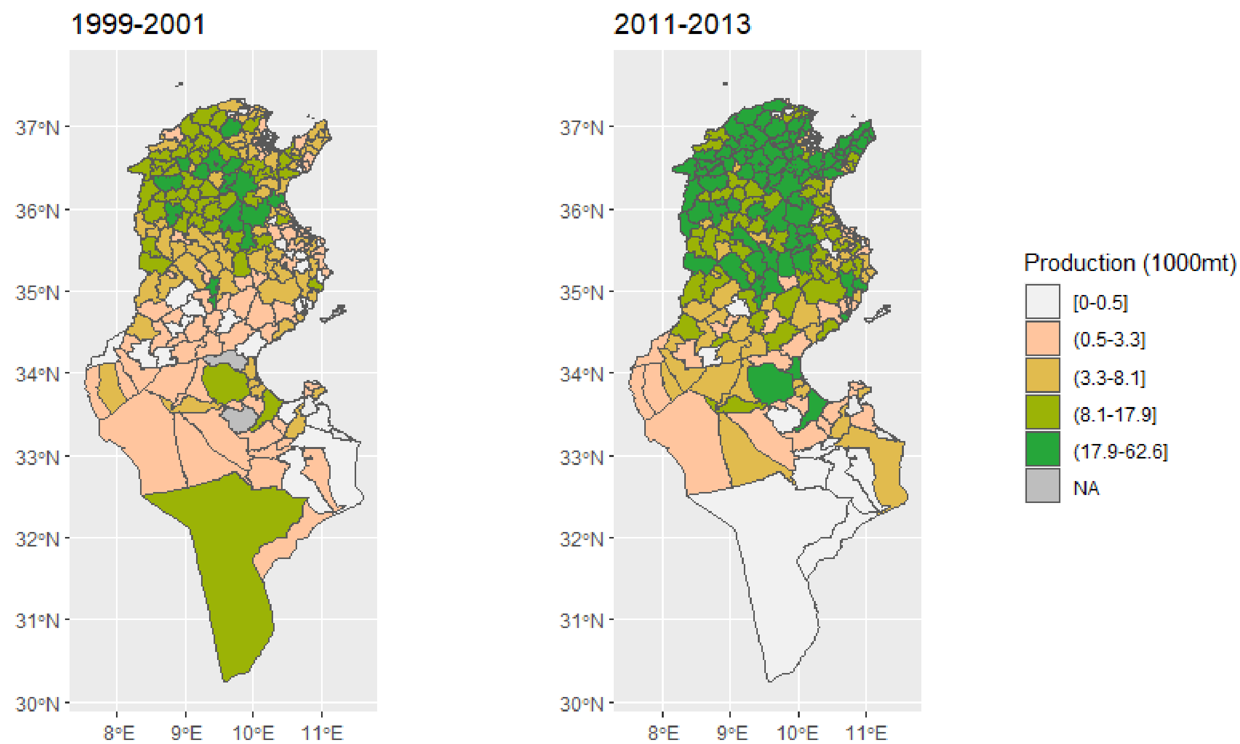


Figure 1: Average SPEI over 2009-2014

physical area, and production in metric tons and monetary value at a fine-grained level (0.1x0.1 degrees). The data covers four crop techniques: irrigated, rainfed high input, rainfed low input, subsistence, and various crop types such as wheat, barley, mill, oil crops. Three waves are available for Tunisia: 1999-2001, 2010 and 2011-2013. Since only the first and third waves span three years, the second wave is excluded from our calculations to maintain consistency in interpretation. Figures 2a and 2b plot the average SPEI and total crop production over comparable periods and delegations. It is visually shown that the weather was much drier in 1999-2001 compared to 2011-2013, corresponding to lower agricultural yields during the former period, except in some southern delegations.



(a) Average SPEI



(b) Agricultural production (SPAM data)

4 Empirical specification

4.1 The agricultural-climate nexus

To test the agricultural-climate nexus, we use the following specification:

$$Y_{j,t} = \beta_0 + \beta_1 SPEI_{j,t} + \delta_j + \delta_t + \epsilon_{j,t} \tag{1}$$

Where $Y_{j,t}$ is the agricultural outcome by delegation j at time t. The outcomes include log of production (mt), log of harvested land (ha) and productivity (USD/ha). We control by district and year fixed effects. To examine the impact of SPEI on the choice of crops, i.e. crop share, we estimate equation (1) using the fractional multinomial logit model, provided by Buis (2008). We can distinguish the effect according to the type of crop: high-input rain-fed, low-input rain-fed, irrigated crops, and subsistence crops.

The impact of SPEI on agricultural production can be decomposed into two channels: the effect on crop structure (between-crop component) and the effect on the productivity of each technology (within-crop productivity component). The expected agricultural production can be expressed as the weighted sum of the production values of each technology: $E(P) = P_c \times S_c$, where P_c and S_c represent the production value and production share of each technology, respectively. Thus, the total effect of SPEI on agricultural production can be decomposed as follows:

$$\frac{\partial E(P)}{\partial SPEI} = \sum_{c=1}^{4} \frac{\partial P_c}{\partial SPEI} \times \hat{S}_c + \sum_{c=1}^{4} \frac{\partial S_c}{\partial SPEI} \times \hat{P}_c \tag{2}$$

where $\frac{\partial P_c}{\partial SPEI}$ and $\frac{\partial S_c}{\partial SPEI}$ are the effect of SPEI on agricultural production and allocation partioned by cultural technologies. $\hat{S}_c$ and $\hat{P}_c$ are predicted share and production of each technology. The decomposition analysis is conducted for agricultural production and productivity.

4.2 Migration-climate nexus

4.2.1 Theoretical considerations and empirical specification

In response to climatic shocks, one adaptation strategy individuals may adopt is migration. We estimate a pseudo-gravity model inspired by the random utility model widely used in the migration literature (Dallmann and Millock; 2017; Beine and Parsons; 2017; Mastrorillo et al.; 2016). This theoretical framework assumes that homogeneous agents decide to stay in their residence locality or to migrate to another locality depending on their utility function which they try to maximize. To do so, they consider the relative incomes they would receive in the two scenarios and compare them with the induced costs of migration. The reference econometric specification is:

$$m_{ijt} = \beta_0 + \beta_1 clim_{it} + \beta_2 clim_{it} * Rural_i + \beta_3 clim_{jt} + \beta_4 clim_{jt} * Rural_j + \delta_{ij} + \delta_t + \epsilon_{iit} \quad (3)$$

Where m_{ijt} is the bilateral migration rate from delegation i to delegation j between year $t-1$ and t, computed from the ratio between the number of migrants M_{ijt} in this time interval and the initial population size in the delegation of origin, Pop_{iit-1}. To test the heterogeneity of climate effects, we construct sub-flows according to individual migrant characteristics, such as gender, activity, reason for migration, etc.

Our variables of interest are $clim_{it}$ and $clim_{jt}$. The literature often focuses on $clim_{it}$, assuming that climate acts as a push factor and influences migration decisions by reducing opportunities in the delegation of origin (Dallmann and Millock; 2017; Beine and Parsons; 2017; Mastrorillo et al.; 2016). We follow their approach by considering the climate in the departure delegation $clim_{it}$, but also consider the climate in the destination delegation $clim_{jt}$ to test whether climate also acts as a pull factor. Indeed, in the case of bilateral migration, decisions also depend on the comparison of opportunities across all other destinations(Anderson; 2011).This requires that agents are well-informed about climate conditions in destinations outside their delegation of origin.

Since we are interested in the total effect of climate change on migration decisions, we follow Dell et al. (2009) and Beine and Parsons (2017)'s approach and include no control in our estimation. As Berlemann and Steinhardt (2017) point out, the controls to include in the estimations are open to debate and depend on the objectives of the researchers. To answer this question, it is important to remind that climate variability is likely to affect internal and international migration decisions through multiple mechanisms. For example, by affecting infrastructure, significant climate events can affect wages and employment. Another natural channel we can think of is the agricultural channel. Indeed, intense droughts are likely to affect crop yields and reduce agricultural income (Cai et al.; 2016). Hsiang et al. (2011) show that climate can also trigger violent conflict and induce migration and refugee flows. Thus, if we are interested in the total effect of climate, including such controls may introduce estimation bias, as these variables are likely to be affected by climate conditions and absorb a part of the effect. Instead, to avoid bad controls (Angrist and Pischke; 2009) and to capture the total effect of climate on migration, we exclude all potential effects of climate variation and estimate a parsimonious model by including only fixed effects and measures of climate change in our estimation.

The use of bilateral data allows us to account for specific migration patterns, disaggregate migration flows by characteristics, and test for heterogeneous effects. For example, we expect climate to affect household welfare, especially in rural areas, by affecting their agricultural productivity (Feng et al, 2010). However, as Marchiori et al. (2012) show in their theoretical model, by reducing opportunities in rural areas, negative climate variability may increase rural-urban migration, exerting downward pressure on urban wages and creating incentives to move abroad. This suggests that climate variability is likely to impact migration from rural areas more strongly than from urban areas. To test this discrepancy between rural and urban areas, we exploit the delegation typology available for both the origin and destination delegation in the Tunisian census. We thus test the heterogeneity of the effect by interacting our climate variable with a variable indicating whether the locality is rural or urban, $rural_i$ and $rural_j$.

We include time-invariant origin-destination fixed effects, δ_{ij}, to control for the specific migration trend of each bilateral corridor. It allows us to explain specific trends between two delegations due to their invariant-time characteristics, such as the distance between these two delegations, whether they share a common border, their cultural and historical proximity. We also add a time trend fixed effect, δ_t to control for the average evolution of migration over time. In other words, we are interested in the total effect of climatic variations, holding all characteristics of bilateral flows fixed over time and controlling for temporal trends.

If we measure weather conditions by a continuous variable of precipitation (SPI) or evapotranspiration (SPEI), we expect an increase in $clim_{it}$ to improve agricultural conditions and to reduce the number of departures, especially in rural areas where we expect the effect to be stronger. On the other hand, we expect that an increase in precipitation in the destination area, $clim_{jt}$, to attract more migrants and have a positive effect on inflows, provided the weather conditions are well known. To test the non-linearity of this relationship, we may also consider climate shocks such as drought, instead of continuous variables.

As the literature on the topic underlines (Berlemann and Steinhardt; 2017), the effects of climate on migration decisions vary with the type of migration, and the conclusions are not the same whether internal or international migration is considered. To provide an overall picture of the effects of climate on migration decisions, we complete the analysis by estimating the following equation:

$$IMR_{it} = \beta_0 + \beta_1 clim_{it} + \beta_2 clim_{it} * Rural_i + \delta_i + \delta_t + \epsilon_{it} \tag{4}$$

Where IMR_{it} is the international migration rate at delegation level j, at time t. We focus on the effects of climate in the delegation of origin, $clim_{it}$, according to the delegation typology, $Rural_i$, and control for delegation fixed effects, δ_i, and a time trend fixed effect, δ_t. IMR_{it} is calculated by enumerating all international departures, regardless of destination. In order to highlight heterogeneous effects, we also distinguish the effects of climate for the main destination countries, namely France, Italy and Libya.

The combination of these two approaches allows us to compare the sensitivity of migration decision to climate depending on the destination localities. In both equations, we exclusively focus on short-term migration decisions in response to prevailing climate conditions.

4.2.2 Econometric concerns

The underlying question is whether the reduced-form, presented in equations 3 and 4 capture the causal effect of climate variability on internal and international migrations.

First, the variables $clim_{it}$ and $clim_{jt}$ are constructed from external weather data to minimize potential biases in estimation. Furthermore, bilateral flow fixed effects in equation 3 and delegation fixed effects in equation 4, are incorporated to mitigate the risk of omitted variables influencing the estimated coefficients related to climate factors. This addition is crucial due to constraints in data availability, which hinder the inclusion of variables potentially linked to both climate and migration. Additionally, period fixed effects are included to account for the historical and structural emigration patterns of certain areas, regardless of their climate relevance. Since we are interested in the causal effect of climate on migration, we decide not to include controls that are also likely to be directly affected by climate to avoid bad control bias.

The variables of interest, bilateral migration between two delegations and emigration, are both expressed as rates between 0 and 1. Assuming there are n delegations, we therefore count n*(n-1) internal flows and n international flows. Due to the construction of these flows, a significant number are zero: about half for internal flows and 15% for international flows.

In order to correctly estimate equations 3, whose dependent variables are non-linear with a high incidence of zero values, we follow the suggestions of Silva and Tenreyro (2006) and Dallmann and Millock (2017)'s approach, and estimate the equations using a Poisson pseudo-maximum likelihood (PPML) estimator. For the equation 4, whose dependent value has a much smaller share of zero values, we follow Defrance et al. (2023)'s approach and estimate with a two-way fixed-effects model, and provide robustness tests with a PPML model.

To control for potential variations in the attractiveness of origin and destination areas for other reasons than climate, we add time-varying destination characteristics and time-varying origin characteristics in a robustness model. The limitation is that including these large sets of fixed effects may capture some of the climate effect. Given the sensitivity of Poisson models to a large number of fixed effects, this model is estimated with an OLS model.

In the reduced-form equations 3 and 4, our focus is on capturing the total effect of climate variability on migration decisions, without delving into the specific mechanisms driving these effects.

5 Results

5.1 The agricultural-climate nexus

Table 1 reports the estimated effects of weather on agricultural output, productivity and harvested land. Panel A shows that more favorable weather leads to better output for rain-fed crops while reducing the total output of crops that needs irrigation. Further investigation into productivity and land gives more insight on the underlying mechanism. Better weather increases productivity of all crops and harvested land of rain-fed crops (Panel B and C), hence, increase the total output of rain-fed crops. Conversely, worsen weather conditions force farmers to increase the share of irrigated land as an adaptation strategy (Panel D). If this strategy had totally compensated the effect of bad weather, we should not have found the total output of all crops sensitive to weather conditions. In other words, the coefficient in Panel A, column 1 should have not been significant.

Table 1: Effects of the SPEI on agricultural production (1999-2013)

	All crops	Irrigated	High-input	Low-input	Subsistence
Panel A: Production, log (mt)					
SPEI	0.951**	-5.350***	4.457***	3.409***	2.347***
	(0.384)	(0.603)	(0.611)	(0.842)	(0.463)
Constant	9.502***	-2.697***	14.08***	11.93***	9.519***
	(0.636)	(1.018)	(1.004)	(1.401)	(0.758)
Observations	522	451	491	490	466
Panel B: Productivity (US/ha)					
SPEI	90.34	2456.0***	1350.3***	1012.3***	352.9**
	(276.3)	(519.4)	(279.1)	(210.1)	(144.5)
Constant	697.1	4805.8***	2866.7***	2220.0***	976.4***
	(461.9)	(868.1)	(470.2)	(336.5)	(241.3)
Observations	522	451	491	490	466
Panel C: Harvested land, log (ha)					
SPEI	1.284***	-6.939***	3.159***	2.110**	1.883***
	(0.373)	(0.725)	(0.657)	(0.881)	(0.492)
Constant	9.927***	-6.739***	11.92***	10.02***	9.147***
	(0.621)	(1.227)	(1.084)	(1.469)	(0.809)
Observations	522	451	491	490	466
Panel D: Land share					
SPEI		-0.223***	0.127*	0.00824	0.0877**
		(0.0398)	(0.0672)	(0.0439)	(0.0428)
Observations		522	522	522	522

Note: Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Decomposition analyses are consistent with the above regressions. More favorable climate conditions improve within-crop productivity. When the weather becomes less favorable, farmers shift toward irrigated crops as an adaptation strategy. However, the between-crop component is much smaller than the within-crop component, suggesting that this adaptation strategy does not sufficiently compensate for the loss caused by unfavorable climate conditions. Therefore, households might have to adopt other strategies, including migration, to shield themselves from the impact of climate change.

Table 2: Between and within effects of the SPEI (1999-2013)

	Production, log (mt)	Productivity (USD/ha)
Between	-0.171***	-357.1***
	(0.0508)	(53.79)
Within	2.156***	1245.9***
	(0.344)	(101.5)
Total	1.984***	888.9***
	(0.394)	(142.5)
Observations	528	528

Note: Boostrapped standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 Internal climate migration

Table 3 presents the estimates of Equation 3. Column 1 and 2 estimate the effect of climate on the standardized log of the migration rate +1 using the OLS estimation. Column 3 estimates the effect of climate on migration flows, computed as a percentage of the initial size of the delegation of origin, using the PPML estimation. The results are consistent with our expectation: better climate conditions in the delegation of origin slow migration to other delegations, and better climate conditions in rural locations in destination delegations increase their attractiveness. The push factor works in both type of localities, and is not significantly stronger in rural localities. The pull factor works only in rural localities.

Table 3: Effect of the SPEI on migration

	Migration flows		
	OLS	OLS	PPML
SPEI in origin	-0.015***	-0.005	-0.199***
	(0.004)	(0.006)	(0.051)
SPEI in origin×Rural	-0.020***	-0.019***	-0.011
	(0.004)	(0.004)	(0.021)
SPEI in destination	-0.009*	-0.002	-0.013
	(0.005)	(0.006)	(0.054)
SPEI in destination×Rural	0.012***	0.009***	0.043*
	(0.003)	(0.003)	(0.025)
Observations	216,820	216,820	214,275
Number of flows	43,364	43,364	43,364
Flow F.E	yes	yes	yes
Year F.E	yes	yes	yes
Destination*Year F.E	no	yes	no
Origin*Year F.E	no	yes	no

Sample: Census from 2014. Note: Robust standard errors in parentheses . ***,**,* mean respectively that the coefficient is significantly different from 0 at the level of 1%, 5% and 10%.

We then divide the migration flows into four categories based on the origin and destination localities: rural-rural, urban-urban, rural-urban, and urban-rural. The estimates are reported in Table 4. Less favorable climate conditions only exacerbate flows toward urban areas (exacerbate the rural exodus and increase flows between two urban localities). We do not observe any significant impact of climate in the delegation of destination.

In Tables 5-10, we distinguish the flows according to migrant characteristics, including gender, educational level, age groups, wealth level, employment status, and type of work. Men are more sensitive to climate conditions than women. Older cohorts seem less sensitive than younger ones. We unexpectedly find an effect of climate on the destination for some

Table 4: Effect of the SPEI on migration flows by type of destination and origin districts

	Rural to Rural	Rural to Urban	Urban to Rural	Urban to Urban
SPEI in origin	-0.125	-0.254**	-0.064	-0.155***
	(0.158)	(0.107)	(0.141)	(0.051)
SPEI in destination	0.143	-0.017	-0.192	-0.090
	(0.156)	(0.111)	(0.127)	(0.056)
Observations	24,440	41,190	37,320	111,325
Number of flows	4,888	7,992	7,268	22,265
Flow F.E	yes	yes	yes	yes
Year FE	yes	yes	yes	yes

Sample: Census from 2014. Note: Robust standard errors in parentheses . ***,**,* mean respectively that the coefficient is significantly different from 0 at the level of 1%, 5% and 10%.

age groups and women. We also find that migrants are likely to be less educated, suggesting that their jobs are more climate-independent. This finding is aligned with the estimates in Table 8: internal migration is more sensitive to climate conditions, as individuals often have precarious positions in the labor market, i.e. engaging in informal work, and depend mainly on agricultural activities. However, given the costs of migration, individuals from wealthy household are more likely to migrate. To our surprise, seasonal workers seem to be less sensitive to climate conditions (Table 9). There are no difference between own account workers and wage workers (Table 10).

Table 5: Effect of the SPEI on internal migration flows

	By gender		By education level		
	Men	Women	Low	Middle	High
SPEI in origin	-0.210***	-0.150***	-0.246***	-0.212***	-0.143***
	(0.042)	(0.038)	(0.058)	(0.051)	(0.049)
SPEI in destination	-0.066	-0.104***	-0.101*	0.020	-0.079
	(0.043)	(0.039)	(0.059)	(0.052)	(0.051)
Observations	111,765	121,985	81,260	88,125	91,330
Number of flow	22,353	24,397	16,252	17,625	18,266
Flow F.E	yes	yes	yes	yes	yes
Year F.E	yes	yes	yes	yes	yes

Sample: Census from 2014. Note: Robust standard errors in parentheses . ***,**,* mean respectively that the coefficient is significantly different from 0 at the level of 1%, 5% and 10%.

When we separate internal migration flows by motives, we once again find that economic motivation are the main channel through which climate affects migration (Table 11). Indeed,

Table 6: Effect of the SPEI on internal migration flows by age categories

	20-29	30-39	40-49	50-59	60-69
SPEI in origin	-0.141***	-0.075	-0.187***	-0.046	0.058
	(0.045)	(0.047)	(0.070)	(0.096)	(0.166)
SPEI in destination	-0.081*	-0.208***	0.004	0.032	-0.397**
	(0.046)	(0.047)	(0.070)	(0.097)	(0.159)
Observations	99,045	102,070	66,150	44,200	23,055
Number of flow	19,809	20,414	13,230	8,840	4,611
Flow F.E	yes	yes	yes	yes	yes
Year F.E	yes	yes	yes	yes	yes

Sample: Census from 2014. Note: Robust standard errors in parentheses . ***,**,* mean respectively that the coefficient is significantly different from 0 at the level of 1%, 5% and 10%.

Table 7: Effect of the SPEI on internal migration flows depending on current level of wealth

	Below the median	Above the median
SPEI in origin	-0.170***	-0.197***
	(0.065)	(0.041)
SPEI in destination	-0.063	-0.073*
	(0.061)	(0.043)
Observations	85,335	108,435
Number of flow	17,067	21,687
Flow F.E	yes	yes
Year F.E	yes	yes

Sample: Census from 2014. Note: Robust standard errors in parentheses . ***,**,* mean respectively that the coefficient is significantly different from 0 at the level of 1%, 5% and 10%.

droughts exacerbate economic migration, but also seem to increase marital migration. In other words, droughts are likely to affect marital decisions. Interestingly, climate conditions in the destination delegation do not seem to have a robust effect in general but increases migration return. This is probably because return migrants have a better understanding of the evolving climate conditions.

Table 8: Effect of the SPEI on internal migration flows

	Informal work	Formal work	Primary activity Outside agriculture	Primary activity in agriculture
SPEI in origin	-0.236***	-0.114***	-0.203***	-0.644***
	(0.046)	(0.042)	(0.039)	(0.202)
SPEI in destination	0.006	-0.132***	-0.052	0.241
	(0.046)	(0.044)	(0.040)	(0.201)
Observations	109,715	105,420	116,810	19,815
Number of flow	21,943	21,084	23,362	3,963
Flow F.E	yes	yes	yes	yes
Year F.E	yes	yes	yes	yes

Sample: Census from 2014. Note: Robust standard errors in parentheses . ***,**,* mean respectively that the coefficient is significantly different from 0 at the level of 1%, 5% and 10%.

Table 9: Effect of the SPEI on internal migration flows by type of work

	Permanent	Temporary	Seasonal
SPEI in origin	-0.226**	-0.222*	-0.154
	(0.096)	(0.130)	(0.108)
SPEI in destination	0.043	-0.060	-0.048
	(0.100)	(0.120)	(0.121)
Observations	39,110	36,795	36,795
Number of flow	7,822	7,359	7,359
Flow F.E	yes	yes	yes
Year F.E	yes	yes	yes

Sample: Census from 2014. Note: Robust standard errors in parentheses . ***,**,* mean respectively that the coefficient is significantly different from 0 at the level of 1%, 5% and 10%.

Table 10: Effect of the SPEI on internal migration flows by status of workers

	Own account	Wage workers	Family workers and others
SPEI in origin	-0.247***	-0.223***	-0.186
	(0.086)	(0.042)	(0.173)
SPEI in destination	-0.076	-0.040	0.047
	(0.078)	(0.044)	(0.174)
Observations	55,300	109,620	14,985
Number of flows	11,060	21,924	2,997
Flow F.E	yes	yes	yes
Year F.E	yes	yes	yes

Sample: Census from 2014. Note: Robust standard errors in parentheses . ***,**,* mean respectively that the coefficient is significantly different from 0 at the level of 1%, 5% and 10%.

Table 11: Effect of the SPEI on internal migration flows depending on the reason

	Economic	Marital	Return	Studies	Family
SPEI in origin	-0.221***	-0.177***	-0.171	0.119	-0.101
	(0.048)	(0.052)	(0.200)	(0.099)	(0.081)
SPEI in destination	-0.062	-0.137**	0.475**	-0.073	-0.011
	(0.051)	(0.055)	(0.197)	(0.100)	(0.081)
Observations	100,295	84,750	16,345	37,735	65,300
Number of flows	20,059	16,950	3,269	7,547	13,060
Flow F.E	yes	yes	yes	yes	yes
Year F.E	yes	yes	yes	yes	yes

Sample: Census from 2014. Note: Robust standard errors in parentheses . ***,**,* mean respectively that the coefficient is significantly different from 0 at the level of 1%, 5% and 10%.

5.3 Drought induced international migration

Table 12 reports the estimates of Equation 4. Column 1 includes all destination countries. Columns 2-4 present separate regressions for the main destinations (Libya, Italy, and France). On average, there is no robust effect of climate conditions on international migration flows. When we look at migration by destination country, we find that better climate conditions in rural localities significantly slow migration to Libya. The results are robust to the climate index used. International migration to OECD countries, where migration costs may be higher, does not seem to be significantly affected by climate conditions. Therefore, we provide the analysis of heterogeneity by taking into account only the international migration to Libya.

Table 12: Effect of climate on international migration flows by destination based on several climate index

	All	Lybia	Italy	France
SPEI	0.397***	-0.067	0.046	0.409***
	(0.125)	(0.097)	(0.147)	(0.127)
SPEI*Rural	0.032	-0.143***	0.036	0.065*
	(0.038)	(0.052)	(0.051)	(0.037)
Seasonal SPEI	0.043	-0.083	0.024	0.020
	(0.091)	(0.118)	(0.193)	(0.087)
Seasonal SPEI*Rural	0.041	-0.142***	-0.032	0.101
	(0.055)	(0.046)	(0.036)	(0.062)
Annual SPEI Drought	0.027	0.082	0.017	0.049
	(0.103)	(0.082)	(0.096)	(0.112)
Annual SPEI Drought*rural	-0.002	0.198***	-0.072	-0.022
	(0.052)	(0.072)	(0.078)	(0.054)
Annual SPI	0.004	0.071	-0.007	-0.003
	(0.038)	(0.051)	(0.059)	(0.034)
Annual SPI*rural	0.011	-0.183*	-0.033	0.061
	(0.048)	(0.098)	(0.050)	(0.046)
Observations	2,568	2,568	2,568	2,568
Number of flows	428	428	428	428
Flow F.E	yes	yes	yes	yes
Year F.E	yes	yes	yes	yes

Sample: Census from 2014. Note: Robust standard errors in parentheses . ***,**,* mean respectively that the coefficient is significantly different from 0 at the level of 1%, 5% and 10%.

The estimates of the climatic effect on migration to Libya by individuals' characteristics are provided in Table 13. International migration is more climate-sensitive for men, whereas there is very little difference between age and education groups.

Table 13: Effect of the SPEI on international migration flows by individuals' characteristics

	By gender		By age groups		By education level	
	Men	Women	Below 40	Above 40	Low	High
SPEI	0.014	-0.078	-0.120	-0.031	-0.053	-0.106
	(0.131)	(0.114)	(0.165)	(0.092)	(0.147)	(0.088)
SPEI *rural	-0.164*	-0.139**	-0.147*	-0.142***	-0.133**	-0.113*
	(0.085)	(0.058)	(0.080)	(0.051)	(0.059)	(0.065)
Observations	1,920	1,920	1,920	1,920	1,920	1,920
Number of flows	320	320	320	320	320	320
Flow F.E	yes	yes	yes	yes	yes	yes
Year F.E	yes	yes	yes	yes	yes	yes

Sample: Census from 2014. Note: Robust standard errors in parentheses . ***,**,* mean respectively that the coefficient is significantly different from 0 at the level of 1%, 5% and 10%.

Further investigation into the motivations behind migration reveals that economic reasons are the primary channel through which climate conditions influence international migration. (Table 14).

Table 14: Effect of the SPEI on international migration flows by destination

	Economic	Marital	Return	Studies	Family
SPEI	-0.057	0.088	-0.089	-0.138	0.209
	(0.110)	(0.141)	(0.090)	(0.211)	(0.140)
SPEI*rural	-0.153***	-0.126	-0.022	-0.023	-0.057
	(0.052)	(0.097)	(0.022)	(0.114)	(0.110)
Observations	1,920	1,920	1,920	1,920	1,920
Number of flows	320	320	320	320	320
Flow F.E	yes	yes	yes	yes	yes
Year F.E	yes	yes	yes	yes	yes

Sample: Census from 2014. Note: Robust standard errors in parentheses . ***,**,* mean respectively that the coefficient is significantly different from 0 at the level of 1%, 5% and 10%.

6 Conclusions

In this paper we analyze household adaptation strategies in response to changing climate conditions, focusing on two main strategies: agricultural production adaptation and migration. We conduct a geographically disaggregated analysis to assess how drought episodes influenced agricultural production from 1999 to 2013, as well as the scale and patterns of migration flows within and out of Tunisia from 2009 to 2014.

We demonstrate that worsening weather conditions force farmers to increase the share of irrigated land. However, this strategy does not completely offset the effects of adverse weather. Consequently, households must adopt other strategies, including migration, to protect themselves from the impact of climate change.

The results show that deteriorating climate conditions (lower precipitation levels) in origin delegations increase migration flows, while better climate conditions in rural locations in destination delegations, increase their attractiveness. A typical internal migrant is likely to be a man, less educated, engaged in informal work, dependent on agriculture, and originating from a wealthier family. Our finding also confirms that economic motivation is the main driver of climate migration.

We also highlight an effect of climate conditions on international migration. Less favorable weather causes higher migration flows to neighboring countries, mainly to Libya. However, it is unclear whether migration to OECD countries is affected by climate conditions.

This study underscores the critical need for policies aimed at enhancing resilience and bolstering adaptive capacity in rural areas. This involves improving water storage and management systems, promoting sustainable land management practices, and fortifying social safety nets to safeguard vulnerable populations during climate-related crises. Additionally, understanding the gender and educational disparities among migrants and how climate shocks impacts the local labor market structure underscores the importance of targeted policies to improve educational access and skills training, particularly for vulnerable groups. Additionally, the study provides valuable insights for policymakers to anticipate demographic pressures on urban areas, helping to inform proactive urban planning and development strategies.

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7 Appendix

7.1 Data

7.2 Robustness checks

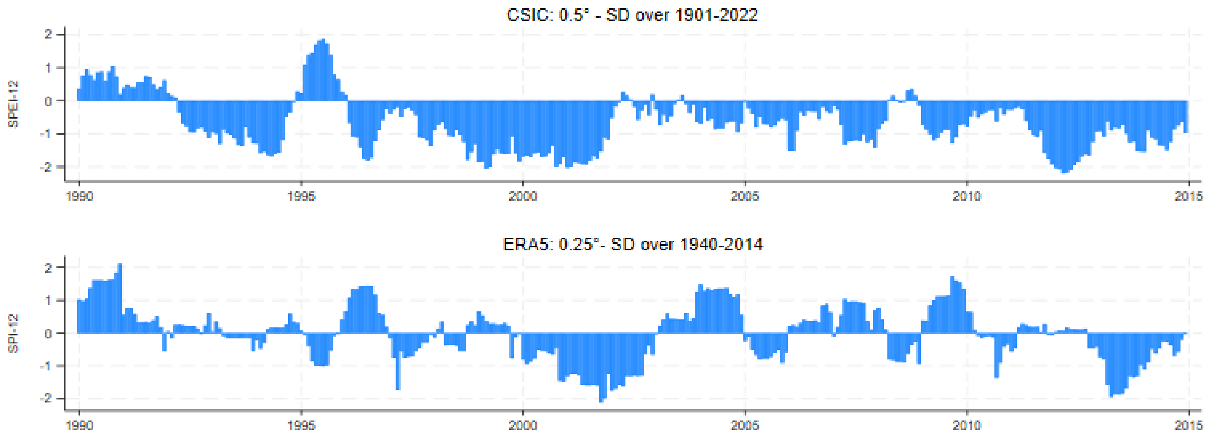

Figure 3: Evolution of SPEI and SPI overtime

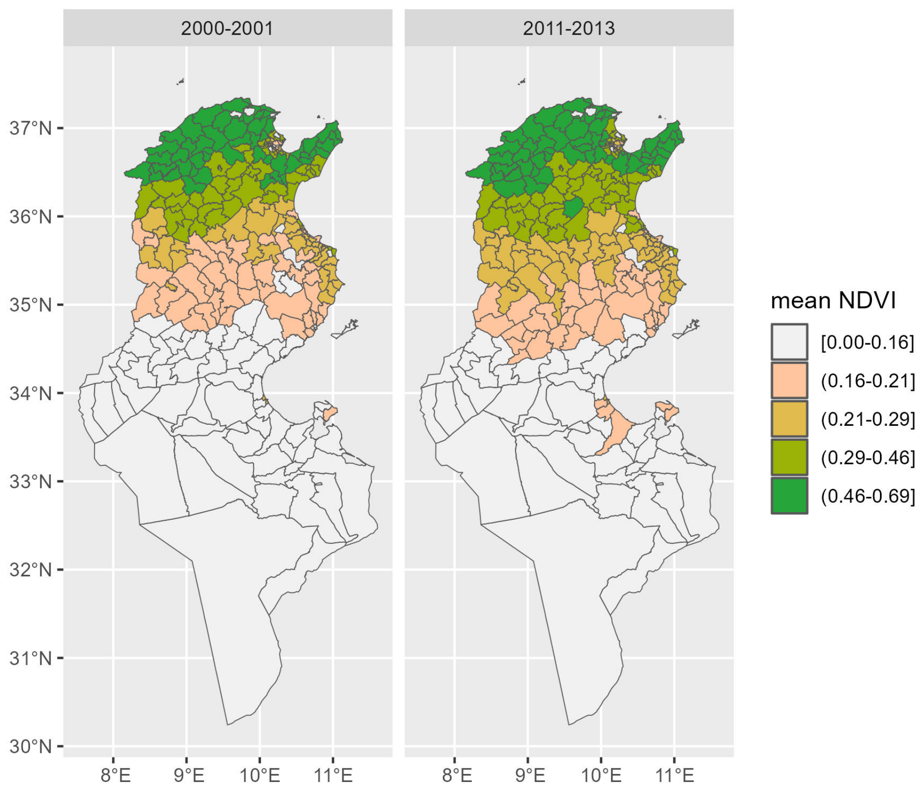

Figure 4: Mean NDVI across delegations

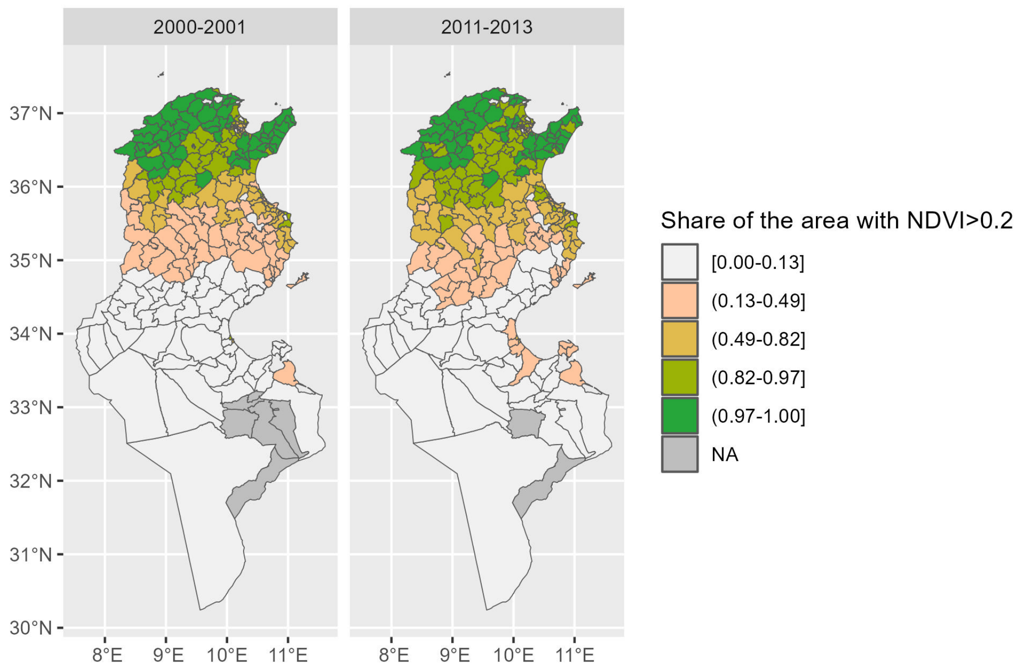

Figure 5: Share of the area NDVI$\leq$ 0.2 across delegations

Table 15: Summary statistics of the SPAM data

	N	Production	Harvested area	Productivity	Land share
All crops	522	8.59	8.1	2.156	1
By techniques					
Irrigated	451	7.302	5.417	7.839	0.164
High-input rainfed	491	6.654	6.599	1.201	0.363
Low-input rainfed	490	6.877	6.817	1.767	0.283
Subsistence	466	6.125	6.236	1.024	0.19
By main crops					
Cereals	505	6.918	6.53	1.538	0.348
Oil crops	497	6.546	6.946	0.75	0.448
Others	518	6.997	5.382	6.441	0.205

Table 16: First stage estimates: Effect of climate variations on the vegetation index

	$NDVI_{t-1}$		$NDVI_t$	
$SPEI_{t-1}$	0.293***			
	(0.057)			
SPI_{t-1}		0.159***		
		(0.031)		
$SPEI_t$			0.060	
			(0.045)	
SPI_t				0.276***
				(0.030)
Observations	930	930	930	930
Flow F.E	yes	yes	yes	yes
Year F.E	yes	yes	yes	yes

Note: Robust standard errors in parentheses . ***,**,* mean respectively that the coefficient is significantly different from 0 at the level of 1%, 5% and 10%.

Table 17: Robustness check: Effects of droughts on agricultural production (2000-2012)

	All	Irrigated	Rainfed high	Rainfed low	Subsistence
Number of intense droughts over the last 3 years					
Droughts	-0.283***	1.140***	-1.308***	0.0119	0.298***
	(0.0646)	(0.118)	(0.131)	(0.181)	(0.101)
Constant	7.714***	2.316***	10.00***	5.795***	4.171***
	(0.194)	(0.368)	(0.393)	(0.537)	(0.294)
Observations	2136	938	1843	1821	1768
R2	0.335	0.809	0.163	0.0711	0.0137
Number of months with intense drought over the last 3 years					
Droughts	-0.0265**	0.186***	-0.194***	0.0334	-0.0209
	(0.0106)	(0.0191)	(0.0171)	(0.0275)	(0.0156)
Constant	7.767***	-0.474	12.66***	4.714***	5.736***
	(0.363)	(0.656)	(0.587)	(0.939)	(0.521)
Observations	2136	938	1843	1821	1768
R2	0.323	0.809	0.156	0.0743	0.00594
Number of intense seasonal droughts over the last 3 years					
Droughts	-0.100**	0.780***	-0.726***	-0.436***	-0.515***
	(0.0428)	(0.0764)	(0.0859)	(0.0949)	(0.0636)
Constant	7.192***	3.393***	8.388***	7.180***	6.637***
	(0.142)	(0.254)	(0.297)	(0.316)	(0.212)
Observations	2136	938	1843	1821	1768
R2	0.320	0.793	0.0883	0.103	0.0924
5-arcminute cell F.E	Yes	Yes	Yes	Yes	Yes
Year F.E	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses . ***,**,* mean respectively that the coefficient is significantly different from 0 at the level of 1%, 5% and 10%.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Robustness checks: Effect of climate on migration based on several climate indexes

Migration flows		
Seasonal SPEI in origin	-0.015***	-0.003
	(0.004)	(0.005)
Seasonal SPEI in origin×Rural	-0.005**	-0.004*
	(0.002)	(0.002)
Seasonal SPEI in destination	-0.014***	-0.014***
	(0.004)	(0.005)
Seasonal SPEI in destination×Rural	0.005***	0.002
SPI in origin	0.005***	0.000
	(0.002)	(0.002)
SPI in origin×Rural	-0.010***	-0.010***
	(0.003)	(0.003)
SPI in destination	-0.001	-0.001
	(0.002)	(0.003)
SPI in destination×Rural	0.013***	0.012***
	(0.002)	(0.002)
Observations	214,610	214,610
Number of flows	42,922	42,922
Flow F.E	yes	yes
Destination*Year F.E	no	yes
Origin*Year F.E	no	yes

Sample: Census from 2014. Note: Robust standard errors in parentheses . ***,**,* mean respectively that the coefficient is significantly different from 0 at the level of 1%, 5% and 10%.

Table 19: Robustness checks: Effect of climate on migration using alternative measures of droughts

	Migration flows	
	Number of droughts over the last 3 years	
Origin	0.004**	0.001
	(0.002)	(0.002)
Origin×Rural	0.010***	0.007***
	(0.002)	(0.003)
Destination	0.006***	-0.000
	(0.002)	(0.003)
Destination×Rural	-0.013***	-0.009***
	(0.002)	(0.002)
	Number of months with drought over the last 3 years	
Origin	0.001***	-0.000
	(0.000)	(0.000)
Origin×Rural	0.001***	0.001***
	(0.000)	(0.000)
Destination	0.001***	0.000
	(0.000)	(0.000)
Destination×Rural	-0.001***	-0.001***
	(0.000)	(0.000)
	Number of seasonal droughts over the last 3 years	
Origin	0.003**	-0.001
	(0.001)	(0.003)
Origin×Rural	0.003*	0.001
	(0.002)	(0.002)
Destination	0.008***	0.000
	(0.002)	(0.003)
Destination×Rural	-0.008***	-0.003**
	(0.001)	(0.002)
	Number of droughts over the last 5 years	
Origin	0.002	-0.003
	(0.001)	(0.003)
Origin×Rural	0.003*	0.001
	(0.002)	(0.002)
Destination	0.008***	0.001
	(0.002)	(0.003)
Destination×Rural	-0.008***	-0.004**
	(0.001)	(0.002)
Observations	214,610	214,610
Number of flows	42,922	42,922
Flow F.E	yes	yes
Destination*Year F.E	no	yes
Origin*Year F.E	no	yes

Sample: Census from 2014. Note: Robust standard errors in parentheses . ***,**,* mean respectively that the coefficient is significantly different from 0 at the level of 1%, 5% and 10%.