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## 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 influences the degree of decreasing returns to labor and capital in agriculture, and thus how sensitive living standards are to shocks in productivity and population that induce movement between agriculture and non-agriculture. Evidence from the post-war mortality transition supports this prediction.

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# 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.<sup>1</sup>

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). The methodology relies on the mobility of labor between districts as well as between agricultural and non-agricultural uses. We show that this mobility is supported in the data, both by reviewing recent research on this subject and by providing evidence drawn from the Demographic and Health Surveys.

Given mobility, 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. Most relevant, 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) agricultural and factor prices at the state level.

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<sup>1</sup>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).

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 Özkan (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 0.239 in temperate districts. In contrast, our baseline estimate of the land elasticity is only 0.088 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 0.15 higher than in tropical districts, and the difference remains statistically significant.<sup>2</sup> 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.<sup>3</sup>

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

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<sup>2</sup>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.

<sup>3</sup>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.<sup>4</sup>

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).<sup>5</sup> 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. The intuition for the importance of the land elasticity is that it dictates, given an assumption of constant returns to scale, the degree of decreasing returns to scale for labor and capital in agriculture. A large land elasticity thus implies more severe decreasing returns to those factors, and in response to shocks to productivity or population, this means more severe movements of those factors into or out of agriculture. Temperate areas, with a larger elasticity, will have exaggerated responses to shocks relative to tropical areas. 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).

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<sup>4</sup>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.

<sup>5</sup>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 versus Cobb-Douglals) than the aggregate function.

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

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.<sup>6</sup> 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.<sup>7</sup> 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.<sup>8</sup>

The paper proceeds as follows. Section 2 describes the basic nature of the district-level data we use, including evidence on mobility across these districts, which informs our estimation. Section 3 shows how we estimate the land elasticity, and which assumptions about mobility are required for identification. Section 4 presents the data and results, while Section 5 discusses the aggregate implications of variation in land elasticity. Section 6 concludes.

## 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.

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<sup>6</sup>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).

<sup>7</sup>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.

<sup>8</sup>Our work is related to several recent studies on 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.

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 government area, which is part of a state. Thus Demsa, in the state of Adamawa, is a district in our data. In total, we have 30,054 districts, coming from 2,325 states in 152 countries.<sup>9</sup>

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.<sup>10</sup>

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.

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

<sup>10</sup>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.

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.<sup>11</sup> Combining 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 from 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 areas. 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.

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<sup>11</sup>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.

### 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,

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

where  $A_{Ais}$  is total factor productivity and  $X_{is}$  is land. The land elasticity we are interested in estimating is  $\beta$ .<sup>12</sup> 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

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

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<sup>12</sup>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.



The first-order conditions of the maximization problem are

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

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

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

Non-agricultural production in the district is given by

$$Y_{Nis} = A_{Nis}K_{Nis}^{\phi}L_{Nis}^{1-\phi} \quad (5)$$

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 arbitrary revenue wedge of  $(1 + \tau_{Ns})$ . Their profits are

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

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

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

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

### 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 between 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.<sup>13</sup>

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

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

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

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

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  $\beta$ . We'll describe in the next section how we measure agricultural 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  $\beta$  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.<sup>14</sup>

<sup>13</sup>In the appendix, we show how our empirical specification would change when dropping this assumption.

<sup>14</sup>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 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.

The threat to our identification of  $\beta$  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.<sup>15</sup> 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  $\epsilon_{is}$  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

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<sup>15</sup>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  $\tau_s$ , across states within a given country.

we will be running this regression for a specific geographic region (e.g. tropical or temperate).

$$\ln A_{Aisg}^{GAEZ} = \alpha_g + \beta_g \ln L_{Aisg}/X_{isg} + \gamma_s + \delta'_g \mathbf{Z}_{isg} + \epsilon_{isg} \quad (10)$$

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  $\beta_g$  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  $\beta_g$ . Our hypothesis is that the values of  $\beta_g$  vary with geographic characteristics, and over the course of the empirical work we will document that there are differences in  $\beta_g$  between geographic regions.

$\alpha_g$  is a constant. The value  $\gamma_s$  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  $\delta'_g$  are the coefficients on those controls. This is the specification we take to the data to estimate  $\beta$ .

**Standard errors:**  $\epsilon_{isg}$  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  $\epsilon_{isg}$ . 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  $\beta_g$  we estimate for one geographic region is statistically different from the  $\beta_g$  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

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

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  $\beta_{Ref}$  and  $\beta_g$  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.<sup>16</sup> 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 found 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

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<sup>16</sup>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>.

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 Özkan (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 Özkan (2016) index, so that we can measure both the total potential calories produced within a given district.<sup>17</sup> We used a subset of the crops in the original Galor and Özkan (2016) dataset, so that we focus on crops that are primary staples.<sup>18</sup> 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 4.98 million calories per hectare, while it is four times higher at the 90th percentile, around 17.03 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 actual productivity, as the suitability indices are not a measure of potential output.

The GAEZ suitability index depends on climate conditions (precipitation, temperature, evap-

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<sup>17</sup>We use the low-input, rain-fed indices of caloric yield provided by Galor and Özkan (2016) in our baseline specification. Our results are robust to using different assumptions on inputs and water use, shown below.

<sup>18</sup>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.

otranspiration), 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 on cultivated area in place of total land.

**Nighttime lights:** We follow Henderson et al. (2016) and use the Global Radiance Calibrated Nighttime 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. Here we define **temperate** districts as those that have any grid cells suitable for barley, buckwheat, rye, oats, wheat, or white potatoes, but have precisely *zero* grid cells suitable for any of cassava, cowpeas, paddy rice, pearl millet, sweet potato, and yams. Suitability for any crop is taken from

the GAEZ.

The **tropical** districts are those that have any grid cells suitable for cassava, cowpeas, paddy rice, pearl millet, sweet potato, or yams, but precisely *zero* grid cells suitable for barley, buckwheat, rye, oats, wheat, and white potatoes.<sup>19</sup> In total, we have 9,404 districts classified as temperate using crop suitability, and 7,229 classified as tropical. There are 13,416 districts that are suitable for *both* types of crops, meaning they contain both temperate and tropical grid cells, or they have grid cells reported by the GAEZ as suitable for both types of crops. These mixed districts are excluded from our baseline analysis, but we return to them later in the paper.

**By frost-free days:** Rather than crop suitability, which combines several climate characteristics, 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 15,260 temperate districts, and 14,794 tropical districts, for total coverage of our sample.<sup>20</sup> 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 10,221 districts as **temperate** and another 10,013 as **tropical**.<sup>21</sup> 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. Figure 1 shows how grid-cells across the world are coded as temperate, tropical, suitable for both

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<sup>19</sup>We have experimented with alternative sets of crops to define the regions, without any material change to our results.

<sup>20</sup>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  $\beta_g$  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.

<sup>21</sup>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).



types of crops, or unsuitable for either type (e.g. deserts or polar regions).<sup>22</sup> While the 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. We will use districts from these areas to show that our estimated land elasticities are robust to excluding the developed countries in Europe and North America from the estimation. The tropical area runs in a zone around the equator that one would expect, and areas suitable for both types of crops tend to exist in between temperate and tropical areas. Given the broad range of these crop classifications and the small size of districts, nearly all districts are found to be homogenous with respect to their classification as temperate or tropical.

Turning to district level characteristics, Figure 2 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 3 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 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 2 and 3 are not driving our results.

### 4.3 Estimates for temperate and tropical regions

Table 3 shows the estimates of  $\beta_g$  for both our temperate and tropical regions. In column (1) of Panel A, one can see the estimate of  $\beta_g$  for temperate districts is 0.239, while in column (2) the estimate of  $\beta_g$  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  $\beta_g$  is equal

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<sup>22</sup>We suppressed the district-level borders from the map as they are so small that it becomes something of a mess, and prevents one from seeing the information about crop types.

to zero, and in both samples we reject this at below 0.1% significance. The second row tests the hypothesis that the  $\beta_g$  from the tropical region is equal to the  $\beta_g$  from the temperate. We can reject that null hypothesis at 0.2%.

Figure 4 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.<sup>23</sup> The difference in the slopes of the lines for tropical and temperate districts imply a difference in the value of the land elasticity,  $\beta_g$ , 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  $\beta_g$  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.  $\beta_g$  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 100,000 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  $\beta_g$  grows somewhat, to 0.276 for temperate districts and 0.092 for tropical districts, which is an absolute difference of 0.184. This difference is again significant.

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<sup>23</sup>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.

Columns (3) and (4) of Panel B excludes districts that have a total population greater than 5% of their state total, which again eliminates large urban areas but also eliminates any districts that may happen to be relatively large in terms of rural population with respect to their state. The worry would be that very large districts may not satisfy the assumption that they share similar prices and wages with other districts in their state. The results conform to those in columns (1) and (2), with a temperate estimate of  $\beta_g$  equal to 0.271, and a tropical estimate of 0.084, a difference that is statistically significant at 0.2%.

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.<sup>24</sup> The finding that districts suitable for tropical crops have a lower land elasticity still holds, with an estimated  $\beta_g$  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  $\beta_g$  for 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

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<sup>24</sup>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.

larger than our baseline, we end up with only 3,520 observations.<sup>25</sup> 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 measures 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  $\beta_g$ .

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  $\beta_g$  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 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  $\beta_g$  could be biased.

To address this, we draw in additional data on land use to eliminate districts that are heavy

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<sup>25</sup>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.

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).<sup>26</sup> The estimated  $\beta_g$  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  $\beta_g$ . If, for some reason, this problem is pronounced in temperate areas, this could explain our finding that temperate areas have high  $\beta_g$  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  $\beta_g$  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  $\beta_g$  estimates 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

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<sup>26</sup>The cash crops we consider are bananas, cocoa, coffee, cotton, jute, palm oil, rubber, sunflower, tea, tobacco, sugarbeets, and sugarcane. Estimates of the land elasticity for districts that are substantial producers of these cash crops are provided in the appendix.

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  $\beta_g$  in temperate zones. To address this, in Panel B we exclude North American and European countries from the sample, and re-estimate  $\beta_g$  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  $\beta_g$  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  $\beta_g$  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  $\beta_g$  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.<sup>27</sup> 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  $\beta_g$  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 demographic 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. This need not be the case, of course, and the different results on  $\beta_g$  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 2 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).<sup>28</sup>

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  $\beta_g$  in all of these sub-regions considered alone, showing no relationship of labor/land and the value of  $\beta_g$ . We can do something similar for temperate areas, and again there is no

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<sup>27</sup>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.

<sup>28</sup>Work by Wilde (2012) indicates that the elasticity of substitution is *less* than one, using historical information from the United Kingdom.

systematic relationship of  $\beta_g$  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  $\beta_g$  for each state in the temperate and tropical regions containing 10 or more districts. We then can plot the values of  $\beta_g$  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  $\beta_g$  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  $\beta_g$ . 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  $\beta_g$ . 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  $\beta_g$  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  $\beta_g$  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  $\beta_g$  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  $\beta_g$  for temperate 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  $\beta_g$  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

To illustrate the distinct difference in land elasticities we have focused on temperate and tropical regions, and those were defined in a stark way. Temperate districts are capable of growing temperate crops (e.g. wheat) but completely unsuitable for tropical crops (e.g. rice), and tropical districts are defined in exactly the opposite way. This definition left out a substantial number of districts that have some suitability for *both* kinds of agriculture. There are 13,416 districts that the GAEZ reports as being capable of growing at least some temperate and tropical crops.

For comparison, we estimated the value of  $\beta_g$  for this mixed group. The results are in Table 7. Column (1) shows the baseline result, with the same controls we used throughout. The estimated elasticity is 0.128, which falls between the 0.088 estimate for tropical districts and the 0.239 for temperate areas. We feel this provides some assurance that our estimates are picking up a realistic difference in the land elasticity between temperate and tropical districts, as those with characteristics of both are found independently to have a land elasticity between the extremes. The difference of the mixed elasticity and the temperate elasticity is significant at 0.3%, while the difference with the tropical elasticity is significant at only 9.3%, as can be seen in the footer of Table 7. The mixed districts are similar to the tropical districts, while the temperate districts appear to be an outlier.

The remaining columns of Table 7 show the estimated  $\beta_g$  under different robustness checks. Excluding urban populations of less than 100,000 people raises the estimate slightly to 0.137, while excluding Europe and North America lowers it to 0.085, close to the baseline tropical average. Using cultivated land in place of total land results in a value of 0.123, while excluding any district with more than 5% of its area under cash crops gives an estimate of 0.133. If we use the GAEZ high input productivity numbers to measure  $A_{isg}^{GAEZ}$ , then we find a value of 0.134. There appears to be a consistent case that the land elasticity for these mixed areas lies in between the tropical and temperate values, and centers around 0.130.

Looming across the columns, one can see that in each case there is a significant difference of the mixed elasticity and the temperate elasticity, with the only possible exception being in column (5) where the p-value reaches 10%. On the other hand, the difference of the mixed elasticity and the tropical elasticity is not always statistically significant, with p-values ranging up to 87.7%. In one case, column (5), the difference is significant at 3.8%.

## 4.9 Aggregate land elasticities

We can combine our full set of estimates to demonstrate how the land elasticity varies across the world. We calculate aggregate land elasticities at the country level. Each district in a country is assigned the baseline land elasticity associated with the geographic 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 0.128. Districts incapable of growing any of those crops are excluded from the aggregation.

The aggregate land elasticity 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).<sup>29</sup> The formula for country  $c$  is

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

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

Table 8 shows the results of this aggregation.<sup>30</sup> Many countries have all their districts with identical geographic classifications, so their aggregate value is identical to one our baseline values. Burkina Faso is entirely tropical, and so the implied elasticity is exactly 0.088, while Denmark is entirely temperate, and so has a value of 0.239. Regardless, one can see the variation across countries that does exist. Some of the more interesting entries involve countries that are heterogenous in climate. Brazil has an aggregate elasticity of 0.101, China a value of 0.133, and the United States a value of 0.162. What does become clear is that there are few countries that are entirely temperate, but those that are are exclusively in northern Europe. Given that, it is perhaps worth reiterating that our estimates of these elasticities did not use any cross-country, or even cross-state, variation. And as shown in Table 3 our estimated value of the temperate elasticity is robust to the exclusion of those European countries entirely. The variation seen in Table 8 is not simply an artefact of the level of development.

## 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  $\beta$  dictates the sensitivity of the agricultural labor share (e.g.  $L_A/L$ ) and

<sup>29</sup>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.

<sup>30</sup>This does not encompass every country in the world, as several do not have 2nd-level districts to use in the aggregation. An alternative is to aggregate up from the pixel level, which produces similar values for the reported countries, and increases the total number of countries reported. Those results are in the appendix.

real income per capita to shocks in productivity and population. As part of that, we provide estimates of  $\beta$  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  $\beta$  are valid. Developing countries that have high  $\beta$  values display larger drops in GDP per capita and GDP per worker following the population increase due to the decline in mortality.

## 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

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

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

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

Note that the sensitivity of  $L_A/L$  to productivity ( $A_A$ ) and population ( $L$ ) depends on the size of  $\beta$ . And the larger is the land elasticity, the *more* sensitive is  $L_A/L$  to both of these terms. The reason is that  $\beta$  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.<sup>31</sup> 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

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<sup>31</sup>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.

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 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 assess whether the variation in  $\beta$  we documented has effects consistent with the intuition presented in the prior subsection. Acemoglu and Johnson (2007) collected 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 used 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  $\beta$  value or a low  $\beta$  value. Based on our simple explanation above, we would expect that living standards in places with the high  $\beta$  should be more sensitive to these mortality shocks than places with low  $\beta$  values. In particular, given that this is a positive shock to population size, our expectation is that high  $\beta$  places will experience a more severe *negative* shock to living standards.

To implement this, we first restrict ourselves to the low and middle income sample from Acemoglu and Johnson. We make this restriction because rich countries, regardless of their value of  $\beta$ , 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.<sup>32</sup> With those low and middle income countries, we then assign them to either a “tropical” or “temperate” group. The assignment is based on the estimated  $\beta$  for each country found in Table 8. Those with a value of  $\beta$  less than or equal to 0.20 are classified as tropical (which in practice includes any area with a significant

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<sup>32</sup>We could 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 35 countries with full data.

amount of mixed land), while those with a value of  $\beta$  above 0.20 are assigned to the temperate category. We make the cut-off relatively high so that we can isolate the true temperate countries in the Acemoglu and Johnson dataset. 30 countries are classified as tropical, and only 5 as temperate.

For both tropical and temperate groups, we use the original data from Acemoglu and Johnson to run panel regressions with the specification of

$$y_{it} = \alpha + \theta x_{it} + \gamma_i + \delta_t + \epsilon_{it} \quad (15)$$

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 expectancy, or log population).  $\theta$  captures the effect of the independent variable on  $y_{it}$ , and we will compare the value of  $\theta$  across samples that differ based on whether they have low land elasticities or high land elasticities.  $\gamma_i$  and  $\gamma_t$  are country and decade fixed effects, while  $\epsilon_{it}$  is the error term. Each country has up to eight decadal observations, running from 1930 to 2000, but the panel is not balanced.<sup>33</sup>

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 seen, the estimated coefficient for tropical countries (0.403) in column (1) is smaller than the estimate for temperate countries (1.226) in column (2). Below these estimates are two hypothesis tests. First, the test that the effect size is zero,  $\theta = 0$ . We can reject zero effect for both temperate and tropical countries. The hypothesis that  $\theta$  is identical for the two samples has a p-value of less than 0.1%. The higher value for temperate countries is consistent with the intuition of the prior subsection, where a high land elasticity is associated with higher sensitivity to shocks.

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 for temperate as for tropical countries. This difference is significant at less than 0.1%, and shows that high land elasticity countries are more sensitive to population shocks low land elasticity 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 tropical countries, the effect of mortality on population was estimated to be smaller than in

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<sup>33</sup>Rather than separating countries into two groups based on  $\beta$  and comparing  $\theta$  between them, an alternative specification would be to interact  $\beta_i$  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  $\theta_1$  would indicate how the effect of  $x_{it}$  differs with the size of  $\beta$ . Doing this produces results consistent with those presented in Table 9.

temperate countries (-0.255 versus -1.442). Thus it may be that the temperate 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. Thus the results in columns (1)-(4) should be interpreted with that caveat in mind.

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 between tropical and temperate countries. For both the effect of higher life expectancy is negative for both GDP per capita and GDP per worker, but was much more severe for the temperate countries.<sup>34</sup> The difference is again significant at less than 0.1%.

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 tropical countries. Both tropical and temperate countries experienced significant population shocks from the rise in life expectancy. But in temperate areas, consistent with the intuition above, this had a more severe negative effect.

The evidence in Table 9 shows that the variation in land elasticity ( $\beta$ ) we identified in the main part of the paper has effects consistent with those predicted by the intuition earlier in this section. Given the differentials we estimated in the effect of the epidemiological transition, the variation in land elasticity appears to have non-trivial implications for development, making temperate areas more sensitive to shocks than tropical areas.

## 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. The method rests mainly on the assumption that labor is mobile across districts within states, something that recent evidence supports.

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,

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<sup>34</sup>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 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 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. This aggregate land elasticity, regardless of the setting, is an important parameter in determining the sensitivity of income per capita and the share of labor in agriculture to shocks in population growth or productivity. 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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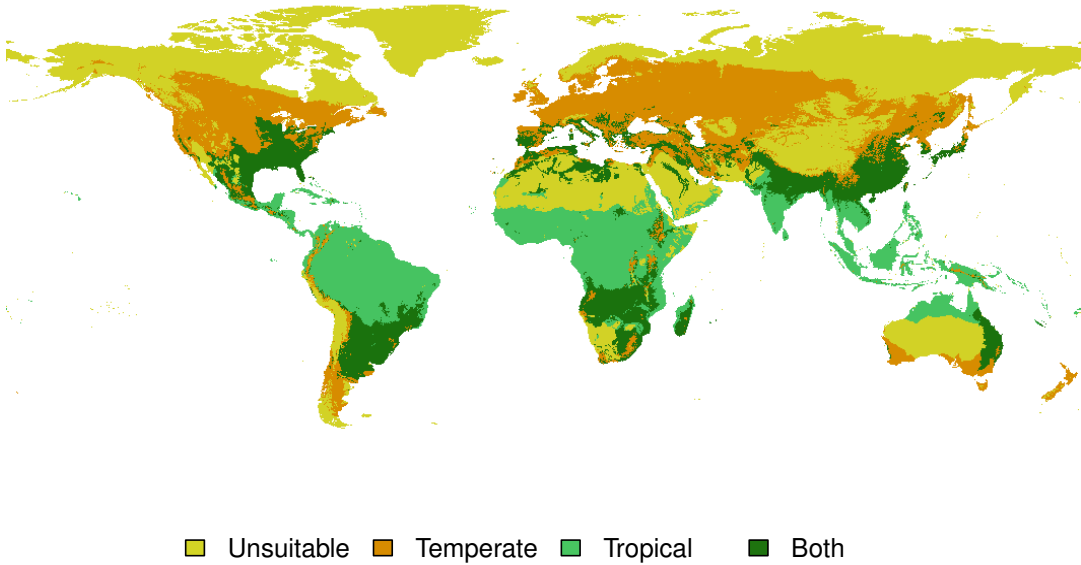
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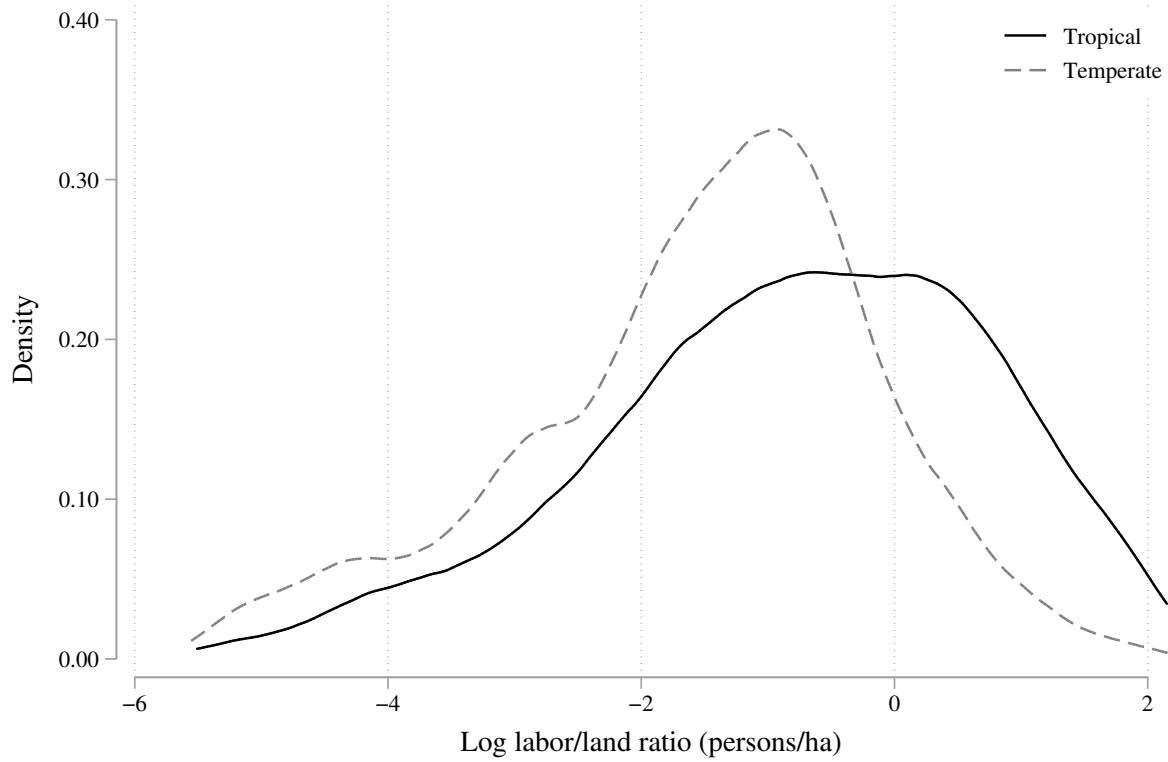
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Figure 1: Map of Geographic Regions



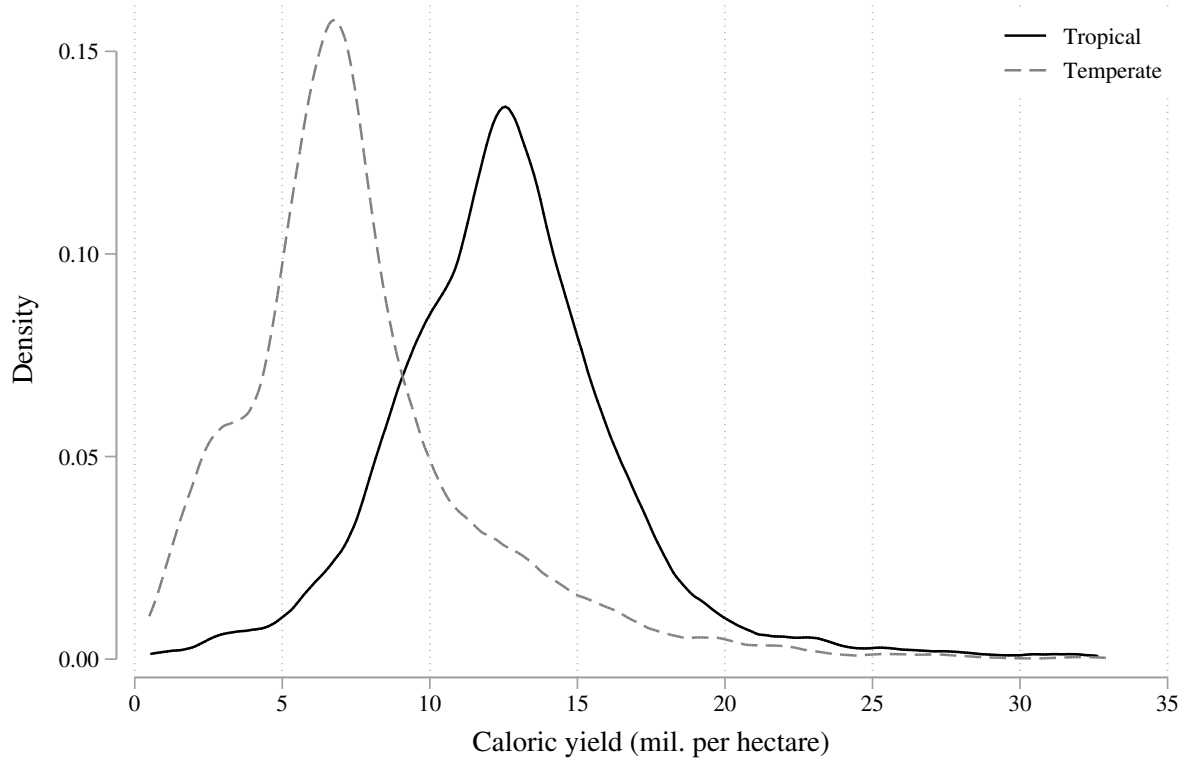
**Notes:** The figure shows the classification of each pixel into geographic regions, along with the baseline estimated land elasticity. “Temperate” pixels are those which are capable of growing the temperate crops (see text) but not tropical crops (see text). “Tropical” pixels can grow tropical crops, 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.

Figure 2: 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.

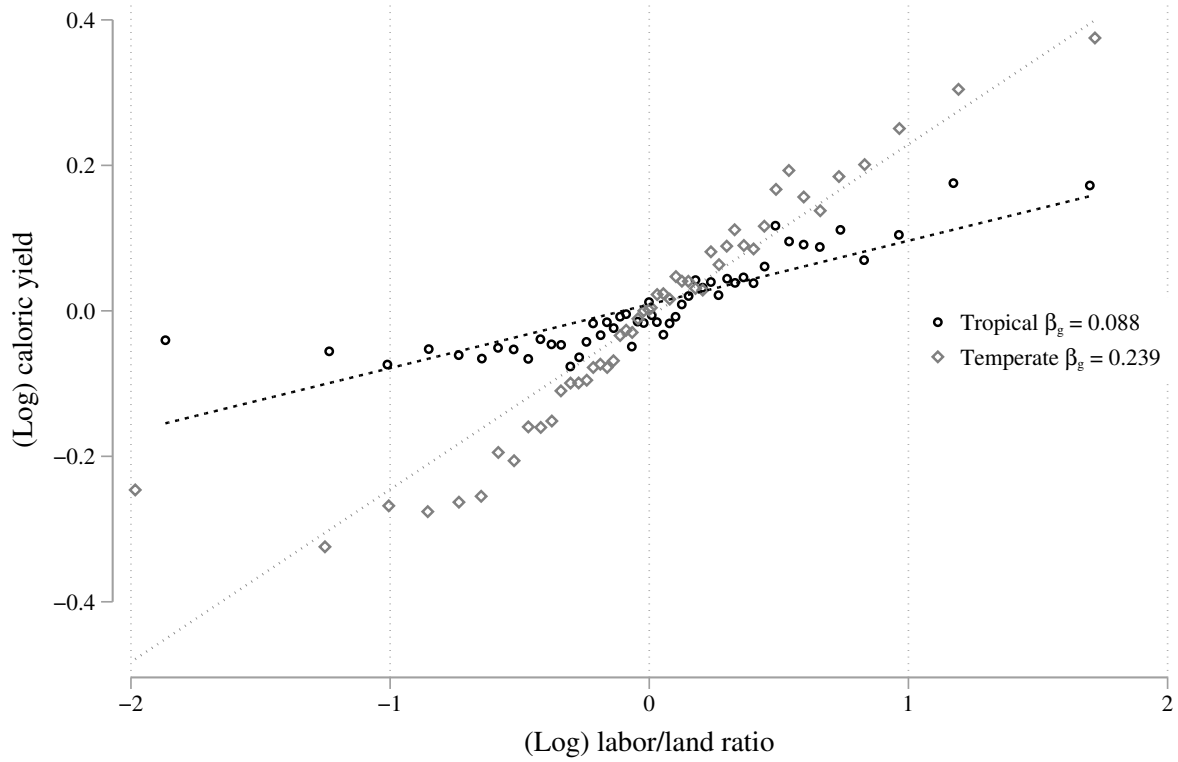
Figure 3: Density Plot of Caloric Yield ( $A_{isc}^{GAEZ}$ ), by Crop Type



**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 4: 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.

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 Nighttime 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,  $\beta_g$ , by Agricultural Type, 2000CEDependent 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 labor/land ratio ( $\beta_g$ )	0.239 (0.045)	0.088 (0.020)	0.218 (0.039)	0.093 (0.012)	0.220 (0.049)	0.081 (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. < 100K:		Pop. share < 0.05:		Ex. Europe/N. Amer.:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log labor/land ratio ( $\beta_g$ )	0.276 (0.047)	0.092 (0.021)	0.271 (0.057)	0.084 (0.022)	0.228 (0.045)	0.087 (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		0.002		0.005
Countries	84	76	74	52	22	68
Observations	8727	6864	7053	4394	880	7151
R-square (ex. FE)	0.26	0.22	0.27	0.22	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  $\beta_g$ , 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 only include districts with less than 100,000 urban residents, include districts that are less than 5% of state population, or exclude districts from any country in Europe (incl. Russia east of the Urals) or North America.

Table 4: Estimates of Land Elasticity,  $\beta_g$ , Additional Robustness ChecksDependent 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 ( $\beta_g$ )	0.227 (0.015)	0.118 (0.019)	0.241 (0.045)	0.088 (0.020)	0.189 (0.070)	0.016 (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 ( $\beta_g$ )	0.219 (0.040)	0.090 (0.022)	0.207 (0.047)	0.061 (0.025)	0.201 (0.037)	0.100 (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  $\beta_g$ , 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,  $\beta_g$ , Alternative Productivity MeasuresDependent 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 ( $\beta_g$ )	0.208 (0.052)	0.084 (0.020)	0.234 (0.046)	0.094 (0.022)	0.206 (0.052)	0.084 (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 ( $\beta_g$ )	0.223 (0.045)	0.083 (0.020)	0.229 (0.041)	0.094 (0.022)	0.224 (0.041)	0.083 (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  $\beta_g$ , 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,  $\beta_g$ , with DHS district controls

Dependent Variable in all columns: Log caloric yield ( $A_{tsg}^{GAEZ}$ )						
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.212 (0.065)	0.088 (0.017)	0.210 (0.066)	0.088 (0.017)	0.205 (0.068)	0.096 (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  $\beta_g$ , 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 demographic 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,  $\beta_g$ , for Mixed Region, 2000CE

Dependent variable: Log caloric yield ( $A_{isg}^{GAEZ}$ )						
	Specification defined by:					
	Baseline	Urban Pop.	Ex. Europe	Land $X_{is}$	Cash crops	GAEZ
	(1)	< 100K	N. Amer.	cult. area	< 5% area	high Input
	(1)	(2)	(3)	(4)	(5)	(6)
Log labor/land ratio ( $\beta_g$ )	0.128 (0.018)	0.137 (0.021)	0.085 (0.013)	0.123 (0.018)	0.133 (0.021)	0.134 (0.019)
p-value $\beta_g = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta_g = \beta_g^{Temp}$	0.003	0.000	0.016	0.003	0.100	0.010
p-value $\beta_g = \beta_g^{Trop}$	0.093	0.087	0.877	0.193	0.038	0.116
Countries	109	106	56	108	58	109
Observations	13416	12136	6598	13367	4665	13340
R-square (ex. FE)	0.18	0.20	0.12	0.19	0.17	0.15

**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  $\beta_g$ , 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 estimates

Country	$\beta$	Country	$\beta$	Country	$\beta$	Country	$\beta$
Afghanistan	0.161	Egypt	0.139	Lithuania	0.239	Senegal	0.088
Albania	0.140	El Salvador	0.091	Luxembourg	0.239	Serbia	0.161
Algeria	0.171	Eq. Guinea	0.090	Macao	0.128	Sierra Leone	0.095
American Samoa	0.088	Eritrea	0.114	Madagascar	0.126	Slovakia	0.229
Angola	0.126	Estonia	0.239	Malawi	0.122	Slovenia	0.231
Argentina	0.139	Ethiopia	0.125	Malaysia	0.098	Solomon Islands	0.088
Australia	0.136	Fiji	0.107	Mali	0.088	Somalia	0.094
Austria	0.239	Finland	0.239	Martinique	0.088	South Africa	0.128
Azerbaijan	0.143	France	0.202	Mauritania	0.095	South Korea	0.149
Bangladesh	0.127	French Guiana	0.088	Mexico	0.125	South Sudan	0.090
Belarus	0.239	Gabon	0.088	Mongolia	0.239	Spain	0.137
Belgium	0.239	Gambia	0.088	Morocco	0.132	Sri Lanka	0.090
Benin	0.088	Georgia	0.147	Mozambique	0.120	Sudan	0.096
Bhutan	0.164	Germany	0.239	Myanmar	0.122	Suriname	0.088
Bolivia	0.118	Ghana	0.088	Namibia	0.128	Swaziland	0.132
Bosnia	0.156	Greece	0.128	Netherlands	0.239	Sweden	0.239
Botswana	0.128	Guadeloupe	0.088	New Caledonia	0.125	Switzerland	0.235
Brazil	0.101	Guatemala	0.118	New Zealand	0.234	Syria	0.159
Brunei	0.088	Guinea	0.100	Nicaragua	0.093	Sao Tome	0.095
Bulgaria	0.163	Guinea-Bissau	0.088	Niger	0.093	Taiwan	0.128
Burkina Faso	0.088	Guyana	0.096	Nigeria	0.090	Tajikistan	0.157
Burundi	0.141	Haiti	0.104	North Korea	0.221	Tanzania	0.118
Cambodia	0.090	Honduras	0.112	Norway	0.239	Thailand	0.100
Cameroon	0.101	Hungary	0.171	Oman	0.133	Timor-Leste	0.091
Canada	0.237	India	0.118	Pakistan	0.131	Togo	0.088
C. African Rep.	0.088	Indonesia	0.102	Palestina	0.142	Tunisia	0.128
Chad	0.089	Iran	0.155	Panama	0.096	Turkey	0.176
Chile	0.216	Iraq	0.132	Papau N.G.	0.115	Uganda	0.103
China	0.133	Isle of Man	0.239	Paraguay	0.126	Ukraine	0.232
Colombia	0.102	Italy	0.128	Peru	0.117	United Kingdom	0.238
Costa Rica	0.107	Japan	0.151	Philippines	0.093	United States	0.162
Croatia	0.170	Jordan	0.196	Poland	0.239	Uruguay	0.128
Cuba	0.090	Kazakhstan	0.234	Portugal	0.139	Uzbekistan	0.207
Czech Republic	0.239	Kenya	0.118	Rep. of Congo	0.089	Vanuatu	0.092
Cote d'Ivoire	0.088	Kosovo	0.203	Reunion	0.130	Venezuela	0.106
D.R. Congo	0.103	Kyrgyzstan	0.230	Romania	0.200	Vietnam	0.115
Denmark	0.239	Laos	0.121	Russia	0.233	Virgin Islands, U.S.	0.088
Djibouti	0.088	Latvia	0.239	Rwanda	0.169	Zambia	0.128
Dominican Rep.	0.106	Lebanon	0.144	Samoa	0.094	Zimbabwe	0.128
Ecuador	0.120	Liberia	0.088				

**Notes:** This table reports the aggregated value of the land elasticity,  $\beta$ , 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	
	Tropical (1)	Temperate (2)	Tropical (3)	Temperate (4)	Tropical (5)	Temperate (6)
Panel A:						
Mortality rate	0.403 (0.151)	1.226 (0.132)	0.418 (0.158)	1.273 (0.140)	-0.255 (0.108)	-1.442 (0.193)
p-value $\theta = 0$	0.008	0.000	0.009	0.000	0.019	0.000
p-value $\theta = \theta^{Trop}$	.	0.000	.	0.000	.	0.000
Countries	30	5	30	5	30	5
Observations	238	40	238	40	238	40
Panel B:						
Log life expectancy	-0.743 (0.290)	-2.180 (0.171)	-0.703 (0.285)	-2.324 (0.187)	1.383 (0.165)	2.870 (0.248)
p-value $\theta = 0$	0.011	0.000	0.014	0.000	0.000	0.000
p-value $\theta = \theta^{Below}$	.	0.000	.	0.000	.	0.000
Countries	30	5	30	5	30	5
Observations	224	40	224	40	224	40

**Notes:** Robust standard errors are reported in parentheses. All regressions include both year fixed effects and country fixed effects. Countries are assigned as either “Temperate” or “Tropical” based on their estimated  $\beta$  from Table 8. Those with  $\beta < 0.20$  are classified as tropical, while those with  $\beta \geq 0.20$  are classified as temperate. 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  $\theta = \theta^{Trop}$  is from a test that the estimated coefficient for temperate countries is identical to the estimated coefficient of tropical countries.