Land Quality and International Agricultural Productivity: A Distance Function Approach[1]

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Increases in agricultural productivity are one of the main drivers of increases in agricultural growth. Agricultural growth in developing countries makes major contributions to overall economic growth and reductions in hunger and poverty. In more developed countries, increases in agricultural productivity have served to keep food inexpensive for consumers and have kept the agricultural sector competitive with other countries.

Economists have a long-standing interest in the study of agricultural productivity. Researchers study cross-country differences in agricultural productivity to gain a better understanding of the factors that are most effective in increasing agricultural productivity. Although analysts have long recognized that land quality plays an important role in agricultural productivity, land quality has been difficult to quantify and include in productivity models due to data limitations.

An important component of productivity measurement is technical efficiency—the measure of how well producers convert inputs to outputs when compared to a given standard. Typically, when comparing producers (such as countries), efficiency is measured relative to a common technology frontier that represents the maximum level of output that can be produced with a given level of input(s). However, differences in production structure may limit the ability of a producer to achieve efficiency relative to this common frontier. Land quality is one such factor that affects production structure and thus the ability to achieve efficiency. For example, a country must take its soil and climate as given and uncontrollable, at least in the short term, even though they contribute greatly to total agricultural output.

Previous studies have attempted to incorporate the impact of land quality on agricultural productivity by including a land quality proxy as an explanatory variable in an econometrically estimated agricultural production function. For example, Hayami and Ruttan (1985) tried to adjust for differences in land quality among countries by including the ratio of irrigated land to total land area and the ratio of cropland to pastureland as variables in their econometric models of agricultural labor productivity.

Peterson's (1987) unpublished land quality index has also been used as a land quality indicator in agricultural productivity studies. Peterson's index is based on the share of a country's agricultural land that is not irrigated, the share of its cropland that is irrigated, and the log of its long-run average annual precipitation, weighted by coefficients derived from a cross-sectional analysis of land prices in the US. Frisvold and Ingram (1995) found this land quality indicator to be highly significant in explaining differences in land productivity for a sample of 28 sub-Saharan African countries.

More recently, Craig, Pardey, and Roseboom (1997) econometrically estimated the agricultural labor productivity of 98 countries and included long-run average rainfall, the percentage of land that was arable, and the percentage of land not irrigated as proxies for land quality. They found that countries with higher land quality had higher labor productivity. Mundlak, Larson, and Butzer (1999) used two proxies for land quality—potential dry matter and a factor of water deficit—and found both to have a significant impact on explaining cross-country differences in agricultural output. Jaenicke and Lengnick (1999) developed a method based on distance functions to derive a soil quality index at the plot level. Soil quality attributes were considered directly as inputs in the production model. A regression model was used to determine the importance of each attribute in explaining productivity differences between plots.

Researchers have had some success using various proxies for land quality in econometric productivity studies. However, newly available, spatially referenced land and climate data have motivated the search for improved land quality indicators. The hope is that such indicators will better describe the land quality environment typically faced by farmers, and thus offer more precise comparisons of productivity. This paper applies an example of this new type of land quality indicator to a study of cross-country technical efficiency in agricultural production.

In this paper, we address two questions. Do variations in land quality between countries affect their technical efficiency, and thus their productivity? If so, how much of the measured inefficiency can be attributed to poor land quality? First, we describe a land quality index (LQI) derived from new global land-cover data (generated from satellite imagery) combined with geo-referenced data on soil qualities, temperature, and precipitation. The LQI is then used in a distance function model to measure the impact of land quality on differences in agricultural efficiency for a cross-section of 110 countries. Distance functions are the first step in constructing intertemporal Malmquist productivity indices (MPIs). Computation of the Malmquist productivity index, which is a composite of four distance functions, requires data from two (or more) time periods. Unrestricted productivity growth and land quality limited productivity growth are compared for the sample of countries to highlight the role of land quality in agricultural productivity growth.

A NON-PARAMETRIC MODEL TO DECOMPOSE LAND QUALITY AND NON-LAND QUALITY EFFECTS

Land Quality and Technical Efficiency

Figure 10.1 depicts a production system with a single input and single output. The line describes the technology frontier for this system. Any producer whose input/output combination lies on the production possibility curve is said to be technically efficient. Observations that lie below the frontier, such as producer *A*, are inefficient because the same level of output could be produced with less input. If the output of producer *A* is held constant, a reduction of input use from *a* to *c* would move *A* to the frontier. This system assumes that all producers can reach the frontier by producing efficiently.

In fact, non-controllable factors may prevent some producers from reaching the efficient frontier, regardless of input level. Figure 10.2 adds a second frontier, inferior to the first, that describes efficient input/output combinations for producers that are limited by some non-controllable factor, such as poor land quality. If producer A is limited by poor land quality, the reduction in input use needed to reach this "achievable" frontier will be less than that implied by the unrestricted frontier. In this case, the reduction in input use that is required to make producer A efficient with respect to the achievable frontier is from *a* to *b*; any further reduction in input use by producer A would result in a decrease in the level of output.

Because producer A is operating in an environment less favorable than the unrestricted environment, its efficiency computed with respect to all countries will be lower than that computed with respect to countries sharing its own environment. The distance between *b* and *c* in Figure 10.2 represents the magnitude of the gap between the two frontiers. This gap between frontiers can be interpreted as the contribution of land quality to technical inefficiency measured with respect to the unrestricted frontier. In the simple single-input/single-output system shown in Figures 10.1 and 10.2, land quality's contribution to technical inefficiency can be expressed as the ratio of the reductions in inputs implied by the two frontiers, namely the ratio cb/ca. For systems of higher dimensionality (i.e. with multiple inputs and/or outputs), the distances must be characterized in a more general fashion.

The relative technical efficiency of producers can be characterized by a distance function. Following Färe, Gosskopf and Lovell (1994), we define an input set *X(y)* as the set of all inputs *x* that can produce a given output level *y*. The input distance function *D(x,y)* is a scalar value that describes the maximum proportional decrease in inputs achievable for a given level of output so that the input level remains in the set *X(y)*.

The input-oriented distance from an observation to the frontier for a production system using *J* inputs and *K* outputs can be expressed as the optimal solution to the following linear program:

$$D(x, y) = \min \theta_d \tag{1}$$

subject to the constraints

$$\begin{aligned} \sum_{i\in I} \lambda_i x_{ij} &\le \theta_d x_{dj}, & j &= 1,\ldots, J \\ \sum_{i\in I} \lambda_i y_{ik} &\le y_{dk}, & k &= 1,\ldots, K \\ \lambda_i &\ge 0 \end{aligned} \tag{2}$$

where the set I contains all the observations that are eligible to define the frontier relative to observation *d*, and x_{dj} and y_{dk} contain the input and output data elements for the observation being evaluated, respectively. The inputs and outputs for each observation are contained in the parameters x_{ij} and y_{ik}. The optimal solution to the linear program for each observation *d* includes the value θ_d, which takes values between zero and one. A value of θ_d equal to one means that the observation lies on the frontier—it is technically efficient. The observations for which λ_i is greater than zero determine the part of the frontier with which the country is being evaluated. It is relative to the performance of these observations that the technical efficiency of observation *d* is measured. This mathematical program is referred to as an input-oriented, constant-returns-to-scale data-envelopment-analysis (DEA) model.

Land Quality and Productivity

Productivity growth (or decline) can be defined as the observed change in outputs over time relative to the observed change in inputs. For production systems with a single output and a single input, productivity change can be defined simply as the change over time in the ratio of output quantity to input quantity. For production systems with multiple inputs and/or multiple outputs, a method that conveniently aggregates inputs and outputs is necessary. The distance function is one method that accomplishes such an aggregation. Expanding the definition of the distance function slightly, we denote the distance from a producer's input and output levels in one period, *s*, relative to the technology defining the frontier in another period, *r*, by the function $D^r(x_s,y_s)$. The Malmquist productivity index is defined by Färe, Grosskopf, and Lovell (1994) as

$$M(x_t, y_t, x_{t+1}, y_{t+1}) = \left(\frac{D^t(x_{t+1}, y_{t+1})}{D^t(x_t, y_t)} \frac{D^{t+1}(x_{t+1}, y_{t+1})}{D^{t+1}(x^t, y^t)} \right)^{1/2} \tag{3}$$

A value of the MPI greater than one signifies productivity improvement, and a number less than one denotes productivity decline. This expression can be further decomposed into terms that distinguish efficiency change and technical change between the two periods:

$$M(x_t, y_t, x_{t+1}, y_{t+1}) = \left(\frac{D^{t+1}(x_{t+1}, y_{t+1})}{D^t(x_t, y_t)} \right) \left(\frac{D^t(x_{t+1}, y_{t+1})}{D^{t+1}(x_{t+1}, y_{t+1})} \frac{D^t(x_t, y_t)}{D^{t+1}(x_t, y_t)} \right)^{1/2} \tag{4}$$

The first term in brackets is the change in efficiency between the two periods. The second term is the geometric mean of the frontier shifts in each time period, representing the change in technology.

To evaluate the influence of land quality on agricultural efficiency (hence productivity), we compute for each observation two groups of distance functions. The first group of distance functions is computed with respect to all producers. That is, the set *I* contains all countries in the data set. These unrestricted distance functions are denoted $D_U(x,y)$. The second group of distance functions is computed for each country only with respect to those countries for which the land quality index is less than or equal to that of the given producer. These land quality-limited distance functions are denoted $D_L(x,y)$. The degree to which the two frontiers are similar is indicated by the ratio of the two efficiency measures:

$$\alpha_{LQ} = \frac{D_U(x,y)}{D_L(x,y)} \tag{5}$$

Since the unrestricted frontier always lies above the limited frontier, an observation will always be farther from the unrestricted frontier than it is from the limited frontier, and thus less efficient relative to the unrestricted frontier than it is relative to the limited frontier. Therefore $D_U(x,y)$ is always less than or equal to $D_L(x,y)$. Since both values are always greater than zero, it follows that $0 \le \alpha_{LQ} \le 1$. A value of $\alpha_{LQ} = 1$ implies that the producer is efficient, or equally inefficient, with respect to both frontiers. In this case land quality does not contribute directly to inefficiency; all inefficiency is attributable to input use. A value of α_{LQ} that is less than one implies that a portion of the inefficiency measured by D_U can be attributed to poor land quality. Since α_{LQ} measures the *agreement* between the two frontiers, the percentage *difference* between the unconstrained and limited measures is given by $100*(1-\alpha_{LQ})$.

Substituting $\alpha_{LQ} D_L(x,y) = D_U(x,y)$ into equation 4 (with $D_U(x,y)$ taking the place of $D(x,y)$) allows further decomposition of the MPI into land quality, technical change, and efficiency change components:

$$M(x_t, y_t, x_{t+1}, y_{t+1}) = \left(\frac{\alpha_{LQ}^{t,t+1} \alpha_{LQ}^{t+1,t+1}}{\alpha_{LQ}^{t,t} \alpha_{LQ}^{t+1,t}} \right)^{1/2} \left(\frac{D_L^{t+1}(x_{t+1}, y_{t+1})}{D_L^t(x_t, y_t)} \right) \left(\frac{D_L^t(x_{t+1}, y_{t+1})}{D_L^{t+1}(x_{t+1}, y_{t+1})} \frac{D_L^t(x_t, y_t)}{D_L^{t+1}(x_t, y_t)} \right)^{1/2} \tag{6}$$

(Productivity growth) = (Land quality contribution)*(Efficiency change)*(Tech. change) where $a_{LQ}^{m,n}$ is the ratio of the unconstrained and constrained efficiency measures evaluated with data at time *n* with respect to the frontier at time *m*. A similar decomposition is derived in Jaenicke and Lengnick (1999). In that work, soil quality measures are considered directly as inputs in the (equivalent) function D_U and are used to derive a soil quality index using a process similar to that described above. In our work, we start with the land quality index as a non-controllable environmental factor, and seek to measure the impact of differences in the index on agricultural efficiency.

GLOBAL AGRICULTURAL PRODUCTIVITY

The Data

Inputs and outputs

Data on output and conventional inputs are taken from published and unpublished sources at the Food and Agriculture Organization (FAO). Data from 1980 to 2003 for 109 countries were used. The output variable is the value of all agricultural production, measured as the sum of price-weighted quantities of all agricultural commodities, expressed in international dollars, after deductions for feed and seed. There are four input variables: agricultural land, represented by the total agricultural land within a country, i.e. the sum of arable land, permanent cropland, and permanent pasture; labor, assumed to be the total economically active population in agriculture; machinery, which refers to the total number of tractors used in agriculture; and fertilizer, which refers to the total quantity of fertilizer consumed in agriculture calculated as a three-year moving average.

Land quality index

We do not use time-variant measures of land quality—the percentage of agricultural land that is classified as arable land or permanent cropland, and the percentage of arable land or permanent cropland that is not irrigated. While frequently used, either directly or indirectly (via the Peterson index), these measures may reflect a variety of economic and other influences in addition to purely physical quality differences. In an effort to better isolate and control for the effects of differences between countries in inherent land quality, we use a land quality indicator that incorporates soil and climate properties of each country's cropland. This measure is based on the FAO's Digital Soil Map of the World and associated soil characteristics (e.g., slope, depth, and salinity), combined with spatially referenced long-run average temperature and precipitation data.

Wiebe et al. (2000) used as their index of land quality the share of each country's cropland that is found in the highest three land quality classes. We use a measure that is based on the same underlying data but incorporates a wider range of both land cover categories and land quality classes: the average quality—on a scale of 3 (poorest) to 11 (best)—of each country's cropland, irrigated cropland, and grassland. (Classes 0-2 represent inland water bodies and other unranked categories.) This measure ranges from a low of 3.04 in Saudi Arabia to a high of 9.86 in Bulgaria, has a median of 6.75, and lies between 6.00 and 8.00 in 77 of the 110 countries studied.

Land Quality's Influence on Agricultural Productivity

Table 1 shows the average annual productivity growth rate from 1980 to 2003. The countries are ranked in order of decreasing land quality index. The third column shows the productivity with respect to the unrestricted frontier, as computed by equation (4). The fourth column shows the productivity with respect to the unrestricted frontier; that is, equation (6) divided by the first term of equation (6).

For the countries with higher land quality, the productivity value differs very little between the unrestricted and restricted measures. For countries with lower land quality, the measures diverge. The divergence can be either negative or positive, depending on whether the first term of equation (6) is greater than or less than one. Some countries, primarily sub-Saharan African countries, experience a switch from positive productivity to negative productivity (Cote D'Ivoire, Ghana, Cameroon, Tanzania, Sierra Leone, N. Korea, Ethiopia, Lesotho, Senegal, Kenya, Mali, Botswana, Afghanistan, Algeria and Egypt). This implies that poor land quality is impeding productivity growth. Other countries show changes from negative productivity to positive productivity (El Salvador, Indonesia, Guinea-Bissau, Angola, Nepal, Mozambique and Niger).

CONCLUSIONS

Land quality is an important factor affecting agricultural efficiency, and as a consequence, the productivity of agriculture over time. The importance of this factor, as one would expect, is greatest in countries with the poorest land quality. At the farm scale, poor soil and grazing land reduces potential crop yields and livestock productivity, limiting both production and income. At the country level, poor land quality translates to lower agricultural output than in non-limited environments, limiting the ability to feed growing populations (whether through domestic production or commercial imports).

Because land quality varies both within and between countries and is largely uncontrollable in the short term, productivity measures for countries with poor land quality may be underestimated relative to the productivity level that they can actually achieve. For the true productivity potential of a country to be measured, it is necessary to separate the share of inefficiency that is attributable to land quality from that which is due to inefficient use of inputs. Productivity measures that do not account for differences in land quality will thus overestimate the potential of countries with poor land quality, and possibly lead to unsound policy decisions. For example, because low levels of land quality restrict production possibilities, increases in input use in low LQI countries will have a smaller impact on agricultural productivity than in countries with a high LQI. The reduced marginal return further limits the use of fertilizers and other inputs. For these resource constrained environments, suitable technologies and policies are needed, such as drought tolerant and nutrient efficient crops.

In this study, we have assumed that all differences between the unrestricted and limited frontiers are attributed to land quality. In reality, there are likely to be other factors that contribute to such differences as well. Therefore, the land quality-constrained measures developed in this work must be viewed as upper bounds on the contribution of land quality to efficiency/productivity differences. Future research is needed to disentangle these multiple factors—including the influence of non-conventional inputs such as research and education—that contribute to differences in efficiency and productivity. Development of time-series data on land quality would also permit improved analysis of changes in productivity over time.

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Figure 1: Technical efficiency

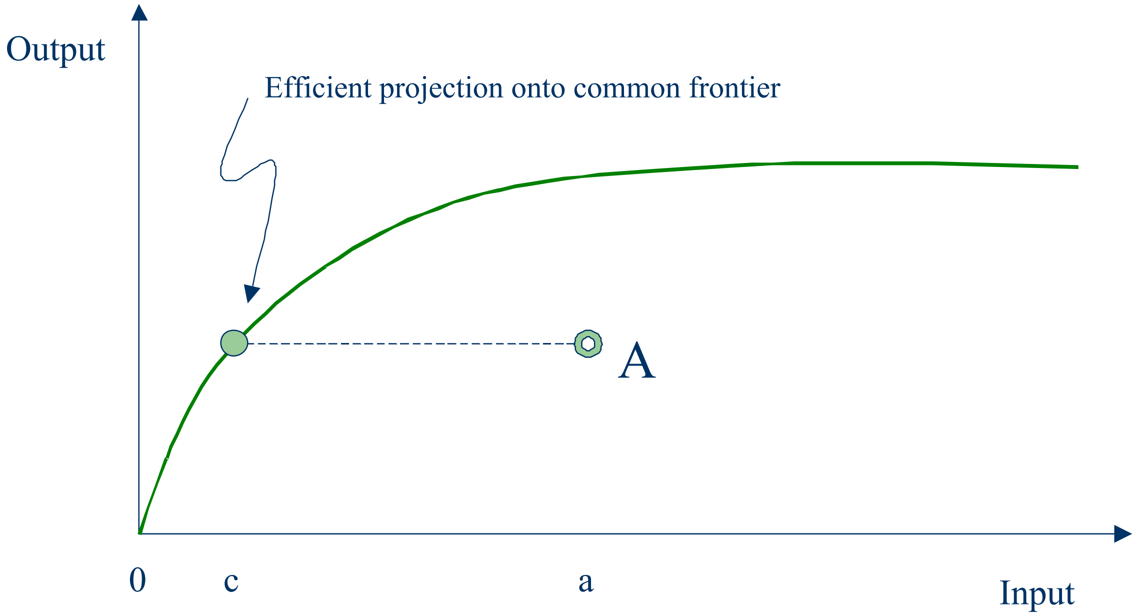

Figure 2: Technical efficiency with respect to the LQ-limited frontier