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Geography and Agricultural Productivity: Cross-Country Evidence from Micro Plot-Level Data

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We quantify the role of geography and land quality for agricultural productivity differences across countries using high-resolution micro-geography data and a spatial accounting framework. The rich spatial data provide for each cell of land covering the entire globe, the potential yield for 18 crops, which measures the maximum attainable crop output given soil quality, climate conditions, terrain topography, and a given level of cultivation inputs. While there is considerable heterogeneity in land quality across space, even within narrow geographic regions, we find that low agricultural land productivity is not due to unfavourable geographic endowments. If countries produced current crops in each cell according to potential yields, the rich-poor agricultural yield gap would virtually disappear, from 214% to 5%. We also find evidence of additional aggregate productivity gains attainable through spatial reallocation and changes in crop production.

Key words: Agriculture, Land quality, Productivity, Spatial allocation, Crop choice, Cross-country

JEL Codes: O11, O13, O40, O41, Q10, R11.

1. INTRODUCTION

Understanding the large differences in labour productivity across rich and poor countries is a fundamental issue on the research agenda in economics. It is well understood that poor countries have disproportionately low agricultural productivity and large agricultural sectors, when compared to rich countries (Gollin *et al.*, 2002; Caselli, 2005; Restuccia *et al.*, 2008). Why is agricultural productivity so low in poor countries? The answer to this question has important implications for poverty reduction, welfare, structural transformation, and development.

There are two possible broad explanations for the disparity in agricultural productivity across countries. First, due to varied institutions, constraints, frictions, or policies, countries make

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different economic choices in agriculture, affecting the level of productivity. Second, due to unfortunate endowments, featuring low land quality, rugged geography, and arid lands, some countries may have a natural disadvantage in agriculture. Understanding which of these two broad explanations is the main source of low agricultural productivity across countries is essential and has dramatically different implications for policy. The vast majority of research has focused on explanations of constrained economic decisions affecting agricultural productivity. The role of land quality and geography, while often presumed and invoked in public debates on development, is largely unexplored on a systematic cross-country basis. We examine the role of geography and land quality in accounting for agricultural productivity differences across countries. While we find evidence of considerable heterogeneity in land quality, even within narrow geographic regions, our main finding is that, at the country level, differences in land quality and geography cannot explain much of the observed differences in agricultural productivity.

A distinctive feature of agriculture is that it is an activity that takes place across space, using location-specific inputs such as soil quality, climate conditions, and terrain topography. These inputs could matter not only for what yield is obtained for any crop cultivated, but also for what crops are ultimately cultivated in each cell (Holmes and Lee, 2012) and what cells are used for agricultural production.

We quantify the role of geography and land quality for agricultural productivity across 162 countries using an accounting framework and high-resolution gridded micro-geography data, covering the entire globe, from the Global Agro-Ecological Zones (GAEZ, 2000) project of the Food and Agricultural Organization (FAO). A land cell in the gridded data is roughly a 10 by 10 km plot, which should not be confused with plots of land operated by individual farms that in developing countries would typically be less than one hectare (Adamopoulos and Restuccia, 2014). GAEZ (2000) provides land quality attributes on each land cell in the world and, more importantly, potential yields for all the main crops, including crops not necessarily produced in the cell. The data on potential yields by crop are generated by combining *cell*-specific land quality attributes with established *crop*-specific agronomic models, for a given level of water supply and cultivation inputs. Potential yields summarize how detailed geographical attributes translate into productivity by crop. That is, differences in potential yields across cells, given inputs, represent a measure of differences in geography total factor productivity.

We develop a spatial-accounting framework that allows us to aggregate up from the cell-crop level resolution to the country level. Within a country, each of a fixed number of cells can produce any of a given number of crops. However, land cells are heterogeneous with respect to their inherent suitability in producing each crop, captured in the GAEZ data by its potential yield. We show that a country's aggregate yield, the value of total output per harvested land ($/ha), can be expressed as a weighted average of the cell-crop yields valued at common prices, where the weights are the cell-crop land shares.[1] We use this expression of the aggregate yield to construct counterfactual yields. Our main counterfactual asks, what would aggregate yields be if each country produced each crop in each cell according to its potential yield, keeping the cell-crop land shares fixed to the actual data? If the disparity in aggregate yields across countries were similar under potential yields, then this counterfactual would indicate that most of the variation in aggregate actual yields is due to geography and land quality differences. In order to focus on the natural suitability of the land, for our baseline results, we use GAEZ's crop-cell potential yields under rainfed water supply and low-input cultivation practices (rainfed low-input scenario),

1. The measure of agricultural productivity that we focus on, given the GAEZ data, is the value of agricultural output per unit of harvested land ($/ha), also known as land productivity or yield. While cross-country differences in aggregate yields account only for a portion of agricultural labour productivity differences, yields encapsulate the role of land quality and geography.

which assumes subsistence based farming, labour intensive techniques, and no application of fertilizers and pesticides. We find that, if the ten percent richest and poorest countries produced crops according to their production-potential yields, the rich–poor agricultural yield gap would virtually disappear, from more than 200% to 5%. The relationship between aggregate production potential and actual yields across all countries is completely flat, implying that cross-country variation in aggregate actual yields is not due to geography and land quality variation. If the ten percent most and least land-productive countries in agriculture produced according to potential yields in each cell and each produced crop, the aggregate yield gap would shrink from a whopping 790% to only 42%.

We also find that the location of crop production within a country and crop choices within cells play important but secondary roles. Spatial reallocation raises productivity in all countries, but slightly more for low income countries. If in addition, the crop mix changes cell-by-cell in each country to the highest value yield, then the aggregate rich-poor yield gap reverses to a 20% advantage for the poorest countries. Changes in spatial and crop choices could reduce aggregate yield gaps across the most and least land productive countries by one fifth. These findings are robust to assumptions about input use and water supply conditions. In addition, the use of irrigation and complementary inputs generates aggregate potential yield gains for all countries, particularly low income countries.

Using a standard two-sector model of agriculture and the rest of the economy, we show that the gains in productivity associated with production-potential yields across countries has important quantitative implications for structural transformation, average farm size, agricultural labour productivity, and income per capita.

Our paper contributes to the growing literature studying agricultural productivity differences across countries. One branch of this literature assesses the contribution of specific factors on agricultural productivity.[2] Another branch focuses on measuring sectoral productivity gaps (Herrendorf and Schoellman, 2015; Gollin *et al.*, 2014a) or agricultural productivity disparities (Prasada Rao, 1993; Restuccia *et al.*, 2008; Gollin *et al.*, 2014b). We instead focus on measuring the role of land quality and geography for agricultural productivity gaps using spatially explicit micro-geography data.

An earlier literature on geography and economic development emphasizes both the direct effect of geography on income (Gallup *et al.*, 1999; Sachs, 2003), as well as its indirect effect through the institutions channel (Acemoglu *et al.*, 2002; Easterly and Levine, 2003; Rodrik *et al.*, 2004). While the above literature relies on country-level data and focuses on aggregate incomes, we use detailed geo-spatial data and focus on the more direct impact of geography and land quality for agriculture, a sector where the observed geographic conditions would tend to matter the most.

It is well documented that countries with higher temperatures tend to be poorer (Nordhaus, 2006; Dell *et al.*, 2009, 2012). The literature that studies the effect of temperature and the potential impact of climate change on agricultural productivity finds that rising temperatures lead to reductions in crop yields, particularly beyond some threshold (Schlenker and Roberts, 2009; Calzadilla *et al.*, 2013; Burke *et al.*, 2015; Zhao *et al.*, 2017). The economics and agronomic literatures have also studied the impact of other geographic attributes on crop yields, such as rainfall (Jayachandran, 2006; Levine and Yang, 2014), soil quality (Cassman, 1999), and topography (Kravchenko and Bullock, 2000). While these studies isolate the impact of individual

2. Examples include low intermediate input use and misallocation of labor between agriculture and non-agriculture (Restuccia *et al.*, 2008); poor transport infrastructure (Adamopoulos, 2011); selection (Lagakos and Waugh, 2013); misallocation of factors across farms within agriculture (Adamopoulos and Restuccia, 2014), international transport frictions (Tombe, 2015); idiosyncratic risk (Donovan, 2020), among others.

attributes, our analysis accounts for all geographic attributes that impact the biological growth of crops.

An agronomic literature estimates yield gaps for particular crops and particular regions (*e.g.* Lobell *et al.*, 2009; Mueller *et al.*, 2012; Tittonell and Giller, 2013; van Ittersum *et al.*, 2013). Instead we assess yield gaps using a consistent methodology on a global scale at various levels of disaggregation and we use potential yields to assess the role of land quality on productivity differences across countries. Other studies focus on cross-country differences in aggregate land quality indices and their effect on agricultural productivity (Wiebe, 2003; Wiebe *et al.*, 2000), whereas we exploit the explicit spatial nature of the micro-geography data in GAEZ using an accounting framework. Our results are consistent with this literature, especially when controlling for agricultural practices and the level of inputs in cross-country regressions of land quality on agricultural productivity.

While the GAEZ data are increasingly used in economics (e.g., Nunn and Qian, 2011; Galor and Özak, 2016; Costinot *et al.*, 2016; Godefroy and Lewis, 2018), we exploit the GAEZ data to study the macro-level implications of land quality endowments for cross-country differences in agricultural productivity, an issue that is paramount for understanding the foundation of poverty across the world.[3] Given that we find additional potential productivity gains from the frictionless reallocation of production across crops and space, our findings are consistent with the literature on the role of spatial frictions and location specific productivity shocks for Ricardian trade and development (Costinot *et al.*, 2016; Costinot and Donaldson, 2016).[4]

The article proceeds as follows. The next section describes the GAEZ data and provides some measures of land quality dispersion across countries. In Section 3, we outline the spatial accounting framework and describe counterfactuals. Section 4 presents the main findings and robustness analysis. In Section 5, we study the sectoral and aggregate implications from a drop in the agricultural productivity gap between rich and poor countries. We conclude in Section 6.

2. DATA

We describe the details of the data and characterize differences in land-quality attributes across countries based on this data.

2.1. *Description*

We use gridded micro-geography data from the Global Agro-Ecological Zones (GAEZ, 2000) project, developed by the Food and Agricultural Organization (FAO) in collaboration with the International Institute for Applied Systems Analysis (IIASA) and aggregate cross-country income data from the Penn World Table, PWTv6.3 (Heston *et al.*, 2009). GAEZ (2000) is a standardized framework for the characterization of climate, soil, and terrain conditions relevant for agricultural production. GAEZ (2000) combines state-of-the-art agronomic models by crop, that account for science-based biophysical growing requirements for each crop, with high resolution spatial data on geographic attributes.

The information in GAEZ is available at the 5 arc-minute resolution. To picture it, imagine super-imposing a grid of about 9 million cells or pixels covering the entire world. Figure 1 displays a grid map of the Montreal and Toronto area in Canada, based on cells of different resolutions,

3. See also Costinot and Donaldson (2012) and the survey in Donaldson and Storeygard (2016) on high-resolution spatial data in economics.

4. See also Gouel and Laborde (2021), Porteous (2019), and Sotelo (2020).

FIGURE 1

Grid resolution example Montreal-Toronto area

Notes: The pink-thin grid represents a 5 arc min; the blue-thicker grid a 30 arc min; and the black-thickest grid a 60 arc min.

where the pink-thin grid represents a 5arc min; the blue-thicker grid a 30 arc min; and the black-thickest grid a 60-arc min. While the size of each cell is constant at 5 arc min in the data, it is not constant in terms of squared kilometres or hectares, as the mapping from arc-minutes to square kilometres depends on the distance from the equator (latitude). As a rough approximation the size of each cell can be described as 10 km $\times$ 10 km.

For each cell in the grid, GAEZ (2000) reports data on the following location-specific geographic attributes that are important for agricultural production: (1) soil quality, which includes depth, fertility, drainage, texture, chemical composition; (2) climate conditions, which include temperature, sunshine hours, precipitation, humidity, and wind speed; and (3) terrain and topography, which include elevation and slope. Importantly, GAEZ calculates a potential yield for a set of crops in each cell, measured as the maximum output (in tonnes) per hectare that can be attained in the cell given the crop's production requirements, the cell's characteristics, and assumptions about input levels such as water supply conditions and cultivation practices. Therefore, differences in potential yields represent measures of total factor productivity differences of cell-level geographic attributes for each crop given water conditions and inputs of cultivation practices. Unfortunately, the GAEZ data do not provide information on actual amounts of inputs. Given that the attainability of potential yields depends on access to inputs, we consider two input scenarios relevant for cross-country comparisons, as detailed below. Potential yields are provided for all major crops including those not actually produced in a particular cell. Note that production statistics of crops are usually measured in fresh weight, whereas GAEZ simulated potential production is measured in dry weight. We use GAEZ standard conversion factors by crop to make the two measurements equivalent.

There are two key ingredients that go into the GAEZ estimation of potential yields for each crop in each cell. First, the detailed micro-geography characteristics on soil quality, climate, and topography outlined above for that particular cell. Second, crop-specific agronomic models that reflect each crop's biophysical requirements for growth. The parameters of the agronomic models capture how a particular set of geographic conditions maps into any given crop's yield. These parameters are based on well tested field and lab experiments by agricultural research institutes, are established in the agronomic literature, and are updated to reflect the latest state of scientific knowledge.[5] We stress that the agronomic model parameters are not based off a regression analysis of observed choices on outputs and inputs across countries, regions, or farms, an analysis that would be subject to serious endogeneity issues.

Potential yields are reported for alternative configurations of water supply conditions and cultivation practices. Water supply conditions include: irrigated, rainfed, and total which covers both rain fed and irrigated land. There are three levels of cultivation practices which specify input intensity use and management: (a) Low level of inputs (traditional management) assumes subsistence based farming, labour intensive techniques, no application of nutrients, chemicals, and pesticides. (b) Intermediate level of inputs (improved management) assumes partly market oriented farming, improved varieties with hand tools and/or animal traction, some mechanization, medium labour intensity, use of some fertilizer, chemicals, and pesticides. (c) High level of inputs (advanced management) assumes mainly market oriented farming, high yield variety seeds, fully mechanized with low labour intensity, optimum application of nutrients, chemicals, and pesticides as well as disease and weed control. The idea is that the resulting crop yield in each cell would depend not only on the "endowment" of land quality and geography but also on the set of complementary inputs applied by the farmer. GAEZ (2000) also reports potential yields for a baseline mixed input scenario covering both irrigated and rainfed land, and assuming a mixed level of inputs, which applies high inputs on the best quality land, intermediate inputs on moderately suitable land, and low inputs on marginal land. This classification of land suitability for agriculture is based on cell-level data on soil type, terrain-slope conditions, and climatic conditions.

In our analysis, we consider two input scenarios: (1) the low input cultivation practices scenario with rainfed water supply conditions, which is the minimum input application in GAEZ; and (2) GAEZ's baseline scenario, which GAEZ considers as a reasonable representation of actual agricultural input application management. Throughout the paper, we refer to scenario (1) as "Low inputs," and scenario (2) as "Mixed inputs." Note that under each scenario we keep water supply and cultivation practice conditions constant across all cells and all countries. This allows for a consistent quantification of potential land productivity around the world.

Potential yields in GAEZ (2000) are calculated for both average historical climate conditions (with the baseline reference period being 1960–1990), individual historical years 1901–2009, as well as projected future climate conditions based on a number of climate models. In our analysis, we use potential yields based on the average historical climate conditions, as they iron-out year-to-year idiosyncratic weather shocks.

The GAEZ (2000) database also provides at the 5 arc min resolution, for the year 2000, estimated data on crop choice, actual production, harvested area, and actual yield, *i.e.*, tonnes of production per hectare (tonnes/ha) by crop. The actual production data for each cell are estimated using a flexible iterative rebalancing methodology that sequentially downscales aggregate and regional agricultural production statistics (see Supplementary Appendix B). The

5. The estimated levels of potential yields by cell are based on the employed agronomic models and the parameterizations adopted by the team of GAEZ agronomists, with possible measurement error. Given that the methodology is common across all grid cells in the globe, what is key for our results is the absence of a systematic bias in the GAEZ estimates or potential measurement error across countries.

actual production data at the cell level are available for all major crops. In addition, the database contains land cover data that classify land in each cell in terms of urban, cultivated, forest, grassland and woodland, water bodies, and other uses.

The data set we work with has global coverage, consisting of 162 countries. In 2000, the countries in our sample account for 87% of the world production of cereal in terms of acreage and 81% of the value of crop production.[6] The count of grid cells (pixels) per country varies widely, from as low as 5 (Antigua and Barbuda) to as high as 421,168 (Russia). The median country in our data set comprises 2827 cells. A complete list of the countries in our data set, along with their cell counts, and their GDP per capita are provided in Table A.1, Supplementary Appendix A. Our analysis focuses on 18 main crops and commodity groups, that cover the majority of produced crops across the world.[7] In 2000, the crops that are covered in our GAEZ analysis account for 83 percent of the harvested area and 60% of the value of production in total crops, across all countries in the world. The coverage of the crops in our analysis for the lower income countries is very similar, both in area and production (FAOSTAT, 2000). While crop production is only one component of the agricultural economy, our focus on crop production and yields is dictated by the available geo-spatial data from GAEZ (2000). In addition, productivity can be more accurately measured and compared across countries for crops than for livestock, and land quality is a more prominent issue for crops than for livestock. Nevertheless, the crop yield is strongly correlated with the overall agricultural yield that includes all forms of agricultural production. For instance, using country-level data from FAOSTAT (2000), the correlation between the log value of agricultural crop output per hectare of cropland and the log value of total (including livestock) agricultural output per hectare of agricultural land is 0.83, both measured in constant 2014–16 US$.

GAEZ (2000) provides the information for each variable in raster (grid cell) files. To aggregate cell-level information to administrative units, such as regions, provinces, and countries, we use shape files from the World Borders dataset of "Thematic Mapping" (TM, 2008).

2.2. *Land characteristics across the world*

We use the micro-geography data from GAEZ (2000) to illustrate the diversity of some key land quality and geographic characteristics across the world. We illustrate these characteristics in a set of maps constructed using ArcGIS for all the cells at the 5 arc min resolution in Figure 2. The soil fertility constraint classifies the soil according to its nutrient availability, which captures soil properties such as texture (*e.g.* clay, silt, sand), organic carbon content, acidity (pH), and the sum of sodium, calcium, magnesium and potassium. Nutrient availability is an important indicator of soil fertility, particularly in environments with low application of intermediate inputs. The classification determines how nutrient constrained the soil in each cell, ranging from no/slightly constrained (index value 1) to very severely constrained (index value 4). Except for the premafrost zones in the north, there is considerable variation in the soil constraint around the globe, that transcends country borders. We also document the median altitude (in meters), the mean temperature (in degrees Celsius), and annual precipitation (in mm) in each cell for the whole world. Altitude is an important indicator of terrain suitability for agricultural production, as it affects solar radiation, oxygen availability as well as temperatures and moisture. The altitude varies substantially across the world, with a high of 6500 meters to a low of -415 m. Temperature is an example of an indicator of thermal regimes, while rainfall is an example of an indicator of

6. Based on data from FAOSTAT (2000).

7. The crops in our data set are: wheat, rice, maize, sorghum, millet, other cereals (barley, rye, oat, and other minor cereals), tubers (white potato, sweet potato), roots (cassava, yam, and cocoyam), sugarcane, sugarbeets, pulses (chickpea, cowpea, dry pea, grams, pigeon-pea), soybean, sunflower, rapeseed, groundnut, oilpalm, olive, and cotton.

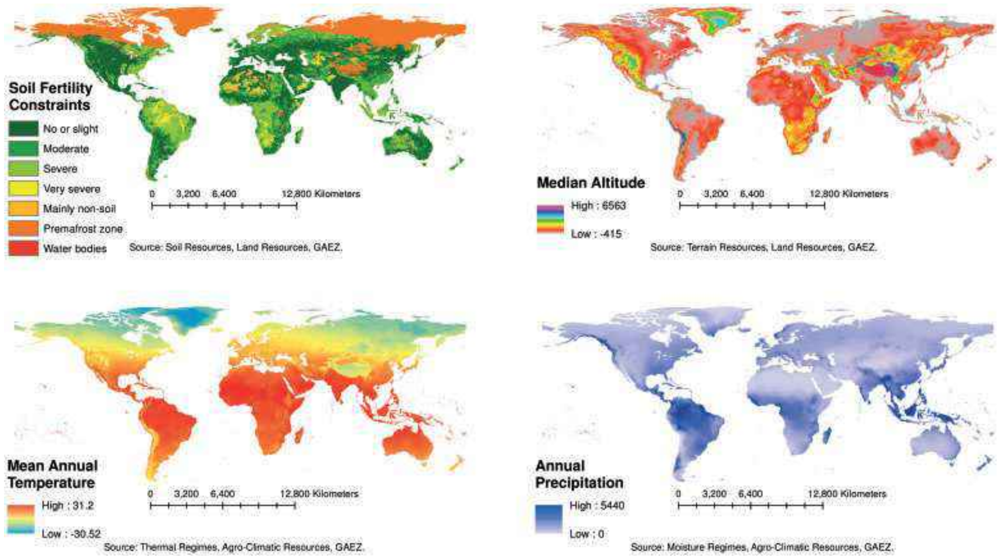

FIGURE 2

Geographic attributes around the world

moisture regimes. Both thermal and moisture regimes are important measures of agro-climatic conditions and serve as key inputs into the GAEZ methodology in constructing crop-specific potential yields by cell. The maps in Figure 2 illustrate the wide diversity in these agro-climatic conditions across the world.

It should not be surprising that there is such wide variation in land quality characteristics across the world. Even within narrow geographic regions some locations are naturally advantaged in terms of one or more characteristics, while others are naturally disadvantaged. The importance of a naturally advantageous geographic environment for agricultural production in a specific location is ubiquitous. However, agricultural productivity differences between the developed and developing world are often framed at the country level. As a result, we are interested in whether the land quality characteristics vary systematically across the most and least developed countries.

We examine cross-country variation in land quality attributes in Table 1 according to mean soil, terrain, and climate conditions. For soil quality conditions we report "fertility," which captures nutrient availability and is measured as an index from 1 (unconstrained) to 4 (constrained), and "depth," which captures rooting conditions, and is also measured as a 1 to 4 index. The terrain conditions we report are "slope," measured as an index between 0 and 100, and "altitude" which measures mean elevation in metres. The slope of a plot is important, as it can affect for example the farming practices employed (standard mechanization can be difficult on steep irregular slopes) and the extent of topsoil erosion. The climatic conditions we report are "temperature," measured in degrees Celsius and "precipitation," measured in millimetres. We report the averages of these attributes across countries in the richest and poorest deciles of the 162 countries in our sample and the averages over the countries with the top and bottom deciles of the cross-country distribution of each attribute.

The main finding from Table 1 is that there is substantial variation in land quality and geographic characteristics around the globe, but that this variation is considerably more compressed across rich and poor countries. In particular, the dispersion in mean attributes, measured as the log difference between rich and poor countries for each attribute, accounts

TABLE 1
Differences in mean geographical attributes

	Rich 10%	Poor 10%	Top 10%	Bottom 10%
Soil quality				
Fertility (1–4 index)	2.37	2.19	3.32	1.10
Depth (1–4 index)	2.19	1.93	3.41	1.08
Terrain conditions				
Slope (0–100 index)	72.0	78.5	96.1	38.1
Altitude (meters)	342.8	824.0	1799.4	60.4
Climate conditions				
Temperature (°C)	12.3	23.2	27.5	2.3
Precipitation (mm)	899.6	1074.9	2474.5	123.3

Notes: Top and bottom 10% refer to the average of the highest and lowest decile in the cross-country distribution for each attribute, whereas Rich and Poor 10% refer to the average attributes of the richest and poorest decile countries in terms of real GDP per capita.

for less than one quarter of the dispersion across the world, and for most attributes less than 10%. This finding suggests that the mean attribute differences are not systematic across the income distribution and as a result the unconditional cross-country variation dwarfs the rich-poor variation in each of the attributes.

While we find some variation between rich and poor countries in terms of soil, terrain, and climate attributes, what matters for aggregate agricultural productivity is how differences in geographical attributes translate into productivity differences across countries. Moreover, agricultural productivity is the result of all geographical conditions combined and differences in a single attribute may not matter as much. For this reason, in the next section we work with potential yields by cell and crop, as a summary measure of how dispersion in geographical attributes translates into productivity differences.

3. ACCOUNTING FRAMEWORK

We develop a spatial accounting framework to study the role of land quality and geographic characteristics on agricultural productivity.

3.1. *The primitives*

We consider a world comprised of a fixed number of administrative units indexed by $u \in \mathcal{U} \equiv \{1,2,...,U\}$. These units are countries in our analysis but in general could be lower administrative units within a country such as states, districts, or counties. Each administrative unit u comprises a finite number G_u of grid cells (or pixels) of fixed size. We index grid cells by $g \in \mathcal{G}_u \equiv \{1,2,...,G_u\}$ and aggregate cells to the country level using a mapping of cells to administrative boundaries in ArcGIS. Each grid cell can produce any of C crops, indexed by $c \in \mathcal{C} \equiv \{1,2,...,C\}$.

Cells are heterogeneous with respect to their land characteristics and as a result differ in the productivity of the land across crops. In particular, a key object reported in the GAEZ data is the *potential* yield or land productivity (tonnes/ha) of each cell for crop c. We denote the potential yield of crop c in grid cell g in unit u by $\hat{z}^c_{gu}$. Note that for each cell g in unit u there are C such numbers, each of which reflects the inherent productivity of that cell in producing crop c under a given input scenario (water conditions and cultivation practices). In other words, the potential yield of crop c in each cell represents the maximum attainable output for that crop given inputs and as such, variation in potential yields with constant inputs reflects variation in total factor productivity of land characteristics. We note that this variation does depend on input conditions and, as such, in our quantitative analysis we consider two inputs scenarios, which consistently characterize potential yields across countries.

In practice, the land in each cell can be used for crop production or some other activity (could be agricultural such as raising livestock or non-agricultural, or some other land cover category). If a portion of the land in a cell is used for crop production, it may produce one or several specific crops which may differ from the crops in which the cell has the highest potential yield. We denote by y^c_{gu} the physical output (in tonnes) of crop c and by ℓ^c_{gu} the amount of harvested land (in hectares) of crop c for any cell g and unit u. We denote by z^c_{gu} the actual yield of crop c which is just the ratio of physical output to land (tonnes/ha) in each cell but note that our analysis does not rely on this disaggregated actual yield nor on actual output by cell from GAEZ. Only the aggregated actual values at the country level matter for the analysis, which match the aggregate actual data by construction. For the purpose of aggregation, in any unit u and cell g, we set the amount of output and land used to zero if there is no production of a given crop c.

Similarly, for the purpose of aggregation of different crops in a location, we denote by p^c the price of each crop (in \$) which we treat as common across space and countries. Note also that the size of each vector is $C\times 1$, corresponding to the total number of crops in the GAEZ project which is 18 crops. In each cell g, all the vectors have non-zero elements only for the crops actually produced. The only vectors that have all non-zero elements for every crop are the potential yield and the price. The potential yield vector is specific to each cell g and unit u.

3.2. *Aggregate variables*

We denote with upper case letters aggregate variables at the country level. We denote by L_u the amount of land used in agricultural production in country u (in hectares), given by,

$$L_u = \sum_{c\in\mathcal{C}} \sum_{g\in G_u} \ell^c_{gu}.$$

We denote by Y_u the total value of agricultural output produced (\$), given by,

$$Y_u = \sum_{c\in\mathcal{C}} \sum_{g\in G_u} p^c y^c_{gu}.$$

Given these aggregates, we define the aggregate actual yield Z_u by the ratio of aggregate value output to land (\$/ha), that is,

$$Z_u = \frac{Y_u}{L_u} = \frac{\sum_{c\in\mathcal{C}} \sum_{g\in G_u} p^c z^c_{gu} \ell^c_{gu}}{L_u} = \sum_{c\in\mathcal{C}} \sum_{g\in G_u} p^c z^c_{gu} \frac{\ell^c_{gu}}{L_u}. \tag{3.1}$$

The aggregate yield is a weighted average of the yields in every crop and location in a given country. Equation (3.1) is key in our accounting analysis as it provides the basis for assessing the role of geography and land quality on agricultural land productivity across countries. Note also that by construction of the disaggregated actual data in GAEZ, the country-level aggregate *actual* yield Y_u/L_u is consistent with aggregate actual data on output and land. The spatially disaggregated data on actual output and yields are not relevant for our country-level analysis, only the disaggregated land-use data ℓ^c_{gu}/L_u as we discuss below.

3.3. *Counterfactuals*

We construct a set of counterfactuals on the aggregate yield for each country u by exploiting the set of potential yields by crop at the cell level g and the spatial distribution of land use by crop across cells. All the counterfactuals involve producing crops at potential and in some cases reallocating across space and crops. Because cell-specific potential yields depend on input conditions, we construct these counterfactuals for the rainfed low input scenario as our baseline, as this involves the least human intervention, and more closely captures the natural suitability of the land. We compare our baseline results to those under the mixed input scenario.

Production potential. We assess the impact on the aggregate yield in the case of countries producing at the potential yield for each crop and each cell. We compute this counterfactual by simply using in equation (3.1) the potential yield $\hat{z}^c_{gu}$ for each crop in each cell:

$$\hat{Z}_u = \sum_{c\in\mathcal{C}} \sum_{g\in G_u} p^c \hat{z}^c_{gu} \frac{\ell^c_{gu}}{L_u}.$$

In this counterfactual only the yield changes, while the weights represented by the share of cultivated land of a crop in each location are kept to the actual values ℓ^c_{gu}/L_u. Note that the construction of the aggregate production-potential yield depends only on the disaggregated data on potential yields and land used by crop.

If cross-country differences in the aggregate production-potential yield are similar to the aggregate actual yields, then production potential at the crop/cell level is an important determinant of the aggregate actual yield differences. Instead, if cross-country differences in aggregate productivity-potential yields are negligible, then geography and land quality are not important determinants of actual yield gaps across countries. A possible issue with this counterfactual may be that potential yields involve the application of inputs that are simply not available in the country. The GAEZ data does not allow us to separate from actual data at the cell or aggregate level the input conditions. As noted above however in our baseline results we consider the rainfed low-input scenario which captures the application of minimum inputs, that should be attainable by all countries and hence mitigates this concern.

Spatial potential. We assess the extent to which reallocation of agricultural production of the different crops to the most productive locations across space can increase aggregate output. This counterfactual combines production potential with a reallocation of crops across space to the most suitable locations. In particular, we reallocate production so that each crop is produced in the cells where it realizes the highest potential yields, keeping constant the amount of harvested land for that crop in the country to the actual level, *i.e.*, $L^c_u = \sum_{g\in G_u} \ell^c_{gu}$. This allocation problem is non-trivial. Some cells within a country may exhibit higher potential productivity for all crops, while the amount of land that can be allocated to a given crop is limited. We reallocate the production of crops to cells to maximize total constant-price value output based on potential yields of the different crops, i.e., to where the relative potential return for each crop is the highest. Formally, this involves solving a large-scale linear programming problem for each country, given by,

$$\max_{\left\{\ell^c_{gu}\right\}} \sum_{c\in\mathcal{C}} \sum_{g\in G_u} p^c \hat{z}^c_{gu} \ell^c_{gu}, \tag{3.2}$$

subject to

$$\sum_{c\in\mathcal{C}} \ell^c_{gu} \leq L_{gu}, \qquad g = 1,2,...G_u; \tag{3.3}$$

$$\sum_{g \in G_u} \ell^c_{gu} \leq L^c_u, \quad c = 1, 2, \ldots C; \tag{3.4}$$

$$\ell^c_{gu} \geq 0, \quad g = 1, 2, \ldots G_u; \quad c = 1, 2, \ldots C. \tag{3.5}$$

The objective is to maximize the total value of output across all cells and crops, subject to three sets of constraints. The first set of constraints restricts that land allocated to the production of the different crops cannot exceed what is available in each cell. The second set of constraints indicates that land allocated to crop c over all cells cannot exceed the total in the data. The third set of constraints allows for the possibility that not all crops are produced in all cells. Note again that the constraints only involve land allocations as the application of inputs in the GAEZ data is embedded in the different input scenarios we consider and cannot be separated out. The low input scenario however maps more directly to the allocation problem in equations (3.2) to (3.5). Given that our focus is on the role of land quality for production, we abstract from demand. This prevents us from drawing implications about welfare and analysing possible changes in local relative prices.

Total potential. We assess the extent to which countries may not be producing the highest yielding mix of crops in each location given their land endowment characteristics. This counterfactual involves computing the aggregate potential yield in each country by picking the crop in each location that maximizes the total value of output. Formally, we solve for ℓ_{gu} in equation (3.2) subject to only the constraints in equations (3.3) and (3.5). This counterfactual involves production potential, reallocation of crops across space, and changes in crop choices in order to maximize the aggregate value of agricultural output ($). It is the allocation that generates the maximum attainable value of output in each country given the total amount of land, and the set of potential yields by cell and crop. The difference between this counterfactual and the production potential counterfactual represents the contribution to the aggregate yield of crop-mix choices and the spatial reallocation of production, whereas the difference with the spatial reallocation is the contribution of crop choice changes to the aggregate yield.

4. RESULTS

We present the results for each counterfactual under our baseline rainfed low-input scenario for potential yields by cell and crop and show how aggregate actual and potential yields vary across countries. We then assess whether aggregate potential yields can account for agricultural land productivity (aggregate actual yield) across countries. We also present results for potential yields under the mixed-input scenario and other robustness results.

4.1. *Baseline results*

We calculate aggregate output per hectare (aggregate actual yield) using FAO international crop prices (Geary–Khamis dollars per tonne) for the year 2000. There are substantial differences in aggregate actual yields across countries. The ratio between the ten percent richest and poorest countries in terms of GDP per capita is a factor of 3.1-fold. This dispersion in aggregate yields is consistent with cross-country estimates using micro-data sources (Gollin *et al.*, 2014b). The aggregate actual yield varies systematically with the level of development (GDP per capita), with a correlation in logs of 0.58.

To what extent are aggregate yield differences across countries the result of differences in land quality and geography? We now address this question using our spatial accounting framework.

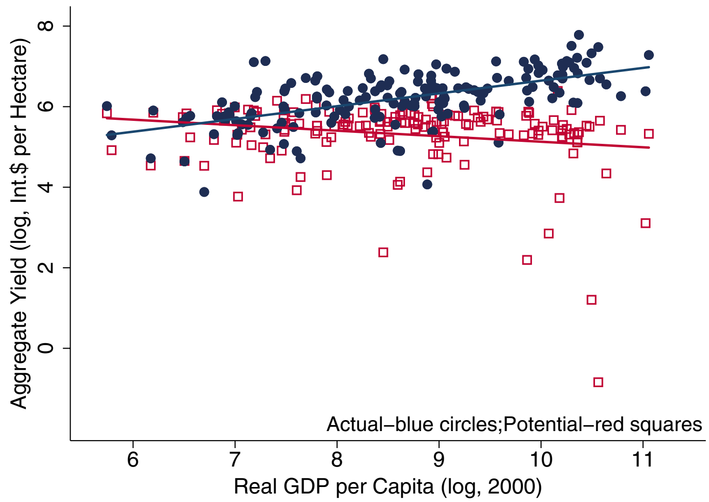

FIGURE 3

Aggregate actual and production-potential yield across countries

Notes: Aggregate production-potential yield under the rainfed low-input scenario.

Production potential. We calculate the aggregate production-potential yield using equation (3.1) and the potential yield for each cultivated crop in each cell under the rainfed low-input scenario, keeping the crop-cell land allocation fixed to the actual one. Given that the low-input scenario has rainfed water conditions and the lowest application of inputs, it more closely captures the productivity afforded by the natural geographic and land quality endowments of each country. Figure 3 documents the aggregate production-potential yield across countries along with the aggregate actual yield. While there is substantial variation in aggregate potential yields across countries, the ratio of the top to bottom deciles in the production-potential yield distribution is a factor of 6, the differences are not systematically related to the level of development. For instance, the disparity in the production-potential aggregate yield between Tanzania and Eritrea, two low-income countries, is roughly the same (around 3-fold) as the disparity between Belgium and Austria, two high-income countries. Unlike the aggregate actual yields, Figure 3 illustrates that there is actually a slight negative relationship between potential aggregate yields and GDP per capita, with a correlation in logs of -0.19. Egypt and countries of the Arabian peninsula stand out as outliers due to large desert areas, which are particularly arid under pure rainfed water conditions and low input application.

In Table 2 Panel A, we report the production-potential yield for the weighted average of each of the richest and poorest decile countries in terms of income per capita. The results are striking. If countries produced the crops they are producing in the cells they are actually producing them but according to the their potential yields, the aggregate yield disparity between rich and poor countries would drop from the actual 3.14-fold to only 1.05-fold, that is the productivity disparity would virtually disappear. In other words, with no complementary inputs and rainfed water conditions, rich countries would only attain a 5% higher aggregate yield than poor countries. Note, that if countries were producing according to their natural endowments without complementary inputs, yields would be lower than actual yields for most countries, particularly for the high-income countries.

TABLE 2
Counterfactual production-potential yield

	Actual yield	Potential yield	Ratio
	Panel A: All crops (*country obs.* = 162)		
Rich 10%	739.5	237.2	0.32
Poor 10%	235.5	225.7	0.96
Ratio	3.14	1.05	1/2.99
	Panel B: Wheat (*country obs.* = 110)		
Rich 10%	2.71	1.36	0.50
Poor 10%	1.07	0.87	0.81
Ratio	2.53	1.58	1/1.61
	Panel C: Rice (*country obs.* = 104)		
Rich 10%	6.64	1.16	0.17
Poor 10%	1.30	1.16	0.89
Ratio	5.10	1.00	1/5.13
	Panel D: Maize (*country obs.* = 142)		
Rich 10%	8.56	2.77	0.32
Poor 10%	1.31	1.73	1.31
Ratio	6.52	1.61	1/4.06

Notes: Rich and Poor refer to the weighted average of the highest and lowest decile of the real GDP per capita distribution in 2000 (Heston *et al.*, 2009). Aggregate actual and potential yields are measured as total value output per hectare in international prices (GK \$/ha). Actual and potential yields by crop are measured as tonnes per hectare. The production-potential yield for each country is constructed by aggregating up from the GAEZ (2000) pixel-level information at the 5 arc min resolution under the low input scenario. Low inputs assumes rainfed water supply and low-input cultivation practices.

Our findings are consistent with an earlier literature on the role of aggregate measures of land quality for agricultural productivity across countries (Wiebe, 2003). For instance, Wiebe *et al.* (2000) find that good soils and climate are associated with a 13% increase in agricultural productivity relative to poor soil and climate. Using these data, we find that when controlling for (log) inputs such as agricultural labour, tractors, and fertilizer, the effect on agricultural productivity becomes statistically insignificant. Despite the limitations of aggregate measures of land quality, our findings with the geospatial data from GAEZ and the accounting framework, are consistent with this earlier literature, in the lack of a systematic relationship between land quality and agricultural land productivity, after controlling for other inputs.

We have used a common set of crop prices to aggregate yields in all locations and countries, however, the conclusions from the production-potential counterfactual remain when focusing on individual crops for which we can use a physical measure of land productivity. Table 2, Panels B–D report the production-potential counterfactual for each of the three most representative crops produced across the world: wheat, rice, and maize. In each case, the yield is measured as crop output in tonnes per unit of land, a physical measure of productivity that does not require prices for aggregation. The rich–poor disparity in the actual yield differs across crops: 2.53-fold for wheat, 5.10-fold for rice, and 6.52-fold for maize. Producing these crops according to the low-input

TABLE 3
Counterfactual aggregate spatial and total potential yields

	Aggregate potential yield with low inputs (*country obs.* = 162)				
	Production	Spatial	Spatial/ production	Total	Total/ spatial
Rich 10%	237.2	288.2	1.22	363.9	1.26
Poor 10%	225.7	307.6	1.36	469.0	1.53
Ratio	1.05	0.94	1/1.11	0.78	1/1.21

Notes: Rich and Poor refer to the average of the highest and lowest decile in the real GDP per capita distribution in 2000 (Heston *et al.*, 2009). "Production" refers to the production-potential counterfactual yield, "spatial" to the spatial-potential counterfactual yield, and "total" to the total-potential counterfactual yield. All yields are measured as total value output per hectare in international prices (GK $/ha), aggregating from the GAEZ (2000) pixel-level information at the 5 arc min resolution under the low input scenario.

potential yields would reduce the rich-poor disparity to 1.58, 1.00, and 1.61-fold for wheat, rice, and maize. Despite differences across individual crops, the main takeaway from the production-potential counterfactual is that the disparity is substantially reduced when producing according to natural endowments, implying a limited role of land quality and geography for differences in agricultural productivity across countries.

We note that the aggregate production-potential yield summarizes a great deal of heterogeneity in land quality between cells in a country. However, we find no systematic relationship between the within-country dispersion in potential yields and the level of development, see Supplementary Appendix C, Figure C.1 for a documentation of this fact.

Spatial potential. A fact of poor and developing countries is the prevalence of large rural populations, often operating at subsistence levels and facing poor infrastructure, conditions that may lead farmers to produce in locations not necessarily suitable for agricultural production (Adamopoulos, 2011; Gollin and Rogerson, 2014; Adamopoulos and Restuccia, 2014). We assess the relevance of spatial reallocation by calculating the aggregate potential yield that would result from reallocating production of crops across cultivated cells according to where they exhibit the highest relative yield value in the country, holding constant the total amount of land allocated to each crop in the country. Table 3 reports the results of this counterfactual in columns two and three (column one repeats the production-potential). Spatial reallocation has a positive effect on agricultural output for both rich and poor countries, but relatively more for poor countries. Under spatial reallocation relative to the production-potential, the aggregate yield for the poorest countries increases on average 36 percent, whereas for the richest the average increase is 22%. This implies a further decline in the rich-poor yield gap to 0.94, relative to the production-potential counterfactual, and a slight reversal of the rich-poor yield gap.

We also note that if spatial reallocation is guided by actual-yield differences across cells rather than potential-yield differences in our spatial counterfactual, there is more of a decline in the dispersion between rich and poor countries, from 3.14-fold in the aggregate actual yield to 2.3-fold. Nevertheless, even though there is more role for spatial reallocation under actual yields, the reduction in the disparity is much lower than producing at potential for each crop and cell which implies an aggregate production potential yield ratio of 1.05-fold.

Total potential. We now assess the effect of crop reallocation by calculating the aggregate potential yield in each country when the highest value-yielding crop is produced in every cell, holding the amount of land in each cell constant. This counterfactual reflects the maximum aggregate value potential yield that can be achieved via production potential across cells and crops within cells. Table 3 reports the results of this total-potential counterfactual, in columns

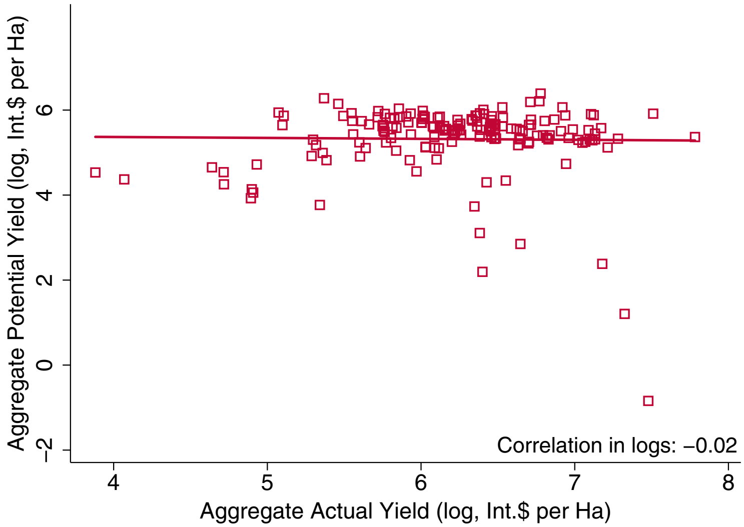

FIGURE 4

Aggregate production-potential versus actual yield across countries

Notes: Aggregate production-potential yield under rainfed low-input scenario.

four and five. If countries shift their crop mix to the highest yielding crops, cell-by-cell, then the aggregate yield disparity would drop between rich and poor countries from the actual 3.14-fold to 0.78-fold. Adjusting the crop mix cell-by-cell to the most suitable given each cell's geographic characteristics, poor countries would be 22% more productive than the rich countries. This occurs because relative to the spatial potential, the total potential increases yields in poor countries by 53 percent, double the increase in rich countries (26%).

Overall, while spatial and crop reallocation both contribute to reduce the dispersion in land productivity between rich and poor countries, most of the reduction in the aggregate yield gap occurs when countries produce each crop in each cell at potential. We note that in our accounting, spatial and crop reallocation measure the increase in agricultural output associated with given geography productivity, but clearly these gains may not be efficient when taking into account other uses of land, cost and demand factors, and potential changes in relative prices. Similarly, the spatial- and total-potential counterfactuals abstract from complementarity in production across crops, and crop rotation associated with best practices of land management, among others.

4.2. *Accounting for actual yields*

We now examine to what extent land quality and geographic differences across countries, captured by the low-input aggregate potential yields, can account for agricultural land productivity differences (aggregate actual yields).

If aggregate potential yields were roughly similar to aggregate actual yields across countries, then when plotting these variables, countries should fall around the 45 degree line. We find in contrast that the relationship between aggregate potential and actual yields is fairly flat. Figure 4 displays the aggregate production-potential yield for the rainfed low-input scenario against the aggregate actual yield. There is a weak relationship between the production-potential yield and actual yield, in fact the correlation is slightly negative, indicating a weak role for geography and land quality in accounting for agricultural land productivity differences.

TABLE 4
Counterfactual potential yields by agricultural productivity

	Actual	Aggregate potential yield with low inputs (*country obs.* = 162)				
		Production	Spatial	Spatial/ production	Total	Total/ spatial
Top 10%	1265.1	208.1	277.3	1.33	365.8	1.32
Bottom 10%	142.0	146.9	212.4	1.45	424.3	2.00
Ratio	8.91	1.42	1.31	1/1.09	0.86	1/1.52

Notes: Top and Bottom refer to the average of the highest and lowest decile of countries in terms of aggregate actual yield (agricultural productivity). "Production," "Spatial," and "Total" refer to the production-potential, spatial-potential, and total-potential counterfactual yields. Aggregate actual and all counterfactual potential yields are measured as total value output per hectare in international prices (GK \$/ha). Production potential yields are constructed by aggregating the GAEZ (2000) pixel-level information at the 5 arc min resolution under the low-input scenario.

In Table 4, we rank countries according to their aggregate actual yield, and show the results of the three counterfactuals for the top and bottom deciles of the actual yield distribution (rather than the rank by real GDP per capita in Tables 2 and 3). The first column shows the aggregate actual yield for the most and least land productive countries, with a disparity in actual yields of 8.91-fold. Under the production-potential counterfactual (second column), where all countries produce according to their potential yields cell-by-cell (holding constant the land and crop allocation), the disparity between the most and least productive countries declines to 1.42-fold. If countries produced according to their raw natural endowment potential the bulk of the staggering 791% land productivity differences would disappear. We conclude that the most land productive countries' agricultural productivity advantage is not primarily driven by favourable natural geographic endowments.

If in addition, crop production could be spatially reallocated within a country (keeping the total amount of land to each crop in a country fixed), then the yield disparity between the most and least productive countries would drop further to 1.31-fold, implying that the relatively least productive countries would benefit more from such a reallocation (columns three and four in Table 4). Under the total potential counterfactual (columns five and six), if countries shift their crop mix to the highest value yielding crops, cell-by-cell, then the aggregate yield disparity between the top and bottom deciles would drop further to 0.86. In other words, by adjusting the crop mix to the most suitable given their geographic characteristics, the least productive countries would be come 14% more productive than the most productive countries.

The potential yield gaps, under the different counterfactuals, show that the agricultural productivity differences are eliminated, in fact reversed, implying that land quality does not play a key role in explaining the actual productivity differences. We decompose the overall reduction in the yield gap between the most and least land productive countries, into the contributions of within cell-crop productivity, spatial reallocation, and crop choice, as implied by our counterfactuals. The disparity in the aggregate yield between the top and bottom 10% of countries in land productivity drops from 8.91-fold in the actual yield to 1.42-fold in the production potential counterfactual, to 1.31-fold in the spatial counterfactual, and to 0.86 in the total counterfactual using the rain and low input scenario. We can decompose the contribution of each factor (production, spatial, and total) to the decline in agricultural productivity disparity as follows:

$$\underbrace{\underbrace{8.91 \times \overbrace{0.16}^{\text{production}}}_{=1.42} \times \overbrace{0.92}^{\text{spatial}}}_{=1.31} \times \overbrace{0.66}^{\text{total}} = 0.86.$$

TABLE 5
Counterfactual potential yields with mixed inputs

	Aggregate potential yield with mixed inputs (*country obs.* = 162)					
	Production	Production/ actual	Spatial	Spatial/ production	Total	Total/ spatial
Rich 10%	1220.0	1.65	1446.0	1.19	2498.3	1.73
Poor 10%	1160.6	4.93	1361.1	1.17	3254.7	2.39
Ratio	1.05	1/2.99	1.06	1.02	0.77	1/1.38

Notes: Rich and Poor refer to the average of the highest and lowest decile in the real GDP per capita distribution in 2000 (Heston *et al.*, 2009). "Production" refers to the production-potential counterfactual yield, "spatial" to the spatial-potential counterfactual yield, and "total" to the total-potential counterfactual yield. All yields are measured as total value output per hectare in international prices (GK \$/ha), aggregating from the GAEZ (2000) pixel-level information at the 5 arc min resolution under the mixed input scenario.

This implies that production-potential contributes 79 percent ($\log(0.16)/\log(0.097)$) to the decline in the productivity ratio, while the spatial reallocation of production accounts for a small 4% and crop reallocation the remaining 17%.

4.3. *Potential gains under mixed inputs*

In our analysis so far, we have focused on aggregate potential yields derived under the rainfed low-input scenario from GAEZ. The main takeaway is that these potential yields do not vary systematically across countries. However, the potential yields based on the low input scenario are typically lower than the actual yields for most countries. This is expected given that they mostly capture the raw natural land endowments of countries under subsistence agricultural practices. Are there potential yield gains that countries can reap given their existing land quality and geographic characteristics? To answer this question, we use by-cell and by-crop potential yields from GAEZ (2000) under the mixed input scenario, which includes both rainfed and irrigated land, as well as a mixed level of cultivation practices and input application, that applies the highest level of inputs to the best land and the lowest level of inputs to the marginal land. GAEZ (2000) considers this as their baseline scenario as it more realistically represents actual input application approaches across the world.

We compute the aggregate counterfactual experiments under the mixed input scenario. In Table 5, we present the production-potential, spatial-potential, and total-potential yields for the 10% richest and poorest countries. The first column reports the aggregate actual yields. Similarly to the low-input scenario, the production-potential in column two shows that if countries produced their crops in the current locations but according to the mixed-input potential yields, the rich-poor disparity would drop from the actual 3.14-fold to 1.05-fold. This conclusion is remarkably robust to the input scenario assumed. However, as column three shows, what is different under the mixed-input scenario is that aggregate production-potential yields are higher than actual yields for both rich and poor countries. Based on the mixed input production-potential yields, the potential productivity gains for the rich countries are 65%, whereas for the poor countries 393%. This implies that, conditional on their land quality, there is considerable untapped potential for poor countries, and that improvements in non-land quality factors (cultivation practices, application of complementary inputs, farm size and organization, managerial operation, among others), rather than land quality, would allow them to realize it.

Figure 5 displays the production-potential yield under the mixed-input scenario and the actual yield for all countries in our sample. Despite the substantial variation in potential yields across

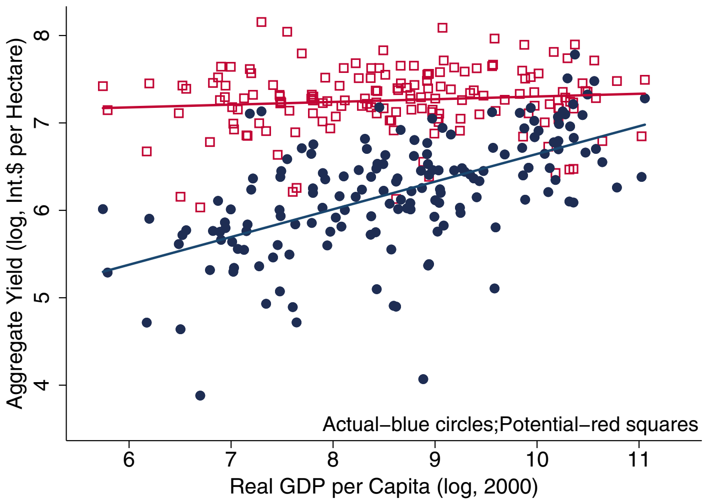

FIGURE 5

Aggregate actual and production-potential yield across countries

Notes: Aggregate production-potential yield under total-water (rainfed and irrigated) and mixed-input scenario.

countries, they do not systematically vary with the level of income per capita, as the aggregate actual yields do. Furthermore, potential yields lie above the actual yields for all countries, particularly the lower income countries. That is, conditioning on the set of crops each country produces on each plot, developing countries produce much further away from their potential than developed countries.

Spatial reallocation (columns four and five in Table 5) has a positive effect on agricultural output, but the magnitude of the effect is similar among rich and poor countries and thus does not further reduce the disparity in agricultural productivity across countries beyond the production potential effect. Columns six and seven show the results of the total-potential counterfactual. If in addition, countries shift their crop mix to the highest yielding crops, cell-by-cell, then the aggregate yield disparity between rich and poor countries would drop to 0.77-fold with mixed inputs, very similar to the 0.78 ratio we found under low inputs. This counterfactual points to poor countries producing systematically lower yielding crops given their internal land quality characteristics.

The conclusions about the lack of a systematic correlation between the potential aggregate yield and GDP per capita, and the reversal of the gap under total-potential yield remain intact between the low and mixed input scenarios. An important element in these cross-country comparisons is that the assumptions on inputs are kept the same in all countries, so the differences in the potential yields for each crop and location reflect variation in the geographical attributes of the land in each location. Interestingly, the similarity in the rich-poor potential yield disparities under the low- and mixed-input scenarios suggest that geographical endowments in poor countries are not less conducive to the use of certain inputs.

Our finding that gaps in potential-to-actual yields under the mixed input scenario are higher in developing than developed countries is consistent with findings in agronomic studies. For example, Van Ittersum *et al.* (2016) find that the average potential-to-actual yield gap across 10 Sub-Saharan African countries for the main cereals is 5, while Schils *et al.* (2018) find that for Northern European countries, the yield gap in cereals is as low as 1.1–1.2.

TABLE 6
Aggregate potential yields using caloric weights

	USDA calorie "Prices" of crops (000s of kcal) (*country obs.* = 162)				
		Potential yields			
	Actual Yield	Production	Production/ actual	Total	Total/ production
Rich 10%	18.20	5.64	0.31	12.36	2.19
Poor 10%	5.10	4.43	0.87	15.05	3.40
Ratio	3.57	1.27	1/2.82	0.82	1/1.55

Notes: Aggregate actual and potential yields are measured as total output in caloric energy (thousands of kcal) per hectare under the rainfed low-input scenario. Calorie "prices" (kcal per 100 g) are obtained from USDA (2015), *National Nutrient Database for Standard Reference*. Rich and Poor refer to the highest and lowest decile of the distribution of real GDP per capita in 2000 (Heston *et al.*, 2009).

4.4. *Robustness*

We examine the sensitivity of our main results to: (a) aggregating crops by weighing them according to their caloric content rather than using FAO international prices and (b) weighing produced crops within cells equally, rather than using the disaggregate cell-level land allocations by crop from GAEZ (2000). We provide further robustness and validation exercises in Supplementary Appendix D.

Caloric content of crops. In developing countries, a large proportion of farmers consume most of the output they produce as the amount of output produced is close to subsistence levels. For these farmers, the caloric intake from the different crops may be more relevant than international prices for the evaluation of the different crops. To examine the robustness of our main results, we consider an alternative to aggregating crops at the country level (in actual and potential yields) that uses instead the crop's caloric content. As in Galor and Özak (2016, 2015) the caloric content of each crop, measured in kilo calories (kcal) per 100g, is obtained from the USDA (2015)'s *National Nutrient Database for Standard Reference*. Table 6 reports the aggregate actual, the production-potential and the total-potential counterfactual yields (thousands kcal/ha) under the rainfed low-input scenario, for rich and poor countries.

We find that the main conclusions of our baseline results remain intact: there are substantial differences in actual yields across countries (3.14 in our baseline, 3.57 with calorie "prices"); producing existing crops according to potential yields removes the vast majority of differences (1.05 in our baseline, 1.27 with calorie "prices"); and allowing for crop mix and location to change reverses the aggregate yields difference between rich and poor countries (0.78 in our baseline, 0.82 with calorie "prices").

Weighting crops within cells. In our counterfactual production-potential yield experiment we used the disaggregated land allocations by crop for each cell from GAEZ (2000). The crop-cell-level potential yields are estimated from agronomic models, given the observed land quality and geographic conditions in each cell. The land allocation however is based on aggregate and regional data that GAEZ, through a downscaling methodology, attributes to cells. We repeat the production-potential counterfactual assuming that each produced crop is equally weighed within each cell, instead of using the GAEZ land allocation weighting (the spatial-potential and total-potential counterfactuals do not rely on the disaggregated GAEZ land allocations since in these experiments the cell-level land allocations are endogenous and solved for as part of our linear programming problems). In Figure 6, we display the production-potential yield under the low-input scenario, with equal weighting of crops within cells, across countries. The actual yield is also

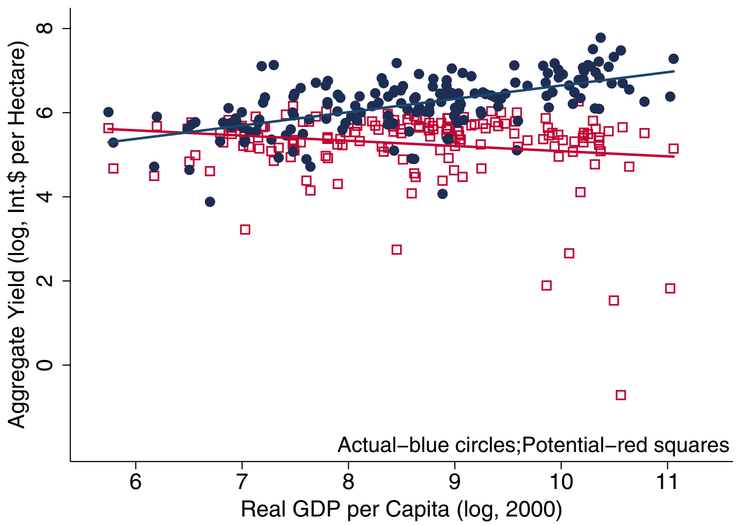

FIGURE 6

Production-potential yield across countries with equal crop weighting

Notes: Aggregate production-potential yield with equal crop weight within each cell instead of the GAEZ actual land allocation.

presented in blue circles. Comparing, Figures 3 and 6, our conclusions about a weak relationship between potential yields and income per capita across countries remain intact. Hence, the lack of a key role for land quality does not hinge on the use of the GAEZ land weights.

5. AGGREGATE IMPLICATIONS

We study the macroeconomic implications from reducing the yield gap from its actual level to its potential level, modelled as a change in agricultural TFP. Under the mixed input scenario, if rich and poor countries produced according to their potential yields, the productivity increase for poor countries would be 3 times that of rich countries. A stylized feature of the process of development is that increases in agricultural productivity lead to a reallocation of factors, in particular labour, from agriculture to the rest of the economy, such that consumption of agricultural goods per capita remains approximately constant (Gollin *et al.*, 2002; Restuccia *et al.*, 2008). What are the sectoral and aggregate implications of higher agricultural productivity in poor countries? To answer this question, we consider a standard quantitative sectoral model following the literature.

At each date there are two goods produced in sectors: agriculture and non-agriculture. Output in agriculture Y_a requires the inputs of land L (in fix supply) and labour N_a, $Y_a = A_a L^{\theta} N_a^{1-\theta}$, where A_a is TFP in agriculture.[8] Output in non-agriculture just requires labour input, $Y_n = A_n N_n$. There is a fixed amount of labour N to be allocated between the two sectors, $N = N_a + N_n$. We assume that in this economy there is a minimum amount of agricultural consumption goods per person

8. Note that we abstract from capital and intermediate inputs. Both of these two types of inputs are known to magnify the productivity and income implications and are discussed in detail in the literature (Restuccia *et al.*, 2008; Adamopoulos and Restuccia, 2014). Also, our results are based on a unitary elasticity of substitution across production factors, implied from the Cobb–Douglas nature of our agricultural production function. For non-unitary elasticity of substitution, that varies with the level of productivity, see Adamopoulos and Restuccia (2014) and Foster and Rosenzweig (2017).

$\bar{a}$ and that after this minimum is satisfied individuals allocate their income to non-agricultural goods.[9]

Denoting per-capita labour in agriculture and land as n_a and l, and combining the demand for agricultural consumption goods and the production function above, we can solve for the share of employment in agriculture:

$$n_a = \left(\frac{\bar{a}}{A_a l^\theta} \right)^{1/(1-\theta)}. \tag{5.1}$$

We can then solve for labour productivity in agriculture $y_a = A_a l^\theta n_a^{-\theta}$ and average farm size $AFS = l/n_a$. Labour productivity in non-agriculture is simply $y_n = A_n$ and income per capita is given by $y = p y_a n_a + y_n(1-n_a)$, where p is the relative price of agricultural goods. Without loss of generality we set $l = 1$.

We now proceed in three steps. (1) We calibrate a benchmark rich economy to data for the United States. We normalize productivity parameters, $A_a = A_n = 1$ and calibrate $\bar{a}$ to the share of employment in agriculture in the U.S. about 1.5%. This procedure implies $\bar{a} = 0.06$, $p = 0.40$, $y_a = 4.05$, and $y = 1.01$. (2) Given the preference parameter $\bar{a}$, we calibrate a poor economy, in particular we choose productivity parameters to jointly match a share of employment in agriculture of 70% and a poor-rich non-agriculture productivity ratio of one fifth. We obtain for the poor country agricultural TFP $A_a^p = 0.077$ and compute "real" income per capita, using the benchmark economy's relative price of agriculture, of $y^p = 0.085$. Note that the rich to poor ratio is 46.7-fold in agricultural labour productivity and average farm size and 12.2-fold in aggregate income per capita. (3) We study an increase in agricultural TFP of a factor of 3-fold in the poor economy consistent with our previous findings. The share of employment in agriculture in the poor economy falls from 70% to 13.5% and the disparities in agricultural labour productivity (average farm size) and income per capita fall from 46-fold to 9-fold and from 12.2-fold to 5-fold. The increase in agricultural TFP reduces the disparity in income per capita by half. The reason for this remarkable reduction in income disparity is that the increase in agricultural TFP reduces the share of employment in agriculture, increasing agricultural labour productivity and average farm size in the poor economy by a factor of 5.2-fold.

The main takeaway from this stylized quantification is that improving agricultural productivity in poor countries unravels a substantial process of structural transformation that can go a long way in reducing the large disparities in sectoral and aggregate outcomes between rich and poor countries.

6. CONCLUSIONS

That land quality and geography matter for agricultural production at the micro-level is ubiquitous as argued by both agronomists (*e.g.* Doorenbos and Kassam, 1979; Steduto *et al.*, 2012; GAEZ, 2000) and agricultural economists (*e.g.* Jaenicke and Lengnick, 1999; Sherlund *et al.*, 2002; Fuwa *et al.*, 2007; Di Falco and Chavas, 2009). Using detailed micro-geography data, in this article we assess the macro-level consequences of land quality for agricultural productivity, measured as output per hectare (yield). In particular, we quantify the potential importance of geography as an explanation for agricultural productivity differences across countries. We find that land quality differences cannot justify the agricultural land productivity gaps between rich and poor countries. If farming practices were the same around the world then land quality would

9. This assumption simplifies the analysis considerably since the total amount of agricultural goods consumed per capita is equal to $\bar{a}$, however, this is a close approximation to a calibration of more general preferences for agricultural and non-agricultural goods (Gollin *et al.*, 2002; Restuccia *et al.*, 2008).

not be a constraint on farmers in poor countries. The majority of the actual yield differences would disappear if countries produced according to their potential, with a secondary role played by what crops are produced and where they are produced within the country.

Under improved agricultural practices for all countries, our analysis illustrates that there are large gaps between actual and potential yields in poor countries, much larger than in rich countries. The implication is that using existing technologies and improving allocations can increase agricultural productivity 5-fold. These seem like sizeable unrealized gains in productivity. One possibility is that the technologies agronomists treat as easily localized (in the calculation of potential yields) cannot be profitably implemented everywhere in the developing world. Another possibility is that there are constraints that prevent the adoption of modern technologies and frictions that prevent markets from efficiently allocating resources in developing countries. In the short run, fixed factors such as infrastructure and capital investments might limit countries from reaching their potential agricultural productivity, but in the long run, even if these limiting factors can be overcome, it would require costly investments and real resources to do so.

While a large body of recent work has been studying the constraints and frictions that impact agricultural productivity, with mounting evidence of their importance, much less work has been done on understanding the localization of agricultural technologies in developing countries. GAEZ has been following a variety of approaches for "ground-truthing" and verifying the results of their crop suitability analysis, but more needs to be done in terms of further validation. At the same time further research is needed to understand what factors constrain the choices of farmers in the developing world, preventing them from better exploiting their land and environmental endowments. Similarly, further work may be needed to better understand the role of non-biophysical factors such as infrastructure for marketing and distribution of agricultural products, constraints on capital and knowledge availability, as well as specific intermediate-input requirements for pest, disease, and weed. We leave these important areas of research for future work.

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Supplementary Data

Supplementary data are available at the *Review of Economic Studies* online. The data and replication files underlying this article are available at Zenodo under: https://doi.org/10.5281/zenodo.5259883.

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