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The role of land in temperate and tropical agriculture

Online Appendix

Robustness checks and alternative assumptions for empirical work from the main paper are contained here. Also included are definitions of countries included in regions used in paper, as well as additional theoretical work related to the model.

Contents

A.1 General version of empirical setup

This is to demonstrate that the elasticity of agricultural productivity with respect to the density of agricultural labor is equal to the elasticity of agricultural output with respect to land given any constant returns to scale production function. Let agricultural production be

$$Y_i = A_i F(X_i, K_i, L_{Ai}) \tag{A.1}$$

for district i in province I, where $F()$ is a constant returns to scale function with respect to the three inputs: land, capital, and labor. As in the main paper, we make the same mobility assumptions for labor and capital across districts, which again implies that K_i/L_{Ai} is identical for all districts.

Dividing the production function through by L_i, and multiplying by ϕ_L (the share of output paid to labor), we have that

$$\phi_L Y_i/L_{Ai} = \phi_L A_i F(X_i/L_i, K_i/L_i, 1). \tag{A.2}$$

Define $x_i = X_i/L_{Ai}$ and $k_i = K_i/L_{Ai}$ as the per-worker amounts of land and capital, and define

$$f(x_i, k_i) = F(X_i/L_i, K_i/L_i, 1) \tag{A.3}$$

as the intensive form of the aggregate production function. By the mobility assumption, we know that $\phi_L Y_i/L_{iA} = w$, where the wage is common across districts. This allows us to write that

$$w = \phi_L A_i f(x_i, k_i). \tag{A.4}$$

Holding this wage constant as it is given by province-level factors, and noting that k_i is also given by province-level factors, we use the implicit function theorem to solve for

$$\frac{\partial A_i}{\partial x_i}\frac{x_i}{A_i} = -\frac{\phi_L A_i f_1(x_i,k_i)}{\phi_L f(x_i,k_i)}\frac{x_i}{A_i} = -\frac{f_1(x_i,k_i)x_i}{f(x_i,k_i)}. \tag{A.5}$$

The elasticity of productivity, A_i, with respect to land per worker, x_i, is equal to the elasticity of $f()$ with respect to land per worker. This simply implies that the relationship of land per worker to productivity depends on how sensitive output per worker is to land per worker.

It is straightforward to show, given the constant returns to scale production function, that

$$\frac{f_1(x_i,k_i)x_i}{f(x_i,k_i)} = \frac{F_1(X_i,K_i,L_i)X_i}{F(X_i,K_i,L_i)} \tag{A.6}$$

or that the elasticity of the intensive production function with respect to land per worker is equal to the elasticity of the aggregate production function with respect to land. Thus it follows that

$$\frac{\partial A_i}{\partial x_i}\frac{x_i}{A_i} = -\frac{F_1(X_i,K_i,L_i)X_i}{F(X_i,K_i,L_i)} \tag{A.7}$$

or that the elasticity of productivity with respect to land per worker, x_i, is equal to the negative of the elasticity of aggregate output with respect to land. It is then trivial that the elasticity of productivity with respect to density, $1/x_i$, is equal to the elasticity of aggregate output with respect to land. The Cobb-Douglas assumption used in the main paper is not necessary to derive the main estimating equation used in the paper.

A.2 Specification with capital immobile between sectors

In our main derivation, we assume that capital can move freely between agriculture and non-agriculture. If that were not true, then equation (8) in the main paper would be

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

and our estimation would be based on

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

Here it becomes obvious that we need to control for *agricultural capital per worker*, rather than aggregate capital per worker. The controls we use - nighttime lights, urban share, and total population - may not be as useful in controlling for this. However, in the robustness checks using DHS data on assets, we do have controls that are explicitly measuring rural assets (livestock, etc..). As these results conform to our baseline, it does not appear that this assumption about mobile capital is driving our results.

A.3 Explicit two-sector model

In Section 2 of the paper we derived our estimation equation for β, and this was done using an aggregate agricultural production function, but without reference to any specific preferences. Here we add assumptions regarding preferences and non-agricultural production so that we can solve for the agricultural labor share and real income per capita in a state as a whole. We show that the elasticity β influences how sensitive real income and the share of labor in agriculture are to population and technological change. That model shows that as β gets *higher*, the economy gets *more* sensitive to population and technological change.

A.3.1 State-level agricultural and non-agricultural production

The agricultural sector operates as described in Section 2 of the main paper. We also continue with the assumptions made in the main paper, namely that $p_{Ais} = p_{As}$, $w_{Ais} = w_{Nis} = w_s$, and $r_{Ais} = r_{Nis}$. To that we add the assumption that $r_{Ais} = r_{Nis} = r_s$, or that capital is mobile across districts within a state.

These assumptions imply that $K_{Ais}/L_{Ais} = K_{Nis}/L_{Nis} = K_{is}/L_{is} = K_s/L_s$, or that the capital output ratio in each sector, in each district, is identical. This can be seen by examining equations (4) and (7) in the main paper, which show the capital output ratio of a sector in a district as proportion to the wage/rental ratio, which is identical across districts.

In equation (8) of the main paper, we derive the following expression relating the agricultural wage, district agricultural productivity, the district labor/land ratio, and the district capital/labor ratio. With the assumptions here on mobility of labor and capital, this can be re-written slightly as

$$w_s = (1-\phi)(1-\beta)p_{As}A_{Ais}\left(\frac{X_{is}}{L_{Ais}}\right)^{\beta}\left(\frac{K_s}{L_s}\right)^{\phi(1-\beta)}. \tag{A.10}$$

This equation holds for any two districts i and j. Hence we can find that

$$A_{Ais}\left(\frac{X_{is}}{L_{Ais}}\right)^{\beta} = A_{Ajs}\left(\frac{X_{js}}{L_{Ajs}}\right)^{\beta} \tag{A.11}$$

for any two districts. In addition, we know that $\sum_i L_{Ais} = L_{As}$. Combining the expression above with this summation, one can solve for

$$\frac{L_{Ajs}}{L_{As}} = \frac{A_{Ajs}^{1/\beta}X_{js}}{\sum_i A_{Ais}^{1/\beta}X_{is}} \tag{A.12}$$

which simply says that the fraction of the states agricultural workers that work in district j depends on the size of productivity and land in district j relative to the aggregate productivity and land in the state. As the capital/labor ratios are identical across all districts, the same expression describes the share of total agricultural capital that is employed in district j.

Based on the district-level production functions from (1) in the main paper, total agricultural supply in state s can be written as

$$Y_{As} = \sum_i A_{Ais}X_{is}^{\beta}\left(K_{Ais}^{\alpha}L_{Ais}^{1-\alpha}\right)^{1-\beta}. \tag{A.13}$$

Combine (A.12) and the equivalent expression for capital with (A.13) and we can solve for

$$Y_{As} = A_{As} \left(\frac{K_{As}}{L_{As}}\right)^{\alpha(1-\beta)} L_{As}^{1-\beta} \tag{A.14}$$

where

$$A_{As} = \left(\sum_j A_{js}^{1/\beta} X_{js}\right)^{\beta}$$

is the measure of aggregate agricultural total factor productivity for the province.

A similar process can be performed for non-agriculture. The aggregate production function for the state is given by

$$Y_{Ns} = A_{Ns} \left(\frac{K_{Ns}}{L_{Ns}}\right)^{\phi} L_{Ns}. \tag{A.15}$$

Note that because capital and labor are perfectly mobile, it will be the case that $A_{Ns} = max(A_{N1s}, ..., A_{NJs})$, where J is the number of districts in the state. That is, all non-agricultural activity will concentrate in the single district with the highest non-agricultural productivity. Given the data we presented on districts, this is not a terrible description of reality, in that many states in our data have mainly rural districts along with one or two significant urban (and hence heavily non-agricultural) districts. If we wanted to allow for more subtlety, we could introduce a fixed factor into non-agriculture, and this would generate a distribution of non-agricultural activity across districts.

A.3.2 Preferences and optimization

For preferences over those consumption goods, we follow **?**, who specifies a functional form for the indirect utility function that allows for analysis of structural change involving income effects.[1] This function results in non-linear Engel curves while still allowing for aggregation across individuals.

Let the amount of agricultural consumption done per person be c_A, the non-agricultural consumption be c_N, and M be the nominal income M. The nominal price of agricultural goods facing the consumer is P_A, and the nominal price of non-agricultural goods is P_N (and hence $p_A = P_A/P_N$). The budget constraint is $M = P_A c_A + P_N c_N$. The demand function for agricultural consumption by individuals with the Boppart preferences is

$$\ln c_A = \ln \theta_A + (1-\epsilon) \ln M + (\gamma - 1) \ln P_A + (\epsilon - \gamma) \ln P_N \tag{A.16}$$

where θ_A is a preference parameter, and with $\gamma < 1$ implying a standard inverse relationship of price and quantity demanded. With $0 < \epsilon < 1$, these preferences imply that the income elasticity of agricultural demand is less than one, capturing Engel's Law. The specific indirect utility function for our model would be $V(P_A, P_N, M) = 1/\epsilon\,(M/P_N)^{\epsilon} - \theta_A/\gamma\,(P_A/P_N)^{\gamma} - 1/\epsilon + \theta_A/\gamma$.

A.3.3 Equilibrium

To go further, the most important assumption we make is that the share of output paid to agricultural land is zero. This simplifies the analysis, and ensures that the solutions are not driven by any connection of β to the share of output paid to land.

[1] The functional form is in the price independent generalized linearity (PIGL) preference family. It has a number of attractive properties that Boppart exploits, but which are not relevant for our analysis.

Total supply must equal total demand, so $Y_{As} = c_A L_s$ and $Y_{Ns} = c_N L_s$, where c_A and c_N are per-capita consumption of agricultural and non-agricultural goods, respectively, and L_s is the total population, with $L_s = L_{As} + L_{Ns}$.

Mobility between sectors ensures that, in nominal terms,

$$P_A \frac{Y_{As}}{L_{As}} = p_N \frac{Y_{Ns}}{L_{Ns}}. \tag{A.17}$$

We can rearrange this to be

$$\frac{P_A c_A}{P_N c_N} = \frac{L_{As}}{L_{Ns}}, \tag{A.18}$$

which shows that the relative amount of labor employed in agriculture and non-agriculture is equal to the relative expenditures on those goods. With the adding up conditions on state labor and the budget constraint for consumers, it follows that in log terms

$$\ln L_{As}/L_s = \ln P_A c_A/M. \tag{A.19}$$

Turning to the demand function from (A.16), we can re-arrange that to

$$(1-\epsilon)\ln P_A c_A/M = \ln \theta_A + (\epsilon - \gamma)(\ln P_N - \ln P_A) - \epsilon \ln c_A.$$

Using the relationships in (A.18) and (A.19), we can find

$$(1-\epsilon)\ln L_{As}/L_s = \ln \theta_A + (\epsilon - \gamma)\left(\ln Y_{Ns}/L_{Ns} - \ln Y_{As}/L_{As}\right) - \epsilon\left(\ln Y_{As}/L_{As} + \ln L_{As}/L_s\right).$$

Collecting terms we have

$$\ln L_{As}/L_s = \ln \theta_A + (\epsilon - \gamma)\ln Y_{Ns}/L_{Ns} - \gamma \ln Y_{As}/L_{As}.$$

Using the production functions in (A.14) and (A.15), we can write this as

$$\ln L_{As}/L_s = \ln \theta_A + (\epsilon - \gamma)\ln\left(A_{Ns}(K_s/L_s)^{\alpha}\right) - \gamma \ln\left(A_{As}(K_s/L_s)^{\alpha(1-\beta)} L_{As}^{-\beta}\right) - \gamma\beta \ln L_s + \gamma\beta \ln L_s,$$

where we've added and subtracted the term involving L_s. At this point, what remains is to separate the productivity and capital terms using the logs, and then straightforward algebra to arrive at

$$\ln L_{As}/L_s = \ln \theta_A + \frac{\beta\gamma}{1-\beta\gamma}\ln L_s - \frac{\gamma}{1-\beta\gamma}\ln A_{As} + \frac{\gamma-\epsilon}{1-\beta\gamma}\ln A_{Ns} + \frac{\alpha(\beta\gamma-\epsilon)}{1-\beta\gamma}\ln K_s/L_s. \tag{A.20}$$

As we'll ultimately be interested in elasticities of the agricultural labor share with respect to other terms, we leave the expression in logs and the elasticities are easy to read off of the right-hand side.

For real income, in agricultural terms we have

$$y_s = \frac{M}{P_A} = c_A + \frac{P_N}{P_A} c_N.$$

Using (A.18) we can write this as

$$y_s = c_A + \frac{P_N c_N}{P_A c_A} c_A = c_A\left(1 + \frac{L_{Ns}}{L_{As}}\right) = c_A \frac{L_s}{L_{As}}.$$

Noting that $c_A = Y_{As}/L_s$, we have that

$$y_s = \frac{Y_{As}}{L_{As}} = A_{As}(K_s/L_s)^{\alpha(1-\beta)}(L_{As}/L_s)^{-\beta}L^{-\beta}.$$

At this point, we can use (A.20) to plug in for L_{As}/L_s, and solve for

$$\ln y_s = \frac{1}{1-\beta\gamma}\ln A_{As} - \frac{\beta}{1-\beta\gamma}\ln L_s + \frac{\beta(\epsilon-\gamma)}{1-\beta\gamma}\ln A_{Ns} + \frac{\alpha(1-\beta)+\alpha\beta(\epsilon-\gamma)}{1-\beta\gamma}\ln K_s/L_s. \quad \text{(A.21)}$$

Again, we leave this in log form to read off the elasticities.

Proposition 1 *The elasticities of the agricultural labor share (L_A/L) and real income (y) with respect to various shocks,*

(a) Agricultural productivity (A_{As}): $\frac{\partial \ln L_{As}/L_s}{\partial \ln A_{As}} = -\frac{\gamma}{1-\beta\gamma}$ *and* $\frac{\partial \ln y_s}{\partial \ln A_{As}} = \frac{1}{1-\beta\gamma}$

(b) Population (L_s): $\frac{\partial \ln L_{As}/L_s}{\partial \ln L_s} = \frac{\beta\gamma}{1-\beta\gamma}$ *and* $\frac{\partial \ln y_s}{\partial \ln L_s} = -\frac{\beta}{1-\beta\gamma}$

(c) Non-agricultural productivity (A_{Ns}): $\frac{\partial \ln L_{As}/L_s}{\partial \ln A_{Ns}} = -\frac{\epsilon-\gamma}{1-\beta\gamma}$ *and* $\frac{\partial \ln y_s}{\partial \ln A_{Ns}} = \frac{\beta(\epsilon-\gamma)}{1-\beta\gamma}$

(d) Capital/labor (K_s/L_s): $\frac{\partial \ln L_A/L}{\partial \ln K_s/L_s} = -\frac{\alpha(\epsilon-\beta\gamma)}{1-\beta\gamma}$ *and* $\frac{\partial \ln y_s}{\partial \ln K_s/L_s} = \frac{\alpha\beta(\epsilon-\gamma)}{1-\beta\gamma}$

are both increasing in absolute value with β.

Proof. This follows from inspection of (A.20) and (A.21). ■

This conforms to the intuition explained in the text. One note is that the *sign* of the elasticities with respect to agricultural productivity and population are unambiguous. Agricultural productivity lowers the agricultural labor share and raises real income per capita. To see this, note that $\gamma < 1$ so that the demand function is downward sloping, and so $1 - \beta\gamma > 0$. For population, an increase will raise the agricultural labor share, but decrease real income per capita.

The *sign* of the elasticities with respect to non-agricultural productivity and the capital/labor ratio are ambiguous, and depend on the relative size of γ and ϵ. If $\epsilon > \gamma$, then the cross-price elasticity of demand for agriculture is positive with respect to non-agriculture prices. In that case non-agricultural productivity will lower the agricultural labor share (as this productivity lowers the price of non-agricultural goods and people substitute towards them) while also raising real income per capita. For the capital/labor ratio, a similar logic holds. Regardless of the exact values, it is the case that the absolute size of the elasticities is increasing in β.

A.4 Adding Malthusian fertility responses

Our main model is static, taking the size of population (and capital) as given. By adding in a simple Malthusian fertility response, one can establish several results related to population density and the land elasticity.

Without specifying a particular utility function, let population growth from t to $t+1$ be a function of income per capita in t

$$n_{t+1} = y_t^{\theta}$$

where $0 < \theta < 1$ so that population growth is a concave function of income per capita. The dynamics of population are thus

$$L_{t+1} = n_{t+1} L_t = \left(A_A A_N^{\beta(\epsilon-\gamma)} \hat{k}^{\Omega} \right)^{\frac{\theta}{1-\beta\gamma}} L_t^{\frac{1-\beta(\theta+\gamma)}{1-\beta\gamma}}.$$

Examining the exponent on L_t, it is clear that this is less than one, making L_{t+1} a concave function of L_t, and thus we have a stable steady state for population. Solving for that steady state by setting $L_{t+1} = L_t$ we have

$$L^* = \left(A_A A_N^{\beta(\epsilon-\gamma)} \hat{k}^{\Omega} \right)^{\frac{1}{\beta}}.$$

From this, one can see the influence of agricultural productivity on population, and hence on population density. Note that the elasticity of steady state population with respect to A_A depends inversely on β. As the land elasticity gets larger, the effect of agricultural productivity on population size decreases. The positive Malthusian relationship of population size and (agricultural) productivity remains, but because the Malthusian constraint is much tighter when β is large, the relationship is not as strong as when β is small.

A.5 Demographic and Health Survey Data

In the main text, we used Demographic and Health Survey (DHS) data to create controls for demographics and assets at the district level. To do this, we started with all available DHS surveys for which latitude/longitude data was provided for the location of each cluster of surveyed individuals. For each survey, we overlaid these points on the map of 2nd-level political units (districts), creating a concordance of clusters to districts.

One note here is that for privacy reasons, the DHS perturbs the actual latitude/longitude point of a cluster by 10km in an arbitrary direction. Thus, for clusters very close to district borders, we may assign them to the incorrect district. Given the large number of clusters within any given district, and the fact that this is done randomly, we do not believe it creates any systematic errors in our ultimate district-level aggregates.

Having linked clusters to districts, we can then link all households in a survey to a district. For each district, we construct several measures of demographics and assets using this household data.

- **Demographics** We calculate the 10th, 50th, and 90th percentile values of the following household variables: years of education of household head (hv107-01), age of household head (hv220), and number of regular household members (hv012).

- **Assets** We calculate the mean value of the following dummy variables for household possession of the following assets: flush toilet (hv205), electricity (hv206), television (hv208), refrigerator (hv209), improved flooring (hv213), agricultural land (hv244), a bank account (hv247), any cattle (hv246a), any draft animals (hv246c), and any sheep (hv246e).

Detailed data on the number of agricultural hectares held, or counts of livestock held, are only available for a small number of recent surveys, so were not used. The mean values of the asset dummies thus indicate the percentage of households in a district that report having these assets. For the demographic data, the percentiles allow us a crude control for the distribution of education, age, and household size.

Given that there are countries which have been surveyed multiple time, we use the latest available survey from any given country. This is done because later surveys have more variables available, allowing us to control for more characteristics.

The specific country surveys that we draw from, and which have districts that fall into our temperate/tropical distinction, are: Albania (2008), Angola (2015), Benin (2012), Bolivia (2008), Burundi (2016), Democratic Republic of the Congo (2013), Cte d'Ivoire (2012), Cameroon (2011), Colombia (2010), Dominican Republic (2013), Ethiopia (2016), Gabon (2012), Guinea (2012), Guatemala (2015), Guyana (2009), Honduras (2011), Haiti (2012), India (2014), Jordan (2012), Cambodia (2014), Kyrgyzstan (2012), Myanmar (2015), Mozambique (2015), Nigeria (2015), Peru (2009), Philippines (2008), Rwanda (2014), Senegal (2015), Chad (2014), Togo (2013), Tajikistan (2012), Timor-Leste (2016), Tanzania (2015), Uganda (2016)

A.6 Alternative Population Data

As mentioned in the main text, given possible issues with the HYDE data on population, we use two alternative sources of population data.

A.6.1 GRUMP Data

We accessed both the gridded population map, and the urban extents grid. The GRUMP data is provided at 30 arc-second grids (rougly 1km squares), a higher resolution than the HYDE data (which has 5 arc-minute grids, or roughly 10km squares). We overlay the urban extents grid on the population map, and retrieve only the population count of grid cells that are not part of an urban extent. We then sum up the population count of grid cells within each district. The district definitions are from GADM, identical to those used with the HYDE data, so we can compare the counts directly.

Because GRUMP counts zero rural residents in an area that is part of an urban extent, and all population in non-urban locations as rural, the variation in rural residents across districts is more severe than with HYDE. Some districts in GRUMP are entirely covered by urban extents, and so have zero rural residents. Hence the GRUMP data leads to 28,471 districts with data on rural density, compared to 35,451 using HYDE. For those 28,471 districts, the correlation of (log) rural density across the two datasets is 0.81, significant at less than 1%.

A.6.2 IPUMS Data

We use 39 countries that have both geographic identifier data (the GEOLEV2 variable from IPUMS) as well as information on individual industry of employment. We create a 0/1 variable indicating whether an individual is an agricultural worker (meaning they are reported as in the workforce). We then aggregate this variable (weighted by their IPUMS provided sampling weight) across individuals within a geographic area to get a count of the total agricultural workers. Using a similar method, we are also able to count the number of urban residents, which allows us to measure the percent urban within a geographic area. We end up with a total of 8,393 geographic areas.

Before we run regressions, the IPUMS data is useful in assessing how good of an approximation rural population (including workers and non-workers) is for the number of agricultural workers. The correlation of (log) rural residents and (log) agricultural workers across the areas is 0.91, significant at less than 1%. There are a few outliers where the number of agricultural workers is high relative to rural residents, which likely represents agricultural processing work in urban areas, or urban farmers with small plots. Our results are not affected by excluding these outliers.

The geographic areas provided by IPUMS in the GEOLEV2 variable are in many cases agglomerations of the districts we use from GADM. This is because IPUMS aggregates districts with fewer than 25000 observations (to protect anonymity) or districts whose boundaries have changed over time (so that the agglomerations are comparable over time for a given country). This means the IPUMS geographic areas are not directly comparable to our districts. Because the IPUMS agglomerations are much larger than districts, it is not practical to use province/state fixed effects, as most of these have only one or two IPUMS areas within them. Hence we run our regressions only with country fixed effects. Because the GEOLEV2 areas are different than the districts in our baseline specifications, we create new GEOLEV2 level versions of our caloric suitability index, night lights data, and other crop suitability measures.

The 39 countries included from IPUMS are, with the census date listed: Argentina (2001), Austria (2001), Bolivia (2001), Brazil (2000), Cambodia (1998), Cameroon (2005), Chile (2002), Colombia (2005), Costa Rica (2000), Ecuador (2001), El Salvador (2007), Fiji (1996), Ghana (2000), Greece (2001), Haiti (2003), India (1999), Iran (2006), Iraq (1997), Jordan (2004), Kyrghzstan (1999), Malawi (1998), Mexico (2000), Morocco (2004), Mozambique (1997), Panama (2000), Peru (2007), Sierra Leone (2004), South Africa (2001), Spain (2001), South Sudan (2008), Sudan (2008), Turkey (2000), Uganda (2002), Egypt (1996), Tanzania (2002), United States (2000), Burkina Faso (1996), Venezuela (2001), Zambia (2000)

A.7 Labor/land and β_g

We can examine how estimated values of β_g vary with labor/land ratios at the state level. We have estimated a separate β_g for each state in our dataset that contains 10 or more districts within it. In each case, we run the same regression as in (10) of the main paper, excluding the state fixed effect but including the normal controls (e.g. night lights). This gives us a total of 1,018 estimates of β_g. In Figure 1 we plot the value of all these β_g estimates against the rural labor/land ratio of the state. These estimates are quite noisy, given that the average number of districts within a state is only 26. That does not represent an issue for our baseline resutls. Our baseline regressions with state fixed effects are effectively finding an efficient combination of these separate state-level estimates.

The dark dashed line shows a simple linear fit for this data. As can be seen there is a slight tendency of the estimated β_g values to get larger as a state gets more dense, although the effect is small. Doubling rural labor/land ratios only increase the estimated β_g by around 0.004. This positive relationship of the land elasticity and rural labor/land is consistent with land and labor being complements, not substitutes. If anything, the higher rural labor/land ratios of tropical areas would push up our estimated value of β_g for that region. The gap in β_g between tropical and temperate areas we find in our main results therefore does not appear to be driven by differences in rural labor/land ratios.

A.8 Alternative measure of A_{isg}

The CSI index used as the baseline measure of A_{isg} combines the raw potential tonnage of production of specific crops with information on their calorie content so that one can compare the *caloric* yield of each crop within a given grid-cell. Then the maximum value of that caloric yield is selected across crops, and those maximums are aggregated across grid-cells in a district to arrive at the A_{isg} measure. This follows Galor and Ozak's (2016) methodology, but there may be an issue with using these calorie counts to compare crops. The calorie count of each crop may not be an accurate measure of the available calories from those crops, given storage and preparation techniques. A worry is that we may have created variation in A_{isg} because of variation in the calorie counts of crops, and that this is driving the results. For example, given paddy rice's very high caloric yield in the Galor and Ozak methodology, it is possible that we are overstating the productivity of districts that are in fact very un-productive from the perspective of farmers, but because they are capable of growing rice, Galor and Ozak have coded them as having very high productivity. This would bias our estimates of β down for these areas.

To see that this is not driving our results, we have performed separate regressions estiamting β where we use a single crop-specific raw yield from GAEZ as the measure of productivity (e.g. wheat or rice). In this case, there is no caloric information employed at all, as we are not trying to combine data across crops. Each district is thus measured on a comparable basis. Table A.1 shows these results. Panel A is for the temperate districts identified in the main paper as those capable of growing the temperate crops, while Panel B is for the tropical districts capable of growing tropical crops. In both panels, the first column replicates our baseline results from Table 2 of the main paper.

For temperate crops, the baseline estimate of β is 0.228. The next six columns show the estimated value of β if in place of the CSI yield from Galor and Ozak as the A_{isg} variable, we use the raw yield of the specified crop. For example, using just the raw yield of barley to measure A_{isg} in temperate districts, we find an estimated β of 0.225. Given that this is nearly identical to the baseline estimate, this indicates that the baseline is not driven simply by the caloric values assigned to barley versus other temperate crops. The rest of the columns show the same kind of result. In each case, the estimate of β is very close to 0.228, indicating that the CSI index is not driven by caloric information, but by common variation in the raw productivity of these crops across districts. In Panel B, a similar story is shown. The baseline estimate for the tropical districts is 0.132, while each of the separate columns delivers a result nearly identical, save pearl millet (although still at 0.145). Again, the baseline estimate using the CSI index is not driven simply by the use of calories to weight the different crops.

The implication of these results is that *any* scheme used to weight raw yields across crops is going to deliver similar results regarding β. Prices, or alternative means of measuring nutritional quality, if used to construct A_{isg} would still show that temperate areas have larger land elasticities than tropical areas.

A.9 Political region results

Table A.4 shows results grouping districts by their "macro-region". Within each of these regions, all districts are assumed to have identical values of β. Given the rough correlation of these regions with different climate types, the pattern of results suggest similar results to the baseline. The

final panel shows separate results for China (separated into a temperate north and tropical south), Japan, and Korea.
Regions: Countries are included as follows:.

- **Central and West Asia**: Afghanistan, Azerbaijan, Bhutan, Georgia, Iran, Iraq, Jordan, Kazakhstan, Kyrgyzstan, Lebanon, Oman, Pakistan, Palestina, Russia (Asia), Syria, Tajikistan, Turkey, Uzbekistan
- **Eastern Europe**: Belarus, Bulgaria, Czech Republic, Hungary, Poland, Romania, Russia (Europe), Slovakia, Ukraine
- **North Africa**: Algeria, Egypt, Morocco, Sudan, Tunisia
- **Northwest Europe**: Austria, Belgium, Denmark, Estonia, Finland, France, Germany, Isle of Man, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Sweden, Switzerland, United Kingdom
- **South Africa**: Botswana, Namibia, South Africa, Swaziland
- **South and Southeast Asia**: Bangladesh, Brunei, Cambodia, India, Indonesia, Laos, Malaysia, Myanmar, Philippines, Sri Lanka, Thailand, Timor-Leste, Vietnam
- **Southern Europe**: Albania, Bosnia and Herzegovina, Croatia, Italy, Portugal, Serbia, Slovenia, Spain
- **Temperate Americas**: Argentina, Canada, Chile, United States, Uruguay
- **Tropical Africa**: Angola, Benin, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Cte d'Ivoire, Democratic Republic of the Congo, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Liberia, Madagascar, Malawi, Mali, Mauritania, Mozambique, Niger, Nigeria, Republic of Congo, Reunion, Rwanda, Senegal, Sierra Leone, Somalia, South Sudan, So Tom and Prncipe, Tanzania, Togo, Uganda, Zambia, Zimbabwe
- **Tropical Americas**: Bolivia, Brazil, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, El Salvador, French Guiana, Guadeloupe, Guatemala, Guyana, Haiti, Honduras, Martinique, Mexico, Nicaragua, Panama, Paraguay, Peru, Suriname, Venezuela

For China-only regressions: We exclude Tibet, Xinjiang, Gansu, and Qinghai entirely, given that their climates do not fit well into the temperate versus sub-tropical distinction we make in the regressions.

- **Temperate provinces**: Hebei, Heilongjiang, Jilin, Liaoning, Nei Mongol, Ningxia Hui, Shaanxi, Shanxi, Tianjin, Sichuan, Shandong, Yunnan
- **Sub-tropical provinces**: Guangxi, Guangdong, Fujian, Jiangxi, Hunan, Guizhou, Chongqing, Hubei, Anhui, Zhejiang, Henan, Jiangsu, Hainan

Russian provinces: We split Russia into separate Asian and European sections for inclusion in the regions. That breakdown takes place at the province level

- **Russia(Asia)**: Altay, Amur, Buryat, Chelyabinsk, Gorno-Altay, Irkutsk, Kemerovo, Khabarovsk, Khakass, Khanty-Mansiy, Krasnoyarsk, Kurgan, Novosibirsk, Omsk, Primor'ye, Sakhalin, Sverdlovsk, Tomsk, Tuva, Tyumen', Yevrey, Zabaykal'ye

- **Russia(Europe)**: Adygey, Arkhangel'sk, Bashkortostan, Belgorod, Bryansk, Chechnya, Chuvash, Dagestan, Ingush, Ivanovo, Kabardin-Balkar, Kaliningrad, Kalmyk, Kaluga, Karachay-Cherkess, Kirov, Komi, Kostroma, Krasnodar, Kursk, Leningrad, Lipetsk, Mariy-El, Mordovia, Moskva, Nizhegorod, North Ossetia, Novgorod, Orel, Orenburg, Penza, Perm', Pskov, Rostov, Ryazan', Samara, Saratov, Smolensk, Stavropol', Tambov, Tatarstan, Tula, Tver', Udmurt, Ul'yanovsk, Vladimir, Volgograd, Vologda, Voronezh, Yaroslavl'

A.10 Climate zone results

For this, we use the Köppen-Geiger scheme, which classifies each grid cell on the planet on three dimensions. First are the *main climate* zones: equatorial (denoted with an "A"), arid (B), warm temperate (C), and snow (D).[2] Second, each grid-cell has a *precipitation* classification: fully humid (f), dry summers (s), dry winters (w), monsoonal (m), desert (D), and steppe (S). Finally, there is the *temperature* dimension: hot summers (a), warm summers (b), cool summers (c), hot arid (h), and dry arid (k).[3] Each grid cell thus receives either a three or two-part code. The area around Paris, for example, is "Cfb", meaning it is a warm temperate area, fully humid (rain throughout the year), with warm summers. The area near Saigon is "Aw", meaning it is equatorial, with dry winters. There is no separate temperature dimension assigned to equatorial zones, as it tends to be redundant.

What we do in Table A.3 is divide districts into regions based on their Köppen-Geiger classifications, as opposed to crop suitability or production data. We do this along each individual dimension (climate, precipitation, and temperature), including a district in a region if more than 66% of its land area falls in the given zone. For example, for the equatorial region, we include all districts in which 66% (or more) of their land area is classified as being in "A" in the Köppen-Geiger system, regardless of their precipitation or temperature codes. Narrowing down to very specific classifications ("Cfb", for example) is impractical because the number of districts becomes very small. Similar to the temperate/tropical regressions, the climate zone regions do not force heterogeneous districts to be lumped into single regions based on their nation.

A.11 Expanded samples

Our baseline samples are Tropical and Temperate. As defined in the main text, the Tropical sample includes districts that are suitable for growing specific crops (cassava, cowpeas, pearl millet, sweet potato, wet rice, yams) but have zero suitability for growing others (barley, buckwheat, oats, rye, white potato, wheat). Temperate is defined in the reverse manner. These definitions exclude 15,692 districts that are capable of growing *both* types of crops.

Column (1) of Table A.6 shows the results for just those districts suitable for growing both kinds of crops. The estimated β is 0.140, roughly in line with the result for the Tropical sample. Column (2) differs by including any districts that are suitable for Temperate crops (regardless of their suitability for growing Tropical crops). This gives a result of 0.180, smaller than our baseline

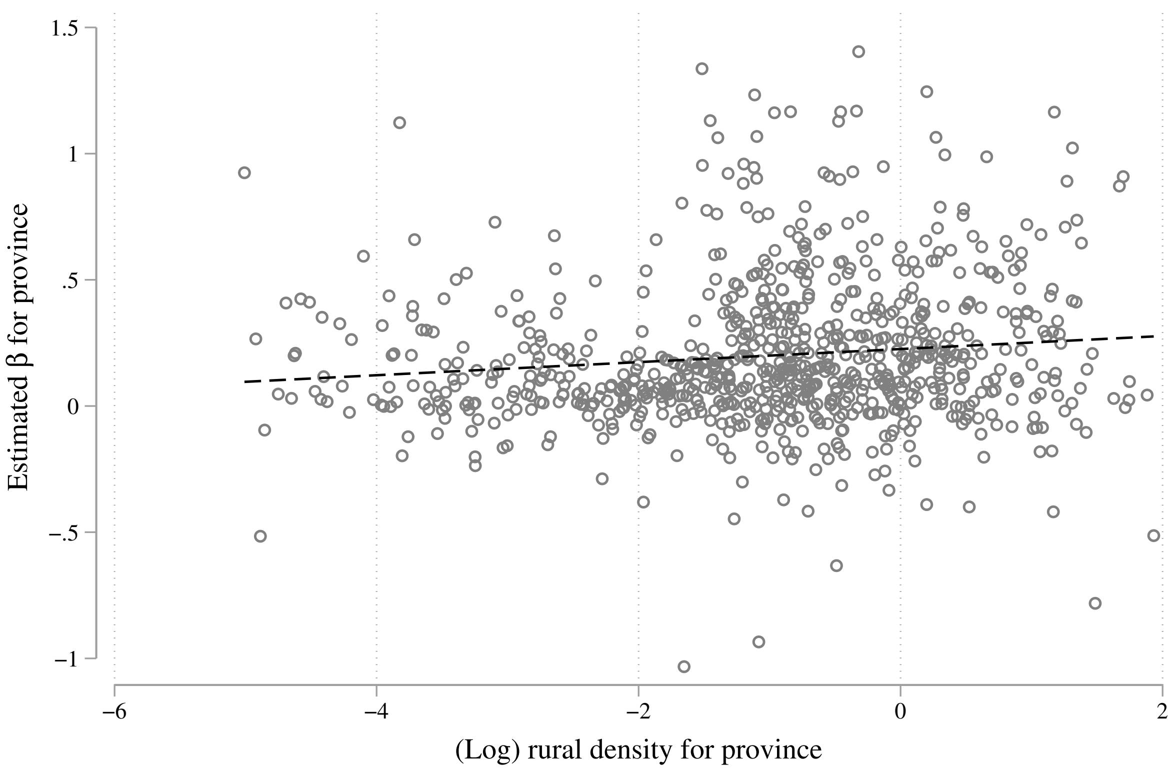
[2] There is another classification of climate, polar (E), but that covers only areas that are uninhabited for all intents and purposes.

[3] There are three other temperature classifications - extreme continental, polar frost, and polar tundra - that also cover only uninhabited areas.

estimate where we focus on districts suitable only for Temperate crops. Column (3) estimates β for any districts that are capable of growing Tropical crops, regardless of their ability to grow Temperate, and the value is 0.132. Again, we see a difference between these two types of regions. However, the gap is smaller, consistent with the fact that we are not distinguishing them as clearly, and the fact that columns (2) and (3) include the 15,692 districts that can grow both kinds of crops. Columns (4)-(6) repeat these regressions, only limiting the sample by excluding districts with large urban areas. We find similar results in this case.

A.12 Figures

Figure 1: Relationship of state-level β_g and Rural Labor/land Ratio



Notes: Plotted are the values of β_g estimated for each individual state in our dataset that contains 10 or more districts. The specification for these regressions is equation (**??**), and includes the controls for (log) night lights, (log) total population, and the percent urban. The value of rural labor/land for a state is total rural population of the state divided by total land area of the state.

A.13 Robustness Tables

List of Tables

Table A.1: Estimates of β using individual crop productivity terms

Panel A: Using only temperate districts defined by crop suitability

	Dependent variable is A_{isg} measured by:						
	CSI (1)	Barley (2)	Buckwheat (3)	Oats (4)	Rye (5)	W. Pot. (6)	Wheat (7)
Log rural density (β_g)	0.228 (0.021)	0.225 (0.019)	0.218 (0.023)	0.222 (0.026)	0.212 (0.020)	0.233 (0.029)	0.227 (0.019)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Countries	91	91	69	68	68	91	91
Observations	10661	10628	9699	9834	9804	10597	10631
R-square (ex. FE)	0.27	0.23	0.19	0.25	0.23	0.25	0.24

Panel B: Using only tropical districts defined by crop suitability

	Dependent variable is A_{isg} measured by:						
	CSI (1)	Cassava (2)	Cowpea (3)	P. Millet (4)	Sw. Pot. (5)	Wet Rice (6)	Yams (7)
Log rural density (β_g)	0.132 (0.018)	0.137 (0.022)	0.137 (0.019)	0.145 (0.019)	0.136 (0.019)	0.134 (0.028)	0.133 (0.020)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Countries	81	76	80	79	79	75	79
Observations	9088	8843	9074	8265	9066	8448	9020
R-square (ex. FE)	0.13	0.11	0.12	0.07	0.12	0.06	0.11

The panels differ in the districts included in each regression. In Panel A, only districts that are suitable for temperate agriculture are inclueded (based on the criteria we outline in the paper based on GAEZ suitability measures). In Panel B, on tropical districts are included. The columns differ by the variable used to measure A_{isg}, inherent agricultural productivity. Column (1) uses the CSI index from Galor and Ozak (2016), as in our baseline results. Columns (2)-(7) use the raw potential yield (in tonnes) of the crop, from the GAEZ, for the crop specified. Additional controls are as in our basline results, and include province fixed effects. Conley standard errors, adjusted for spatial auto-correlation, are shown in parentheses.

Table A.2: Estimates of Land Elasticity, β_g, with Polynomial Controls

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

Panel A: Regions defined by:

	Crop suitability:		Frost Days:		Koeppen-Geiger:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density (β_g)	0.243	0.115	0.228	0.105	0.239	0.090
	(0.026)	(0.018)	(0.022)	(0.012)	(0.027)	(0.015)
p-value $\beta_g = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta_g = \beta_{Temp}$		0.000		0.000		0.000
Countries	91	81	94	107	88	83
Observations	10660	9086	17746	17698	11615	12289
R-square (ex. FE)	0.28	0.24	0.25	0.21	0.29	0.23

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

	Urban Pop. $< 25K$:		Urban Perc. < 50:		Ex. Europe/N. Amer.:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density (β_g)	0.287	0.120	0.297	0.132	0.273	0.114
	(0.030)	(0.022)	(0.036)	(0.022)	(0.045)	(0.019)
p-value $\beta_g = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta_g = \beta_{Temp}$		0.000		0.000		0.001
Countries	83	75	84	76	24	70
Observations	7648	6661	6569	5851	824	8824
R-square (ex. FE)	0.31	0.26	0.32	0.27	0.22	0.18

Notes: Conley standard errors, adjusted for spatial auto-correlation with a cutoff distance of 500km, are shown in parentheses. All regressions include province fixed effects, a constant, and controls for the district urbanization rate, log density of district nighttime lights, and log total population. In addition to these standard controls, quadratic terms of each control, as well as their interactions, are included. The coefficient estimate on rural population density indicates the value of β_g, see equation (**??**). Rural population is from HYDE database (**?**), and caloric yield is the author's calculations based on the data from **?**. Inclusion of districts in the regression is based on the listed criteria, either crop suitability, the number of frost-free days, or Köppen-Geiger climate zones. See text for details of how temperate and tropical regions are defined in each case. In Panel B, the columns either exclude districts with more than 25,000 urban residents, exclude districts from any country in Europe (incl. Russia east of the Urals) or North America, or with a percent of urban residents below 50 percent.

Table A.3: Estimates of Land Elasticity, β, by Köppen-Geiger Zone, 2000CE

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

Panel A: Climate Zones

	Equatorial (1)	Arid (2)	Temperate (3)	Snow (4)
Log rural density (β_g)	0.112	0.158	0.164	0.230
	(0.015)	(0.025)	(0.017)	(0.026)
p-value $\beta = 0$	0.000	0.000	0.000	0.000
p-value $\beta = \beta_{Equa}$		0.115	0.007	0.000
Countries	79	56	94	40
Observations	11461	2822	13717	6327
R-square (ex. FE)	0.12	0.12	0.15	0.20

Panel B: Precipitation Zones

	Fully Humid (1)	Dry Summer (2)	Dry Winter (3)	Monsoon (4)	Desert (5)	Steppe (6)
Log rural density (β_g)	0.185	0.170	0.113	0.127	0.147	0.166
	(0.024)	(0.018)	(0.016)	(0.023)	(0.050)	(0.028)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.003	0.000
p-value $\beta = \beta_{Humid}$		0.616	0.015	0.073	0.487	0.568
Countries	98	45	74	42	30	54
Observations	17327	3150	9224	1816	364	2339
R-square (ex. FE)	0.22	0.22	0.19	0.22	0.22	0.21

Panel C: Temperature Zones

	Hot Summer (1)	Warm Summer (2)	Cool Summer (3)	Hot Arid (4)	Cold Arid (5)
Log rural density (β_g)	0.144	0.219	0.286	0.179	0.186
	(0.014)	(0.029)	(0.054)	(0.033)	(0.034)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta_{Humid}$		0.004	0.010	0.289	0.248
Countries	61	84	26	43	27
Observations	9312	9858	540	1582	1160
R-square (ex. FE)	0.17	0.23	0.18	0.16	0.19

Notes: Conley standard errors, adjusted for spatial auto-correlation with a cutoff distance of 500km, are shown in parentheses. All regressions include province fixed effects, a constant, and controls for the district urbanization rate and log density of district nighttime lights. The coefficient estimate on rural population density indicates the value of β_g. Inclusion of districts is based on whether they have more than 50% of their land area in the given Köppen-Geiger zone. See text for details.

Table A.4: Estimates of Land Elasticity, β, by Regions, 2000CE

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

Panel A

				Excl. China, Japan, Korea	
	North & Western Europe (1)	Eastern Europe (2)	Southern Europe (3)	South & Southeast Asia (4)	Central & West Asia (5)
Log rural density (β_g)	0.159	0.303	0.278	0.145	0.177
	(0.041)	(0.078)	(0.085)	(0.039)	(0.033)
p-value $\beta = 0$	0.000	0.000	0.001	0.000	0.000
p-value $\beta = \beta_{NWEur}$		0.098	0.201	0.812	0.730
Countries	16	9	8	13	18
Observations	1412	4812	947	3184	2208
R-square (ex. FE)	0.34	0.33	0.38	0.26	0.24

Panel B

	Temperate Americas	Tropical Americas	Tropical Africa	South Africa	North Africa
Log rural density (β_g)	0.137	0.079	0.071	0.103	0.363
	(0.040)	(0.015)	(0.017)	(0.071)	(0.048)
p-value $\beta = 0$	0.001	0.000	0.000	0.145	0.000
p-value $\beta = \beta_{NWEur}$	0.710	0.071	0.063	0.502	0.002
Countries	5	22	39	4	5
Observations	3011	8653	2638	154	1186
R-square (ex. FE)	0.24	0.13	0.22	0.32	0.32

Panel C

	All China (1)	Temperate China (2)	Sub-Tropical China (3)	Japan (4)	North & South Korea (5)
Log rural density (β_g)	0.259	0.369	0.054	0.121	0.139
	(0.068)	(0.059)	(0.029)	(0.015)	(0.010)
p-value $\beta = 0$	0.000	0.000	0.066	0.000	0.000
p-value $\beta = \beta_{NWEur}$	0.209	0.004	0.042	0.402	0.650
Countries	1	1	1	1	2
Observations	190	99	91	848	237
R-square (ex. FE)	0.35	0.35	0.34	0.36	0.32

Notes: Conley standard errors, adjusted for spatial auto-correlation with a cutoff distance of 500km, are shown in parentheses. All regressions include province fixed effects, a constant, and controls for the district urbanization rate and log density of district nighttime lights. See appendix for lists of exact countries included in each region. The coefficient estimate on rural population density indicates the value of β_g, see equation (**??**). The countries included in each region can be found in this appendix.

Table A.5: Estimates of Land Elasticity, β, Expanded Definitions

Dependent Variable: Log caloric yield (A_{isg})

	Suitable for:			Urban Pop. $< 25K$ Suitable for:		
	Temperate and Tropical	Any Temperate	Any Tropical	Temperate and Tropical	Any Temperate	Any Tropical
	(1)	(2)	(3)	(4)	(5)	(6)
Log rural density (β_g)	0.140	0.179	0.132	0.156	0.202	0.145
	(0.013)	(0.017)	(0.011)	(0.015)	(0.020)	(0.013)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
Countries	119	137	137	110	131	130
Observations	15692	26353	24780	11008	18656	17670
R-square (ex. FE)	0.14	0.19	0.13	0.15	0.21	0.14

Notes: Conley standard errors, adjusted for spatial auto-correlation with a cutoff distance of 500km, are shown in parentheses. All regressions include province fixed effects, a constant, and controls for the district urbanization rate and log density of district nighttime lights. The coefficient estimate on rural population density indicates the value of β_g. "Temperate and tropical" includes all districts that are suitable for *both* tropical and temperate crops (as defined in the text). "Any temperate" includes any district that is suitable for temperate crops (regardless of their suitability for tropical crops), and "Any tropical" is defined similarly for tropical crops regardless of suitability for temperate.

Table A.6: Country-level aggregate land elasticity estimate

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

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