August 30, 2019

The role of land in temperate and tropical agriculture

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Abstract

We document that the elasticity of agricultural output with respect to land differs across temperate and tropical regions of the world. We show how to estimate this elasticity using the relationship of rural labor/land ratios and agro-climatic constraints. Using global district-level data we find the elasticity in temperate areas (0.24) is higher than the tropics (0.09), and this is not an artifact of the level of development. The land elasticity determines how sensitive the marginal product of labor in agriculture is to population and technology shocks, and thus how sensitive living standards are to those shocks as well. Evidence from the post-war mortality transition supports this prediction.

JEL Codes: O1, O13, O44, Q10

Keywords: land constraints, land elasticity, agricultural productivity, agro-climatic, temperate, tropical

Contact information: 201C McElhinney Hall, U. of Houston, Houston, TX 77204, devollrath@uh.edu. We thank Tasso Adamopoulos, Francesco Caselli, Areendam Chanda, Martin Fiszbein, Oded Galor, Remi Jedwab, Nippe Lagerlöf, Debin Ma, Stelios Michalopolous, Nathan Nunn, Ömer Özak, Stephen Smith, Enrico Spolaore, Joachim Voth, and David Weil, as well as seminar participants at LSU, York University, London School of Economics, Texas A&M Ag. Econ, the Brown Conference on Deep-rooted Determinants of Development, George Washington University, and the University of Houston brown bag series for their comments. This paper previously circulated under the title "How Tight are Malthusian Constraints?". All errors remain our own.

1 Introduction

Agricultural production relies on the use of a finite (or inelastically supplied) resource, land. But that reliance on land need not be identical in different locations. To be specific, the elasticity of agricultural output with respect to land may differ by climate or the type of crops suitable for production. This land elasticity is relevant to any study of growth and development that includes an agricultural sector, as with the mild assumption of constant returns to scale, one minus the land elasticity tells us how sensitive agricultural output is to the use of non-land inputs like capital and labor. This in turn determines how many non-land inputs move out of (or into) agriculture in response to shocks to productivity and population. Differences in the land elasticity by crop or climate thus imply differences in the reaction of economies to such shocks, with implications for studies of comparative development, structural change, Malthusian stagnation, the take-off to sustained growth, and long-run growth prospects with finite resources.[1]

In this paper, we estimate the land elasticity, and show that it varies across different agricultural regions and climate types. Estimating the parameter(s) of an agricultural production function is not straightforward, for the standard reasons that total factor productivity is unobserved and inputs may be mis-measured. To address these issues, we first develop a method for estimating the aggregate land elasticity using the relationship between the labor/land ratio in agriculture and the potential agro-climatic yield across small geographic units (e.g. 2nd-level districts within states/provinces). Our method allows for inputs other than land and labor in the production function, but does not require us to identify exactly what those other inputs are, avoiding mis-measurement issues. We use agro-climatic yield data to give us a source of exogenous variation in productivity, and combine that with measures of district-level development (e.g. night lights and urbanization) to control for other unobservable elements of agricultural productivity. In addition, our estimates are made using only within-state variation across districts, meaning that unobservable variation in productivity across states, as well as across countries, is excluded from the estimates. Finally, our framework is robust to arbitrary distortions (e.g. taxes, subsidies) in agricultural output and factor prices at the state level.[2]

[1] Agriculture and land feature in stories of divergence across global regions (Kogel and Prskawetz, 2001; Galor and Mountford, 2008; Vollrath, 2011; Voigtländer and Voth, 2013*b*,*a*; Cervellati and Sunde, 2015). On structural change, see Gollin, Parente and Rogerson (2007); Restuccia, Yang and Zhu (2008); Weil and Wilde (2009); Gollin (2010); Eberhardt and Vollrath (2018). For Malthusian stagnation, see Ashraf and Galor (2011) for a baseline model, and Galor (2011) for a review of major contributions to the literature on the take-off to growth (Galor and Weil, 2000; Galor and Moav, 2002; Hansen and Prescott, 2002; Doepke, 2004; Cervellati and Sunde, 2005; Lagerlöf, 2006; Crafts and Mills, 2009; Strulik and Weisdorf, 2008). On the relevance of resources for long-run growth, see Peretto and Valente (2015).

[2] There are two main studies that focus on the spatial distribution of labor (in general) and economic activity. The first is Motamed, Florax and Masters (2014). Those authors examine the growth of urbanization at the grid-cell level over the last two-thousand years. The second is Henderson et al. (2016), who examine the spatial distribution of economic activity (associated with urbanization) at the grid-cell level using night lights, relating it to geographic characteristics associated with either agriculture or trade.

We assemble data at the district level for rural population labor/land ratios in the year 2000, and combine that with a measure of potential agro-climatic yield in districts built from the data of Galor and Özak (2016). As in their work, our measure is built on constraints plausibly unaffected by human activity (e.g. soil quality and length of growing season) from the Global Agro-Ecological Zone (GAEZ) project (Food and Agriculture Organization, 2012), combined with information on the calorie content of various crops. Grid cell potential caloric yields are aggregated to the district level to serve as our measure of agro-climatic yield.

In the end, we have a dataset of 30,054 districts, coming from 2,325 states in 152 countries. Using this data, we divide districts into "temperate" and "tropical" regions based on their agro-climatic characteristics. In our baseline, we make this division based on the types of crops that can be grown within a district. The temperate region includes districts that can grow crops such as wheat, barley, and rye, while the tropical region includes districts that can grow crops such as paddy rice, cassava, and pearl millet. We also divide districts based on their frost-free days (e.g. tropical areas are frost-free all year round, while temperate areas are not), or by their Köppen-Geiger climate classification (Kottek et al., 2006), and our results are similar. Regardless of the definition, our assignment of districts allows us to separate temperate and tropical areas within countries, so that we do not have to assume that agriculture has a homogenous land elasticity within a country, or even within a given state.

Our baseline estimate is that the land elasticity is 0.238 in temperate districts. In contrast, our baseline estimate of the land elasticity is only 0.119 for tropical districts. The difference is statistically significant, and is robust to the exclusion of districts that contain large urban areas or of districts from any developed country. Further, the results are consistent if we use alternative measures of rural population labor/land ratios, alternative measures of the potential agro-climatic yield, or alternative measures of the area of agricultural land used within a district. In all cases, the aggregate land elasticity in temperate districts remains approximately 0.10-0.12 higher than in tropical districts, and the difference remains statistically significant.[3] As the measure of agro-climatic yield we use is based on staple crops, these results should be interpreted as differences in the land elasticity in staple crop production, and may not be relevant for areas that rely heavily on livestock or cash crop production.[4]

Relative to the existing literature, our approach to estimating the aggregate land elasticity has several advantages. The standard approach has been to use country-level panel data (Hayami and Ruttan, 1970, 1985; Craig, Pardey and Roseboom, 1997; Martin and Mitra, 2001; Mundlak, 2000; Mundlak, Butzer and Larson, 2012; Eberhardt and Teal, 2013) to estimate agricultural production

[3] These results are consistent with the work of Ruthenberg (1976) and Bray (1994), who discuss the inherent differences in the response of tropical crops (rice, in particular) to the application of labor. They both cite the relatively *high* elasticity of output with respect to labor in tropical agriculture, which is consistent with a low elasticity of output with respect to land.

[4] We show as part of our robustness checks that our results hold if districts that are large livestock or cash crop producers are included or excluded from the regressions.

functions, with a common set of coefficients across countries for each input, including land. Issues arise with unobserved productivity, the measurement of non-land inputs, and the assumption that coefficients are common to all countries. Some have examined heterogeneity in these coefficients (Gutierrez and Gutierrez, 2003; Wiebe et al., 2003) by continent, while others have attempted to estimate country-level coefficients using factor analysis to address unobserved productivity (Eberhardt and Teal, 2013; Eberhardt and Vollrath, 2018). Compared to this, our district-level data allows us to control for unobserved country and state-level effects, and the use of agro-climatic yield data gives us an explicit measure of productivity.

As may be apparent, we are not estimating the elasticity of a *farm*-level production function, but rather for an *aggregate* production function. Farm-level estimates of the land elasticity would not necessarily be informative about the aggregate production function, given that those estimates would refer to farmers using a given technique, while the aggregate function can be thought of as an envelope across techniques available to farmers (Hayami and Ruttan, 1970).[5] The aggregate land elasticity is a useful parameter for studying the role of the agricultural sector and its interaction with other sectors at the macro level, as we discuss below, while farm-level elasticities would be useful for studying farm-level policies or outcomes within the agricultural sector itself. This distinction explains one of the limitations of our study, which is that we cannot use our results to identify why the aggregate land elasticity differs between temperate and tropical regions. An explanation would require details on the interaction of farmers with biological production functions for specific crops that are beyond the scope of this paper.

With that caveat in mind, we show in the second half of the paper that the aggregate land elasticity is central to any study that looks at the relationship of agriculture to non-agriculture, and the variation we have identified between temperate and tropical regions has implications for development. To show this we first describe a model that incorporates both an agricultural as well as a non-agricultural sector, allows for the movement of labor and capital between those sectors, and incorporates preferences that lead to Engel's Law holding for the demand for agricultural output.

The model shows that the sensitivity of both real income per capita and the share of labor in agriculture with respect to shocks in either population or TFP depend on the size of the land elasticity. The larger is the land elasticity, the more sensitive are real income per capita and the share of labor in agriculture to population and TFP. This is a benefit to temperate areas when shocks are positive (e.g. higher TFP or lower population growth), but a burden in the face of negative shocks (e.g. lower TFP or higher population growth).

In the last part of the paper we confirm these predictions by using data from Acemoglu and Johnson (2007) to examine the effect of population shocks arising from the epidemiological transition after World War II. The shock to mortality had a negative impact on GDP per capita, and per

[5]More general treatments of this idea can be found in Houthakker (1955) and Jones (2005). In short, the farm-level land elasticities may not be informative on the aggregate land elasticity, and farm-level production functions may well take on different forms (i.e. Leontief verus Cobb-Dougals) than the aggregate function.

worker, across all developing countries. But we find that the size of that negative effect was three times larger for countries with high land elasticities compared to countries with low land elasticities, consistent with our theoretical predictions. The difference in effect size is statistically significant, and holds whether we measure the population shock in terms of mortality, life expectancy, or population size.

At a broader level, variation in the land elasticity may be relevant for the study of historical and contemporary development. For any given positive shock to productivity (or negative shock to population growth), areas with temperate land elasticities will experience more urbanization and faster growth in living standards, whatever the fundamental driver of those shocks: institutions, geography, or culture.[6] This may help explain why it was that western Europe, with a high aggregate land elasticity, diverged from even the more advanced areas of Asia, with a low aggregate land elasticity, even if western Europe did not have an advantage in technological or institutional improvements.[7] It may also help explain why the tropical areas of Central America and Sub-Saharan Africa, with relatively low land elasticities, lagged behind other areas following decolonization.[8]

The paper proceeds XXXXX

2 District level characteristics

It will be useful to first establish the characteristics of the districts we use as our units of observations, as well as review recent evidence on the mobility of workers within and across those districts. This will inform our method for identifying the land elasticity, which will rely on comparing districts with one another.

A district, as the term is used in our paper, is a second-level administrative unit within a country, regardless of the terminology used. It is thus part of a first-level administrative unit, which we call a state. In India our terminology matches the local terminology. For example, the district of Kadapa lies within the state of Andhra Pradesh. For the United States, a "district" is referred to as a county. Marathon County, in the state of Wisconsin, is a district in our data. In Nigeria, a "district" is a local goverment area, which is part of a state. Thus Demsa, in the state

[6] It would be hopeless to summarize or cite all the research on comparative development. Several useful reviews of this literature can be found in Acemoglu, Johnson and Robinson (2005); Nunn (2009); Galor (2011); Spolaore and Wacziarg (2013); Vries (2013).

[7] The divergence of China, and the lower Yangtze region in particular, from north-western Europe is the subject of a large literature. Pomeranz (2000) is the standard starting point, while Allen et al. (2011); Huang (2002); Ma (2013); Lee, Campbell and Feng (2002); Broadberry and Gupta (2006) are a brief selection of relevant papers.

[8] Our work is related to several recent studies on the the role of geography and/or inherent agricultural productivity in development (Olsson and Hibbs, 2005; Ashraf and Galor, 2011; Nunn and Qian, 2011; Nunn and Puga, 2012; Michalopoulos, 2012; Alesina, Giuliano and Nunn, 2013; Cook, 2014*a*,*b*; Fenske, 2014; Alsan, 2015; Ashraf and Michalopoulos, 2015; Dalgaard, Knudsen and Selaya, 2015; Galor and Özak, 2016; Litina, 2016; Andersen, Dalgaard and Selaya, 2016; Frankema and Papaioannou, 2017). Unlike those papers, ours does not propose a direct causal relationship between geography and development, but rather suggests that *any* proposed causal impact has differential effects based on the size of the land elasticity.

of Adamawa, is a district in our data. In total, we have 30,054 districts, coming from 2,325 states in 152 countries.[9]

These districts tend to be small, both in absolute terms and relative to the states in which they reside. Table 1 shows summary statistics on population from Goldewijk et al. (2011) for districts in Panel A. The mean population of districts is 142 thousand people, although the median district only has 26,000. For our empirical work, the rural population will be crucial. The rural population of districts is even smaller, with a mean value of 81,000 and a median of 12,600.[10]

By nature, urban population is concentrated into small areas, so the distribution of urban populations across districts is more skewed. Average urban population is around 61,000, but the median district has an urban population of only 5,500, and at the 10th and 25th percentiles of the distribution the urban population is zero. Thus for many districts, the urban share of district population is zero, and at the median the share is only about one-quarter, 0.28. At the other extreme, districts at the 90th percentile are 0.85 urban, with 161 districts in the world reported as having 0.99 or higher for a share of urban population.

As a proportion of their state, most districts are quite small. The average district represents only 6% of its state population, with a median of only 2%. For most states, one district often represents the majority of state population. This holds, naturally, for urban population as well. The median district has about zero percent of the state urban population, and in most states the vast majority of urban population lives in one or two districts. Thus most districts, and especially those dominated by rural populations, are small relative to the total population of their state. This holds as well for area, where the average district represents only about 7% of total state area, and the median district is only 3% of state area. The absolute area of most districts is also quite small. The median district encompasses 65,800 hectares, or about 658 square kilometers. That represents a square of only about 25 kilometers on each side.

The districts in our data are small in absolute and relative terms, but beyond that we can establish that there is significant movement of workers across districts. Recent work by Young (2013) and Hicks et al. (2017) has established two salient facts regarding migration and wages. First, within developing countries there is significant movement of workers between urban and rural areas on a regular basis. This includes both rural-to-urban movement, but also substantial urban-to-rural movement. Second, consistent with economic intuition, this movement is associated with an equalization of the wage per unit of human capital across urban and rural areas.[11] Combining

[9]This covers nearly every country in the world, save Libya and Saudi Arabia, for which usable maps of the district level were not available.

[10]There are a handful of very highly population districts, of course, representing large urban areas. In our data, 1,040 districts have populations above 1 million people. But that represents less than 3% of all districts. Our results are all robust to the exclusion not just these districts, but to the exclusion of districts with more than 50,000 urban residents.

[11]Note that this does not imply equalization of total *earnings*, given differences in average human capital per person in the two areas. But both papers establish that conditional on measures of human capital, there does not appear to be any significant wage premia simply for living in urban areas.

the first finding with our summary statistics showing the concentration of urban population in a handful of districts, the implication is that there is - at a minimum - movement of people between districts within any given state. There may be more extensive movement of people between states themselves, but for our empirical setting movement between districts within a state is most relevant.

To illustrate the amount of migration within developing countries, in particular, we use data from the Demographic and Health Surveys (ICF, 1986-2017) similar to what Young (2013) used. Table 2 shows summary statistics on migration taken fro 86 separate DHS surveys (Panel A), or 68 surveys (Panel B). The numbers reported in the table are summary statistics of survey level averages. Thus line one shows that, on average across the 86 surveys, 49% of respondents report moving at some point in their life. Even at the 10th percentile, 32% of individuals report moving at some point.

If we restrict ourselves to people who moved within the last 5 years, the average across all surveys is still 21%. If we limit ourselves instead to only those who are 25-50 years old, prime working ages, then the percentage that have moved at some point is 54%, and the tenth percentile is 35%. Many people within these developing countries have moved at some point, and many in recent periods of time.

Of course, that movement may not reflect a large geographic change, or a change from rural to urban ares. In Panel B, we look at the self-reported origin of those who moved into either urban or rural areas. Of those who moved into urban areas, on average across surveys 40% reported being from the "country", with a 10th percentile across surveys of 19% and a 90th percentile of 59%, indicating that urban in-migrants were not simply arriving from other cities or towns. In the last line, we look instead at the percent of movers to rural areas who reported being from either "city" or "town". On average 17% came from those areas. These numbers are lower, consistent with Young (2013), and in part reflects the general drift of urbanization over time.

Overall, what the district-level statistics and the migration data indicate is that there is likely substantial movement of workers across districts within states. There may in addition be movement of people between states within a given country, but as noted that is not something we will rely on empirically. We focused on developing countries in this section, as concerns about frictions in the movement of people at the district level may be most pronounced for them, relative to developed nations where the movement of workers is most likely taken for granted. Our results are all robust to excluding developed nations.

3 Identifying the aggregate land elasticity

Given the information on the small size of districts relative to their states, the evidence on the movement of people between urban and rural areas (and thus across districts in many cases), and the finding that this movement is associated with equalized wages between areas, we use this to build up an identification strategy for the land elasticity. In short, we will be using variation in the labor/land ratio and agricultural productivity across districts *within* states to identify this elasticity, where the movement of workers across districts *within* states will allow us to eliminate several confounders by using state fixed effects. To do this, we will essentially be deriving a labor demand function for the agricultural sector of a district, given some assumptions about the production function in both agriculture and non-agriculture.

3.1 Production and optimization

Consider district i located in a state s. There are a total of L_{is} workers in the district, who work in either the agricultural (A) or non-agricultural sector (N), so that $L_{is} = L_{Ais} + L_{Nis}$. There is also a total amount of capital K_{is}, which is also used in both sectors, so that $K_{is} = K_{Ais} + K_{Nis}$.

Let the agricultural production function for a district be given by,

$$Y_{Ais} = A_{Ais} X_{is}^{\beta} \left(K_{Ais}^{\phi} L_{Ais}^{1-\phi} \right)^{1-\beta} \tag{1}$$

where A_{Ais} is total factor productivity and X_{is} is land. The land elasticity we are interested in estimating is β.[12] We assume that agricultural operators in a district try to maximize profits, and take the wage of agricultural workers (w_{Ais}), the rental rate of agricultural capital (r_{Ais}), and the price of agriculture goods relative to non-agricultural goods (p_{Ais}) facing them as a given. All three are expressed relative to the non-agricultural good, the numeraire. We also allow for some arbitrary state-level "revenue wedge", $(1 + \tau_{As})$, which could reflect any kind of subsidy or tax (explicit or implicit) on the agricultural producers.

The profits of the agricultural sector in district i are

$$\pi_{Ai} = (1 + \tau_{As}) p_{Ais} Y_{Ais} - w_{Ais} L_{Ais} - r_{Ais} K_{Ais} \tag{2}$$

The first-order conditions of the maximization problem are

$$\begin{aligned} w_{Ais} &= (1-\phi)(1-\beta)(1+\tau_{As}) p_{Ais} \frac{Y_{Ais}}{L_{Ais}} \\ r_{Ais} &= \phi(1-\beta)(1+\tau_{As}) p_{Ais} \frac{Y_{Ais}}{K_{Ais}}. \end{aligned} \tag{3}$$

Given these two conditions, the agricultural capital/labor ratio used in the district will be

$$\frac{K_{Ais}}{L_{Ais}} = \frac{\phi}{1-\phi} \frac{w_{Ais}}{r_{Ais}}. \tag{4}$$

[12]While we have written the function here as Cobb-Douglas, this is solely for ease of exposition. The analysis does not require this. In the Appendix we show that one could use a general constant returns to scale function to derive a similar estimation equation.

Non-agricultural production in the district is given by

$$Y_{Nis} = A_{Nis} K_{Nis}^{\phi} L_{Nis}^{1-\phi} \tag{5}$$

and the non-agricultural operators are also cost minimizers, who take the wage of non-agricultural workers (w_{Nis}) and the rental rate of non-agricultural capital (r_{Nis}) as given. They face an abitrary revenue wedge of $(1 + \tau_{Ns})$. Their profits are

$$\pi_{Ni} = (1 + \tau_{Ns}) Y_{Nis} - w_{Nis} L_{Nis} - r_{Nis} K_{Nis} \tag{6}$$

$$\begin{aligned} w_{Nis} &= (1-\phi)(1+\tau_{Ns}) \frac{Y_{Nis}}{L_{Nis}} \\ r_{Nis} &= \phi(1+\tau_{Ns}) \frac{Y_{Nis}}{K_{Nis}}, \end{aligned}$$

which will result in a capital/labor ratio in non-agriculture of

$$\frac{K_{Nis}}{L_{Nis}} = \frac{\phi}{1-\phi} \frac{w_{Nis}}{r_{Nis}}. \tag{7}$$

3.2 Mobility and the labor/land ratio

At this point we appeal to the characteristics of districts and the migration evidence from the prior section to apply several assumptions. First, given the small size of districts relative to their states, and given that many districts do not contain substantial urban populations, we assume that both agricultural and non-agricultural goods move between districts until $p_{Ais} = p_{As}$, or there is a common state-level relative price of agricultural goods. Second, based on the evidence from Young (2013), Hicks et al. (2017), and Table 2, we assume that labor is mobile across districts such $w_{Ais} = w_{As}$, or there is a common agricultural wage. Third, based on the same sources just cited, we assume that labor is mobile between the agricultural (mainly rural) and non-agricultural (mainly urban) sectors, so that $w_{Ais} = w_{Nis}$ within any given district.

The last assumption we make is that capital is also mobile *within* a district bewteen agriculture and non-agriculture such that $r_{Ais} = r_{Nis}$, although it need not be mobile across districts. This assumption we did not provide direct evidence for, as with the migration data. Making this assumption (or dropping it) would change the nature of controls we need to ultimately include in our regressions, and we show later in the paper that for a subset of districts for which certain agricultural-specific capital controls are available, our results hold.[13]

With the assumptions that capital and labor are moving between agricultural and non-agricultural

[13] In the appendix, we show how our empirical specification would change when dropping this assumption.

sectors within districts, then given (4) and (7) it will be the case that

$$\frac{K_{Ais}}{L_{Ais}} = \frac{K_{Nis}}{L_{Nis}} = \frac{K_{is}}{L_{is}},$$

or that the capital/labor ratio in both sectors will be equal to the aggregate capital/labor ratio of a given district.

Incorporate that into the first-order condition for agricultural labor in (4), substitute in for the production function in (1), and apply the assumptions that $p_{Ais} = p_{As}$ and $w_{Ais} = w_{As}$, and we arrive at

$$w_{As} = (1-\phi)(1-\beta)(1+\tau_{As})p_{As}A_{Ais}\left(\frac{X_{is}}{L_{Ais}}\right)^{\beta}\left(\frac{K_{is}}{L_{is}}\right)^{\phi(1-\beta)}, \tag{8}$$

which represents a labor demand curve relating w_{As} to L_{Ais}, conditional on productivity, the capital/labor ratio, and the relative price of agricultural output.

Take logs of (8) and re-arrange to the following

$$\ln A_{Ais} = \beta \ln L_{Ais}/X_{is} - \phi(1-\beta)\ln K_{is}/L_{is} - \ln w_{As}/p_{As} - \ln(1+\tau_{As}) + \ln(1-\phi)(1-\beta). \tag{9}$$

Examining equation (9), there is a linear relationship between (log) productivity and the (log) labor/land ratio in agriculture, and the coefficient on the labor/land ratio is simply β. We'll describe in the next section how we measure aricultural productivity, A_{Ais}, but for the moment take that as given. In principle, we should be able to use the relationship of (log) agricultural productivity and (log) labor/land ratios across districts to identify the value of β in a regression.

Doing this requires that we account for the additional terms in equation (9). The first is the (log) capital/labor ratio in the district, which would independently influence the labor/land ratio by affecting the productivity of workers. For this term we will introduce controls into our regressions, such as the density of night lights and/or measures of real assets owned by households from the Demographic and Health Surveys.[14]

The final terms in equation (9) are all state-specific, but not district-specific. As such, they can be accounted for by state fixed effects. The real wage, w_{As}/p_{As}, is common to all districts given the movement of labor and the relatively small size of districts within the state economy. The other term is $(1+\tau_{As})$, a state-level wedge on agricultural revenues. This captures any arbitrary distortion to the relative price of agricultural goods within the state. The wage and distortion are both state-specific, thus allowing for heterogeneity in wages and distortions across *states* within a given country in our empirical work. This further implies that country-level distortions to agricultural prices (e.g. tariffs, subsidies, taxes) do not bias our results in any way.

[14] If one were to assume that capital was also mobile across districts within a state, then these controls would not be necessary. The capital/labor ratio would then be identical across districts, and state fixed effects would absorb the capital/labor term.

The threat to our identification of β comes from the possibility that the real wage, w_{As}/p_{As}, is not equalized across districts within states. In that case, the equation in (9) still holds for each individual district, but without an explicit way to control for the real wage, we would have a built-in bias of our estimate towards zero, as the labor/land ratio and the unique real wage within a district (an omitted variable) would be negatively related by definition. As we have argued, the evidence on migration and the small size of districts would support the assumption that the real wage is state-specific, and thus this bias is not present.[15] We will also, as part of our robustness checks, exclude districts from our regressions that one may worry would not conform to the assumption of a common real wage (e.g. large urban districts), and all the results go through.

4 Estimates of the aggregate land elasticity

To build our final estimation equation, we need to specify one final thing, the measurement of agricultural productivity, A_{Ais}. To do this, we rely on the work of Galor and Özak (2016), which it itself built on the Global Agro-Ecological Zone (GAEZ) project of the Food and Agriculture Organization (2012). We describe the GAEZ data in detail below, but consider it to be a noisy measure of true agro-climatic productivity. We thus break down agricultural productivity as follows,

$$\ln A_{Ais} = \ln A_{As} + \ln A_{Ais}^{GAEZ} + \epsilon_{is},$$

where $\ln A_{As}$ captures the state-specific level of non-agro-climatic productivity (e.g. culture or institutions) while $\ln A_{Ais}^{GAEZ}$ captures the agro-climatic elements of productivity, and ϵ_{is} represents noise in this measure of true agro-climatic conditions. In short, we assume that the GAEZ did not make systematic errors in measuring agro-climatic productivity.

We combine this relationship for agricultural productivity with the relationship in (9) to form our estimation specification, which includes an additional subscript g to account for the fact that we will be running this regression for a specific geographic region (e.g. tropical or temperate).

$$\ln A_{Aisg}^{GAEZ} = \alpha_g + \beta_g \ln L_{Aisg}/X_{isg} + \gamma_s + \delta_g' \mathbf{Z}_{isg} + \epsilon_{isg} \tag{10}$$

where i denotes a district (e.g. Saoguan) in state s (e.g. Guangdong in China), which is part of a geographic region g. As can be seen, the coefficient β_g is unique to a geographic region. We will assign districts to a geographic region based on some physical characteristic (e.g. temperate climate), and all districts within that geographic region will be assumed to have an identical value for β_g. Our hypothesis is that the values of β_g vary with geographic characteristics, and over the

[15] It is worth stressing that our assumption involves mobility across districts *within* states, and hence equalization of real wages *within* states. There could well be substantial heterogeneity of real wages, or of the distortion term τ_s, across states within a given country.

course of the empirical work we will document that there are differences in β_g between geographic regions.

α_g is a constant. The value γ_s is the state fixed effect, and it picks up the real wage, w_{As}/p_{As}, any distortion, $(1+\tau_{As})$, as well as the state-specific level of non-agro-climatic productivity, A_{As}. The term $\mathbf{Z}_{isg}$ is the set of controls we use to proxy for the district capital/labor ratio, K_{is}/L_{is}, and δ'_g are the coefficients on those controls. This is the specification we take to the data to estimate β.

Standard errors: ϵ_{isg} is a noise term, and we allow that it may be spatially auto-correlated. To account for this in our standard errors, we use Conley standard errors. For any given district i, the error term of any other district that has a centroid (lat/lon) within 500km of the centroid (lat/lon) of district i is allowed to have a non-zero covariance with ϵ_{isg}. The covariance of all other districts outside that 500km window is presumed to be zero. Allowing the weight on the covariance to decay with distance from the centroid of i does not change the results in a material way. We also experimented with other windows (1000km, 2000km), but we obtain the largest standard errors using 500km and hence report those.

Hypothesis testing: We will be estimating (10) for geographic regions, g. The typical significance test of estimated coefficients, with a null hypothesis that $\beta_g = 0$, is a test of whether the land elasticity is zero in region g. As will be seen in the results, we can reject this null hypothesis in all sub-samples.

What is more relevant is whether the β_g we estimate for one geographic region is statistically different from the β_g we estimate using a different region. We choose one region to be a reference region, and then test the estimated $\hat{\beta}_g$ values for all *other* regions against the $\hat{\beta}_{Ref}$. In practice, this is implemented as a simple interaction regression, where $I(Ref)$ is an indicator variable for inclusion in the reference region. The specification is

$$\begin{aligned} \ln A^{GAEZ}_{isg} &= \alpha_g + \beta_g \ln L_{Aisg}/X_{isg} + (\beta_{Ref} - \beta_g) \ln L_{Aisg}/X_{isg} \times I(Ref) + \gamma_s \\ &\quad + \delta'_g \mathbf{Z}_{isg} + (\delta'_{Ref} - \delta'_g)\mathbf{Z}_{isg} \times I(Ref) + \epsilon_{isg}. \end{aligned} \tag{11}$$

We then perform a statistical test with the null of $H_0 : (\beta_{Ref} - \beta_g) = 0$ using the results of this interaction regression. Rejecting this null indicates that β_{Ref} and β_g are statistically different, and for our purposes this is the hypothesis of interest.

4.1 District population and productivity data

Population: The underlying population data comes from GRUMP (Center for International Earth Science Information Network (CIESIN), Columbia University et al., 2011), and is provided at a 30 arc-second (approximately 1km) grid-cell resolution. This project provides counts of total population as well as urban and rural population for each cell, and is an extension of the Gridded Population of the World data.[16] Our baseline uses their population counts from 2000CE, the latest year available.

Because the cell population counts are allocated from higher level data (e.g. sub-national population counts), the grid-cell level counts are inappropriate for our purposes. If we use the grid-cell population data, we will be estimating their algorithm, and not the relationship of labor/land and productivity. Therefore, we only use their data at the level of districts (or states). We overlay 2nd-level political boundary data from the Global Administrative Areas project (Global Administrative Areas Project, 2019) on top of the GRUMP grid-cell data, and use this to rebuild the population count data for each district.

The estimation in (10) requires data on *agricultural* population, and GRUMP provides a measure of *rural* population. There is not a perfect overlap of these two sets, but in the absence of any way of measuring the spatial distribution of agricultural workers, we use the rural data as a proxy. After the main results, we discuss several alternative sources of data to control for agricultural workers. We also use data on the urbanization rate within states and districts, as well as (log) total population. This can be recovered from GRUMP using their counts of total population (rural plus urban) and urban population.

Using the data from GRUMP from 2000CE, we calculate the labor/land ratio for each district. We then discard all observations above the 99th percentile and below the 1st from that overall sample, to avoid outliers that may drive results. We also excluded all districts with fewer than 100 total rural residents, again to avoid outliers. Regressions including these observations do not appear to change the results. Summary statistics for the remaining data on the labor/land ratio can be round in Table 1 in Panel B. For our entire sample, which covers 30,054 districts for the year 2000CE, there are 0.73 rural residents per hectare. The percentile distribution of this is shown as well, ranging from only 0.04 per hectare at the 10th percentile to 1.86 at the 90th.

Inherent agricultural productivity: We rely on the work of Galor and Özak (2016) to provide our measure of agricultural productivity, A_{isg}^{GAEZ}. The authors form a measure of the potential caloric yield at a grid-cell level, combining crop yield information from the GAEZ with nutritional information on those crops. As argued by Galor and Özak (2016), the caloric suitability index is more informative for analysis of agricultural productivity than raw tonnes of output, as it relates to the nutritional needs of humans. We address the use of calories to compare crops below in the robustness section, and this is not driving our results.

For our purposes, we use the crop-specific data underlying the Galor and Özak (2016) index, so that we can measure both the total potential calories produced within a given district.[17] We

[16] Links to the raw files for population, and all other data used in this paper, along with code to build our datasets, and replicate all regressions, can be found at https://github.com/dvollrath/Crops.

[17] We use the low-input, rain-fed indices of caloric yield provided by Galor and Özak (2016) in our baseline specifi-

used a subset of the crops in the original Galor and Özak (2016) dataset, so that we focus on crops that are primary staples.[18] Those authors provide details of the construction of this data, but we can provide a summary. For each grid-cell, we calculate the total potential calories each crop will provide, given the potential production from the GAEZ project (Food and Agriculture Organization, 2012) combined with information on calories per tonne for each crop. Within each cell, we then identify the maximum amount of calories possible across the different crops. Finally, for a given district one can sum up those maximum calories to arrive at A_{isg}^{GAEZ}.

After we calculate A_{isg}^{GAEZ} for each district, we discard values above the 99th and below the 1st percentile from that total sample to avoid outliers. Our results are not sensitive to this trimming. Summary statistics for A_{isg}^{GAEZ} in the remaining districts can be found in Table 1 in the second row on Panel B, reported in millions of calories per hectare. The mean is 10.65 million calories per hectare. At the 10th percentile of the trimmed distribution, the caloric yield is only 4.89 million calories per hectare, while it is four times higher at the 90th percentile, around 16.79 million calories per hectare. The maximum caloric yield in our sample is 32.64 millions calories, while the lowest is only 0.48 million calories.

Crop suitability: As a way of creating geographic regions of districts based on crop types, we use "crop suitability indices", which are also from the Global Agro-ecological Zones (GAEZ) project (Food and Agriculture Organization, 2012), and are provided for each grid-cell on a scale of 0 to 100. Using this to identify which districts are suitable for wheat or rice (for example) avoids errors we may have introduced by introducing calorie counts to our measure of A_{isg}^{GAEZ}, and serves as a validation check. The GAEZ crop suitability indices are used to divide districts based on the types of crops they produce, but we continue to use our A_{isg}^{GAEZ} to measure actualproductivity, as the suitability indices are not a measure of potential output.

The GAEZ suitability index depends on climate conditions (precipitation, temperature, evapotranspiration), soil (acidity, nutrient availability), and terrain (slope). For districts of a country, we construct an overall suitability index as a weighted (by area) sum of the grid-cell suitability indices. Given that the grid-cell suitability measures run from 0 to 100, our aggregated index for each district also runs from 0 to 100.

Land area: Our measure of land area, X_{isg}, is the total land area of a district, without adjusting for cultivated area. We will thus be estimating the elasticity of output with respect to the *possible* stock of land. Choosing to not crop certain plots is akin to choosing to apply zero labor or capital to those plots. We discuss after the main results that our estimates do not differ if we use information

cation. Our results are robust to using different assumptions on inputs and water use, shown below.

[18]The specific crops included in our calculation are: alfalfa, banana, barley, buckwheat, cassava, chickpea, cowpea, drypea, flax, foxtail millet, greengram, groundnut, indica rice, maize, oat, pearl millet, phaselous bean, pigeon pea, rye, sorghum, soybean, spring wheat, sweetpotato, rape, wet/paddy rice, wheat, winter wheat, white potato, and yams.

on cultivated area in place of total land.

Nighttime lights: We follow Henderson et al. (2016) and use the Global Radiance Calibrated Nightime Lights data provided by NOAA/NGDC, described in Elvidge et al. (1999), and reported at 1/120 degree resolution. This dataset contains more detail on low levels of light emissions (thus capturing detail for undeveloped areas), and avoids most top-coding of areas saturated by light (thus capturing more detail in developed areas). To match the data we use on population, we use the dataset from 2000, and create district-level measures of nighttime light density by averaging across the pixels contained within each district.

We adjust for the fact that the lights data are reported with zero values, which is part of an adjustment from NOAA/NGDC to account for possible noise in pixels that report very small amounts of light. Similar to Henderson et al. (2016), for any district that has a raw value of zero for night lights, we replace that with the minimum positive value found in the rest of the sample of districts. This prevents us from understating light density in those districts. Once this adjustment is made, we take logs of the average lights in a district. Summary statistics for the final night lights data can be found in Table 1 in Panel B.

4.2 Defining temperate and tropical regions

Our primary distinction of a region g is as either temperate or tropical. There is no definitive way of assigning districts to either temperate or tropical regions, so we pursue several possibilities. Regardless of the assignment rule, it is worth reiterating that it is applied at the district level, and countries (and states) are not assumed to be homogenous.

By crop suitability: The first way of denoting temperate and tropical is through the types of crops capable of being grown, as this depends on the overall agro-climatic characteristics of a region. Here we define **temperate** districts as those that have positive GAEZ suitability for any of barley, buckwheat, rye, oats, wheat, or white potatoes, but have precisely *zero* suitability for all of cassava, cowpeas, paddy rice, pearl millet, sweet potato, and yams. The **tropical** districts are those that have positive GAEZ suitability for any of cassava, cowpeas, paddy rice, pearl millet, sweet potato, or yams, but precisely *zero* suitability for barley, buckwheat, rye, oats, wheat, and white potatoes.[19] In total, we have 10,661 districts classified as temperate using crop suitability, and 9,088 classified as tropical. There are 15,692 districts that are suitable for *both* types of crops, and these are excluded from the analysis when we use this definition.

By frost-free days: Rather than crop suitability, which combines several climate characteristics,

[19] We have experimented with alternative sets of crops to define the regions, without any material change to our results.

we can narrow the assignment down to a single characteristic, frost-free days. Frost plays a role in agriculture through culling various micro-organisms related to plant disease and the mineralization of organic matter (Masters and McMillan, 2001), and its presence or absence can be a useful indicator. We define **temperate** districts as those which have fewer than 365 frost-free days, meaning that they experience at least one frost day during the year, on average. We define **tropical** districts as those with 365 frost-free days, meaning they do not experience any frost, on average. This gives us 17,750 temperate districts, and 17,701 tropical districts, for total coverage of our sample.[20] Data on frost-free days is from the GAEZ.

By Köppen-Geiger climate zones: A final classification is to use direct climate characteristics. We use the Köppen-Geiger scheme to assign 11,618 districts as **temperate** and another 12,292 as **tropical**.[21] This broad classification also does not result in exclusive assignment, and there are 446 districts that qualify as *both* temperate and tropical, as their land area is split across both definitions. Excluding or including those districts with an overlap has no effect on our results.

Our results are not contingent of the choice of definition for temperate/tropical, as will be shown below. For much of the paper, we will focus on the first definition, based on crop suitability. Using that definition of temperate and tropical, Figure 1 shows the density plots of (log) rural labor/land for the two regions. One can see that rural labor/land tends to be higher in tropical districts, with a peak between 0.33 rural residents per hectare (i.e. log value of -1) and 1.0 rural residents per hectare (i.e log value of 0). In comparison, while there are a few districts in the temperate group with densities as high as 1.0 rural resident per hectare, the peak is around 0.33 rural residents per hectare (i.e. log of -1), and more districts with lower densities of rural workers per hectare.

There is a similar distinction in the density plots of caloric yield, A_{isg}^{GAEZ}, for districts in the tropical and temperate groups. Figure 2 shows these plots, and the tropical districts have a strong peak around 12-15 million calories per hectare, while the peak for temperate districts is closer to 5 million calories, although the tail of the temperate distribution runs as high as for tropical districts. This reflects both inherent agro-climatic productivity differences, and the fact that the calories per tonne of the crops defining the tropical districts (e.g. cassava, wet rice, etc.) are much higher than the calories per tonne defining temperate districts (e.g. barley and wheat). We discuss below that

[20] There are reasons to believe that frost may raise the productivity *level* of agriculture by killing off pests and organisms that mineralize organic matter, but this difference in productivity does *not* have anything to do with our results. Our estimates of β_g are made within-state for districts that have the *same* frost characteristics, and are not based on any comparison of frost versus frost-free districts.

[21] The Köppen-Geiger scheme has several levels. For temperate, we use districts that have any land in their climate class "C" (warm temperate) or "D" (snow), and also having any land in their temperature class "b" (warm summer) or "c" (cool summer). For tropical, we use districts that have any land in their climate class "A" (Equatorial). There are no temperature sub-divisions within the Equatorial class. There are also precipitation classifications, but we do not use those for either temperate or tropical assignment. Pixel-level data on Köppen-Geiger classification is from Kottek et al. (2006).

the calories per tonne values for each crop cannot explain our results.

These two plots capture the raw information about rural labor/land and calories per hectare, but note that the distinction in medians and modes between temperate and tropical districts are immaterial to our estimation. We will only be using the district-level variation in rural labor/land and caloric yield *within* states, and only for districts that share a common definition of temperate or tropical. Hence the shifts in the distributions seen in Figures 1 and 2 are not driving our results.

4.3 Estimates for temperate and tropical regions

Table 3 shows the estimates of β_g for both our temperate and tropical regions. In column (1) of Panel A, one can see the estimate of β_g for temperate districts is 0.239, while in column (2) the estimate of β_g for tropical districts is 0.088, a difference of approximately 0.15. Below these estimates are two hypothesis tests. The first row tests the hypothesis that the true β_g is equal to zero, and in both samples we reject this at below 0.1% significance. The second row tests the hypothesis that the β_g from the tropical region is equal to the β_g from the temperate. We can reject that null hypothesis at 0.2%.

Figure 3 plots the residual relationship of log caloric yield and log rural labor/land found from columns (1) and (2) of the Table, controlling for state fixed-effects, log light density, log population, and the urban percentage in a district. Given the large number of observations, we plot the average values of the residuals for 50 different quantiles of our data to make the figure more legible, and as these are residuals the values of rural labor/land and caloric yield are all centered around zero.[22] The difference in the slopes of the lines for tropical and temperate districts imply a difference in the value of the land elasticity, β_g, and as the table indicates that difference is statistically significant. The additional value of the Figure is that it allows us to assess our linearity assumption, and judge if there are outliers perhaps driving the results. Overall, the linearity assumption appears solid, despite some outliers at the lowest level of density. At very low levels of rural labor/land ratios among (below -1) the quantile averages appear to diverge from the estimated relationship. These represent only 6% of the total data points, and if we exclude them from our regressions we obtain similar results.

Returning to Table 3, the remainder of the Panel A shows variations on our baseline result using different definitions of temperate and tropical districts. In columns (3) and (4), we use the definition of temperate and tropical based on the number of frost-free days. The results are similar to our baseline, with an estimated β_g of 0.218 for temperate districts, but only 0.093 for tropical ones. The gap here is about the same as our baseline results from columns (1) and (2), and is significant at 0.2%. Columns (5) and (6) use the Köppen-Geiger definition of temperate and tropical regions. Here, the results are similar to those using the crop suitability definition.

[22] Using the quantiles still gives an accurate indication of the relationships in the data. See Chetty, Friedman and Saez (2013) for an explanation and example of this kind of figure.

β_g is estimated to be 0.220 in temperate districts, and only 0.081 in tropical ones, for a difference of about 0.14, again statistically significant at 0.7%. Our results are not sensitive to the exact definition of temperate/tropical.

Panel B of Table 3 provides an initial set of robustness checks on the results. In all regressions in Panel B, the definition of temperate versus tropical region is based on crop suitability, as in the first two columns of Panel A. In Panel B, columns (1) and (2) exclude any district with a reported urban population greater than 25,000 people. The worry is that highly urbanized districts may operate a different type of agricultural technology and/or may skew the labor/land ratio near them (perhaps due to definitions of urban areas), and that our original results were affected by this. As can be seen from the table, however, the distinction in β_g grows, 0.330 for temperate districts and 0.093 for tropical districts, which is an absolute difference of 0.237. This difference is again significant. This is due to the fact that districts with urban populations over 25,000 tend to have higher productivity than their neighbors but lower labor/land ratios, which is consistent with the findings in Henderson et al. (2016) that urban areas in developed areas tend to be located near high agricultural productivity locations.

Columns (3) and (4) of Panel B exclude districts where the urban share of population is above 50 percent, to again eliminate districts that are mainly urban areas. The results conform to those in columns (1) and (2), with a temperate estimate of β_g equal to 0.339, and a tropical estimate of 0.099, a difference that is statistically significant at less than 0.1%. Finally, columns (5) and (6) of Panel B exclude both Europe (including Russia west of the Urals) and North America from the samples, to address the worry that these areas may use different types of agricultural technologies than other places at lower development levels.[23] The finding that districts suitable for tropical crops have a lower land elasticity still holds, with an estimated β_g of 0.087 compared to 0.228 for temperate districts. The difference is significant at 0.5%, with the higher p-value a result of the smaller sample size (880) of temperate districts in this restricted sample.

Arguably the results excluding the urban districts in columns (1)-(4) of Panel B may be more appropriate to our empirical setting. Districts with larger urban populations may be less likely to share a common relative price for agricultural goods with their more rural neighbors, or perhaps have district-specific wedges and distortions that set them apart. Excluding them results in an even more exaggerated difference in temperate and tropical land elasticities. Our baseline results may well be understating the gap between temperate and tropical regions.

4.4 Robustness checks

Rural labor/land data: Panel A of Table 4 shows results using different sources for the rural population data, L_{Ai}. In columns (1) and (2) of Panel A we re-estimate the values of β_g for

[23] Advanced economies with modern farming like Japan and South Korea are already excluded from our regressions by how we defined tropical and temperate areas, given that they are capable of growing both kinds of crops.

temperate and tropical regions using population data from GRUMP, but from 1990CE. The results of 0.227 for temperate and 0.118 for tropical show a slight narrowing of the gap, but they remain significantly different and our results are not the result of using the 2000CE data. In columns (3) and (4) we show that our results are not driven by using GRUMP as the data source. Instead we use the HYDE 3.1 database (Goldewijk et al., 2011) for 2000. Again, the results conform to our baseline, with 0.241 for temperate and 0.088 for tropical areas.

In the last columns of Panel A, we turn to the International Public-Use Microdata Series (IPUMS) database to extract individual level data for 39 countries that have geographic identifiers at the sub-national level. Using this, we can accomplish two things. We can find direct information on the number of people living within a given geographic area, as opposed to relying on GRUMP. Because of the limited country coverage of IPUMS, and because the "districts" IPUMS uses are larger than our baseline, we end up with only 3,520 observations.[24] Nevertheless, in columns (5) and (6) the results are consistent with our baseline, although shifted down in both cases slightly. The temperate elasticity is estimated to be 0.189, while the tropical elasticity is only 0.016.

The second use for IPUMS is that it has information on occupation and/or industry. This allows us to distinguish agricultural workers from rural residents. Hence the meaures of L_{Ai} in columns (5) and (6) is based on those who report agriculture as their industry of employment. An additional reassurance for our baseline results is that the IPUMS data show that the correlation of rural residents with the number of agricultural workers is 0.91, and significant at less than 1%. Thus our baseline GRUMP data on rural residents is not making systematic errors in measuring agricultural worker labor/land ratios.

Land area: As noted above, our baseline results measure land, X_i, in a district as the total area, as this represents the stock of *possible* agricultural land. Choosing not to cultivate land is indicated by having no labor (or other inputs) used on that land, leading to a low rural labor/land ratio. As such, that labor/land ratio is still informative about the value of β_g.

However, we can restrict ourselves to looking at the labor/land ratio of agricultural workers on actual cultivated land. We use GAEZ to build a measure of the area of cultivated land in a given district as X_i^C. Our baseline rural labor/land ratio can thus be written as $\ln L_{Ai}/X_i = \ln L_{Ai}/X_i^C + \ln X_i^C/X_i$. The first term on the right is the (log) ratio of agricultural workers per cultivated land, while the second term is the (log) share of cultivated land in total land area. We can include both of the right-hand side terms as controls in our regressions, and recover the estimate of β_g from the coefficient on $\ln L_{Ai}/X_i^C$, labor/land measured per unit of cultivated land. In Panel B of Table 4, columns (1) and (2), we present results using cultivated land to measure

[24]Because district-level boundaries can change over time, IPUMS aggregates to the largest possible units that are stable over time, which means fewer districts. This also means that there are far fewer districts within any given state (and in some cases even states are aggregated), and so we use country-level fixed effects with the IPUMS regressions, rather than state-level.

rural labor/land ratios. Again, the results are consistent with our baseline (0.219 for temperate areas and 0.090 for tropical).

Cash crops and livestock: Our measure of A_{isg}^{GAEZ} is based on staple crops, as opposed to cash crops (e.g. cocoa) or livestock production. If some districts within a state produce mainly cash crops or livestock, A_{isg}^{GAEZ} may be a poor proxy for the actual agricultural total factor productivity in that district. A particular problem would be if some districts within a state focus on cash crops or livestock, while other districts focus on staple crops. The differences in labor/land ratios between these districts would not be related to our measure of staple crop productivity, A_{isg}^{GAEZ}, and thus our estimate of β_g could be biased.

To address this, we draw in additional data on land use to eliminate districts that are heavy cash crop or livestock producers. In columns (3) and (4) of Panel B in Table 4 we drop any district that has more than 5% of its harvested area coming from cash crops. Data on the harvested area is from Monfreda, Ramankutty and Foley (2008).[25] The estimated β_g in temperate areas, 0.207, remains about three times as large as the estimate for tropical areas, 0.061, and that difference remains significant. Columns (5) and (6) drop any districts that have more than 20% of their area devoted to pasture, using data from Ramankutty et al. (2008). Again, the temperate estimate is around our prior estimates, 0.201. The tropical estimate, 0.100, is slightly higher than found in wider samples, but remains significantly different from the temperate estimate.

Productivity data: Another possible concern with the existing results is that they are reliant on the specific caloric suitability index A_{isg}^{GAEZ} that we derived. In particular, we used the underlying data from the GAEZ for "low-input, rain-fed" agriculture to construct this index, matching Galor and Özak (2016). This could over-state the variation in "true" productivity (A_{isg} in our prior notation) across districts within states, because it ignores the possibility that inherently low-productivity districts can adopt the use of fertilizer and/or irrigation to bring their productivity up to match other districts in their state. If A_{isg}^{GAEZ} over-states the variation in productivity across districts, then we may be over-stating the size of β_g. If, for some reason, this problem is pronounced in temperate areas, this could explain our finding that temperate areas have high β_g values. Alternatively, A_{isg}^{GAEZ} may understate variation in A_{isg} if irrigation or modern inputs allow some districts to increase their total factor productivity relative to others. If this is true in tropical regions, we would be under-estimating β_g for tropical areas.

To address these concerns, in Table 5, Panel A, we show results where we reconstruct the index A_{isg}^{GAEZ} using different underlying data on productivity from the GAEZ. In columns (1) and (2), for example, we use their "medium-input, irrigated" estimates of productivity to derive A_{isg}^{GAEZ}, and then re-run our regressions. As can be seen, the gap between temperate and tropical β_g estimates

[25] The cash crops we consider are bananas, cocoa, coffee, cotton, jute, palm oil, rubber, sunflower, tea, tobacco, sugarbeets, and sugarcane.

narrows slightly (0.208 for temperate and 0.084 for tropical) compared to our baseline estimate. But the gap remains 0.12, and is significant at conventional levels.

In columns (3) and (4) of the same panel, we do a similar exercise, but now use the "high-input, rain-fed" productivity data from GAEZ to construct A_{isg}^{GAEZ}. Here the results are nearly identical to our baseline (0.234 for temperate and 0.094 for tropical). Columns (5) and (6) use the "high-input, irrigated" productivity data to construct A_{isg}^{GAEZ}, and the results are similar to when we use the irrigated productivity measures from the first two columns. The estimated effects (0.206 for temperate and 0.084 for tropical) are again a little closer than in our baseline, but remain significantly different.

While everything we estimate is within-state, so that cross-country differences are not used directly, a further worry may be that within the states of rich countries, there is more scope for inputs and irrigation to reduce the gap in actual productivity between districts, and that we are doing a particularly bad job of capturing true productivity differences by using A_{isg}^{GAEZ}. Given that rich countries tend to be predominantly composed of temperate areas, we are perhaps over-estimating β_g in temperate zones. To address this, in Panel B we exclude North American and European countries from the sample, and re-estimate β_g under the different assumptions regarding inputs and water use. As can be seen, regardless of the choice of inputs and water use, the gap in β_g between temperate and tropical regions remains, and is in fact larger than estimated using the full sample in Panel A, similar to our baseline results.

A final issue with the construction of A_{isg}^{GAEZ}, regardless of the choice of inputs and water use, is that it relies on the calorie content of different crops to make them comparable to one another. It could be that the calorie counts used by Galor and Özak (2016), that we adopt, are incorrect. Or perhaps calories are an imperfect way of comparing crops, and we should be using something like relative prices. We address this by using the individual crop-level measures of raw productivity (in tonnes, rather than calories) from GAEZ as our measure of A_{isg}^{GAEZ}. For temperate regions, for example, we run separate regressions using the raw potential barley yield as our measure of A_{isg}^{GAEZ}, and then do so for buckwheat, then oats, etc. We do similar regressions for tropical areas with raw yields of the tropical crops. The full results are available in the Appendix.

In all cases, the estimated size of β_g using the individual crop raw potential yields give us nearly identical results to what we find in our baseline using the caloric suitability index. The consistency of the results using separate crop-specific raw potential yields shows that weighting crop yield by calorie counts to aggregate them together are not important to our results. Further, this consistency across crops also implies that *any* weighting scheme to compare the value of crops (e.g. prices) would also yield similar results for β_g as our baseline.

4.5 Demographic and asset controls

The state fixed effects and controls for night lights, urban share, and total population may not control fully for district-level variation in the capital/labor ratio, in particular due to differences in the characteristics of the population in a district (e.g. education) and the availability of capital (e.g. livestock or the presence of electrical service). To assess if this is biasing our results, we run the same regressions for a limited sub-sample of districts for which we can assemble detailed data on demographics and assets.

We use the Demographic and Health Surveys (DHS), which provide individual and household level data in a consistent manner across a wide range of developing countries. Many of these surveys contain GIS information on the latitude and longitude of the surveyed clusters (e.g. a village), which allows us to identify which clusters are located within which districts. For those surveys with GIS data, we create district-level aggregate demographic and asset measures.[26] With the DHS data, this gives us a sample of 2,106 districts, of which 331 are part of our temperate region, and 1775 part of our tropical region. Details on the countries from which these districts are drawn are available in the appendix.

Table 6 shows the results of estimating β_g for temperate and tropical regions. Columns (1) and (2) are limited to those districts that have DHS data, but this data is not included as controls in these regressions. The results here, with a land elasticity of 0.212 for temperate districts and 0.088 for tropical districts, conform in size to the estimates we received in our larger samples. In columns (3) and (4), we repeat these regressions, but now include the DHS demographic data. The results are nearly identical, with a small drop in the temperate estimate to 0.210, while the tropical estimate remains similar at 0.088. Columns (5) and (6) include both the DHS demograhpic and asset data, and again the results are nearly identical.

The results using the DHS data provide some reassurance that the main findings are not due to unobserved district-level variation in the composition of the labor force or availability of capital. These DHS controls should also alleviate some concern about unmeasured differences in agricultural productivity across districts within a state, to the extent that they proxy for the level of technology used within a district.

4.6 Production function specification

For expositional purposes, we specified a Cobb-Douglas production function in equation (1), which implies that the land elasticity does not vary with the endowment of land, labor, or other inputs.

[26]On the demographic side we have the median, 10th, and 90th percentile of household head's age, years of education, and typical number of household residents. On the asset side we have the fraction of households with the following: toilet, electricity, television, refrigerator, improved flooring, any agricultural land, a bank account, any cattle, any draft animals, and any sheep. Some surveys contain measures of the amount of agricultural land, as well as counts of livestock, but there are too few of these to do a comparison across temperate and tropical regions.

This need not be the case, of course, and the different results on β_g for temperate and tropical areas may not reflect a fundamental difference in the production function, but rather a difference in those endowments. In particular, we know from Figure 1 that tropical areas have higher rural densities than temperate areas. If the elasticity of substitution between land and labor were more than one, then higher rural labor/land ratios would be associated with a lower land elasticity (and a higher labor elasticity).[27]

We do not believe this can explain our results. First, while tropical areas on average have a higher labor/land ratio, there are numerous examples of low density tropical areas (parts of Central and South America, areas in Sub-Saharan Africa). In the Appendix, we show that we get similar estimates for β_g in all of these sub-regions considered alone, showing no relationship of labor/land and the value of β_g. We can do something similar for temperate areas, and again there is no systematic relationship of β_g to the labor/land ratio of the temperate sub-regions. As a second check, also to be found in the appendix, we estimate a separate value of β_g for each state in the temperate and tropical regions containing 10 or more districts. We then can plot the values of β_g against the labor/land ratio, and there is no systematic relationship.

4.7 Comparison to factor shares

A possible point of comparison for our estimates of β_g is the factor share of land in agricultural output. With competitive markets for *all* inputs to agriculture, the factor share of land should be equal to the elasticity β_g. There is variation in these factor shares across countries, but they are not always consistent with our estimates. Fuglie (2010) reports factor share estimates for a set of countries, finding shares between 0.22 and 0.33 for land and structures. The inclusion of structures muddies the comparison with our estimate of β_g. Nevertheless, he reports land shares between 0.22 and 0.25 for India, Brazil, and Indonesia. There is substantial heterogeneity within each of these countries in climate and crop type, but our estimates would suggest values of β_g between 0.08 and 0.10, based on the prevalence of tropical agriculture. The factor share of land and structures for China is 0.22, which is difficult to compare to our results given the heterogeneity in climate zones within China.

Reported factor shares for land and structures in the US (0.19) and former Soviet Union (0.21 - 0.26) are in line with our β_g estimates for areas using temperate agriculture, although both of those countries also contain heterogeneity in climate zones. A study by Jorgenson and Gollop (1992) reported a land share of 0.21 for the U.S., close to our estimates for β_g areas. Fuglie reports a factor share of 0.17 for land and structures in the UK, lower than the value we get for temperate zones. However, Clark (2002) reports long-run factor shares of land for England, and that share is between 0.30-0.36 for several centuries, somewhat higher than our estimated β_g for temperate

[27] Work by Wilde (2012) indicates that the elasticity of substitution is *less* than one, using historical information from the United Kingdom.

areas. Hayami, Ruttan and Southworth (1979) provide longer-run estimates of land shares for several east Asian economies, finding estimates between 0.3 and 0.5 for Taiwan, Japan, Korea, and the Philippines from the late 1800's until the middle of the 20th century. These numbers cannot be directly compared to our β_g estimates, as much of Japan and Korea, and all of Taiwan, are excluded from our analysis because they are suitable for *both* temperate and tropical crops, as we've defined them.

Comparing to land shares thus provides mixed results. Nevertheless, we think there is information in our estimates. Our estimates are built using the assumption of mobility of labor between districts, but is robust to arbitrary distortions to wages between agriculture and non-agriculture, or arbitrary distortions in the relative price of agriculture (which could include market power in either sector). In contrast, for factor shares to be good estimates of the elasticities, it would have to be that returns are equalized across districts *and* there are no distortions or frictions in the state-wide factor markets, so that factor shares are in fact identical to elasticities. There is not an obvious reason to think that those assumptions about perfect factor markets conditions hold. Furthermore, the factor share data is an aggregation from a snapshot of *farm*-level payments to land, but as noted before the farm-level production function may not be equivalent to the aggregate production function we are estimating. It is not clear that the factor share data cited should be privileged in terms of its relevance for the question at hand.

4.8 Districts suitable for both kinds of agriculture

4.9 Aggregate land elasticities

We can combine our full set of estimates to demonstrate how the land elasticity varies across the world. The first way we do this is by mapping our assignment of geographic region, so that one can see where precisely the temperate and tropical regions lie, as we define them using crop suitability. For this exercise, we make the assignment at the pixel (rather than the district) level. Those pixels were used by us to derive the district-level classifications used in the regressions, but the pixel level gives a more nuanced picture of the variation.

For each pixel, then, we assign it one of four values. If the pixel cannot grow *either* temperate or tropical crops, as we defined them earlier, then it is labelled as "unsuitable". If a pixel can grow temperate crops, but not tropical crops, then it is labelled "temperate". The reverse situation, where the pixel can grow temperate but not tropical crops, is labelled "tropical". And finally, a pixel that is suitable for both types of crops is labelled "both". Figure 4 shows the pixel-level map of the globe, with the four categories indicated by color. In addition, the baseline estimate of the land elasticity for each region (excluding unsuitable areas) is noted in the legend.

Several things are interesting to note here. While the unique temperate (orange) area covers much of North America and Eurasia, as expected, there are several pockets of temperate areas around the world. Central Mexico, a strip down the spine of South America, the Tigris/Euphrates watershed, an area roughly corresponding to Manchuria, and a few pockets in East Africa all fall in our temperate region. These are the places that were used to show that the estimated land elasticity in temperate regions was robust to excluding North America and Europe. Also of note is that by definition our estimates were made excluding much of the eastern United States, which is classified as "both" due to some suitability for both temperate and tropical crops, similar to much of China.

A second way to show the variation in land elasticity is to calculate aggregate values at the country level. This aggregation is done at the district level (pixel-level aggregations deliver similar results). Each district is assigned the baseline land elasticity associated with the region to which it was assigned in our regression analysis. Temperate districts thus receive a value of 0.239, tropical districts a value of 0.088, and districts capable of growing both receive the value of 0.131. Districts incapable of growing any of those crops (there are only a handful) are excluded from the analysis.

The aggregation is a weighted average of the district-level elasticities, with the weights based on the total potential calories that can be produced by a district relative to the country as a whole. Those potential calories are built as in Galor and Özak (2016).[28] The formula for country c is

$$\beta_c = \sum_{i \in I_c} \frac{cal_{ic}}{\sum_{j \in I_c} cal_{jc}} \beta_{ic} \tag{12}$$

where I_c is the set of districts in country c, cal_{ic} are the potential calories in district i in country c, and β_{ic} is the land elasticity of district i from country c.

Table 8 shows the results of this aggregation. Many countries have all their districts with identical geographic classifications, so their aggregate value is identical to one our baseline values.

5 Implications of variation in land elasticities

Having established that the elasticity of agricultural output with respect to land varies across climate types, we now want to show the relevance of this variation for development. We first discuss how the size of β dictates the sensitivity of the agricultural labor share (e.g. L_A/L) and real income per capita to shocks in productivity and population. As part of that, we provide estimates of β at the country level by aggregating up from our district-level results. Second, we show using evidence from the epidemiological transition after World War II that the predictions regarding sensitivity to shocks and the value of β are valid. Developing countries that have high β values display larger drops in GDP per capita and GDP per worker following the population increase due to the decline in mortality.

[28] Conceptually, the weights should properly be based on the share of real output produced by each district. In the absence of real agricultural output data at the district level, we use the calories as a proxy.

5.1 Aggregate land elasticities and shocks

The importance of the land elasticity for development comes from a combination of the low income elasticity for agricultural goods, and the (relatively) fixed nature of land. Some combination of these two features is part and parcel of nearly every description of the structural transformation out of agriculture (Kogel and Prskawetz, 2001; Gollin, Parente and Rogerson, 2007; Restuccia, Yang and Zhu, 2008; Gollin, 2010; Vollrath, 2011; Alvarez-Cuadrado and Poschke, 2011; Herrendorf, Rogerson and Valentinyi, 2014; Duarte and Restuccia, 2010). To see the logic involved, consider a very simplified model where L people have a fixed demand for agricultural goods of $\bar{c}_A$, and only land and labor are involved in production. Equating demand and supply, we have

$$\bar{c}_A L = A_A X^{\beta} L_A^{1-\beta}, \tag{13}$$

which can be solved for the share of labor in agriculture,

$$\frac{L_A}{L} = \left(\frac{\bar{c}_A L^{\beta}}{A_A X^{\beta}}\right)^{1/(1-\beta)}. \tag{14}$$

Note that the sensitivity of L_A/L to productivity (A_A) and population (L) depends on the size of β. And the larger is the land elasticity, the *more* sensitive is L_A/L to both of these terms. The reason is that β dictates the degree of decreasing returns to scale for labor in agriculture. A larger land elasticity implies more severe decreasing returns. Hence larger movements of labor into or out of agriculture are necessary to keep the supply of agricultural goods equal to the demand.[29] Given that non-agricultural labor is the alternative use for labor, this means that changes in non-agricultural employment (and hence urbanization to some extent) also depend on the land elasticity.

The variation in the land elasticity we found between temperate and tropical regions thus has a significant effect on how these places respond to technological improvements in either sector or population growth. And this may have led to significant differences in long-run development. A temperate and tropical area starting out with identical living standards and share of workers in agriculture could end up far different over time, even if they faced the same trend growth in productivity. The temperate area would have a larger fraction of workers in non-agriculture (and plausibly a higher urbanization rate and living standards) than the tropical area. If there were agglomeration effects in urban areas, or demographic effects of a declining agricultural labor share, then any initial advantage conveyed on a temperate area by having a large land elasticity may have been exaggerated over time.

That said, it is not the case that temperate areas with high land elasticities must necessarily

[29] In the appendix we present a richer two-sector model that allows for more nuanced income and substitution effects in the demand for agriculture, capital in the production function, and an endogenous relative price of agricultural goods that demonstrates the same conclusion we describe here.

have an advantage in development. The high land elasticity also makes temperate areas more sensitive to *negative* shocks to productivity, and to increases in population. Tropical regions with low land elasticities would thus be able to survive poor weather or unexpected population increases with a smaller effect on the agricultural labor share (and plausibly on urbanization and living standards). The low land elasticity may have allowed tropical regions to be more resilient in the face of shocks compared to temperate regions.

5.2 Evidence from the epidemiological transition

The epidemiological transition that occurred following World War II provides a useful context in which to test the effects of variation in β. Acemoglu and Johnson (2007) collect mortality rate data from the post-war period for a set of 15 infectious diseases (e.g. tuberculosis and malaria). They argue that the epidemiological transition formed an exogenous shock to population health, and therefore population size, in developing countries, and use it to identify the causal impact of health on living standards. We can use the same empirical setting to ask whether the impact of these plausibly exogenous health interventions *differed* based on whether countries had a high β value or a low β value. Based on our simple model, we would expect that living standards in places with the high βshould be more sensitive to these mortality shocks than places with low β values.

To implement this, we first estimate a separate β for each country. We use all districts within a country, and then estimate equation (10), including the state-level fixed effects. Given heterogeneity of climate types within countries, this is not ideal, as it assumes that all districts of the country have an identical value of β. However, the data from the Acemoglu and Johnson paper is at the country level, so in order to have a single observation for each country, we make the assumption that β is homogeneous within each.

We restrict ourselves to the low and middle income sample from Acemoglu and Johnson, which gives us 32 countries. We make this restriction because rich countries, regardless of their value of β, are not going to be affected by the decreasing returns in the agricultural sector to any meaningful degree given their low agricultural labor share to begin with. For the 32 low and middle income countries, we then split them into two groups based on whether their β is below the median of the 32 countries (low land elasticity) or above the median (high land elasticity).[30]

For each group, we use the original data from Acemoglu and Johnson to run panel regressions with the specification of

$$y_{it} = \alpha + \theta x_{it} + \gamma_i + \delta_t + \epsilon_{it} \tag{15}$$

where y_{it} is one of three different dependent variables (log GDP per capita, log GDP per worker, or log population), and x_{it} is one of three different independent variables (mortality rates, log life

[30] We can expand the data to include up to 45 countries in some regressions where we have sufficient mortality and GDP data. To create comparable samples across all of our regressions, we limit ourselves to the 32 countries with full data. Our results are not affected in a material way by including all possible countries in each regression we run.

expectancy, or log population). θ captures the effect of the independent variable on y_{it}, and we will compare the value of θ across samples that differ based on whether they have low land elasticities or high land elasticities. γ_i and γ_t are country and decade fixed effects, while ϵ_{it} is the error term. Each country has up to eight decadal observations, running from 1930 to 2000, but the panel is not balanced.[31]

Table 9 presents the results. In Panel A, the explanatory x_{it} variable is the original mortality instrument from Acemoglu and Johnson, which measures the mortality rate from the 15 infectious diseases that were affected by the interventions following World War II. In columns (1) and (2), we show the effect of mortality rates on (log) GDP per capita. As can be see, the estimated coefficient for low-β countries (0.333) in column (1) is smaller than the estimate for high-β countries (0.723) in column (2). Below these estimates are two hypothesis tests. First, the test that the effect size is zero, $\theta = 0$. We cannot reject zero for low-β countries (p-value of 22.0%), but reject zero for high-β countries. The hypothesis that θ is identical for the two samples has a p-value of 19.9%, given the large standard error for the low-β sample, and we cannot reject equality at standard levels. Nevertheless, the pattern of results is consistent with our predictions.

Columns (3) and (4) of the same panel repeat this test, but now using (log) GDP per worker as the dependent variable. The effect of mortality is estimated to be almost three times larger when β is high than when it is small (0.776 vs. 0.284). This difference is significant at 10.2%, and shows that high-β countries are more sensitive to population shocks than low-β countries. These columns show that mortality shocks affected the average output of each *worker*, and the effect on per capita GDP did not arise because of short-run changes in the age structure of the economy.

The final columns, (5) and (6), show the effect of the mortality shocks on population size. In low-β countries, the effect of mortality on population was estimated to be smaller than in high-β countries (-0.361 versus -0.597), although we cannot reject that these effect sizes are the same (a p-value of 32.7%). Thus it may be that the high-β countries were hit by a larger shock to their population due to the epidemiological transition, perhaps acting as part of the explanation for their stronger response to the mortality changes, although the differences across samples are not statistically significant.

Panel B of Table 9 repeats the regressions, but now uses life expectancy itself as the explanatory variable x_{it}, matching Acemoglu and Johnson's original work. Whether looking at GDP per capita (columns 1 and 2) or GDP per worker (columns 3 and 4), we have large and statistically significant differences in the estimated effects of life expectancy in low and high-β samples. For low-β countries, the implied effect of rising life expectancy is close to zero (or positive) for both GDP per capita

[31] Rather than separating countries into two groups based on β and comparing θ between them, an alternative specification would be to interact β_i with x_{it}, as in $y_{it} = \alpha + \theta_0 x_{it} + \theta_1 \beta_i \times x_{it} + \gamma_i + \delta_t + \epsilon_{it}$. In this case, the estimated value of θ_1 would indicate how the effect of x_{it} differs with the size of β. Doing this produces results consistent with those presented in Table 9.

and GDP per worker.[32] In contrast, for high-β countries the estimated effect of life expectancy is negative and statistically significant for both GDP per capita and per worker. We can reject, at less than 0.1%, that the estimated effects in the two sets of countries are similar.

In contrast, in columns (5) and (6), the effect of life expectancy on population size is positive in both sets of countries, with a smaller estimated effect size in low-β countries, although the difference is significant at only 12.8%. Both low and high-β countries experienced significant population shocks from the rise in life expectancy, but this had more severe negative effects in high-β countries on living standards, consistent with the predictions in the prior section.

Finally, Panel C looks at the relationship of living standards and the size of population. This test is speculative, as population size is influenced by far more than the mortality shocks occassioned by the epidemiological transition. The pattern of are consistent, though, in that the correlation of population size and living standards (whether measured as GDP per capita or GDP per worker) is larger when β is high then when β is low. The scale of the difference is similar to the mortality results, with the coefficient size for high-β countries about twice that found for low-β countries. The statistical test for equality of the two coefficients has a p-value less than 1.0% in both cases.

The evidence in Table 9 shows that the variation in β we identified in the main part of the paper has effects consistent with those predicted by the model in this section. Given the differentials we estimated in the effect of the epidemiological transition, the variation in β appears to have non-trivial implications for development.

6 Conclusion

The role that land plays in agricultural production is relevant to any study of agriculture and development. We estimated the elasticity of aggregate agricultural production with respect to land, and found that it differed significantly between temperate and tropical regions of the world.

Our estimates are made by looking at the relationship between agricultural worker labor/land ratios and potential agro-climatic yield at the district level (e.g. 2nd level administrative units) from 154 countries. Our methodology lets us use the district variation within states to identify the land elasticity, and avoids the need to specify or measure other inputs directly. This also avoids comparing countries - or even states - at different levels of development. Our baseline finding, that the land elasticity in temperate areas is about 0.24 while it is only 0.09 in tropical areas, is robust to different ways of measuring rural labor/land ratios and potential yield, and robust to alternative definitions of what constitutes tropical versus temperate areas. What our estimation technique does not provide is a way of identifying *why* the aggregate elasticities vary so much between tropical

[32]Whether changes in health, as proxied by life expectancy, are in fact positive or negative in the long run for development is beyond the scope of this paper, and the original findings of Acemoglu and Johnson are debated (Bloom, Canning and Fink, 2014).

and temperate areas, and whether that is due to biological requirements of certain crops, or the constraints imposed by aspects of the climate itself.

These estimates are for the aggregate land elasticity, and as such are informative for research that studies the role of the aggregate agricultural sector in development, whether that is related to structural change in developing countries today, or related to historical development in standard Malthusian settings. We showed that this aggregate land elasticity, regardless of the setting, is a central parameter in determining the elasticity of income per capita and the share of labor in agriculture with respect to shocks in population growth or productivity. In short, the larger the land elasticity, the more sensitive an economy is to those shocks. We confirmed this prediction by showing that in response to the epidemiological transition following World War II, countries with larger land elasticities did see more severe changes in their GDP per worker and GDP per capita.

More generally, we contribute to the understanding of relative development levels in tropical and temperate areas of the world. By making temperate areas more sensitive to shocks, a high aggregate land elasticity allowed them to leverage positive shocks to productivity (e.g. technological improvements) and population growth (e.g. the demographic transition) to accelerate their growth relative to tropical areas. Slower development in tropical regions - either historically or in the current era - may reflect in part differences in the size of the aggregate land elasticity, rather than any deficiency in productivity or population growth.

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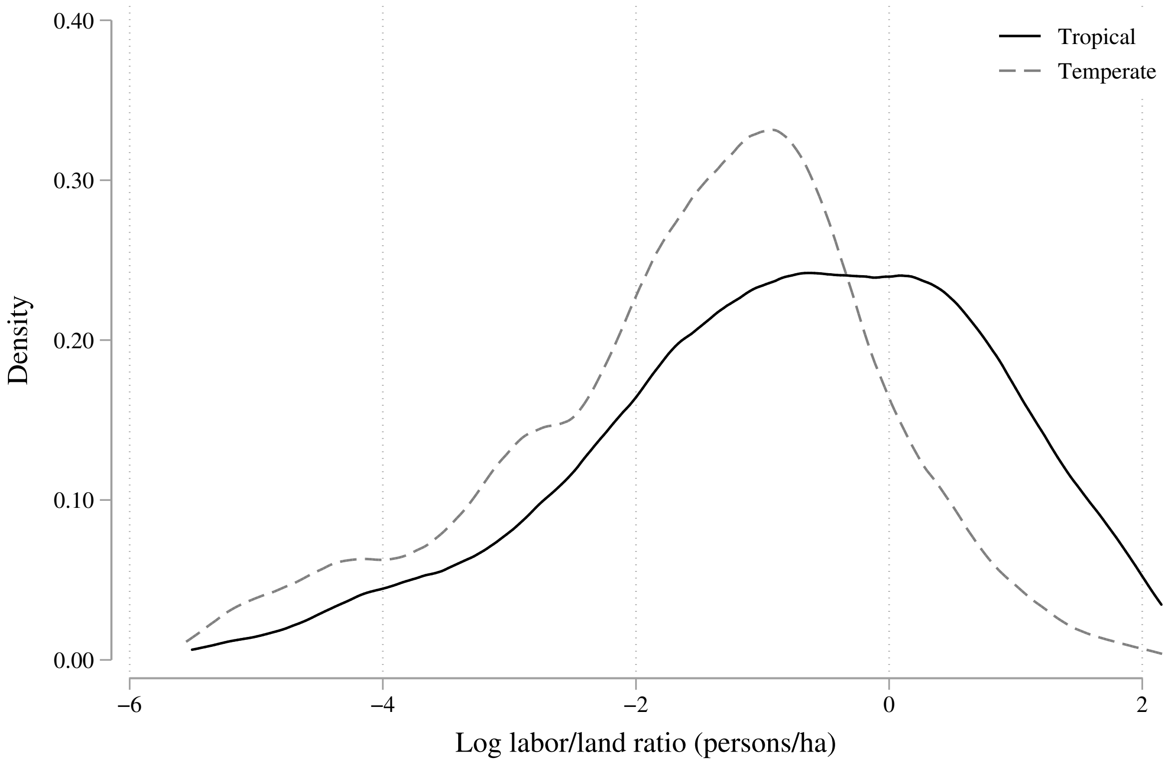
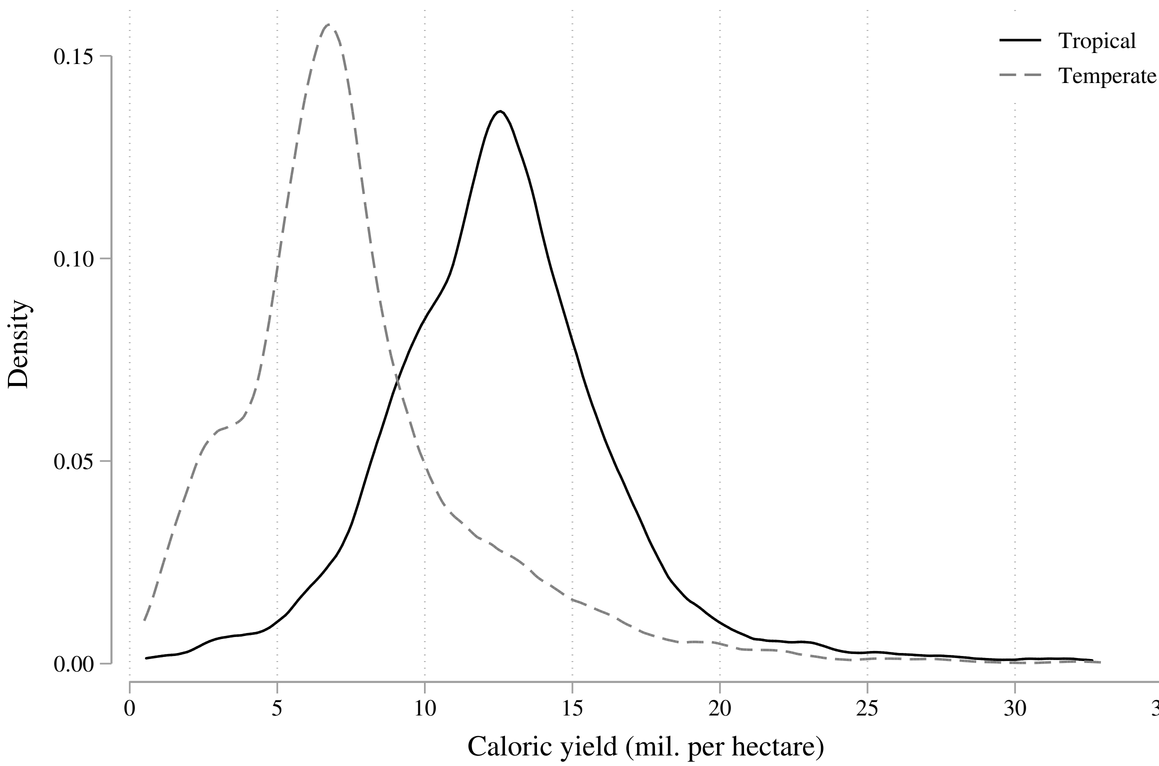
Figure 1: Density Plot of Log Rural Labor/land Ratios (L_{Aisc}/X_{isc}), by Crop Type, 2000CE



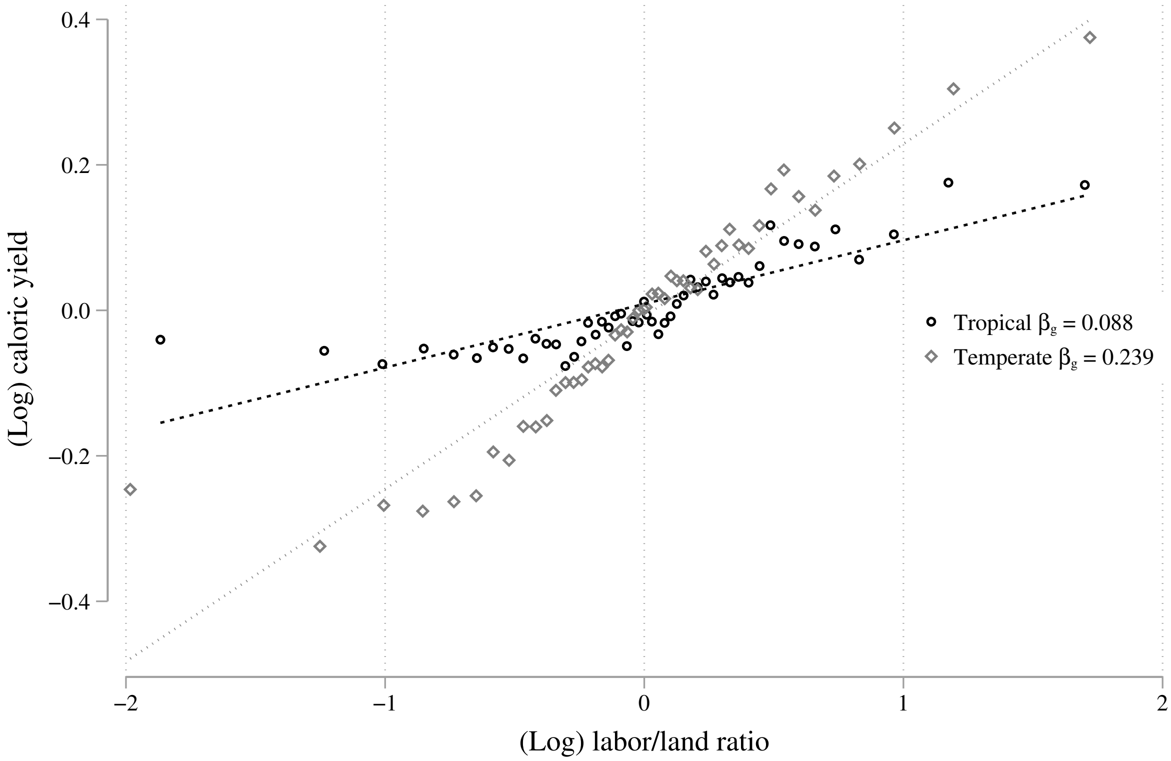
Notes: Kernel density plot, Epanechnikov kernel, of the (log) rural labor/land, L_{Aisc}/X_{isc}, at the district level, calculated by the authors using data from Goldewijk et al. (2011) for rural population. "Temperate" includes districts that are suitable for growing barley, buckwheat, oats, rye, wheat, and white potatoes, but have zero suitability for cassava, cowpeas, pearl millet, sweet potato, wet rice, and yams. "Tropical" includes districts suitable for the latter set of crops, but zero suitability for the former.

Figure 2: Density Plot of Caloric Yield (A_{isc}^{GAEZ}), by Crop Type



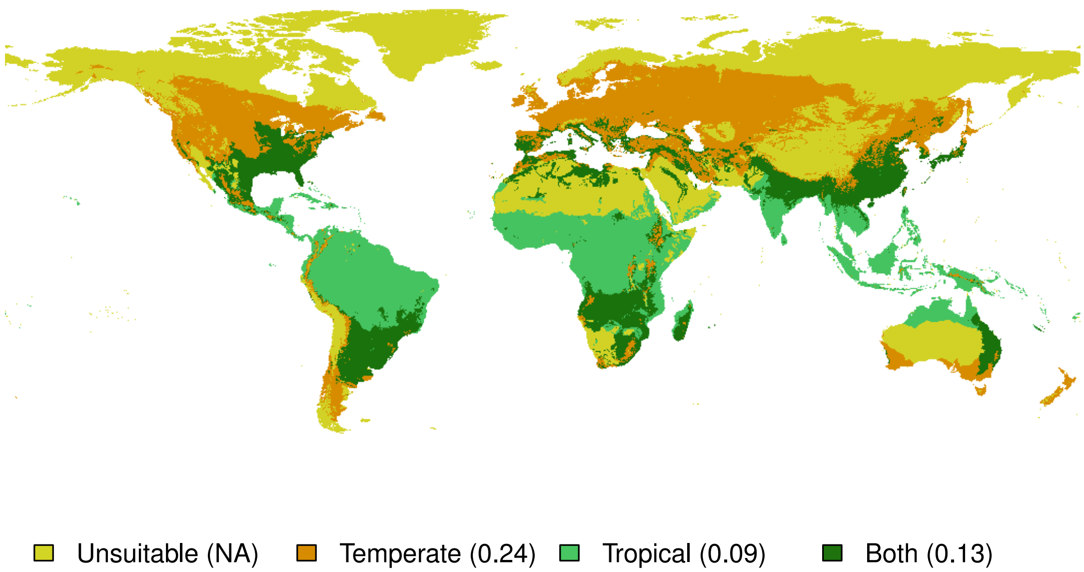
Notes: Kernel density plot, Epanechnikov kernel, of the caloric yield, A_{isc}, at the district level, calculated by the authors using data from Galor and Özak (2016). See text for details. This measure sums the maximum calories available per grid cell within a district, then divides by total area of the district. "Temperate" includes districts that are suitable for growing barley, buckwheat, oats, rye, wheat, and white potatoes, but have zero suitability for cassava, cowpeas, pearl millet, sweet potato, wet rice, and yams. "Tropical" includes districts suitable for the latter set of crops, but zero suitability for the former.

Figure 3: Residual Relationship of Caloric Yield (A_{isc}^{GAEZ}) and Rural Labor/Land Ratios



Notes: Plotted are the quantile averages of both log caloric yield and log rural labor/land for each sample, temperate and tropical. 50 quantiles are used in each sample. The quantiles are taken from the residuals of caloric yield and rural labor/land after controlling for log light density, urban percentage in 2000, and state fixed effects. Linear fits are shown, and the estimated slopes are in the legend. The `binscatter` command from Stata was used to prepare the figure. "Temperate" includes districts that are suitable for growing barley, buckwheat, oats, rye, wheat, and white potatoes, but have zero suitability for cassava, cowpeas, pearl millet, sweet potato, wet rice, and yams. "Tropical" includes districts suitable for the latter set of crops, but with zero suitability for the former.

Figure 4: Map of Geographic Regions and Land Elasticities



Notes: The figure shows the classification of each pixel into geographic regions, along with the baseline estimated land elasticity. "Temperate" pixels are those which are capable of growing the temperate crops (see text) but not tropical crops (see text). "Tropical" pixels can grow tropical crops, but not temperate crops. "Both" pixels are capable of growing both temperate and tropical crops. "Unsuitable" pixels can grow neither kind of crops. Crop suitability is assessed using the GAEZ (Food and Agriculture Organization, 2012). These pixels are what the assignment of districts to "Temperate" or "Tropical" regions are based on.

Table 1: Summary Statistics for District Level Data, 2000CE

	Mean	SD	Percentiles: 10th	25th	50th	75th	90th
Panel A: Population and area							
Total population (000s)	112.9	486.2	3.9	8.9	24.3	66.1	168.5
Rural population (000s)	72.3	348.3	2.8	5.9	15.0	38.6	98.2
Urban population (000s)	40.6	211.1	0.0	0.0	0.1	18.3	73.0
Urban share of district pop.	0.23	0.32	0.00	0.00	0.01	0.45	0.78
Share of state population	0.06	0.10	0.00	0.00	0.02	0.06	0.15
Share of state urban pop.	0.04	0.14	0.00	0.00	0.00	0.02	0.11
Share of state area	0.06	0.09	0.00	0.01	0.02	0.07	0.14
Total area (000s ha)	175.2	465.5	8.4	16.5	51.0	158.0	381.9
Panel B: Labor/land ratios and yields							
Labor/land (persons/ha)	0.73	1.17	0.04	0.12	0.32	0.77	1.86
Caloric yield (mil cals/ha)	10.85	4.89	4.98	7.17	10.65	13.86	17.03
Log light density	-2.82	2.93	-6.14	-3.83	-2.51	-0.89	0.35

Notes: These are summary statistics for districts used in the regression analysis. There are a total of 30,054 observations for each variable (these come from 2,325 states in 152 countries). All population data is derived from Goldewijk et al. (2011). Districts are defined by the Global Administrative Areas Project (2019), and correspond to 2nd-level administrative areas within countries (e.g. counties). Caloric yield, A_{isc}, is calculated by the authors using data from Galor and Özak (2016). Rural labor/land ratios, L_{Aisc}/X_{isc}, is calculated by the authors using data from Goldewijk et al. (2011) for rural population. Both caloric yield and rural labor/land ratios were trimmed at the 99th and 1st percentiles of their raw data prior to calculating the summary statistics in this table. Log mean light density is derived from the Global Radiance Calibrated Nightime Lights data provided by NOAA/NGDC, as in Henderson et al. (2016).

Table 2: Summary Statistics on Migration from DHS Surveys

	Mean	SD	Percentiles: 10th	25th	50th	75th	90th
Panel A: Share moving measured by							
All movers / all inds.	0.49	0.14	0.32	0.42	0.50	0.59	0.67
Movers in last 5 years / all inds.	0.21	0.09	0.11	0.15	0.21	0.26	0.33
Movers aged 25-50 / all aged 25-50	0.54	0.15	0.35	0.43	0.55	0.66	0.73
Panel B: Share of movers to location by self-reported origin:							
To urban areas from country	0.40	0.15	0.19	0.32	0.41	0.51	0.59
To rural ares from city or town	0.17	0.12	0.03	0.07	0.14	0.27	0.35

Notes: This table shows the overall prevalence of migration (Panel A), and the prevalence of migration between different areas (Panel B). These are summary statistics of shares calculated from individual DHS surveys (ICF, 1986-2017). The top panel is based on 86 surveys representing 43 countries, and a total of 2,194,187 individuals. The bottom panel is based on 68 surveys representing 34 countries, and a total of 1,125,895 individuals.

Table 3: Estimates of Land Elasticity, β_g, by Agricultural Type, 2000CE

Dependent Variable in all panels: Log caloric yield (A_{isg}^{GAEZ})

Panel A: Regions defined by:

	Crop suitability:		Frost Days:		Koeppen-Geiger:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density (β_g)	0.239	0.088	0.218	0.093	0.220	0.081
	(0.045)	(0.020)	(0.039)	(0.012)	(0.049)	(0.016)
p-value $\beta_g = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta_g = \beta_{Temp}$		0.002		0.002		0.007
Countries	84	76	91	101	86	78
Observations	9404	7229	15260	14794	10221	10013
R-square (ex. FE)	0.24	0.20	0.21	0.18	0.23	0.18

Panel B: With other restrictions (using crop suitability to define temperate/tropical)

	Urban Pop. $< 25K$:		Urban Perc. < 50:		Ex. Europe/N. Amer.:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density (β_g)	0.330	0.093	0.339	0.099	0.228	0.087
	(0.055)	(0.023)	(0.060)	(0.025)	(0.045)	(0.020)
p-value $\beta_g = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta_g = \beta_{Temp}$		0.000		0.000		0.005
Countries	81	76	81	72	22	68
Observations	7317	6122	6880	6211	880	7151
R-square (ex. FE)	0.30	0.25	0.30	0.25	0.18	0.14

Notes: Conley standard errors, adjusted for spatial auto-correlation with a cutoff distance of 500km, are shown in parentheses. All regressions include state fixed effects, a constant, and controls for the district urbanization rate, log density of district nighttime lights, and log total population. The coefficient estimate on rural population labor/land indicates the value of β_g, see equation (10). Rural population is from GRUMP database (Center for International Earth Science Information Network (CIESIN), Columbia University et al., 2011), and caloric yield is the author's calculations based on the data from Galor and Özak (2016). Inclusion of districts in the regression is based on the listed criteria, either crop suitability, the number of frost-free days, or Köppen-Geiger climate zones. See text for details of how temperate and tropical regions are defined in each case. In Panel B, the columns either exclude districts with more than 25,000 urban residents, exclude districts with an urban percent above 50, or exclude districts from any country in Europe (incl. Russia east of the Urals) or North America.

Table 4: Estimates of Land Elasticity, β_g, Additional Robustness Checks

Dependent Variable in all panels: Log caloric yield (A_{isg}^{GAEZ})

Panel A: Different rural population sources

	GRUMP 1990:		HYDE 2000:		IPUMS (various):	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log labor/land ratio (β_g)	0.227	0.118	0.241	0.088	0.189	0.016
	(0.015)	(0.019)	(0.045)	(0.020)	(0.070)	(0.017)
p-value $\beta_g = 0$	0.000	0.000	0.000	0.000	0.007	0.348
p-value $\beta_g = \beta_{Temp}$		0.000		0.002		0.010
Countries	84	75	84	76	23	24
Observations	8723	6754	9404	7229	1104	2416
R-square (ex. FE)	0.26	0.22	0.24	0.20	0.15	0.11

Panel B: Different land assumptions (with GRUMP labor/land ratio)

	Cultivated Area:		Cash crops < 5% area:		Pasture < 20% area:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log labor/land ratio (β_g)	0.219	0.090	0.207	0.061	0.201	0.100
	(0.040)	(0.022)	(0.047)	(0.025)	(0.037)	(0.025)
p-value $\beta_g = 0$	0.000	0.000	0.000	0.014	0.000	0.000
p-value $\beta_g = \beta_{Temp}$		0.005		0.006		0.024
Countries	83	72	57	35	75	71
Observations	9359	7175	4591	1677	5616	4548
R-square (ex. FE)	0.26	0.21	0.20	0.17	0.20	0.18

Notes: Temperate and tropical samples are defined by the suitability measures described in Table 3. Conley standard errors, adjusted for spatial auto-correlation with a cutoff distance of 500km, are shown in parentheses. All regressions include state fixed effects, a constant, and controls for the district urbanization rate, log density of district nighttime lights, and log total population. The coefficient estimate on rural population labor/land indicates the value of β_g, see equation (10). Caloric yield is the author's calculations based on the data from Galor and Özak (2016). In Panel A, the population data used to define rural labor/land differs based on the heading in the table (see text for details). In Panel B, the first set of results use rural population (from GRUMP) relative to cultivated land area (as opposed to actual land area) to measure labor/land ratios. The second set drops districts that have less than 5% of their area in cash crops (see text for list of those crops), and the third set shows results for districts that have less than 20% of their area as pasture land.

Table 5: Estimates of Land Elasticity, β_g, Alternative Productivity Measures

Dependent Variable in all panels: Log caloric yield (A_{isg}^{GAEZ})

Panel A: Caloric yield based on GAEZ input/water use:

	Medium/Irrigated:		High/Rain-fed:		High/Irrigated:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density (β_g)	0.208	0.084	0.234	0.094	0.206	0.084
	(0.052)	(0.020)	(0.046)	(0.022)	(0.052)	(0.020)
p-value $\beta_g = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta_g = \beta_{Temp}$		0.027		0.006		0.028
Countries	84	76	84	74	84	76
Observations	9404	7229	9371	7214	9404	7229
R-square (ex. FE)	0.20	0.18	0.22	0.18	0.20	0.18

Panel B: Excluding Europe and North America, caloric yield based on GAEZ input/water use:

	Medium/Irrigated:		High/Rain-fed:		High/Irrigated:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density (β_g)	0.223	0.083	0.229	0.094	0.224	0.083
	(0.045)	(0.020)	(0.041)	(0.022)	(0.041)	(0.020)
p-value $\beta_g = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta_g = \beta_{Temp}$		0.005		0.004		0.002
Countries	22	68	22	67	22	68
Observations	880	7151	873	7138	880	7151
R-square (ex. FE)	0.18	0.15	0.18	0.13	0.18	0.15

Notes: Temperate and tropical samples are defined by the suitability measures described in Table 3. Conley standard errors, adjusted for spatial auto-correlation with a cutoff distance of 500km, are shown in parentheses. All regressions include state fixed effects, a constant, and controls for the district urbanization rate, log density of district nighttime lights, and log total population. The coefficient estimate on rural population labor/land indicates the value of β_g, see equation (10). In Panel A, the construction of the A_{isg}^{GAEZ} caloric suitability yield differs across the columns. In (1) and (2), the yield is derived from the underlying GAEZ medium input-irrigated data, and the following columns use the high input, rain-fed data, or the high input, irrigated data, as noted. Panel B is identical, but excludes North American and European countries.

Table 6: Estimates of Land Elasticity, β_g, with DHS district controls

Dependent Variable in all columns: Log caloric yield (A_{isg}^{GAEZ})						
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.212	0.088	0.210	0.088	0.205	0.096
	(0.065)	(0.017)	(0.066)	(0.017)	(0.068)	(0.017)
Demog. controls	No	No	Yes	Yes	Yes	Yes
Asset controls	No	No	No	No	Yes	Yes
p-value $\beta_g = 0$	0.002	0.000	0.002	0.000	0.003	0.000
p-value $\beta_g = \beta_{Temp}$		0.010		0.012		0.039
Countries	16	29	16	29	16	29
Observations	309	1363	309	1363	309	1363
R-square (ex. FE)	0.80	0.79	0.80	0.80	0.80	0.80

Notes: Temperate and tropical samples are defined by the suitability measures described in Table 3. Conley standard errors, adjusted for spatial auto-correlation with a cutoff distance of 500km, are shown in parentheses. All regressions include state fixed effects, a constant, and controls for the district urbanization rate and log density of district nighttime lights. The coefficient estimate on rural population labor/land indicates the value of β_g, see equation (10). The districts included in these regressions have villages/clusters that took part in a Demographic and Health Survey (DHS). Using the DHS data, the columns include district level means or medians of demograhpic variables (e.g. household head education and age) and asset variables (e.g. household ownership of cattle or use of electricity), see text for details of the precise controls.

Table 7: Estimates of Land Elasticity, β_g, for Mixed Region, 2000CE

Dependent variable: Log caloric yield (A_{isg}^{GAEZ})

	Specification defined by:					
	Baseline (1)	Urban Pop. $< 25K$ (2)	Ex. Europe N. Amer. (3)	Land X_{is} cult. area (4)	Cash crops $< 5\%$ area (5)	GAEZ high Input (6)
Log labor/land ratio (β_g)	0.131	0.160	0.091	0.128	0.130	0.132
	(0.017)	(0.024)	(0.013)	(0.017)	(0.021)	(0.018)
p-value $\beta_g = 0$	0.000	0.000	0.000	0.000	0.000	0.000
Countries	109	101	56	108	57	108
Observations	13416	10276	6598	13367	4635	13293
R-square (ex. FE)	0.15	0.19	0.10	0.16	0.15	0.13

Notes: For all regressions, the sample includes districts that are suitable for both temperate and tropical crops, as defined in the text. Conley standard errors, adjusted for spatial auto-correlation with a cutoff distance of 500km, are shown in parentheses. All regressions include state fixed effects, a constant, and controls for the district urbanization rate, log density of district nighttime lights, and log total population. The coefficient estimate on rural population labor/land indicates the value of β_g, see equation (10). Rural population is from GRUMP database (Center for International Earth Science Information Network (CIESIN), Columbia University et al., 2011), and caloric yield is the author's calculations based on the data from Galor and Özak (2016). Inclusion of districts in the regression is based on the listed criteria. Column (4) uses cultivated land (rather than total land) to measure the labor/land ratio. Column (5) excludes districts that have more than 5% of their total land used for cash crops. Column (6) measures the caloric yield with the GAEZ high input measure of agricultural potential (as opposed to the low input baseline).

Table 8: Country-level aggregate land elasticity estimate

Country	β	Country	β	Country	β	Country	β
Afghanistan	0.163	Egypt	0.141	Lithuania	0.239	Senegal	0.088
Albania	0.143	El Salvador	0.091	Luxembourg	0.239	Serbia	0.163
Algeria	0.173	Eq. Guinea	0.090	Macao	0.131	Sierra Leone	0.096
American Samoa	0.088	Eritrea	0.116	Madagascar	0.129	Slovakia	0.229
Angola	0.129	Estonia	0.239	Malawi	0.125	Slovenia	0.231
Argentina	0.142	Ethiopia	0.128	Malaysia	0.099	Solomon Islands	0.088
Australia	0.138	Fiji	0.109	Mali	0.088	Somalia	0.095
Austria	0.239	Finland	0.239	Martinique	0.088	South Africa	0.131
Azerbaijan	0.146	France	0.203	Mauritania	0.095	South Korea	0.151
Bangladesh	0.130	French Guiana	0.088	Mexico	0.128	South Sudan	0.090
Belarus	0.239	Gabon	0.088	Mongolia	0.239	Spain	0.140
Belgium	0.239	Gambia	0.088	Morocco	0.135	Sri Lanka	0.090
Benin	0.088	Georgia	0.150	Mozambique	0.123	Sudan	0.097
Bhutan	0.166	Germany	0.239	Myanmar	0.125	Suriname	0.088
Bolivia	0.120	Ghana	0.088	Namibia	0.131	Swaziland	0.135
Bosnia	0.158	Greece	0.131	Netherlands	0.239	Sweden	0.239
Botswana	0.131	Guadeloupe	0.088	New Caledonia	0.128	Switzerland	0.235
Brazil	0.102	Guatemala	0.119	New Zealand	0.234	Syria	0.161
Brunei	0.088	Guinea	0.101	Nicaragua	0.094	Sao Tome	0.096
Bulgaria	0.165	Guinea-Bissau	0.088	Niger	0.094	Taiwan	0.131
Burkina Faso	0.088	Guyana	0.097	Nigeria	0.090	Tajikistan	0.159
Burundi	0.143	Haiti	0.105	North Korea	0.222	Tanzania	0.120
Cambodia	0.090	Honduras	0.114	Norway	0.239	Thailand	0.101
Cameroon	0.102	Hungary	0.173	Oman	0.134	Timor-Leste	0.092
Canada	0.237	India	0.120	Pakistan	0.134	Togo	0.088
C. African Rep.	0.088	Indonesia	0.104	Palestina	0.145	Tunisia	0.131
Chad	0.089	Iran	0.157	Panama	0.097	Turkey	0.178
Chile	0.216	Iraq	0.135	Papau N.G.	0.117	Uganda	0.104
China	0.136	Isle of Man	0.239	Paraguay	0.129	Ukraine	0.232
Colombia	0.103	Italy	0.132	Peru	0.119	United Kingdom	0.238
Costa Rica	0.108	Japan	0.154	Philippines	0.094	United States	0.164
Croatia	0.172	Jordan	0.197	Poland	0.239	Uruguay	0.131
Cuba	0.091	Kazakhstan	0.234	Portugal	0.141	Uzbekistan	0.208
Czech Republic	0.239	Kenya	0.120	Rep. of Congo	0.090	Vanuatu	0.093
Cote d'Ivoire	0.088	Kosovo	0.204	Reunion	0.133	Venezuela	0.108
D.R. Congo	0.104	Kyrgyzstan	0.230	Romania	0.201	Vietnam	0.118
Denmark	0.239	Laos	0.124	Russia	0.233	Virgin Islands, U.S.	0.088
Djibouti	0.088	Latvia	0.239	Rwanda	0.170	Zambia	0.131
Dominican Rep.	0.107	Lebanon	0.147	Samoa	0.095	Zimbabwe	0.131
Ecuador	0.122	Liberia	0.088				

Notes: This table reports the aggregated value of the land elasticity, β, for each country. The aggregate value is a weighted average of the value for tropical districts (0.088), temperate districts (0.239), and "both" districts (0.131) that can grow both tropical and temperate crops. The weights in the average are the maximum calories that can be produced in a district relative to the maximum calories that can be produced by all districts in the country.

Table 9: Panel Estimates of Effect of Population Change, by Land Elasticity

	Dependent Variable:					
	Log GDP per capita		Log GDP per worker		Log population	
	β <Median (1)	β >Median (2)	β <Median (3)	β >Median (4)	β <Median (5)	β >Median (6)
	Panel A:					
Mortality rate	0.032	0.762	-0.076	0.834	-0.666	-0.311
	(0.257)	(0.155)	(0.246)	(0.161)	(0.196)	(0.160)
p-value $\theta = 0$	0.903	0.000	0.757	0.000	0.001	0.053
p-value $\theta = \theta^{Below}$	.	0.016	.	0.002	.	0.163
Countries	13	14	13	14	13	14
Observations	104	112	104	112	104	112
	Panel B:					
Log life expectancy	0.309	-2.007	0.214	-1.928	1.910	1.564
	(0.393)	(0.308)	(0.387)	(0.309)	(0.235)	(0.229)
p-value $\theta = 0$	0.434	0.000	0.582	0.000	0.000	0.000
p-value $\theta = \theta^{Below}$	.	0.000	.	0.000	.	0.292
Countries	13	14	13	14	13	14
Observations	99	106	99	106	99	106
	Panel C:					
Log population	-0.379	-0.812	-0.415	-0.753		
	(0.104)	(0.110)	(0.102)	(0.103)		
p-value $\theta = 0$	0.000	0.000	0.000	0.000		
p-value $\theta = \theta^{Below}$	.	0.005	.	0.021		
Countries	13	14	13	14		
Observations	104	112	104	112		

Notes: Robust standard errors are reported in parentheses. All regressions include both year fixed effects and country fixed effects. The value of β for each country was found by estimating equation (10) separately for each, including state-level fixed effects. Countries are then included in a regression here based on how their β compares to the median from the 32 countries. The mortality rate used as an explanatory variable in Panel A is the mortality rate from 15 infectious diseases, as documented by Acemoglu and Johnson (2007). All data on GDP per capita, GDP per worker, population, and life expectancy is also taken from those author's dataset. The p-value of $\theta = \theta^{Below}$ is from a test that the estimated coefficient in a column for countries with elasticities above the median is equal to the estimated coefficient of countries below the median.