Is climate change driving urbanization in Africa?

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Abstract

This paper documents a significant impact of climate variation on urbanization in sub-Saharan Africa, primarily in more industrialized and arid areas. By lowering farm incomes, reduced moisture availability encourages migration to nearby cities, while wetter conditions slow it. Rural-urban income linkages are also important. In regions with a larger industrial base, reduced moisture shrinks the agricultural sector and raises total incomes in nearby cities. However, if local cities depend entirely on servicing agriculture, reduced moisture tends to reduce local urban incomes. Finally, the paper shows that climate also induces employment changes within the rural sector itself. Drier conditions induce a shift out of farm activities, especially for women, into non-farm activities, and especially out of the work force. Overall, these findings imply a strong link between climate and urbanization in Africa.

JEL Codes: O10, O55, R12

Key words: Africa, Urbanization, Climate Change

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1. Introduction

Sub-Saharan Africa (hereafter Africa) is urbanizing quickly, with cities and towns growing at an annual rate of close to four percent over the last 20 years. Its urban population of 335 million now exceeds the total population of the United States. Nevertheless, almost two-thirds of Africa's population still lives in rural areas. How urbanization evolves in Africa over the next decades will determine where people and jobs locate and where public services should be delivered. A longstanding debate in the global development literature about the relative importance of push versus pull factors in urbanization has focused recently on Africa. Papers have assessed the contribution of pull factors including structural transformation driven by human capital accumulation and trade shocks (e.g., Fay and Opal 2000; Henderson, Roberts and Storeygard 2013) and of resource rent windfalls spent in cities (Jedwab, 2011; Gollin, Jedwab and Vollrath 2013). Other papers examine push factors including civil wars (Fay and Opal 2000), poor rural infrastructure (Collier, Conway and Venables 2008), and our focus, climate variability and change (Barrios, Bertinelli and Strobl 2006).

This paper analyzes the consequences of climate variability and change for African urbanization and the transformation of the rural sector. Over the last 50 years much of Africa has experienced a decline in moisture availability. Figure 1 shows average moisture for different areas of Africa in the 1950s and 1960s, where moisture is measured by an index combining precipitation and potential evapotranspiration (which is a function of temperature). A moisture level under 1 indicates that there is less rainfall available than would evaporate given prevailing temperature. This is the cut-off we use to define "arid" areas.[1] As Figure 2 shows, much of the strongest (10-50%) decline in moisture over the subsequent forty years occurred in parts of Africa that were initially relatively dry (moisture under 0.65 or between 0.65 and 1.0 in Figure 1), increasing the vulnerability of these already vulnerable areas. This decline in moisture has surely affected agricultural productivity.

We address three related questions. The first question is whether adverse changes in climate push people out of rural areas because of reduced agricultural productivity. We find strong evidence of this, but only in particular and limited circumstances. The second inter-related question is whether that push increases the total income of local cities. We find evidence supporting this hypothesis, but again

[1] We use "arid" as shorthand for areas that also include dry-subhumid, semi-arid and hyper-arid climates (see UNEP 1992).

only in certain limited circumstances. Our final question is whether adverse climate change also alters occupation choices within the rural sector itself, pushing people away from farming. We find more general evidence of this.

We find consistent patterns when analyzing these issues over different time and spatial scales. Specifically, first we look at local, within-district urbanization for an unbalanced 50-year panel of census data for 369 districts in 29 African countries. Typical intervals between censuses in the panel are 10-15 years. Two types of heterogeneity are critical to our analysis and define the limited circumstances in which climate change affects urbanization. The first is whether the district is likely to produce manufactures for export outside the district, and the second is whether the district is arid.

Our model implies there are climate effects on urbanization only in districts that have some industry, not in districts producing agriculture almost exclusively. When the local agricultural sector is competing for labor with an urban sector engaged in production of goods for export outside the district, declines in moisture encourage urbanization by offering alternative employment for farmers. If, however, local towns exist only to serve agriculture with local services not traded across districts, then a decline in moisture has little or no effect on city population because the two sectors are not in competition for labor for export activity. About 20-25% of districts in our sample show evidence of an industrial base. Among the approximately half of these industrialized districts that are in moist areas, we expect weaker climate effects, since reduced moisture may be less harmful to farmers. For an arid industrialized district, a one standard deviation increase in a district's annualized moisture growth rate lowers the annualized growth rate of its urban share by about 57% of the mean growth rate. Moreover, across the range of annualized growth in moisture, moving from the lowest to highest moisture growth rate (in a slightly trimmed sample) lowers the annualized growth in urban share by over 250% of the mean, a huge effect.

We next consider whether adverse changes in climate raise total urban income and stimulate the development of the urban sector. The answer is theoretically ambiguous and again depends critically on the initial state of the urban sector. When the local agricultural sector is competing for labor with urban production of goods for export outside the district, total city population and also total income rise with a decline of moisture. However if cities only exist to serve agriculture, then a decline in moisture generally leads to a decline in total city income. Our empirical analysis is based on much more recent, annual data for 1992 to 2008 on city and town income growth and rainfall in their immediate agricultural hinterlands. City income growth is proxied by growth in night lights (Henderson, Storeygard, and Weil 2012). For the cities most likely to have an export base in arid regions, the point estimate of the elasticity of lights with respect to rainfall is at least -0.16. However, when cities are likely to just provide services to farmers, the point estimate of the elasticity is positive, although small.

Finally, we ask how moisture changes affect a related margin of adaptation: occupational choice in the rural sector. This question is motivated by the little-noticed transformation of the rural sector over the last 20 years in many African countries, signified by a large shift into non-farm occupations.[2] For example, data for Benin, Malawi, and Niger in the period 1987-1996 all showed between 85 and 91% of the rural male labor force working in agriculture. This low proportion of rural workers in non-farm activity contrasts with countries like India or China, even 25 years ago. However Africa is now transforming. By 2006 to 2008, only 57-72% of the rural male labor force in these countries remained in agriculture.[3] Has climate played a role in this transformation? Based on individual-level observations from the Demographic and Health Surveys (DHS), we show that decreases in moisture decrease the probability of working in agriculture. For women, a one standard deviation (levels) decrease in moisture decreases the probability of working in farm activities by about 0.03 from a mean of 0.44, a 7% decrease, mostly through increased probability of not working (0.027). Decreasing moisture across its full range lowers the probability of working on the farm by 0.18, a 40% decrease. For men, for a one standard deviation decrease in moisture, there is a similar (0.034) decrease in the probability of working on the farm but it comes at the expense of off-farm work (0.028). When moisture declines, women are more likely to drop out of the measured rural labor force altogether, while men are likely to shift into non-farm activities.[4]

While our analysis necessarily focuses on the impacts of past climate variability, the specter of future climate change is a strong motivation. The combination of an already difficult climate, significant projected climate change and limited adaptation capacity has led some observers to state that Africa will be more affected than other regions by climate change (e.g., Collier, Conway and Venables 2008). Barrios, Bertinelli and Strobl (2010) argue that unfavorable rainfall trends may have already contributed to Africa's poor growth performance over the last 40 years, explaining between 15 and 40 percent of today's gap in African countries' GDP relative to other developing countries. While the precise pattern of future change for individual regions is highly uncertain, further drying is the most common prediction for parts of Africa. Overall, our results suggest that if future climate change will have the negative

[2] Concurrent work by McMillan and Harttgen (2014) has also noted this.
[3] We are comparing the 1996 and 2006 DHS surveys in Benin, the 1992 and 2006 DHS in Niger, and the 1987 and 2008 censuses of Malawi.
[4] While we acknowledge the difficulty of defining labor force participation in this context, we are simply comparing answers to the same questions asked to succeeding cohorts.

impacts on agriculture in Africa that many climate scientists and agronomists expect, there will be an increased pace of urbanization in selected parts of Africa. Where towns have started to industrialize, total town populations and incomes will likely grow, but we have no evidence about per capita income, and the transition may be more problematic in less industrialized regions. Transformation of the rural sector may also continue, as people move out of farming into non-farm rural production.

The following section reviews the literature on predicted impacts of climate change in Africa and on the link between climate and development outcomes including urbanization. Section 3 develops a model of how changes in climate will affect (a) the division of population between the urban and rural sector and (b) urban incomes. Section 4 describes the construction of the core climate and urbanization indicators used in the main analysis in Section 5. Other data sets used are described in the relevant empirical sections. Section 5 presents the analysis of the impact of changes in moisture availability on local urbanization. Section 6 examines the effects on urban incomes. Section 7 analyzes work activity responses within the rural sector. Section 8 concludes.

2. Literature on climate change and its impacts in Africa

2.1 Urbanization, local city growth and climate

The key paper on climate change and urbanization in Africa is Barrios, Bertinelli and Strobl (2006), who estimate an increase in the national urban share of 0.45 percent with a reduction in national rainfall of 1 percent. Henderson, Roberts and Storeygard (2013) revisit the question and find an imprecise effect of rainfall after controlling for agricultural price indices. Both papers have two limitations we overcome in the present work. First, they use national data, when there is significant within-country variation in climate change and most migration in Africa is local (Jonsson, 2001). We exploit within-country heterogeneity for a more nuanced and precise analysis of the effects of climate changes on urbanization. Second, those papers examine national urbanization using population data at regular 5- or 10-year intervals. Such data rely heavily on interpolation, especially in Africa where many censuses are infrequent and irregularly timed. We construct a new data set of urban growth for sub-national regions based on actual census data, not interpolations.

Related studies use micro data to study the effect of rainfall on migration per se, rather than urbanization. They are very informative and examine issues not covered in our approach, including movement across rural areas, between countries, and from rural area to cities (see Henry, Schoumaker, and Beauchemin 2004 on Burkina Faso) and temporary or circular movement (Parnell and Walawege

2011).[5] These studies typically interview rural residents about their migration history, thereby omitting permanent moves to cities, though the Demographic and Health Surveys could be useful for that purpose (Young, 2013). We limit our scope to net effects on urbanization within districts over long time periods of climate change. This approach allows us to consider a broad swath of African countries.

Two other papers indirectly consider how climate change might affect African urban incomes. Jedwab's (2011) historical study of Ghana and Cote d'Ivoire suggests that conditions in agriculture have a strong effect on nearby market towns that serve them. Gollin, Jedwab, and Vollrath (2013) explore how natural resource income affects urban development, extending the simple two-sector model of the rural-urban divide to include multiple urban economic sectors that may be differentially affected. We will model the effect of climate change on district urban incomes using insights from these two papers.

2.2 Climate change in general

Like other large world regions, sub-Saharan Africa has a highly diverse and variable climate. Moisture availability ranges from the hyperarid Sahara and Kalahari deserts to the humid tropics of Central Africa. In places like the West African Sahel, long droughts have followed extended wet periods. Africa's climate is shaped by the intertropical convergence zone, seasonal monsoons in East and West Africa, and the multi-year El Nino/La Nina Southern Oscillation (ENSO) phenomenon in which changes in Pacific Ocean temperatures indirectly affect African weather (Conway 2009). These processes influence temperatures and precipitation across the continent including extreme events like meteorological droughts, especially in the Sahel, the Horn of Africa and the Southern African drylands, as well as severe floods, such as in Kenya in 2013. Climate records indicate a warming trend over Africa during the 20th Century, continuing at a slightly faster pace in the first decade of the 21st Century, independently of ENSO impacts (Collins 2011; Nicholson et al. 2013; see also Giannini, Saravanan, and Chang 2003 and Held et al. 2005).

[5] We have focused in the text on papers of immediate relevance. We note that migration may be affected by the development of networks in destinations (Munshi, 2003). Recorded urban versus rural population growth may be affected by differential fertility rates and by the classification of what is urban (McGranahan, Mitlin, Satterthwaite, Tacoli, and Turok 2009). Recent macro-level studies have investigated the role of climate factors in African migration including international migration (e.g., Naudé 2010 and Marchiori, Maystadt, and Schumacher 2012). Marchiori et al. (2012) divide drivers of migration into those related to (dis-)amenities (potential spread of disease; risk of floods or heat waves) and economic geography (most importantly, agricultural performance). They find both channels to be important, estimating that temperature and rainfall anomalies have triggered 5 million migration episodes between 1960 and 2000. There has been much less consideration of year-to-year climatic variability in such models, despite evidence that the length of growing period, for instance, varies considerably in much of Africa (Vrieling, de Beurs and Brown 2011; Vrieling, de Leeuw and Said 2013). An exception is Marchiori, Maystadt and Schumacher (2013) who suggest that environmentally induced income levels—proxied by per capita GDP—may be more important for migration decisions than variability.

Climate researchers predict future climate change using various emission scenarios as inputs to several different assessment models. The underlying scenarios range from aggressive mitigation of greenhouse gases to a continuation of current trends. While there is fairly broad consensus about global average temperature trends, regional scenarios of temperature and particularly of precipitation patterns remain quite uncertain. Researchers from the Potsdam Institute for Climate Impact Research recently reviewed the predictions of a number of credible climate models for regional climate change in Africa (World Bank 2013). In general, average summer temperature is expected to increase by 1.5°C by 2050 in Africa under an optimistic (2°C) global warming scenario. The area exposed to heat extremes is expected to expand to 45 percent of the region by 2050.[6] Under a more pessimistic (4°C) global scenario, these trends would be exacerbated. Falling precipitation and rising temperatures would likely worsen agricultural growing conditions in large parts of Africa, especially in coastal West African countries and in Southern Africa.

Agriculture worldwide will feel the effects of climate change more directly than any other sector, but extreme climate conditions on the continent mean that many African farming systems operate in fairly marginal conditions even in the best of times.[7] A significant literature on climate change and African agriculture is emerging and helps inform and motivate some of our specifications. The majority of studies predict yield losses for important staple and traded crops of 8 to 15 percent by mid-century, with much higher losses of more than 20 percent and up to 47 percent by 2090 for individual crops (especially wheat) under more pessimistic climate scenarios (Kurukulasuriya, Mendelsohn, Hassan, et al. 2006, Kurukulasuriya and Mendelsohn 2008; Lobell, Burke, Tebaldi, et al. 2008; Schlenker and Lobell 2010; Thornton, Jones, Ericksen and Challinor 2011; Calzadilla, Zhu, Rehdanz, Tol and Ringler 2013; the meta-analyses by Piguet 2010; Roudier, Sultan, Quirion and Berg 2011; and Knox, Hess, Daccache and Wheeler 2012).[8] Assessing potential effects has been challenging in part because adaptation in the agricultural sector appears to be more difficult in Africa. Fertilizer use, for instance, has stagnated in Africa at low levels since 1980, while it has risen tenfold in Asia and Latin America (Cooper, Stern, Noguer and Gathenya 2013), and only 4 percent of agricultural land is irrigated

[6] The report defines heat extremes as 3-sigma events with respect to the 1951-1980 local distribution.
[7] A number of studies have estimated the impact on the value of crop and livestock production under various scenarios, with a focus on the United States (Mendelsohn, Nordhaus and Shaw 1994, Schlenker, Hanemann and Fisher 2006, Deschênes and Greenstone 2007).
[8] Some studies find modest or even positive impacts under optimistic scenarios of limited climate change and successful adaptation (Kurukulasuriya, Mendelsohn, Hassan, et al. 2006, Kurukulasuriya and Mendelsohn 2008; Calzadilla, Zhu, Rehdanz, Tol and Ringler 2013).

compared to 18 percent globally (You, Ringler, Nelson, et al. 2010). These studies motivate some of the specifications we test below.[9]

3. A Model of the impact of climate variability on local urbanization

We model movement between an urban and a rural sector which together comprise a district. While migration across district boundaries, for example to capital cities, clearly plays a role in this context, our focus is on local migration, which is very important in many African countries (Jonsson, 2010). Our goal is to model the effect of a change in moisture in a district on the urban-rural division of population and on city total income. We will show that if, as we have modeled, cities have an exporting industrial sector in addition to a service sector trading with local agriculture, a decline in moisture will lead to increased urbanization and increased total city income. The model does not address occupational choice as considered in our final empirical exercise.

3.1 The basic model

3.1.1 Urban sector

The urban sector (city) produces services and manufacturing. Output per unit labor is b in services and cL_m^{ε} in manufacturing, where L_m is total labor units in manufacturing and $\varepsilon > 1$. Services, produced with constant returns to scale, represent non-agricultural items produced and sold locally, but not traded outside the district. Scale economies in manufacturing, represented by ε, can come from information spillovers or from diversity of local intermediate inputs in a monopolistic competition framework.[10] Final output of manufactures is tradable nationally or internationally at fixed prices to the city. Given these two sectors, the wage rate per unit labor in the city is

$$w = p_s b = cL_m^{\varepsilon} \qquad (1)$$

where p_s is the price of services and manufacturing is the numeraire.

[9] Besides urbanization and local city development, an emerging literature is finding broader impacts of variations in temperature and rainfall on a variety of human capital, economic, and political outcomes. These include birth weight effects with long term consequences (Deschênes, Greenstone and Guryan 2009), childhood effects on health, schooling and socioeconomic status (Maccini and Yang 2009), later childhood effects on schooling (Shah and Steinberg 2013), and effects on the risk of conflict in Africa (Burke, Dykema, Lobell, Miguel and Satyanath 2009; Hsiang, Meng and Cane 2011; O'Loughlin, Witmer, Linke, et al. 2012).

[10] In the latter context, output of any final goods firm is $m = \left(\int_0^n z(h)^{1/(1+\varepsilon)} dh \right)^{1+\varepsilon}$ where output of any intermediate input producer employing $l(h)$ workers is $z(h) = \gamma l(h) - \lambda$ and n is the number of local intermediate input producers a city can support. Solving the monopolistic competition problem, the equilibrium wage of a worker in the manufacturing sector has the form cL_m^{ε}.

Following standard urban models (Duranton and Puga, 2004), workers live in a city where they must commute to work in the city center. Each worker is endowed with 1 unit of labor and commuting reduces time spent working at a rate of $4t$ per unit distance commuted. Those living far from the city center spend less on land rents to compensate for their higher commuting costs, or lost labor earnings. City land rents are redistributed to urban workers. Per worker net income, after commuting and land rents are paid and land rent income is redistributed, is

$$y = w(1-tN_U) = p_s b(1-tN_U) \qquad (2)$$

where N_U is city population.[11]

City effective total labor supply net of time spent commuting, L, is

$$L_s + L_m = L = N_U(1-tN_U) \qquad (3)$$

where L_s is the labor force in services.

3.1.2 The rural sector and equilibrium conditions for the district

The other part of the district is the rural sector producing agricultural products, sold at a fixed price p_a in international markets. Per worker income in the agricultural sector is given by

$$p_a f(N_A, R), \quad f_1 < 0, \; f_2 > 0 \; . \qquad (4)$$

The rural (agricultural) population is N_A and the total land area is shared equally among that population. Per worker output (either marginal or average output depending on how agricultural rents are distributed) is declining in total farm workers and increasing in moisture or rainfall, R.

Migration arbitrage between the urban and rural sector equalizes incomes and there is full employment in the district so that

$$p_a f(N_A, R) - p_s b(1-tN_U) = 0 \qquad (5)$$

$$N_U = N - N_A \qquad (6)$$

[11] Following Duranton and Puga (2004), in a linear city, where each worker is endowed with 1 unit of time and working time is $1-4tu$ where u is distance from the city center and $4t$ unit commuting costs, it is easy to derive expressions for city labor force L as a function of population N_U (by integrating over the two halves of the city each of length $N_U/2$), for the city rent gradient (equating rent plus commuting costs for a person at *u* with that of a person at the city edge where rents are 0, so they are equally well off in equilibrium) and for total rents. These have forms respectively:

$$L = N_U(1-tN_U); \quad R(\mathrm{u}) = \mathrm{wt}(2N_U - 4u); \quad \text{total rents} = wtN_U^{\,2}$$

where w is the wage rate. A person living at the city edge and paying zero rent earns in net $w(1-2tN_U)$, with the diseconomy arising from increasing commuting distances reducing time available to work. After getting a share in urban rent income their net income is $y = w(1-tN_U)$.

N is district total population. The model is closed by noting that the untraded services market must clear. Total production is bL_s and total demand is $N\ D\left(y, p_a, p_s\right)$ for the individual demand function $D\left(y, p_a, p_s\right)$. Thus we know using (2) and (5) that

$$bL_s = N\ D(p_a f(N_A, R),\ p_a,\ p_s) \qquad (7)$$

3.2 Comparative Statics when the local urban sector exports manufacturing.

We seek the effect of moisture change on city (or conversely agricultural) population and total city income. That is, we want to solve for dN_A / dR and $d(y\,N_U)/dR$.

3.2.1 Changes in urbanization

First we solve for the effect on the population allocation. We differentiate (1), (7), (3) and (5), having used (6) to substitute for N_U. We define income and own-price elasticities of demand for services, $\eta_y > 0, \eta_{p_s} < 0$ in the usual fashion. The results are

$$\frac{dp_s}{p_s} = \varepsilon \frac{dL_m}{L_m} \qquad (8a)$$

$$\frac{dL_s}{L_s} = \eta_y \frac{f_1}{f} dN_A + \eta_y \frac{f_2}{f} dR + \eta_{p_s} \frac{dp_s}{p_s}, \qquad \eta_{p_s} < 0 \qquad (8b)$$

$$dL_s + dL_m = -[1 - 2t(N - N_A)]dN_A \qquad (8c)$$

$$\frac{f_1}{f} dN_A + \frac{f_2}{f} dR - \frac{dp_s}{p_s} - \frac{t}{1 - t(N - N_A)} dN_A = 0 \qquad (8d)$$

Using (8a) and (8b) to substitute for dL_m and dL_s in (8c) and solving for dp_s / p_s we get

$$\frac{dp_s}{p_s} = -\varepsilon\ [1 + \varepsilon \frac{L_s}{L_m} \eta_{p_s}]^{-1} \left(\left[\frac{1 - 2t(\mathrm{N} - \mathrm{N}_A) + L_s \eta_y \dfrac{f_1}{f}}{L_m} \right] dN_A + \frac{L_s}{L_m} \eta_y \frac{f_2}{f} dR \right) \qquad (9)$$

We substitute (9) into (8d) to get

$$\frac{dN_A}{dR} = -\frac{f_2}{f}\ \frac{L_m + \varepsilon L_s(\eta_y + \eta_{p_s})}{Z} \qquad (10)$$

$$Z \equiv \frac{f_1}{f}[L_m + \varepsilon L_s(\eta_y + \eta_{p_s})] - \frac{t}{1 - t(N - N_A)}(L_m + \varepsilon L_s \eta_{p_s}) + \varepsilon[1 - 2t(N - N_A)]$$

To sign this expression we first need to sign Z. Stability of migration between the urban and rural sector requires that the differential in (5) be decreasing in N_A, and therefore that the expression in (8d) divided by dN_A is negative when $dR = 0$. This reduces to

$$Z(L_m + \varepsilon L_s \eta_{p_s})^{-1} < 0. \qquad (11)$$

As long as the local urban manufacturing sector is not negligible (i.e. L_m / L_s is not too small) then $(L_m + \varepsilon L_s \eta_{p_s})$ > 0,. For example if $\eta_{p_s} = -1$, we require that $L_m / L_s > \varepsilon$. Given the literature believes ε < 0.08 for example, then as long as the local city has a modicum of manufacturing, $(L_m + \varepsilon L_s \eta_{p_s})$ >0, and stability implies $Z < 0$. We focus on this case here, and the opposite case in section 3.3.

Returning to (10), given $(L_m + \varepsilon L_s \eta_{p_s})$ > 0 and therefore $Z < 0$, $dN_A / dR > 0$ follows directly. The magnitude of response depends on the magnitude of f_2 / f. Of course, as moisture changes all variables change, but we can say that as f_2 approaches zero, so does the response. f_2 / f plays an important role in the empirical formulation in Section 5.

3.2.2 Changes in city income

Next we turn to the effect of moisture on city income. Total city income is

$y(N - N_A) = p_a f(N_A, R)\ (N - N_A)$. Thus

$$\frac{dy(N - N_A)}{dR} = p_a f_2 Z^{-1}[1 - t(N - N_A)]^{-1} * M \qquad (12)$$

where

$$M \equiv [L_m + \varepsilon L_s(\eta_y + \eta_{p_s})][1 - 2t(N - N_A)] + t(N - N_A)\varepsilon L_s \eta_y + (N - N_A)\varepsilon[1 - 2t(N - N_A)][1 - t(N - N_A)]$$

Under the current assumption that $(L_m + \varepsilon L_s \eta_{p_s})$ > 0, $Z < 0$. If we further require that city earned incomes ($[1 - 2t(N - N_A)]$) be positive, M must be positive. Given that *Z* is negative, $dy(N - N_A) / dR$ is negative.

In sum we have the following proposition relevant to our empirical work:

Proposition 1. *If the city has a tradable manufacturing sector that is not too small relative to its local service sector so that* $(L_m + \varepsilon L_s \eta_{p_s})$ *> 0, a decline in moisture will lead to an increase in urban population and total city income.*

For completeness, the expression for the change in city per capita income is:

$\frac{dy}{dR} = p_a f_2 Z^{-1}\{-(L_m + \varepsilon L_s \eta_{p_s})\frac{t}{1-t(N-N_A)} + \varepsilon[1-2t(N-N_A)]\}$. In the current situation, given $Z < 0$, $L_m + \varepsilon L_s \eta_{p_s} >$ 0, and the definition of Z, $dy/dR > 0$. In our empirical work, total income or expenditure in the city will be measured by night lights data, which are recorded over time periods incompatible with the bulk of the population data. Income is nominal in a context where the price of services will change, but for a broad class of utility functions, the city's sum of utilities is affected in qualitatively the same way as city income.[12]

3.3 Comparative statics with minimal local manufacturing.

If the local traded good manufacturing sector is very small so $(L_m + \varepsilon L_s \eta_{p_s}) < 0$, then the fortunes of the city are tied to the local agricultural sector, as in Jedwab (2011).[13] Stability thus requires $Z > 0$, and the sign of dN_A / dR in eq. (10) is ambiguous. As a simple example, if $\eta_y + \eta_{p_s} = 0$, then $dN_A / dR < 0$. In that case, as $L_m \to 0$, $dN_A / dR \to 0$. When $L_m = 0$, the sign of dN_A / dR depends entirely on the sign of $\eta_y + \eta_{p_s}$. There, if $\eta_y + \eta_{p_s} = 0$, there is no effect of rainfall on the rural-urban population allocation, because migration effects only come through changes in demand for services (and the effect on demand for services of reduced price is exactly offset by the effect on demand of reduced per person income). Ambiguity arises in the general case in (10), if $\eta_y + \eta_{p_s} < 0$.

Total urban income from (12) is more consistently increased by rainfall. Given $Z > 0$, if $\eta_y + \eta_{p_s} \geq 0$, we can unambiguously show that $dy(N - N_A)/dR > 0$. Increased rainfall raises local farm productivity and all local incomes.[14] With city population modestly affected, total city incomes must rise. However, if $\eta_y << |\eta_{p_s}|$, so that city population declines a lot, we cannot rule out the possibility that urban incomes decline as well.

[12] We examine the sum of utilities based on a log linear indirect utility function, but it applies to any indirect utility function where doubling income doubles utility. For $V(y, \vec{p})N_U = AN_U y p_s^{\sigma_s}$ where σ_s is the expenditure share of services and differentiating we can show that

$$\frac{d(N_U y p_s^{\sigma_s} C)}{dR} = p_s^{-\sigma_s} C N_U y \frac{f_2}{f} Z^{-1}\left[(1-\alpha)\varepsilon[1-2t(N-N_A)] + \frac{[1-2t(N-N_A)](L_m + \varepsilon\eta_{p_s} L_s) + [1-(1+\sigma_s)t(N-N_A)]\varepsilon\eta_y L}{[1-t(N-N_A)](N-N_A)}\right].$$

If $Z < 0$ this expression is negative.

[13] We describe this case assuming the local manufacturing sector exists, but the situation is analogous in the case where there is no manufacturing at all and per worker output of the service sector is given by $bL_s^{\varepsilon_s}, \varepsilon_s \geq 0$.

[14] See the expression for changes in per capita income above.

Proposition 2. *If the city has a traded good manufacturing sector that is tiny or non-existent so that* $(L_m + \varepsilon L_s \eta_{p_s}) < 0$*, the effect of a decline in moisture on city population is ambiguous and tends to zero as* $L_m \to 0$ *when* $\eta_y + \eta_{p_s} = 0$ *. However total city income declines, assuming* $\eta_y + \eta_{p_s}$ *is not strongly negative*.

This strict difference between the effect of moisture changes on local city incomes depending on whether manufacturing has a noticeable local presence will inform the empirical work in Section 6.

Whether a city has manufacturing is of course endogenous. In our static framework, an absence of manufacturing implies that the wage the first worker in manufacturing would receive in the city, c, is less than the equilibrium wage in the service sector ($p_s b$). Manufacturing arises if either local (potential) productivity, c, rises with, for example, enhanced education, or if the price of the manufactured good rises relative to the other goods. This latter case could be driven by changes in international prices or changes in the cost of transporting products between the local city and a port.[15] Studying the development of local industry is beyond the scope of our work and for most Sub-Saharan African countries lack of data would make such a study difficult. We study whether climate affects urbanization and local incomes given existing industrial composition, but not whether it contributes to changes in industrial composition.

4. Data on urbanization, climate, and industrialization

In this section we discuss our basic measures of urbanization, moisture and extent of industrialization of districts, data we need to conduct the first analysis of the effect of climate on urbanization. We leave the description of night lights and DHS occupational data to the relevant sections.

4.1 Urbanization

Scarcity of demographic and economic data hampers empirical research on climate effects in Africa. Many countries carry out censuses only irregularly, and sample surveys such as the DHS are infrequent and provide little information before 1990.[16] While there are now a number of geographically detailed climate data sets that are increasingly used by economists (see Auffhammer, Hsiang, Schlenker, and Sobel 2013), most studies have employed national level population and economic data sets which are

[15] Other work such as Atkin and Donaldson (2013) and Storeygard (2014) considers the transport cost story in Africa directly.

[16] The World Fertility Surveys of the late 1970s and early 1980s (DHS precursors), are less consistently available to researchers.

readily available from the UN and other agencies and which, for African countries, rely heavily on imputations and interpolations.

We collected urban and rural population measures for sub-national regions (provinces and districts) from census reports. We include countries with at least two available censuses with the relevant information for a complete or nearly complete set of sub-national units, where either district boundaries changed little or common units over time can be defined. The data were extracted mostly from hardcopy census publications obtained from the U.S. Census Bureau library, the U.S. Library of Congress, the LSE library, and the British Library. The collected sample covers 32 countries but Namibia and Congo-Brazzaville are dropped because of problems with urban or district definitions.[17] We limit the panel sample to intercensal periods (L) of less than 20 years, so Liberia is omitted because its two available censuses were 34 years apart. We have information from 2 to 5 censuses between 1960 and 2010 for each remaining country (Figure 3 and Appendix Table A1). Kenya is effectively treated as two countries, before and after rapid redistricting and urban redefinition of the 1990s. Each country is divided into a number of sub-national units we call districts. The 369 districts used in panel estimation are shown in Figure 3.

The most notable omission is Nigeria, Africa's most populous country, because of concerns over the quality of census figures (see, e.g., Okafor, Adeleke and Oparac 2007). Other Sub-Saharan African countries are missing because either they had no censuses with needed information or in a few cases because we were unable to obtain the printed volumes. Finally, we do not include South Africa because it is more developed, province maps were redrawn post-Apartheid, and pre-Apartheid migration restrictions make it a special case.

4.2 Climate

With few exceptions, most studies of climate impacts on agriculture focus exclusively on precipitation. However, moisture available for plant growth is also a function of evapotranspiration. Thus, dividing precipitation by potential evapotranspiration (PET), which is a non-linear function of temperature, increasing in the relevant range, is viewed as a better measure of climatic agricultural potential. Although this measure is often called an aridity index and used to define aridity zones (UNEP 1992), we call it a moisture availability index, because larger values indicate relatively greater water availability, with values above one indicating more moisture than would be evaporated given prevailing temperature. Precipitation and temperature data are from the University of Delaware gridded climate

[17] For Namibia, the problem is changing district boundaries and urban definitions. For Congo most districts were originally drawn to be either wholly urban or wholly rural, making within-district analysis impossible.

data set (Willmott and Matsuura 2012). We estimated monthly PET from 1950 to 2010 using the Thornthwaite (1948) method based on temperature, number of days per month and average monthly day length, and subsequently summed monthly values to obtain annual totals (see, e.g., Willmott, Rowe and Mintz 1985 for details).[18]

Figure 4 shows average annual country-level moisture trends for the countries in our sample, indicating the long term downward trend over the last 60 years, consistent with Figure 2. It also shows the high inter-annual variability of moisture in these countries, even with three-year smoothing. The climate data sets have a spatial resolution of 0.5 degrees, which corresponds to about 3000 km^2 at the equator. To generate district level climate indicators, we average grid cell values that overlap with the corresponding sub-national unit, weighting by area in the case of cells that cross district boundaries.[19]

4.3 Extent of industrialization

Our model suggests that places with export industries will respond differently than other districts. Sub-national data on industrialization in African countries is scarce; even data on the share of GDP in manufacturing at the national level is scare before 1985. So for the first analysis of urbanization based on outcomes from 1960 onwards, we need a base from that time period. The *Oxford Regional Economic Atlas, Africa* (Ady 1965) maps all industries by type and city location in Africa, based on an in-depth analysis from a variety of documents and census sources from the late 1950s and early 1960s. We integrated these maps with our census data to locate all places with any of 16 different "modern" manufacturing industries: iron and steel, electrical equipment, general engineering equipment, cement, other building materials, rubber, petroleum refining, printing, footwear, four types of textiles, chemicals paints, glass and pottery. Following Moradi (2005), we call the first five key industries, meaning they provide inputs to other downstream industries, and we consider these separately. Figure 5a shows the total count of industries found in each of our districts, where the maximum is 8 of the 16. Only 16% of our districts had any of these industries, suggesting that there may be limited scope for the induced industrialization channel in our model. Figure 5b maps all industries from Ady (1965), combining the 16

[18] More specifically, potential evapotranspiration (PET) for month *i* is calculated as:

$$PET_i = \left(\frac{N_i}{30}\right)\left(\frac{L}{12}\right)\begin{cases} 0, \ T_i < 0°\text{C} \\ 16(10T_i/I)^{\alpha}, \ 0 \le T_i < 26.5 \\ -415.85 + 32.24T_i - 0.43{T_i}^2, \ T_i \ge 26.5 \end{cases},$$

where T_i is the average monthly temperature in degrees Celsius, N_i is the number of days in the month, L_i is day length at the middle of the month, $\alpha = (6.75 \times 10^{-7})I^3 - (7.71 \times 10^{-5})I^2 + (1.792 \times 10^{-2})I + 0.49$, and the heat index $I = \sum_{i=1}^{12}\left(\frac{T_i}{5}\right)^{1.514}$ where T_i indicates the 12 monthly mean temperatures. The Penman method provides a more precise estimate of PET, but requires data on atmospheric conditions that are not available consistently for the area and time period of this study.

[19] In practice, we use the number of 0.1-degree sub-cells as a weight.

modern industries with 10 agricultural processing industries: brewing, wine/spirits, tanning, canning, and the processing/milling/refining of sugar, oil, cotton, grain, tobacco and timber. Twenty-three percent of the sample has an industry in this wider set, with at most 13 different industries in a single district.

In our empirical work, we try three measures of 1960s industrial activity: presence of a key industry, count of modern industries, and count of all industries. We also consider distance to the coast as a proxy, although it is clear from Figure 5 that the correlation between the extent of industry at the end of the colonial period and distance to the coast is not very strong for most countries. For the analysis of growth in night lights in Section 6, which starts 30 years after these industry data, we will rely more on country-level measures of the extent of industry to proxy for whether a city is likely to export manufactures.

5. Empirical analysis of the effect of climate on urbanization

5.1 Specifications

We estimate the effect of growth in moisture on growth in urbanization for a panel of districts that is highly unbalanced because different countries conduct censuses in different years. Growth rates are annualized to account for these intercensal periods of different lengths. The base specification is

$$u_{ijt} = \beta w_{ijt,smooth} + \beta_0 X_{ij} + \beta_1 X'_{ij} w_{ijt,smooth} + \alpha_{jt} + \varepsilon_{ijt} \qquad (13)$$

where variables for district i, in country j, in year t, are defined as follows:

u_{ijt} is annualized growth of the urban population share from $t - L_{jt}$ to t;

$w_{ijt,smooth} = \left[lnW_{ij,t,smooth3} - lnW_{ij,t-L_J,smooth3}\right]/L_{jt}$;

$W_{ij,smooth3}$ is average moisture from $t-2$ to t;

L_{jt} is the number of years between year t and the prior census;

X_{ij} are time invariant controls, including initial levels of variables;

α_{jt} is a country-year fixed effect controlling for time-varying national conditions; and

ε_{ijt} is an error term clustered by district.

In (13), growth in urbanization is a function of growth in moisture. The growth specification removes the effect of time-invariant district characteristics (distance to markets, soil quality and the like) on urbanization *levels*. Some of these factors (X'_{ij}) may also affect the impact of climate changes on urban share *growth rates*, yielding heterogeneous effects. We control for country-year fixed effects to account for national time-varying conditions driving urbanization overall in a country. This also controls to some extent for variation between countries in the definition of urban areas, which poses a significant problem in cross-country urban analysis. What we are doing is demanding on the data—identification of climate effects on urbanization must come from within-country differences across districts in annualized growth rates of moisture.

We smooth the moisture levels over three years, on the assumption that potentially permanent decisions are more likely to be based on average recent experience rather than one good or bad year. As an example of the smoothing, the annualized rate of change in urban share between censuses in 1965 and 1980 is estimated as a function of the annualized rate of change in moisture between the average for 1963, 1964 and 1965 and the average for 1978, 1979 and 1980. Although this smoothing period is somewhat arbitrary, our results are robust to reasonable adjustments as noted later.

Our theoretical model suggests two important forms of heterogeneity, based on industrial capacity and aridity (L_m / L_s and f_2 / f in equation 10). Our primary measures of industrial capacity come from Ady (1965). We try both country and district-level measures of aridity for 1950-69. We examine these two dimensions separately and together. In Section 5.4, we briefly consider heterogeneity based on several additional factors: soil quality, irrigation potential, rainfall concentration with the year, variability or noisiness in moisture changes over our intervals, and changes in climate variability over time.

In Table 1 we present summary statistics on the estimating variables for all countries and for the more arid ones. The average annualized growth rate of moisture is negative, consistent with Figure 2, and the average growth rate in the urban share is positive. We are concerned that outliers in these variables could reflect measurement problems. For example, an extremely high urban share growth rate could be due to a poorly measured low base. An extremely high or low moisture growth rate could reflect intercensal changes in the density of weather stations, especially in arid regions. We thus trim 0.5% from the top and bottom of the distribution of growth in both urban share and in moisture, a total of 16 observations for the whole sample. We comment on the effects of trimming when presenting results.

5.2 Identification

Our chief identification concerns are insufficient within-country variation and omitted variables. In Figure 6a, the growth in moisture variable has more density to the left of zero, consistent with drying; and it has a large spread of positive and negative values. However, Figure 6b shows that spread does shrink somewhat after factoring out country-year fixed effects.

With respect to omitted variables, since changes in climatic conditions are exogenous and in principle randomized by nature across districts, estimates of reduced form (or net) effects may appear to be unbiased. We have differenced out time-invariant factors affecting urbanization levels. However, it is possible that unobservables affecting growth in urbanization could be correlated with climate change within our limited sample. We thus control for initial urbanization, which might represent a variety of factors. For example, initial urbanization might be correlated with both growth in urbanization (e.g., mean reversion) and growth in moisture (by chance). Figure 7 shows a modest positive correlation (significant at the 10% level) for arid countries, which are our focus.

5.3 Base specification results

Tables 2-4 report on three basic specifications of the effect of moisture growth on urbanization. In Table 2, after showing the effect with no allowance for heterogeneity, we explore the effects of allowing for heterogeneity in the likelihood of having industry. Table 3 explores effects allowing for heterogeneity in initial moisture level, and Table 4 combines the two sources of heterogeneity. We focus on qualitative results in Tables 2 and 3, deferring most quantitative comparisons until Table 4 where both sources are present. In Table 2, column 1, the effect of moisture growth alone on urbanization is insignificant, suggesting that there are no effects on average. Significant and distinct effects only arise when heterogeneity is introduced, and thus these effects apply only to particular sub-samples.

5.3.1 Likelihood of industrialization

The rest of Table 2 explores heterogeneity based on the likelihood of having manufactures for export, as opposed to only agriculture and local services. In column 2, we interact the moisture effect with a dummy for whether the district has no key industries in the Oxford Atlas, so the base coefficient applies to areas with key industries, about 11% of the sample. It is insignificant, but consistent in sign with the rest of the table. In column 3 we use a proxy for the extent of agriculture, based on the number of modern (non-agriculture based) industries present. The measure has a value of zero if a district has the maximal count (8) of these industries and then rises, as the number of industries declines, to a maximum of 8 in districts with no industries (84% of the sample), so the uninteracted moisture coefficient applies directly to the most industrial districts. This continuous measure is broadly analogous to L_s / L_m in equation (10) of our model, representing not only the likelihood of industry but its possible extent. Column 4 applies an analogous measure to a broader industry measure that includes the agricultural processing industries. 77 % of districts had no industry of any type in the early 1960s.

Based on either modern or all industries, point estimates in columns 3 and 4 suggest a very large effect for the most likely industrialized districts of -0.73 and -0.89. Here a one standard deviation decrease in the growth rate of moisture increases the growth rate of share urban by about 0.012, where that growth rate has a mean of 0.03. In both of these columns, as the extent of industry decreases, the effect diminishes at rates of 0.10 and .075, respectively, per industry lost. Thus for districts with no industry the net marginal effects of moisture growth are an insignificant 0.07 and 0.08 in the two columns. These results are consistent with the theory we presented: strong negative effects of moisture growth on urbanization in industrialized districts but little or no effect in agricultural ones. In the last column we use distance to the coast as a proxy for industrial activity and find no base or interactive effect.

All results so far have imposed smoothing over 3 years (0 to 2 before each census) and trimming. Appendix Table A2 varies these assumptions, starting from the Table 2, column 4 specification. Smoothing over 3-4 periods appears to provide optimal variation. Smoothing over 2 periods leaves more noise and over 5 limits variation. By contrast, trimming is conservative. Without trimming, both the base effect and the rate of diminution are much stronger; further trimming beyond the 16 observations we removed has modest effects on results.

5.3.2 Heterogeneity based on initial aridity

Table 3 examines the effect of moisture growth allowing for heterogeneity in just initial aridity. Column 1 shows the effect of allowing for heterogeneity at the country level based on whether the country overall is moist (moisture index in excess of 1.0). With this country level distinction, we have a significant negative effect of moisture growth in arid countries as expected. The net effect for moist countries is positive but imprecisely measured. It may seem odd to use a country level index, when we know moisture by district. The problem is that our identification comes from within-country variation in moisture growth. Defining aridity based on districts leaves little such variation: in 11 of 17 arid countries all districts are arid, and in 2 more, 2 or fewer districts are non-arid. In essence, for many countries the country-level designation applies perfectly or nearly perfectly to all districts. We try two alternatives to focus on district-level heterogeneity. First, in column 2 we draw the country line for moist at 0.75, rather than our preferred 1.0, This achieves variation in all but three our countries. This does not give significant results here, but it is stronger when both sources of heterogeneity are included in Table 4. Second, in column 3, we impose a linear structure on heterogeneous effects by interacting moisture change with the initial (1950-69 average) level of moisture in a district, a continuous variable. Here results are reasonably consistent with those in column 1 although precision is limited. An arid district with initial moisture of 0.5 has a moisture growth elasticity of -0.22 compared to an overall -0.29 for arid countries in column 1.

5.3.3 Heterogeneity of aridity and industrialization

In Table 4 we combine the two sources of heterogeneity, to distinguish industrialization effects in arid versus moist areas. All columns have all appropriate interactions, but only the key coefficients are shown. In the top row we show the effect of moisture growth in arid places that most likely have industry, varying the definition of industry and arid places across columns. These are all large effects. Heterogeneity is more distinct across levels of industry likelihood than levels of moisture, with differential effects for moist places not being significant. However distinguishing moist places increases and in some specifications sharpens the climate change effects in industrialized districts.

Columns 1-4 define industry likelihood analogously to columns 2-5 of Table 2, and aridity at the country level as in Table 3, column 1. In column 1, using the key industry dummy, there is a strong negative effect of -0.84 in industrial districts of arid countries, and a smaller, insignificant negative net effect of -0.22 for their moist country counterparts. In column 2, the moisture growth effect starts at -1.16 in the most industrial districts and decreases to an insignificant net effect of -0.24 in the most agricultural districts. In column 3, using the all industries measure, the effect starts at -1.184 in the most likely to be industrialized areas (with 13 industries in the 1960s) and declines at a rate of 0.073 per industry, reaching a net effect of -0.23 in the most agricultural districts. This is our main result. For the most industrialized areas in an arid country, a one standard deviation increase in moisture reduces urbanization by 0.018, or 57% of the mean growth rate in share urban. Moving from the minimum to maximum (trimmed) growth in moisture gives a decrease in the urban share growth rate of 0.116, about 274% in excess of the mean.

In column 4, we use distance to the coast as the industry measure. There is a strong effect at the coast and a rate of diminution that is positive as expected, but only significant at the 10% level. By the maximum distance in the sample, climate effects are close to 0.

The effects in column 1-4 do not show significant differences for moist countries. For districts that have industry (23%), about half are in arid countries and half in moist. It is clear there is limited cell size to make nuanced distinctions between moist and arid. In columns 5 and 6, we use all industries as in column 3, but moisture distinctions done at the district, rather than country level. In both cases, using a binary cut-off at a 0.75 and a continuous measure, moist results are imprecise.

In summary, we can distinguish effects of moisture growth in districts that are more (likely) industrialized compared to districts that have no industry. However, in our limited sample we see no strong evidence of a diminution of effects in more moist areas once we control for the industry distinction. The moisture distinction just enlarges and in some cases sharpens the industry distinction in arid areas.

5.4 Other dimensions of heterogeneity

The effect of moisture on urbanization may differ along many other dimensions. We focus on six here, fully interacting each with the Table 4, column 3 specification.[20] As we thus create quadruple interactions, it is not surprising that we find no compelling results for any new dimension overall, and specifically, we find no evidence that they affect the marginal effect of moisture growth in industrialized arid areas. The first three are measures of agricultural productivity that might influence the effect of moisture changes: soil water capacity and total soil suitability from Ramankutty et al. (2002), and evidence of modern irrigation infrastructure from Siebert et al. (2007).[21] The other three are measures of weather variability within and across years, which might make farmers more or less vulnerable to changes. One is a Gini of rainfall across months within the year to measure rainfall concentration within the year, using baseline 1950-69 data. The other two are the standard error of the linear prediction of rainfall between censuses to measure noise in the growth in climate variable,[22] and the intercensal change in the standard deviation of rainfall in the 10 (or 17) years before a census.

6. Climate change and city income

Having shown evidence of the population effects predicted by our model, we turn to effects on city total income. Our theory indicates that if the local town or city performs an exportable activity, then reduced (increased) moisture unambiguously raises (lowers) city income. However if the local town exists solely to provide farmers with services (or potentially goods) that are not traded outside the district, then the fortunes of the urban and rural sector are tied. Decreased moisture is then likely to decrease local city income.

Data on income or city product are not consistently available for African cities, so we use an indirect measure. Following the approach in Henderson, Storeygard and Weil (2011, 2012), we test

[20] Each new variable is interacted with are Δmoisture, Δmoisture*(8-#industries), Δmoisture*1(country moisture>1), Δmoisture*(8-#industries)*1(country moisture>1), 1(country moisture>1), (8-#industries), (8-#industries)*1(country moisture>1).

[21] Although soil degradation can change soil conditions over the time scale of decades (see UNEP 1992), data on these dynamics are not consistently available, so soil quality is time invariant in our analysis.

[22] Based on the annualized growth rate, $w_{ijt,smooth}$, from equation (13), we can formulate the predicted value for moisture in any year between census intervals as $\hat{W}_{ijt,smooth3} = W_{ijt-L_j,smooth3} e^{w_{ijt,smooth}}$. From that we form the standard error of prediction: $SEP_{ijt} = \sqrt{\sum_{s=t-L_j}^{t} (\hat{W}_{ijs,\mathrm{smooth}3} - W_{ijs,\mathrm{smooth}3})^2 / (L_j - 2)}$.

whether the intensity of nighttime light emitted by a city is affected by the amount of rainfall within a 30 km radius around each city in the current or prior year (see Figure 8). The nighttime lights data come from the U.S. Defense Meteorological Satellite Program (DMSP), a weather satellite system that captures visible light between about 8:30 p.m. and 10 p.m. We use annual data from 1992 to 2008 for 30 arc-second grid cells (0.86 km^2 at the equator). The data product typically used for socioeconomic analysis contains only stable lights after temporary light sources such as forest or savannah fires have been removed (e.g., Elvidge et al 1997). We further remove gas flares based on Elvidge et al. (2009). Light intensity for each pixel is expressed as a "digital number" (DN) linearly scaled between 0 and 63.

6.1 Specification

Our analysis includes 1,158 cities and towns, in 42 countries (all of mainland sub-Saharan Africa except Somalia, plus Madagascar). We define cities as contiguous lit areas in the DMSP data set for which a population estimate is available from a comprehensive census database.[23] More specifically, we overlay lit areas for all years and find the outer envelope of lights as pictured in Figure 8. The city's total amount of light for each year is the sum of the digital number (light intensity) over all grid cells that fall within this outer envelope (maximum extent) of the city light footprint. Rainfall measures are from the Africa Rainfall Climatology Version 2 (Novella and Thiaw 2012), which combines weather station data with satellite information, resulting in a shorter time series but finer spatial resolution (0.1 degree) than Wilmott and Matsuura (2012). We use rainfall rather than moisture in this section because we are unaware of any temperature measures at such fine resolution that do not heavily rely on interpolation of sparse data. Each city's hinterland annual average rainfall is calculated as an average of grid-cell values within 30 km of the ever-lit area. Summary statistics are in Appendix Table A3.

Our specification is

$$\ln\left(light_{ict}+1\right)=\sum_{j=0}^{k}\beta_j \ln rain_{ic,t-j}+\sum_{j=0}^{k}\gamma_j \ln(rain_{ic,t-j})*X_i+\phi_i+\lambda_t+\alpha_c t_c+\varepsilon_{ict} \quad (14)$$

where

$light_{ict}$ is light DN summed over all pixels in city i, country c, in year t;

$rain_{ict}$ is average rainfall in millimeters per day within 30 km of city i;

X_i are country-level indicators for moisture level and agricultural share, as well as city-level indicators;

$\emptyset_i$ and λ_t are city and time fixed effects;

$\alpha_i t$ is a city-specific linear time trend;

[23] http://www.citypopulation.de

ε_{ict} is an error term, clustered at the city level to capture city-specific serial correlation.

Equation (14) is an annual panel specification for cities. To identify rainfall effects on lights, we control for time-invariant city conditions, time effects (to account for annual differences in sensor settings across and within satellites), and city-specific linear growth trends. The idea in empirical implementation is that each city is on a growth path and rainfall fluctuations in the local area cause it to deviate from that growth path. If climate changes are more permanent then the growth path is shifted up or down.

The empirical context is different from the urbanization analysis of Section 5 in two important respects. First, we are looking at year-to-year fluctuations rather than 10-15 year changes. This suggests local migration and income responses may be small, but empirically we do find effects. Second, because night lights data are only available after 1991, the period of analysis is shorter and starts later. This affects how we define 'likely to be industrialized'. Using a map from 30 years before our sample period may not give the best information. As before we use distance to the coast which may be more relevant now, well after the colonial era and with the increase in world trade. By 1990 we also have full data at the national level on the extent of industrialization. Based on the national agriculture share in GDP data for 1989-1991, we say that districts in a country are likely to be just agricultural if the share of agriculture in GDP exceeds 30%. That leaves 25% of the large sample of cities defined as likely to have industry.[24] We use the same moist/arid cutoff of 1.0 at the country level as in most of Table 4. As in Tables 2-4 and the theory, these distinctions are critical.

6.2 Results

6.2.1 Results with heterogeneity by likelihood of the city being industrialized

Table 5 shows effects with heterogeneity based on having industry. As for urbanization, in column 1 the average impact of rainfall on city income (lights) overall is zero. However once we isolate the much smaller subsample of cities likely to have industry for export outside the local area, we see effects. In column 2 where we define this likelihood based on national share of agriculture, the elasticity of lights with respect to rainfall for industrialized areas is -0.12. A one standard deviation increase in rainfall reduces city lights by 4%. Rainfall draws people out of the city and results in a loss in total city income. For agricultural areas the net coefficient is positive (0.067) but not significant. It hints at the idea that increased rainfall in agricultural areas might benefit local towns because migration effects are small but all incomes are larger.

[24] We assume that Nigeria's agricultural share (net of resource rents) is higher than 30% based on the earliest available data, from the 2000s, when it is above 50%.

In column 3 we use the strongest extent of agriculture measure from the 1965 map for this case: modern industries. Covariates have the expected signs but effects are insignificant, consistent with a problem of poor assignment from dated maps. In column 4, we turn to the coastal specification which is compelling. The elasticity of lights with respect to rainfall for coastal cities which are the ones most likely to have industry is -0.225, diminishing at a rate of 0.019 per log point of distance to the coast (almost significant at the 5% level). By 140 kilometers, effects are zero. If we take the result in column 2 as the main result with an elasticity of -0.12 and apply the lights-GDP elasticity of about 0.3 from Henderson, Storeygard and Weil (2012), this implies a rainfall-city product elasticity of about -0.036 for more industrialized places. If we use column 4, with the base case being coastal cities, the elasticity almost doubles.

6.2.2 Rainfall change effects: Industrialization and initial moisture heterogeneity

In Table 6, we check whether initial area moisture levels affect the marginal effects of rainfall variation found in Table 5. Here, based on both results from Section 5 and the fact that we don't have aridity defined for these data at the city level, we focus on the country-level aridity distinction. In column 1, differentiation of rainfall effects by the moisture dummy produces no significant results. In the remaining columns, the moist or not distinction serves to mostly enhance and sharpen the differentials in rainfall effects between cities likely to be industrialized and others, just like in Table 4. In column 2, using country share of agriculture in GDP in arid countries, the elasticity of lights with respect to rainfall is now -0.16 for industrialized cities and the net effect for agricultural cities is 0.05 (although not significant). Column 3 uses modern industry extent based on the 1965 map. Now by focusing on arid areas, effects are stronger than in Table 5. The cities most likely to be industrialized have an elasticity of -0.20, while those with maximal agriculture (8) have a zero effect. Finally in the last column using coastal distance, results for arid areas are sharper than in Table 5. For cities on the coast in arid areas the elasticity of lights with respect to rainfall is -0.37, decreasing again to zero at about 370 km, and then becoming positive. Overall, for the most industrialized areas in arid regions, the elasticity of lights with respect to rainfall ranges from -0.16 to -0.37. Using -0.25 as a central estimate, a one standard deviation increase in rainfall reduces lights by 8.3%. The diminution for moist areas is clearer in this table than previously but still insignificant. In either industrialized or agricultural cities, if one adds the relevant coefficients together, net effects in moist areas are close to zero.

Overall the results are consistent with our model. Rainfall declines raise local city incomes in total for industrialized cities, as labor moves to the urban sector. But for agricultural cities, rainfall declines have if anything a negative effect on total city incomes. This suggests that local urban areas will be hurt by any further drying out in the future unless they have an industrial base. Unfortunately, only a fraction of African urban areas do.

6.2.3 Leads and Lags

In Table 7 we test for lagged and lead effects of rainfall. While we continue to rely on clustered errors at the city level to account for serial correlation, as a robustness check here we also try imposing an AR[1] structure. Columns 1 and 2 show the result from Table 6 column 2 with clustering and AR[1]. The specification with AR[1] has quantitatively somewhat different coefficients, but the same qualitative pattern. In columns 3 and 4 we look for lagged effects. In column 3 with clustered errors, increased lagged rainfall in industrialized arid areas has a small additional negative effect on city lights, about half of the contemporaneous effect, which disappears for moist areas (but the offset effect is not significant). In column 4 with an AR[1] process, lagged effects are much stronger. This difference in effects dependent on specification and the more modest effects with clustered errors led us to decide that trying to tease out longer lag structures would not produce robust results; and in general longer lags are not precisely estimated. In columns 5 and 6 we tried lead rainfall as a placebo test. For both clustered errors and the AR[1] process there are no significant effects, just as should be the case. For the base case, industrialized cities in arid regions, the effect of leads is zero.

6.2.4 Other considerations

In work not reported here, we examined whether effects differ for cities that are likely to be served by hydro power. Our concern is that lights could be affected directly by electricity availability and pricing, which could be affected by climate directly, independently of climate effects on income. However, because most towns are served by national grids with uniform pricing, we don't actually expect differential effects. When we fully interacted our Table 6, column 2 specification with a measure of hydropower reliance, we found no differential effect.

7. Occupational choice within rural areas

Migration, whether temporary or permanent, is not the only possible response to adverse climate fluctuations or long term changes in the rural sector. Drier growing conditions will lower the returns to farming and farmers may stop working or switch to non-farm activities. In this section, we find evidence of both, with differential patterns by gender. These possible responses must be seen in the overall context of climate change in rural economies. As noted above, if farm incomes drop, there will be less money in the rural economy in general, so alternative work opportunities may be scarce, muting the expected benefit of switching to a non-farm occupation. We looked only at responses in the rural sector.

Our data do not provide industry information to analyze shifts between services and manufacturing in the urban sector (which in themselves may be second order effects) nor do they provide relevant migration information.

7.1 Data and specifications

We test whether changes in climate have an impact on employment by sector within rural areas using individual-level data from the Demographic and Health Surveys (DHS, Macro International) for 18 African countries, all but two of which are in our urbanization dataset (Appendix Table A4). DHS use a two-stage sampling design, first randomly selecting enumeration areas in a country and then surveying a cluster of about 30 randomly selected households in each. The surveys oversample female household members since one of the primary purposes is to collect data on fertility and reproductive health. We compile DHS data from 2-3 repeated cross-sections for each country. In total we use 43 surveys from between 1996 and 2011, and only include people in rural locations. Our sample is restricted to those DHS that record cluster location, whether a respondent worked in the last year or not, and if so in what occupation. Work need not be paid. Summary statistics are in Appendix Table A5. Sample size is 100,788 men and 312,769 women aged 15-49.[25]

While the majority of males and females do report working (paid or unpaid), the percentages are only 82% and 67% respectively for our sample. We don't think of this as the usual selection problem of whether to work or not and, if so, what occupation to choose based on wage differentials. Working is closely tied to the farm and the decision for many may be more whether to work on the farm or to carry out other household responsibilities not considered work. We thus model a multinomial choice between not working, working in agriculture, and working in a non-agricultural occupation. Thus, an increase in agricultural work may both draw people into the workforce and draw people out of non-agricultural work activities. We note that a comprehensive study of intra-household dynamics and choices is beyond the scope of this paper. Instead, we are estimating the reduced form effects of rainfall on occupation as stated in the surveys.[26]

For both men and women, the dominant activity is working in agriculture but this is especially true of men, both in terms of the choice among the 3 activities (58 vs. 44%) and conditional on working

[25] Reducing the sample to the 25-49 age group to include only respondents who have completed all possible education does not change results.

[26] Furthermore, we are aware that people in different places may conceptualize work in different ways. Thus while we cannot be sure that we are capturing precisely the same margin in all contexts, we are identifying local changes over time in the way people answer the same question of whether they are working, and if so in what occupation.

(71 vs. 66%). The average age of respondents is between 28 and 29 for both men and women. Men generally have more education with about 66% reporting at least primary school versus 53% for women.

Since all DHS used in our study are georeferenced at the cluster level, matching to the Willmott and Matsuura (2012) climate data is straightforward. However, different rounds of the DHS do not survey the exact same clusters, and the number of clusters typically increases over time. We created "superclusters" by matching each cluster to the geographically closest cluster in the first survey in its country.

We estimate the multinomial choice of not working, working in agriculture, and working in a non-agricultural occupation. Agricultural work is the reference occupation, so covariates' effects on it are a residual (since marginal effects must sum to zero across the three choices). The general specification is

$$y_{icjt} = \alpha x_{icjt} + \beta \overline{W}_{cj,(t-1,t-3)} + d_{jt} + f_c + e_{icjt} \qquad (15)$$

where

y_{icjt} is a choice for individual i in district c, in country j and year t (i.e., not work, work in agriculture, work in non-agriculture);

x_{icjt} are individual characteristics: age (and age squared) and education dummies;

$\overline{W}_{cj,(t-1,t-3)}$ is average moisture over the three previous years;

f_c is a supercluster (or province) fixed effect;

d_{jt} is a country-year fixed effect; and

e_{icjt} is an error terms clustered at the supercluster level.

We control for predetermined individual characteristics age and education in x_{icjt}, and estimate separate regressions by gender. We do not include controls for marital status, number of children or other indicators that could plausibly be affected by climate and instead estimate a reduced form model of climate impacts on choice. We again smooth moisture over 3 years to remove noise, but since survey timing varies within the calendar year and this year's climate may not yet have an effect at survey time, we use years *t-3* to *t-1*. We cluster standard errors by supercluster, as measured moisture does not vary within them.

Since these are not individual panel data, we cannot first- or long-difference them, but supercluster fixed effects perform an analogous role in controlling for time-invariant local effects. Inclusion of supercluster fixed effects ensures identification is based on within-cluster variation in rainfall. This is important. For example, in dry and drying areas, non-farm opportunities may be limited and there may be a low probability of non-farm work per se, so simple correlations might suggest a negative association between drying out and non-farm work.

Our main specification is a linear probability model (LPM) with supercluster fixed effects. We also estimate the model by logit and probit, but with 3,939 superclusters for females and 3,751 for males, supercluster fixed effects are not computationally feasible. In these nonlinear models we instead include province fixed effects, assuming that clusters within (larger) provinces have similar conditions. We also control for country-year effects. Multinomial logit and probit marginal effects are almost identical, so we report just the probit.[27]

7.2 Results

The results are in Table 8. We focus on the LPM results in columns 1-3 for women in panel A and for men in panel B. The effects for men and women differ. More moisture draws women out of the home and into farming, with no response in off-farm work. More moisture draws men out of non-farm work into farm work. This presumably reflects an average gendered division of labor for this sample. A one standard deviation increase in moisture (about 0.5) increases the probability of women working in farming by 0.03 from a mean of 0.44. Increasing moisture across its full range (3.5) raises the probability of working on the farm by 0.18, a 40% increase. A one standard deviation increase in moisture reduces the probability of men working off farm by about 3%. The control variables have expected effects: the more educated and younger women are, the less likely they are to work in agriculture. Results restricting to the first and last survey in each country are similar (not shown).

As noted above, the province fixed effects used in the probit specification are a much weaker control for underlying local conditions than supercluster fixed effects. Results for the probit in columns 4-6 of Table 8 are different from the LPM. For women probit effects are larger, perhaps reflecting identification problems in the probit, or attenuation bias from the supercluster fixed effects in the LPM. One might thus be tempted to think of the LPM estimates as a lower bound and the probit as an upper bound. However for men the probit results are much smaller than the LPM, only marginally different from zero for not working. Reestimating the LPM with just district fixed effects suggests that most of these differences are explained by the differences in fixed effect specification, not in estimation procedure (not shown).

[27] Note that the covariance structure with cross-choice correlation in errors is not identified when there is no variation in covariates across choices (only across individuals).

In summary, based on OLS estimation with supercluster fixed effects, when climate for farming improves, women are more likely to leave household work behind to engage in farming, while men are more likely to leave non-farm work. For men at least, drying drives movement into non-farm occupations within the rural sector.

8. Conclusions

With a high dependence on agriculture and an already highly variable and often marginally suitable agro-climate, Africa may be at higher risk from climate change than most other world regions. Agricultural adaptation through improved seeds and increased irrigation may mitigate this risk. But technological change in Africa has been slow and, despite frequent droughts in the past, irrigation infrastructure remains scarce. So for many farmers facing adverse climatic conditions the only option may be to migrate to urban areas.

Our analysis suggests that agro-climatic conditions do indeed influence urbanization rates, with better conditions retarding urbanization and unfavorable conditions leading to greater urban population growth. However strong effects are confined to about 10-15% of Sub-Saharan African districts, in arid local areas that have some degree of industrialization.

As our model predicts, decreased moisture increases total city populations and incomes in districts whose cities are likely to have manufacturing, and are therefore more likely to be able to absorb workers leaving the farm into the urban labor force. Again as theory predicts, in the more usual context where local cities are unlikely to have manufacturing and rely on demand from local farmers, we find that reduced moisture leads to reduced or unchanged city incomes. Finally, we find some evidence of alternative adaptation strategies. When growing conditions are unfavorable, rural females are more likely to report not working and rural males are more likely to move from farm to non-farm work.

These results confirm the strong link between climatic conditions and urbanization but just in particular circumstances, adding to the growing economic literature on climate and development. Our results suggest that more severe and persistent climate changes, which will likely increase the challenges faced by Africa’s farmers, could further accelerate migration to cities, but only in more industrialized areas. Support for agricultural adaptation, and creating conditions for urban economic growth, are therefore even more urgent priorities.

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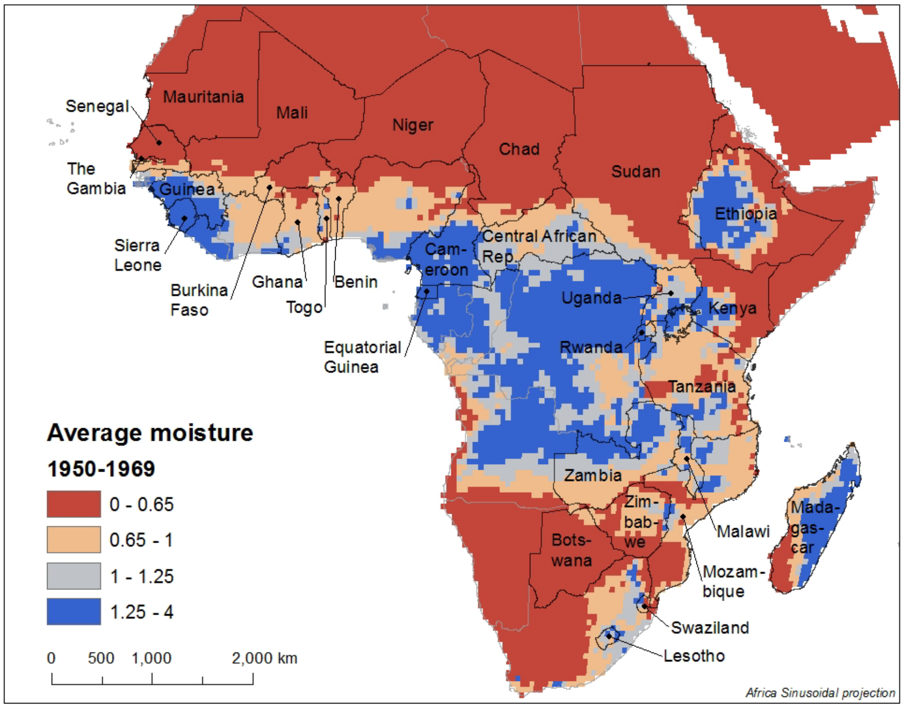
Figure 1: Historical levels of moisture (precipitation / potential evapotranspiration)



Note: Map boundaries reflect the situation during the time period covered by this study. See Appendix Table A1 for details on the time periods used for each country.

Figure 2: Decreasing moisture in Africa in the second half of the twentieth century

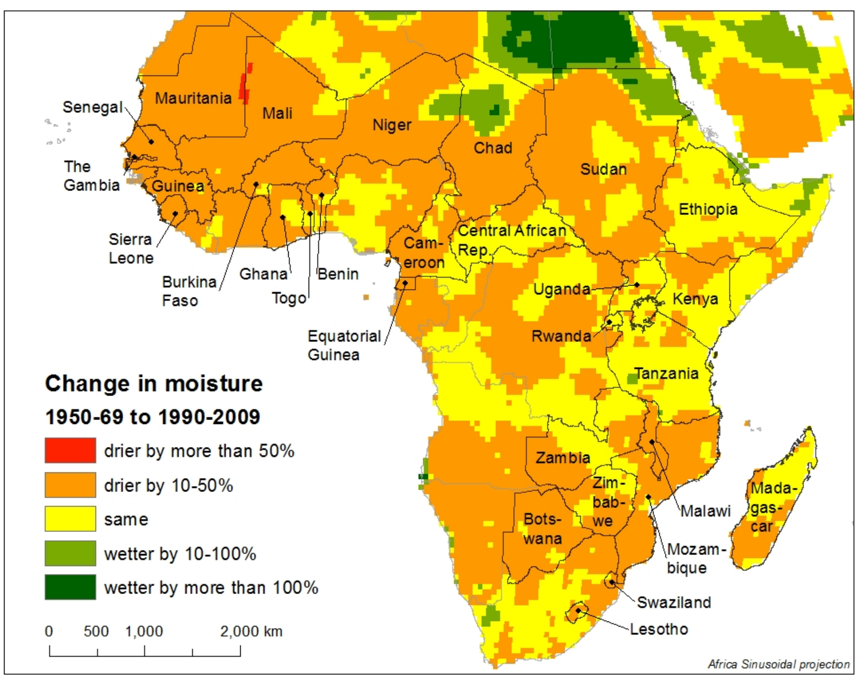
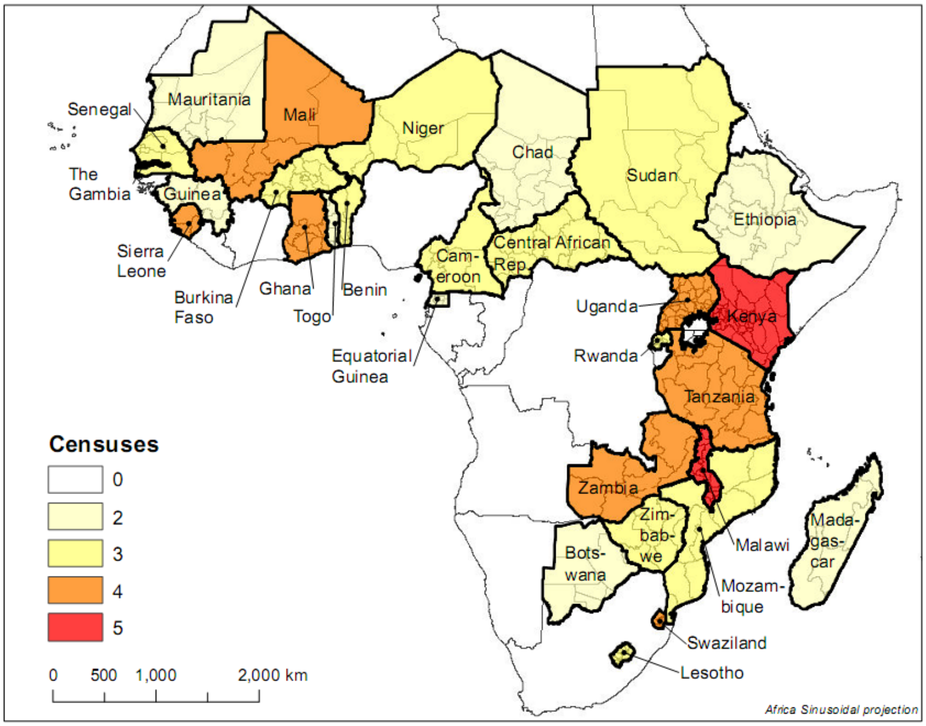


Figure 3. Census data sample



Note: Map boundaries reflect the situation during the time period covered by this study. See Appendix Table A1 for details on the time periods used for each country.

Figure 4. Variability in climate change in Africa

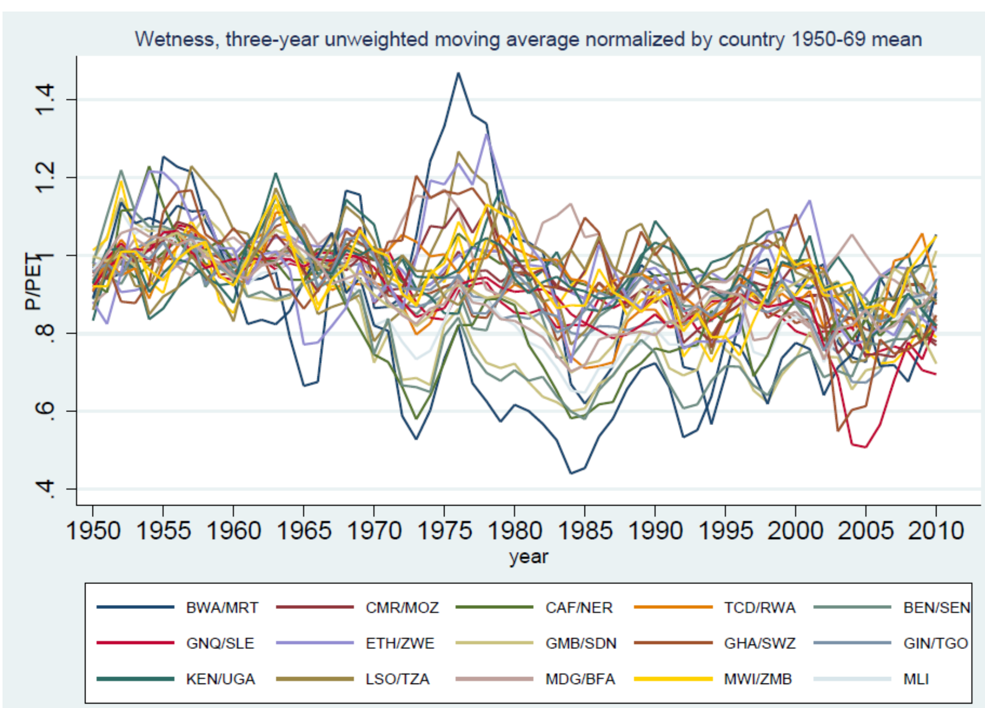


Figure 5a. Extent of industry 1965, modern (non-food processing) industries

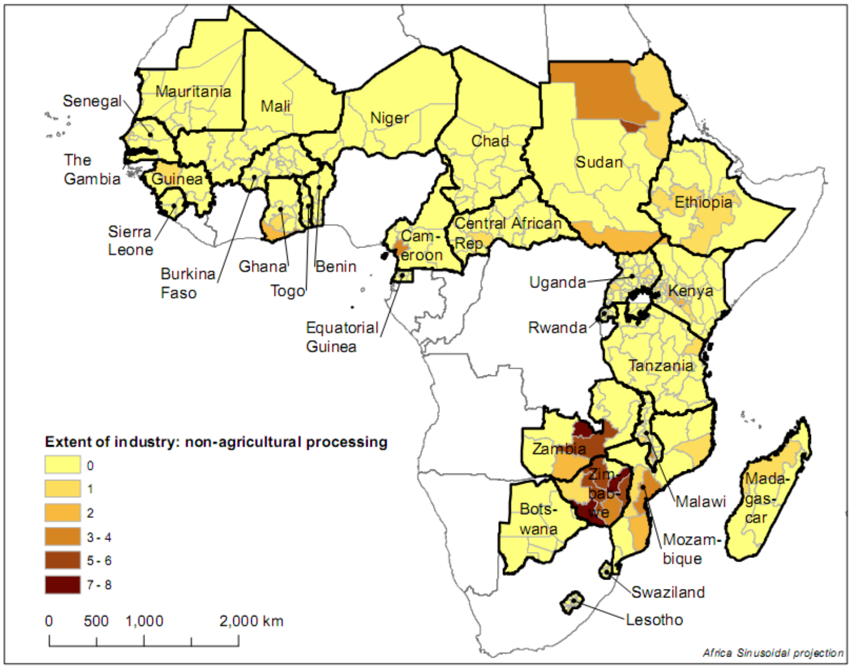


Figure 5b. Extent of industry 1965, all industries

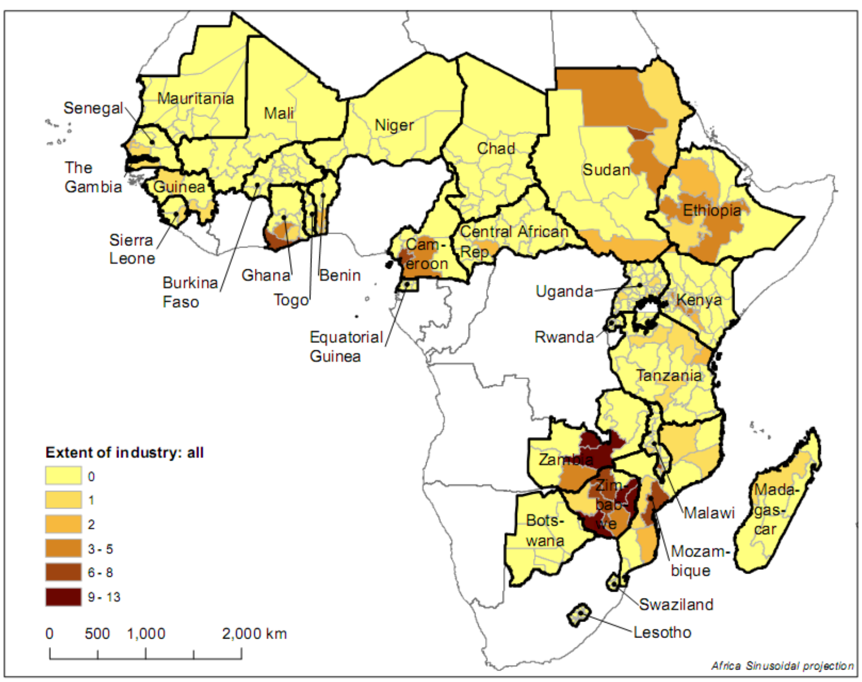
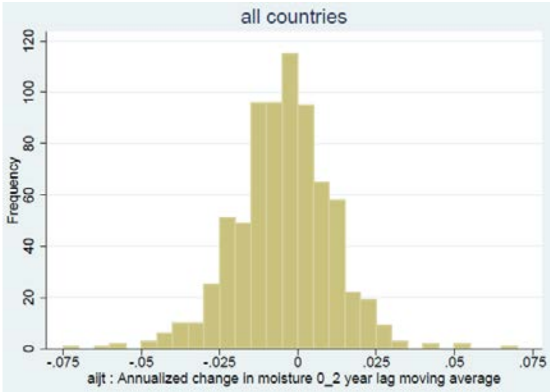


Figure 6. Spread of Dependent Variable

a. Raw data



b. Factoring out country fixed effects

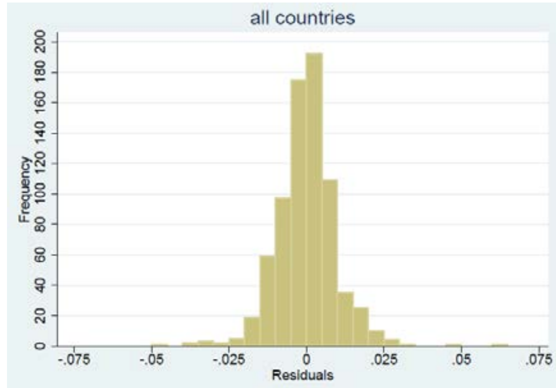


Figure 7. Initial urbanization and moisture growth: arid countries

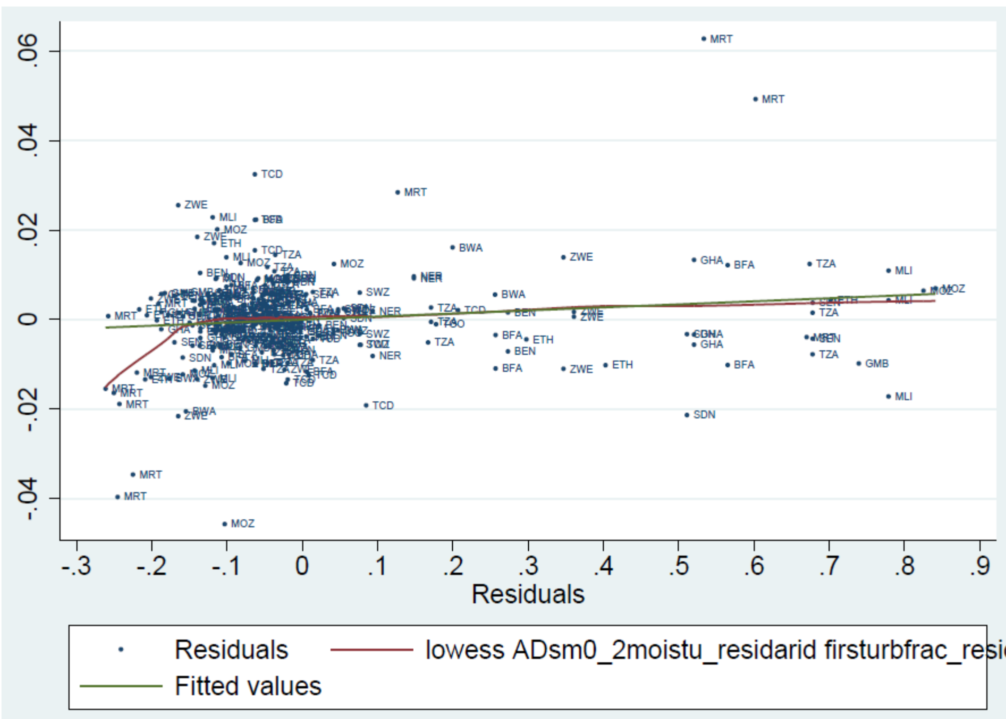


Figure 8: Spatial data integration to obtain city level lights and rain catchment data

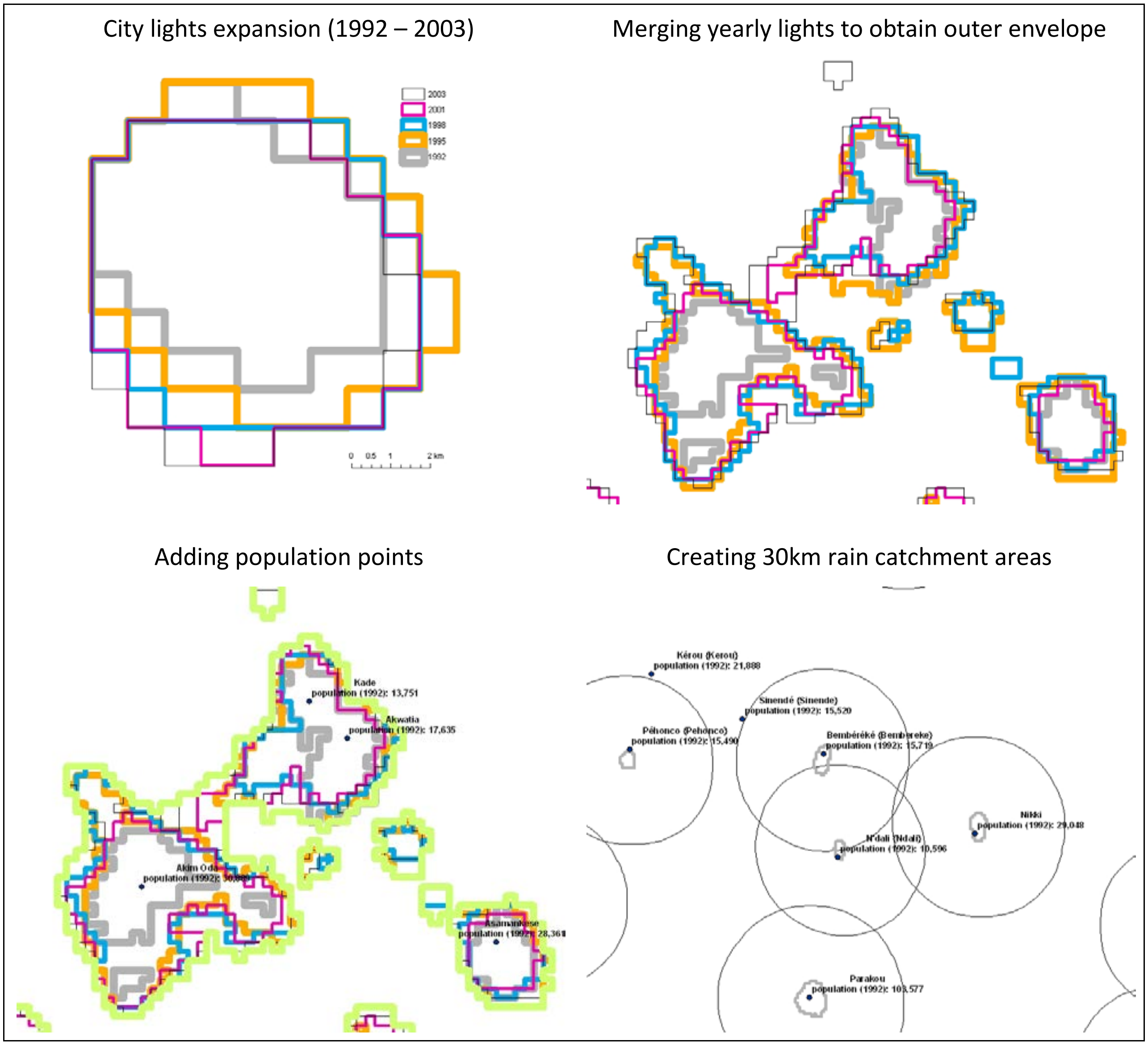


Table 1. Summary Statistics: Urban share growth

	full (N=725)				arid (N=290)			
	mean	sd	min	max	mean	sd	min	max
Annual moisture growth	-0.0046	0.014	-0.058	0.035	-0.0018	0.014	-0.047	0.035
District avg. moist. 1950-69	0.980	0.448	0.031	2.291	0.654	0.301	0.031	1.293
Annual growth: urban share	0.031	0.043	-0.126	0.195	0.026	0.034	-0.126	0.165
Initial urban share	0.137	0.210	0	1	0.180	0.225	0	1
ln(distance to coast (km))	5.964	1.226	0	7.476	5.689	1.339	0	7.419
area (square kilometers)	33357	63561	53.182	503510	60472	89136	53.182	503510
1(No key industries)	0.892	0.310	0	1	0.879	0.326	0	1
8 - #modern industries	7.527	1.393	0	8	7.400	1.628	0	8
13 - #all industries	12.112	2.336	0	13	11.852	2.704	0	13
D_moist_dist > 0.75	0.692	0.462	0	1	0.366	0.482	0	1

Note: the arid sample is countries with an average 1950-69 moisture index of less than 1

Table 2 Effect of moisture change on urbanization: Heteogeneity by likelihood of industry

	(1)	(2)	(3)	(4)	(5)
Δmoisture	0.014	-0.463	-0.728**	-0.892***	-0.245
	(0.169)	(0.322)	(0.341)	(0.343)	(0.461)
Δmoisture*1(No key industries)		0.548*			
		(0.321)			
Δmoisture*(8 - #modern industries)			0.0996**		
			(0.044)		
Δmoisture*(13- #all industries)				0.0747***	
				(0.027)	
Δmoisture*ln(distance to coast)					0.0403
					(0.079)
ln(distance to coast)					0.0019
					(0.002)
1(No key industries)		0.0021			
		(0.005)			
8 - #modern industries			-0.00035		
			(0.001)		
13 - #all industries				0.00018	
				(0.001)	
Initial share urban	-0.053***	-0.0545***	-0.058***	-0.056***	-0.0498***
	(0.005)	(0.007)	(0.009)	(0.008)	(0.005)

Notes: Each column is a separate regression with 725 observations for 365 districts. The dependent variable is growth in the urbanization rate. 8 and 13 are the maximum number of modern and total industries, respectively, in any given district. Distance to coast is measured in km. Robust standard errors, clustered by district, are in parentheses. All specifications include country*year fixed effects.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3. Effect of moisture change on urbanization: heterogeneity by degree of aridity

	(1)	(2)	(3)
Δmoisture	-0.325**	-0.156	-0.430*
	(0.138)	(0.174)	(0.224)
Δmoisture*1(country moisture>1)	0.498*		
	(0.281)		
Δmoisture*1(district moisture>0.75)		0.246	
		(0.244)	
1(district moisture>0.75)		0.0110**	
		(0.005)	
Δmoisture*District moisture 1950-69			0.409
			(0.259)
District moisture 1950-69			0.0175***
			(0.005)
Initial share urban	-0.043***	-0.045***	-0.045***
	(0.005)	(0.006)	(0.010)
Initial share urban*1(country moisture>1)	-0.017*		
	(0.009)		
Initial share urban*1(district moisture>0.75)		-0.012	
		(0.010)	
Initial share urban*District moisture 1950-69			-0.0076
			(0.010)

Notes: Each column is a separate regression with 725 observations for 365 districts. The dependent variable is growth in the urbanization rate. Robust standard errors, clustered by district, are in parentheses. All specifications include country*year fixed effects. *** p<0.01, ** p<0.05, * p<0.1

Table 4. Effect of moisture change on urbanization: heterogeneity by industrialization and aridity

	(1)	(2)	(3)	(4)	(5)	(6)
industry measure	**Key**	**Modern**	**All**	**Coast**	**All**	**All**
aridity measure		**1(country moisture>1)**			**1(dist. moisture>0.75)**	**dist. moisture**
Δmoisture	-0.835***	-1.156***	-1.184***	-1.273**	-1.147*	-1.948**
	(0.192)	(0.363)	(0.367)	(0.578)	(0.622)	(0.967)
Δmoisture*1(No key industries)	0.616***					
	(0.186)					
Δmoisture*(8 - #modern industries)		0.114**				
		(0.047)				
Δmoisture*(13- #all industries)			0.073**		0.0808	0.124
			(0.029)		(0.050)	(0.078)
Δmoisture*ln(distance to coast)				0.158*		
				(0.096)		
Δmoisture*1(country moisture>1)	0.549	0.514	0.306	0.744		
	(0.549)	(0.587)	(0.622)	(0.951)		
Δmoisture*1(district moisture>0.75)					0.374	
					(0.617)	
Δmoisture*District moisture 1950-69						1.080
						(0.994)
Δmoisture*1(No key industries)*1(country moisture>1)	-0.102					
	(0.536)					
Δmoisture*(8 - #modern industries)*1(country moisture>1)		-0.0069				
		(0.074)				
Δmoisture*(13- #all industries)*1(country moisture>1)			0.0123			
			(0.049)			
Δmoisture*ln(distance to coast)*1(country moisture>1)				-0.051		
				(0.159)		
Δmoisture*(13- #all industries)*1(district moisture>0.75)					-0.0084	
					(0.055)	
Δmoisture*(13- #all industries)*District moisture 1950-69						-0.053
						(0.081)

Notes: Each column is a separate regression with 725 observations for 365 districts. The dependent variable is growth in the urbanization rate. 8 and 13 are the maximum number of modern and total industries, respectively, in any given district. Distance to coast is measured in km. Robust standard errors, clustered by district, are in parentheses. All specifications include country*year fixed effects and controls for the industrialization, initial moisture and initial urbanization measures as well as the industrialization and initial urbanization measures interacted with moisture measure. *** p<0.01, ** p<0.05, * p<0.1

Table 5. City output and rainfall: heterogeneity by industrialization

	(1)	(2)	(3)	(4)
ln(rain)	-0.0011	-0.121***	-0.103	-0.225*
	(0.025)	(0.035)	(0.085)	(0.115)
ln(rain)*1(agriculture/GDP>30%)		0.188***		
		(0.047)		
ln(rain)*(9 - #modern industries)			0.012	
			(0.0103)	
ln(rain)*ln(distance to coast)				0.0190*
				(0.010)

Notes: Each column is a separate regression with 19,685 observations for 1,158 cities. The dependent variable is ln(lights digital number + 1). Rainfall is measured within a 30 km radius of the city-light. Distance to coast is measured in meters. Robust standard errors, clustered by district, are in parentheses. All specifications include city and year fixed effects and linear city-specific time trends. *** p<0.01, ** p<0.05, * p<0.1

Table 6. City output and rainfall: industrialization and aridity

	(1)	(2)	(3)	(4)
ln(rain)	-0.026	-0.163***	-0.196**	-0.372***
	(0.025)	(0.029)	(0.083)	(0.105)
ln(rain)*1(agriculture/GDP>30%)		0.213***		
		(0.043)		
ln(rain)*(9 - #modern industries)			0.019*	
			(0.010)	
ln(rain)*ln(distance to coast)				0.029***
				(0.010)
ln(rain)*1(country moisture>1)	0.112	0.187	0.330*	0.427
	(0.077)	(0.122)	(0.190)	(0.321)
ln(rain)*1(country moisture>1)*1(agriculture/GDP>30%)		-0.117		
		(0.155)		
ln(rain)*1(country moisture>1)*(9 - #modern industries)			-0.025	
			(0.025)	
ln(rain)*1(country moisture>1)*ln(distance to coast)				-0.026
				(0.029)

Notes: Each column is a separate regression with 19,685 observations for 1,158 cities. The dependent variable is ln(lights digital number + 1). Rainfall is measured within a 30 km radius of the city-light. Distance to coast is measured in meters. Robust standard errors, clustered by district, are in parentheses. All specifications include city and year fixed effects and linear city-specific time trends. *** p<0.01, ** p<0.05, * p<0.1

Table 7. City output and rainfall: leads and lags

	(1)	(2)	(3)	(4)	(5)	(6)
ln(rain(t))	-0.163***	-0.099**	-0.121***	-0.186***	-0.169***	-0.108**
	(0.029)	(0.044)	(0.027)	(0.056)	(0.032)	(0.050)
ln(rain(t))*1(agriculture/GDP>30%)	0.213***	0.160***	0.190***	0.331***	0.235***	0.199***
	(0.043)	(0.055)	(0.043)	(0.071)	(0.046)	(0.061)
ln(rain(t))*1(country moisture>1)	0.187	0.109	0.092	0.075	0.197*	0.073
	(0.122)	(0.100)	(0.117)	(0.119)	(0.105)	(0.107)
ln(rain(t))*1(agriculture/GDP>30%)*1(country moisture>1)	-0.117	-0.179	-0.072	-0.193	-0.185	-0.108
	(0.155)	(0.124)	(0.147)	(0.149)	(0.147)	(0.134)
ln(rain(t-1))			-0.069***	-0.205***		
			(0.230)	(0.057)		
ln(rain(t-1))*1(agriculture/GDP>30%)			0.052	0.272***		
			(0.040)	(0.071)		
ln(rain(t-1))*1(country moisture>1)			0.190**	0.119		
			(0.082)	(0.122)		
ln(rain(t-1))*1(agriculture/GDP>30%)*1(country moisture>1)			0.038	-0.00798		
			(0.130)	(0.152)		
ln(rain(t+1))					0.00095	0.030
					(0.026)	(0.049)
ln(rain(t+1))*1(agriculture/GDP>30%)					0.044	0.017
					(0.042)	(0.062)
ln(rain(t+1))*1(country moisture>1)					-0.168	-0.088
					(0.116)	(0.105)
ln(rain(t+1))*1(agriculture/GDP>30%)*1(country moisture>1)					0.305*	0.120
					(0.161)	(0.131)
Observations	19,685	18,527	18,527	17,369	18,527	17,369
Cities	1,158	1,158	1,158	1,158	1,158	1,158
Standard Errors	Cluster	AR(1)	Cluster	AR(1)	Cluster	AR(1)
Rho (autoregressive parameter)		0.313		0.298		0.295

Notes: The dependent variable is ln(lights digital number + 5.5). Rainfall is measured within a 30 km radius of the city-light. Robust standard errors, clustered by district, are in parentheses. All specifications include city and year fixed effects and linear city-specific time trends. *** p<0.01, ** p<0.05, * p<0.1

Table 8. Probability of working in agriculture, other sectors

Panel A: women	**Linear Probability Model**			**Probit**		
	(1)	(2)	(3)	(4)	(5)	(6)
	not work	work non-farm	work farm	not work	work non-farm	work farm
average moisture	-0.055***	-0.004	0.059***	-0.074***	-0.022**	0.096***
	(0.018)	(0.015)	(0.022)	(0.010)	(0.009)	(0.014)
age	-0.044***	0.022***	0.021***	-0.051***	0.024***	0.027***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$age^2/1000$	0.57***	-0.31***	-0.26***	0.65***	-0.32***	-0.33***
	(0.012)	(0.011)	(0.011)	(0.015)	(0.012)	(0.014)
primary education	-0.018***	0.064***	-0.046***	-0.028***	0.079***	-0.051***
	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)	(0.006)
secondary	0.064***	0.130***	-0.194***	0.087***	0.175***	-0.262***
	(0.005)	(0.004)	(0.006)	(0.007)	(0.006)	(0.009)
Higher	-0.074***	0.435***	-0.360***	0.126***	0.488***	-0.613***
	(0.014)	(0.016)	(0.010)	(0.019)	(0.014)	(0.021)
area fixed effects	supercluster	supercluster	supercluster	province	province	province

Panel B: men	**Linear Probability Model**			**Probit**		
	(1)	(2)	(3)	(4)	(5)	(6)
	not work	work non-farm	work farm	not work	work non-farm	work farm
average moisture	-0.012	-0.055**	0.067***	-0.011*	-0.008	0.019
	(0.013)	(0.022)	(0.025)	(0.006)	(0.011)	(0.013)
age	-0.064***	0.040***	0.025***	-0.053***	0.038***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$age^2/1000$	0.88***	0.57***	-0.31***	0.72***	-0.55***	-0.17***
	(0.016)	(0.018)	(0.018)	(0.015)	(0.021)	(0.022)
primary education	0.028***	0.085***	-0.113***	0.052***	0.110***	-0.162***
	(0.003)	(0.004)	(0.005)	(0.004)	(0.006)	(0.006)
secondary	0.122***	0.140***	-0.262***	0.139***	0.199***	-0.338***
	(0.005)	(0.006)	(0.007)	(0.005)	(0.007)	(0.008)
higher	0.074***	0.453***	-0.527***	0.203***	0.496***	-0.700***
	(0.009)	(0.013)	(0.011)	(0.010)	(0.012)	(0.016)
area fixed effects	supercluster	supercluster	supercluster	province	province	province

Notes: Each LPM column reports coefficients from one regression. The three probit columns report marginal effects from a single multinomial regression with farm work as the reference category. Female sample size is 312,769 individuals in 3,939 superclusters in 148 provinces in 18 countries over 43 country-years. Male sample size is 100,788 individuals in 3,751 superclusters in 121 provinces in 16 countries over 37 country-years. All regressions contain country*year fixed effects, in addition to the smaller area fixed effects listed. Robust standard errors, clustered by supercluster, are in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table A1 Urbanization country sample

Country	# units	Year 0	Year 1	Year 2	Year 3	Year 4	Cen-suse	mis-sing*	panel units	LD units	LD end	LD note	LD mis-
Benin	6	1979	1992	2002			3		12	6	2002		
Burkina Faso	12	1985	1996	2006			3		24	12	2006		
Botswana	8	1991	2001				2		8				
C. Afr. Rep.	16	1975	1988	2003			3		32	16	2003		
Cameroon	7	1976	1987	2005			3		14	7	2005		
Eq. Guinea	6	1983	1994				2		6				
Ethiopia	11	1994	2007				2		11				
Ghana	7	1960	1970	1984	2000		4		21	7	2000		
Guinea	4	1983	1996				2		4				
Gambia	7	1993	2003				2		7				
Kenya	39	1969	1979	1989			3	8	70	31	1989		8
Kenya (2)	40	1999	2009				2		40				
Lesotho	10	1986	1996	2006			3		20	10	2006		
Madagascar	6	1975	1993				2		6	6	1993		
Mali	8	1976	1987	1998	2009		4		24	8	2009		
Mozambique	11	1980	1997	2007			3	1	21	10	2007		1
Mauritania	13	1977	1988				2		13				
Malawi	23	1966	1977	1987	1998	2008	5		92	23	2008		
Niger	7	1977	1988	2001			3		14	7	2001		
Rwanda	9	1978	1991	2002			3		18	9	2002		
Sudan	9	1973	1983	1993			3		18	9	1993		
Senegal	8	1976	1988	2002			3		16	8	2002		
Sierra Leone	4	1963	1974	1985	2004		4		12	4	2004		
Swaziland	4	1966	1976	1986	1997		4		12	4	1997		
Chad	14	1993	2009				2		14	10	2009	LD from 1964	4
Togo	5	1970	1981				2		5	5	2010	LD to 2010	
Tanzania	21	1967	1978	1988	2002		4	1	62	20	2002		1
Uganda	38	1969	1980	1991	2002		4	8	106	32	2002		6
Zambia	8	1969	1980	1990	2000		4	1	23	7	2000		1
Zimbabwe	8	1982	1992	2002			3		16	8	2002		
Liberia										6	2008	LD 1974-2008	
Total	369			30 countries			89	19	741	265		24 count-ries	21

*= sample is smaller by this number in the initial intercensal period (first two in Uganda) because of some units with zero urban population.

Appendix Table 2: Varying smoothing, trimming and controls in Table 2, column 4

	(1)	(2)	(3)	(4)	(5)
Δmoisture	-0.892***	-0.366	-0.925**	-1.000*	-1.420**
	(0.343)	(0.271)	(0.363)	(0.568)	(0.583)
Δmoisture*(13- #all industries)	0.075***	0.028	0.072**	0.079*	0.121***
	(0.027)	(0.023)	(0.030)	(0.046)	(0.046)
13 - #all industries	0.00018	0.000036	0.000071	0.00018	-0.0019
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Initial share urban	-0.056***	-0.054***	-0.055***	-0.055***	-0.082***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.015)
Observations	725	725	725	725	741
Districts	365	365	365	365	369
Trimming	Yes	Yes	Yes	Yes	No
Smoothing	0-2	0-1	0-3	0-4	0-2

Notes: Each column is a separate regression with 725 observations for 365 districts. The dependent variable is growth in the urbanization rate. 8 and 13 are the maximum number of modern and total industries, respectively, in any given district. Robust standard errors, clustered by district, are in parentheses. All specifications include country*year fixed effects.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A3: Summary statistics for lights data

variable	count	mean	sd	min	max
ln(rain) 30km	19685	0.701	0.69	-8.589	2.469
%GDP (net of res. rents) in agriculture (89-91)	18359	37.23	15.4	3.19	68.63
Population > 50k in 1992	19685	0.249	0.43	0	1
Dummy: closest power plant is hydro	15622	0.482	0.5	0	1
Dummy: %GDP in agriculture > 30%	19685	0.738	0.44	0	1
Δln(rain) 30 km	18527	0.011	0.33	-4.996	6.022
Δln(lights+1)	18527	0.096	1.03	-8.401	8.58
Extent_ag_mod	19705	8.833	0.85	0	9
ln(dist to coast (meters))	19464	12.543	1.58	3.59	14.34

Table A4: DHS data sets used in the occupational choice analysis

Country	Years	Note
Benin	1996, 2001	
Burkina Faso	1998-1999, 2003, 2010-2011	
Cameroon	2004, 2011	
Ethiopia	2000, 2005, 2010-2011	
Ghana	1998-1999 (female only),	
Guinea	1999, 2005	
Kenya	2003, 2008-2009	
Lesotho	2004-2005, 2009-2010	
Madagascar	1997, 2008	female only
Malawi	2000, 2004-2005, 2010	
Mali	1995-1996, 2001, 2006	
Namibia	2000, 2006-2007	
Nigeria	2003, 2008	
Rwanda	2005, 2010-2011	
Senegal	2005, 2010-2011	
Tanzania	1999, 2009-2010	female only
Uganda	2000-2001, 2006, 2011	
Zimbabwe	1999 (female only), 2005-	

Table A5. Summary statistics for the DHS data

	Men (N=100,788)				Women (N=312,769)			
	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
Agriculture	0.585	0.493	0	1	0.439	0.496	0	1
Not Working	0.178	0.382	0	1	0.334	0.472	0	1
Other Occupation	0.238	0.426	0	1	0.227	0.419	0	1
Primary	0.425	0.494	0	1	0.377	0.485	0	1
Secondary	0.248	0.432	0	1	0.152	0.359	0	1
Post-secondary	0.027	0.161	0	1	0.01	0.098	0	1
Age	28.36	9.847	15	49	28.624	9.61	15	49
Avg. moisture	0.874	0.48	0.02	3.49	0.881	0.489	0.02	3.491