Is Land Quality Enough? Agricultural Production and Climate Adaptation in Latin America*

Tasso Adamopoulos
York University

December 2025

Abstract

I study how current geography and projected climate change impact agricultural productivity in Latin America, a region with exceptionally high natural land potential but large productivity differences across and within countries. Using high-resolution agro-ecological data combined with a spatial accounting framework, I decompose actual agricultural productivity into the contribution of land suitability and the organization of production across inputs, crops, and space. Natural land potential cannot explain the region's productivity differences: most countries substantially underutilize their biophysical endowments, and with improved input use many could double agricultural productivity. Additional, though smaller, gains arise from reallocating production spatially and shifting toward higher-value crops. Incorporating climate-change projections for the 2050s into the same framework, I show that climate change reshapes the geography of production possibilities: average potential yields decline, but increased heterogeneity in impacts across locations nearly doubles the gains from spatial reallocation. The results highlight the central role of production organization, rather than land quality alone, for current productivity gaps and future climate adaptation in Latin America.

JEL classification: O11, O14, O4, Q10, Q54, R11.

Keywords: Agriculture, Land Quality, Climate Change, Productivity, Spatial Allocation, Crop Choice, Latin America.

*Contact: Tasso Adamopoulos, aadamo@yorku.ca. This paper supersedes a previous version circulated under the title "Geography and Agricultural Productivity: The Case of Latin America and the Caribbean." I thank Julieta Caunedo, Chaoran Chen, Román Fossati, and Diego Restuccia for their feedback. I have benefited from comments received by seminar participants at York University, and the CAF Development Bank of Latin America and the Caribbean. I gratefully acknowledge the support from CAF. All potential errors are my own.

1 Introduction

Large differences in agricultural productivity across and within countries are a defining feature of the development landscape. Understanding the sources of these gaps, and how they may evolve, is central to debates on structural change, food security, and sustainability. Although agricultural outcomes are inherently tied to geographic and biophysical conditions such as soil quality, climate, and topography, they are also shaped by economic institutions and frictions that influence production choices. Disentangling the role of land quality from the role of economic constraints is essential for policy. Given the increased environmental challenges associated with global warming, and their high priority on policy agendas, a key question is how climate change will interact with underlying geography to determine future productivity and the scope for adaptation.

Latin America offers a natural laboratory for examining whether "good land quality" alone is sufficient for high agricultural performance. The region contains some of the world's most inherently productive agricultural land and spans a wide range of agro-ecological environments, all subject to significant climate variability. Agriculture remains an important source of output and employment, yet the region does not display the extreme income or structural differences seen in global comparisons between the richest and poorest countries. Latin American countries also share elements of culture, history, and civil-law tradition, limiting some of the institutional heterogeneity inherent in broader cross-country samples. Despite these favorable endowments, agricultural productivity still varies greatly within and across countries. Brazil and Argentina rank among the world's leading agricultural exporters, while other countries with similarly advantageous geographic conditions exhibit much lower productivity. This combination of shared advantages and divergent outcomes makes Latin America a distinctive setting for studying the relative importance of geography and production choices for current productivity gaps and understanding future climate-adaptation strategies.

In this paper, I quantify the role of land quality, production organization, and climate change in shaping agricultural productivity across and within Latin American countries. I combine high-resolution geospatial data on crop yields reflecting biophysical conditions with a spatial accounting framework, to assess the role of land quality relative to a set of economic choices: input use, crop choice, and spatial reallocation, for current productivity gaps. Using spatially granular climate change projections on yields I assess the scope of different economic choice adaptation margins for the future evolution of agricultural productivity. I find that while Latin America has higher natural land quality than the world's richest agricultural producers, it is largely unexploited. Actual yields vary widely and are essentially uncorrelated with natural suitability. With reasonable improvements in input use, agricultural yields can roughly double in most countries. Additional, but smaller, gains are available from the reallocation of agricultural production across space, and the shift to higher value crops. As a result, the variation in productivity in Latin America arises not from geography, but from the way production is currently organized. Incorporating climate-change projections for the 2050s substantially alters production possibilities. While average potential yields decline in most countries, the impacts are highly uneven across space: some locations lose suitability for current crops, while others gain. This increased heterogeneity nearly doubles the potential gains from spatial reallocation relative to today, mitigating a portion of the climate-induced productivity losses. These findings highlight that even in regions endowed with "good geography," the organization of production is paramount for realizing high productivity today and tomorrow.

To assess the role of current land quality across and within Latin American countries, I use pixel-level (5-arc-minute, roughly 10×10 km) gridded micro-geography data from the FAO's Global Agro-Ecological Zones (GAEZ v3.0) project (GAEZv3.0, 2012). GAEZ provides spatially detailed information on land quality, climate, and terrain, and combines these conditions with state-of-the-art crop-specific agronomic models to estimate each crop's potential yield, the maximum output per unit of land under given conditions. The database reports crop-cell potential yields worldwide for various input and water-supply scenarios. I use two measures for current geographic conditions: the low-input scenario, which assumes minimal inputs and rainfed water, approximating each cell's natural suitability; and the mixed-input scenario, which assumes intermediate inputs, targeted cultivation, and both irrigated and rainfed water, reflecting typical current practices. To study climate change effects, I use potential-yield projections from GAEZ v4.0 (GAEZv4.0, 2021), which incorporate recent climate change scenarios and their impacts on crop-cell production conditions. I examine projections for the 2050s under two climate models that feature moderate temperature increases and carbon-fertilization effects.

I combine GAEZ geospatial data for Latin America with country and first-administrative-level borders and the spatial accounting framework of Adamopoulos and Restuccia (2022) to decompose agricultural productivity gains. The framework aggregates crop yields across all cells within an administrative unit, expressing actual aggregate yield—output per unit of harvested land—as a weighted average of crop-cell yields using land-allocation shares. This framework allows the construction of counterfactual yields. My main counterfactual is the *production-potential* yield, which replaces actual crop-cell yields with potential ones while holding the observed spatial and crop allocations fixed. This summarizes the natural productivity of land given current land quality, geography, and production patterns. A second counterfactual, the *spatial-potential* yield, reallocates production across cells within administrative boundaries to maximize output while keeping total land per crop fixed. A third, the *total-potential* yield, assigns each cell to its highest-value crop, allowing both spatial reallocation and changes in crop composition.

In analyzing the effects of climate change within this setting, I adopt an approach that complements but differs from much of the climate-economics literature. In my framework, crop production is reallocated across space within countries according to comparative advantage, based on biophysical suitability. Climate change alters the crop-by-cell pattern of potential yields, reshaping the geography of comparative advantage within countries. By feeding these cell-level and crop-level changes in suitability into the spatial accounting framework, I can quantify how the feasible set of agricultural production shifts through spatial and crop reallocation within countries. The approach imposes minimal structure, mainly physical resource constraints, allowing me to isolate the physical scope for adaptation: how much agricultural output is achievable through spatial and crop reorganization alone, even in the absence of changes in preferences, technologies, or policy.

There are three central results that emerge from the analysis. First, natural land quality cannot account for agricultural productivity differences in Latin America. Although the region lies on the upper end of the global productivity distribution, its average production potential, measured under low-input rainfed conditions, is higher than that of the world's most productive agricultural producers. This implies that the region's productivity shortfall relative to the global frontier does not stem from natural endowment limitations. The variation of actual yields across Latin American countries is completely uncorrelated with the variation in production-potential yields, under the low input scenario. This disconnect also appears within countries: sub-national regions, states or provinces, with high biophysical potential are not necessarily the ones where production is concentrated. The mis-alignment of actual production and potential yields indicates that countries systematically under-utilize their natural endowments.

Second, improving the organization of agricultural production could generate large productivity gains. I estimate production-potential yields under the mixed input scenario that reflects intermediate use of inputs and cultivation practices, as well as irrigation. There is a closer alignment of actual and mixed-input potential yields, indicating that the actual suitability of the land when appropriately interacted with inputs can partly account for the variation of agricultural productivity across Latin American countries. The production potential yields under the mixed input scenario exceed actual yields in all countries. Most countries could more than double their aggregate agricultural productivity. I show that these potential yield gains have substantial aggregate implications in terms of structural change and development, particularly for lower income countries. Additional gains arise from reallocating crops across space and from shifting toward higher-value crops, although these margins are generally smaller than the gains from improved input use. These findings highlight the central role of production organization, namely inputs, crop choices, and spatial allocation, in translating land quality into actual productivity.

Third, incorporating into the same framework climate-change projections on cell-by-cell and crop-by-crop potential yields I find that climate change reshapes the geography of production possibilities and comparative advantage within countries. Under moderate climate change scenarios, average production-potential yields decline in most countries, but the impacts are highly heterogeneous across space and crops within countries. This increased heterogeneity nearly doubles the gains from spatial reallocation relative to today, even as the gains from shifting crop composition moderate. The results indicate that the responsiveness of production to spatial differences in suitability will become an increasingly important adaptation mechanism in a warming climate.

Although the discussion so far has emphasized regional mechanisms, there is meaningful heterogeneity across countries in the extent to which land quality is translated into actual agricultural productivity. Argentina illustrates the upper end of this spectrum: it combines very high biophysical potential with substantial unrealized output gains, both from improved input use and from reassigning crops to the locations where they are most suitable. Several Central American and Caribbean countries—such as Honduras, Nicaragua, and Cuba—also exhibit large gaps between actual productivity and what is attainable given their underlying land quality. By contrast, countries including Brazil, Colombia, Costa Rica, and Jamaica make fuller use of their biophysical endowments, though important opportunities for improvement remain. Climate change further amplifies cross-country differences: in countries where projected impacts vary sharply across space and crops—such as Peru, Chile, Mexico, and parts of the Caribbean—the potential benefits from reorganizing production across locations become considerably larger. These patterns motivate the detailed country-level and sub-national analyses that follow.

This paper contributes to a large literature in macroeconomics and development trying to understand the role of agriculture for structural change and the process of economic development (Kuznets, 1966; Gollin et al., 2007; Caselli, 2005; Restuccia et al., 2008). A fundamental question in this literature is understanding what accounts for the large measurable differences in real agricultural productivity across countries and between agriculture and non-agriculture within countries. The vast majority of the macro-development literature on the determinants of agricultural productivity has focused on the role of several frictions, institutions, policies constraining economic choices in agriculture, both across countries as well as within countries: intermediate inputs (Restuccia et al., 2008); farm size (Adamopoulos and Restuccia, 2014); spatial transport connectivity (Sotelo, 2020; Adamopoulos, 2025); land misallocation (Adamopoulos et al., 2022); selection (Lagakos and Waugh, 2013; Adamopoulos et al., 2024); idiosyncratic agricultural risk (Donovan, 2021); trade risk and uncertainty (Adamopoulos and Leibovici, 2025); capital intensity and quality (Chen, 2020; Caunedo and Keller, 2021), among many others. None of this literature however has considered the role of land quality. An exception is Adamopoulos and Restuccia (2022), who study the contribution of current geography to global cross-country productivity differences using a spatial accounting framework. The present paper differs in three key respects: it focuses on Latin America, a region with exceptionally high land quality but substantial productivity dispersion; it exploits sub-national variation to study geography within countries; and it extends the framework to projected climate conditions, showing that climate change reshapes comparative advantage across space and increases the value of reallocation as an adaptation margin.

There is an economics and agronomic literature that studies the role of individual geographic attributes, such as temperature, rainfall, soil quality, and topography on crop yields (Levine and Yang, 2014; Schlenker and Roberts, 2009; Cassman, 1999; Kravchenko and Bullock, 2000). Instead, the analysis here accounts for all geographic attributes that impact the biological growth of crops, summarized through potential yields. There is an earlier literature on cross-country growth analyses that use aggregate land quality indices or geography measures (Gallup et al., 1999; Sachs, 2003; Wiebe, 2003). In contrast here, I utilize the explicit spatial nature of the micro-geography data in GAEZ using an accounting framework, to aggregate up to various administrative levels, namely country and sub-national levels.

According to the United Nations' *Intergovernmental Panel on Climate Change* mean temperatures have risen, and are projected to increase further in the coming decades.[1] The impact of climate change, mitigation strategies, and the adaptation of economies to global warming feature prominently on policy agendas of governments and international institutions. A growing empirical and macroeconomic literature documents that temperature and climate variation affect economic outcomes at the micro, macro, and spatial levels (Nordhaus, 2006; Dell et al., 2009, 2012; Hsiang et al., 2017; Somanathan et al., 2021; Desmet and Rossi-Hansberg, 2024). There is however no other sector that is affected more directly by climate change than the agricultural sector (Cruz, 2024), where production depends directly on location-specific climatological conditions.

Rising temperatures reduce crop yields, especially beyond some threshold, giving rise to non-linear effects (Schlenker and Roberts, 2009; Calzadilla et al., 2013; Burke et al., 2015; Zhao et al., 2017). To cope with climate change in agriculture the literature has examined several adaptation and mitigation strategies: adjusting agricultural inputs (Jagnani et al., 2021); changing global patterns of production and trade (Costinot et al., 2016; Gouel and Laborde, 2021); sectoral reallocation interacting with the food problem and trade barriers (Nath, 2025); directed innovation (Moscona and Sastry, 2023); internal migration (Gröger and Zylberberg, 2016); international migration (Conte, 2022); long-run adaptation (Burke and Emerick, 2016), among others. My paper complements this work by studying how projected climate change reshapes agricultural productivity through its

[1] https://www.ipcc.ch/assessment-report/ar6/

effect on biophysical suitability. By embedding projected crop-cell level potential yields in a spatial accounting framework, I quantify how climate change alters the pattern of comparative advantage within countries and how the resulting reorganization of farming across space and crops can serve as an adaptation mechanism.

The rest of the paper proceeds as follows. In Section 2, I briefly examine the sectoral structure of Latin American countries and describe the gridded data I use. In Section 3, I present the spatial accounting framework. Section 4 presents the accounting decomposition across countries using current climate conditions. Section 5 extends the analysis to sub-national administrative units within countries. Section 6 applies the same framework to projected climate scenarios for the 2050s, quantifying how climate change alters the geography of production potential and the gains from spatial reallocation. I conclude in Section 7.

2 Data

I first examine the sectoral structures and incomes of Latin American and Caribbean economies, along with Portugal and Spain (LAC for short) and then present the spatial micro-geography data. Throughout the paper I include Spain and Portugal because, despite being geographically located in Europe, they share strong cultural, historical, and institutional ties with Latin America, and provide useful reference points for agricultural productivity in countries that developed from similar historical origins.

2.1 Sectoral Composition

Before considering the role of land quality and climate for agricultural productivity across LAC countries, I report data for the sectoral composition of their economies and their relative aggregate income. Table 1 displays the share of employment in agriculture (first column), the share of agricultural value added in GDP (second column), and real GDP per capita, PPP in constant 2021 international $ (third column). All data are from the *World Development Indicators* of the World Bank for the year 2010.[2] I report the data by LAC country, their average as well as for Canada, the United States and the top (20 percent richest) and bottom (20 percent poorest) quintiles of the world real GDP per capita distribution. The fourth column reports the ratio of each country's real

[2] Due to missing or inaccurate data the agricultural employment and output shares for Argentina are from the Groningen Growth and Development Centre's *Economic Transformation Database* (de Vries et al., 2021) for the year 2010, and Antigua and Barbuda's agricultural employment share is from the Food and Agricultural Organization for the year 2013 (FAO, 2015).

GDP per capita relative to the 20 percent richest countries.

On average, LAC countries are only at 29 percent of the richest countries in terms of GDP per capita, which is roughly in the middle of the distribution, and well below the other countries in North America. This average confounds the variation across LAC countries, with Portugal and Spain being at 60 and 70 percent of the richest countries, while Bolivia, Honduras and Nicaragua at about 10 percent. The share of employment in agriculture, a measure of the extent of structural change in a country, varies significantly across LAC countries from 30 percent and above in Bolivia, Guatemala, Honduras, Nicaragua to 4 and 6 percent in Spain and Argentina respectively. To put these numbers into perspective, in high income countries like Canada and the United States the agricultural employment share is under 2 percent while in the poorest countries in the world this is over 60. Similar conclusions are drawn by looking at the output share of agriculture. Most major LAC countries, in terms of their sectoral structure, are in the fourth quintile of the income distribution.

2.2 Global Agro-Ecological Zones (GAEZ) Data

This section describes the agronomic data associated with current land quality and geography, with the goal of characterizing the biophysical production possibilities that underlie agricultural outcomes in Latin America.

I use spatial micro-geography data from the Global Agro-Ecological Zones project, GAEZ v3.0 (GAEZv3.0, 2012), of the Food and Agricultural Organization (FAO) and the International Institute for Applied Systems Analysis (IIASA). GAEZ provides gridded datasets on a rich set of current land quality and geographic characteristics at the 5-arc minute resolution. The spatial unit of observation is a cell or pixel in this grid that is roughly 10 by 10 kilometers, with the mapping from arc minutes to square kilometers depending on the latitude. GAEZ offers a cell-by-cell characterization of the conditions relevant for agricultural production in terms of: a) soil attributes (e.g., depth, fertility, drainage, texture, chemical composition); b) climate attributes (e.g., temperature, sunshine hours, precipitation, humidity, and wind speed); c) terrain attributes (e.g., elevation, slope). This information is used to identify local biophysical constraints and limitations across cells.

GAEZ feeds the cell-specific information on geographic characteristics into well-established state-of-the-art agronomic models for each crop, that account for science-based biophysical growing requirements for each crop. A key output of this procedure is the estimation of a potential yield for each crop for each cell, which captures the highest output per hectare that can be attained in the

Table 1: Role of Agriculture and GDP per capita

	Agr. Empl. Share (%)	Agr. VA Share (%)	Real GDP pc (PPP, int $)	Real GDP pc Rel. to Rich 20%
North America				
Canada	1.8	1.5	52474.6	0.86
Mexico	14.6	3.1	20052.6	0.33
United States	1.7	1.0	59799.3	0.98
Central America				
Belize	18.5	8.8	11868.4	0.19
Costa Rica	12.4	6.5	18668.3	0.30
El Salvador	20.8	7.0	8648.9	0.14
Guatemala	33.5	11.2	9828.4	0.16
Honduras	36.5	11.6	5396.1	0.09
Nicaragua	29.6	17.0	5654.4	0.09
Panama	17.4	3.6	22739.1	0.37
Caribbean				
Antigua and Barbuda	21.0	1.2	25831.8	0.42
Bahamas	3.3	1.1	32702.0	0.53
Cuba	18.6	3.6		
Dominican Republic	12.4	6.1	14853.6	0.24
Jamaica	17.7	5.3	9654.1	0.16
South America				
Argentina	6.0	7.8	28056.3	0.46
Bolivia	31.7	10.4	7571.7	0.12
Brazil	11.5	4.1	18062.2	0.29
Chile	10.1	3.5	24148.3	0.39
Colombia	18.5	6.3	14012.0	0.23
Ecuador	27.9	8.3	11651.3	0.19
Guyana	21.4	28.5	10374.4	0.17
Paraguay	25.6	13.0	12738.6	0.21
Peru	28.0	6.8	12061.2	0.20
Uruguay	11.6	7.2	24960.7	0.41
Venezuela	8.5	5.4		
Europe				
Portugal	11.2	1.9	36670.0	0.60
Spain	4.2	2.4	42657.0	0.70
LAC countries	18.2	7.4	17869.2	0.29
Rich 20% of all countries	3.2	2.0	61312.2	1.00
Poor 20% of all countries	58.3	25.7	2596.0	0.04

Notes: Data from the World Bank's *World Development Indicators* for the year 2010, except for Argentina's agriculture shares (GGDC) and Antigua and Barbuda's agricultural employment share (FAO).

cell given: the crop's growing requirements; the cell's characteristics; and assumptions about water supply conditions and cultivation practices. In sum, potential yields encapsulate the importance of location-specific land quality and geography for the production of particular crops. The crop-specific agronomic model parameters are based on well tested field and lab experiments by agricultural research institutes, reflecting the latest state of scientific knowledge (rather than estimated from reduced-form regressions).

The estimated potential yields, for the year 2000, are reported for different water supply conditions (irrigated, rainfed, total) and type of cultivation practices (low, intermediate, high, mixed).[3] I focus my analysis on two scenarios: (a) the *low input* scenario, with rainfed water supply conditions and the low level of cultivation practices, meant to capture the natural suitability of the land for the production of different crops; (b) the *mixed input* scenario that assumes total water supply conditions and mixed level of inputs, which assumes high inputs on the best land, intermediate inputs on moderately suitable land, and low inputs on marginal land, a scenario GAEZ considers a reasonable representation of current cultivation conditions. I use potential yields for baseline historical climate conditions (1960-1990). In the main analysis, I focus on 18 major crops and commodity groups,[4] and examine the robustness to including cocoa, tea and coffee, which are high value cash crops.

The GAEZ database also provides at the 5 arc-minute resolution, for the year 2000, data on crop choice, actual production, actual area cultivated, and actual yield, i.e., tonnes of production per hectare of the crop actually planted. The actual production data for each cell are estimated using a flexible iterative rebalancing methodology that sequentially down-scales regional agricultural production statistics. The actual production data at the cell level are available for all major crops.

To aggregate the cell-level information provided by GAEZ to administrative units, countries and states or provinces, I use shape files from the World Borders data set of "Thematic Mapping" for countries and shape files from "GADM" for sub-national units.[5]

[3]Low level of inputs (traditional management), assumes subsistence based farming, labor intensive techniques, no application of nutrients, chemicals, and pesticides. Intermediate level of inputs (improved management), assumes partly market oriented farming, improved varieties with hand tools and/or animal traction, some mechanization, medium labor intensity, use of some fertilizer, chemicals, and pesticides. High level of inputs (advanced management) assumes mainly market oriented farming, high yield variety seeds, fully mechanized with low labor intensity, optimum application of nutrients, chemicals, and pesticides as well as disease and weed control.

[4]The crops 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, cotton.

[5]Available through http://thematicmapping.org/downloads/world_borders.php and https://gadm.org/data.html for sub-national units.

2.3 Climate Change Data

I use the updated future potential yields from GAEZ v4.0 (GAEZv4.0, 2021) based on the latest climate change projections of the Intergovernmental Panel of Climate Change (IPCC) in its fifth Assessment Report (AR5). GAEZ v4.0 provides climate change-based projections of future potential yields by crop and cell for the entire world, based on different climate models, Representative Concentration Pathways (RCPs), water supply conditions, with and without CO_2 fertilization. Different climate models use different parameterizations of climate processes. Different RCPs, developed by climatologists, represent different greenhouse gas concentration trajectories over time, leading to different levels of global warming by the year 2100. An RCP's radiative forcing value (measured in W/m^2) captures the energy flow over a surface area due to greenhouse gas concentrations, leading to a warming effect. With CO_2 fertilization higher levels of carbon dioxide (CO_2) in the atmosphere can be used in the process of photosynthesis by plants, potentially enhancing crop yields, with variation by crop and location. I use future potential yields for the 2050s (period 2041-2070) by crop and cell from two climate models, GFLD-ESM2M (climate model "M1" below) and IPSL-CM5A-LR (climate model "M2" below), with CO_2 fertilization and with only rainfed water supply, in order to obtain cleaner effects of climate change. For both climate models, I use an intermediate balanced RCP, RCP4.5 (radiating forcing value of 4.5 W/m^2), achievable under moderate emission mitigation measures. All future projections of potential yields due to climate change are provided by GAEZ v4.0 only for the a high level of inputs, under the implied assumption that by that time agricultural practices would reflect everywhere what is considered high input application and practices today. Overall, the projected potential yields take into account how different expected temporal patterns of warming and precipitation will affect the growth cycle of different crops in each spatial pixel.

3 Spatial Accounting Framework

I combine the potential yields from GAEZ with the spatial accounting framework developed in Adamopoulos and Restuccia (2022), which allows me to aggregate up yields from the cell-crop level resolution to any administrative unit level. This section describes the general setup of the framework, how aggregation occurs across crops and locations, and the counterfactual experiments I run through this framework to assess the role of land suitability, spatial distribution of production, and crop choice. This framework provides the basis for quantifying the role of current geography and land quality as well as projected climate change.

3.1 Setup

There is a fixed number of administrative units indexed by $i \in \mathcal{I} \equiv \{1, 2, ..., I\}$. These units could be countries or states/provinces within a country. Each administrative unit i has a finite number J_i of grid cells of fixed size. Grid cells are indexed by $j \in \mathcal{J}_i \equiv \{1, 2, ..., J_i\}$. Each grid cell can produce any of C crops, indexed by $c \in \mathcal{C} \equiv \{1, 2, ..., C\}$.

Cells differ in the productivity of the land across crops, captured by the crop-specific *potential* yield or land productivity (tonnes per hectare) of each cell. The potential yield from producing crop c, in grid cell j, in unit i, is given by $\hat{y}^c_{ji}$. That is, for each cell j in unit i there are C such land productivity numbers.

The actual crops produced in a cell may differ from the crops in which the cell has the highest potential yield. Denote by q^c_{ji} the real output (in tonnes) and by ℓ^c_{ji} the amount of cultivated land in hectares of crop c, cell j, and unit i. I denote by y^c_{ji} the *actual* yield which is just the ratio of real output to land, $y^c_{ji} = q^c_{ji}/\ell^c_{ji}$.

To aggregate the value of crops in a location I use international prices p^c of each crop which are common across cells and administrative units.

3.2 Aggregation

I denote with upper case letters aggregate variables. L_i is the amount of land used in agricultural production in administrative unit i, given by,

$$L_i = \sum_{c \in \mathcal{C}} \sum_{j \in J_i} \ell^c_{ji}.$$

I denote by Q_i the amount of real agricultural output produced in administrative unit i, given by,

$$Q_i = \sum_{c \in \mathcal{C}} \sum_{j \in J_i} p^c q^c_{ji},$$

Given these aggregates, I define the actual aggregate yield Y_i by the ratio of aggregate real output to land used in the unit, that is,

$$Y_i = \frac{Q_i}{L_i} = \frac{\sum_{c \in \mathcal{C}} \sum_{j \in J_i} p^c y^c_{ji} \ell^c_{ji}}{L_i} = \sum_{c \in \mathcal{C}} \sum_{j \in J_i} p^c y^c_{ji} \frac{\ell^c_{ji}}{L_i}. \tag{1}$$

The aggregate yield is a weighted average of the yields in every crop and location in a given country. Equation (1) is the key equation in the accounting analysis as it provides the basis for assessing the key determinants of low agricultural productivity in poor countries, that is, whether the differences in aggregate yields arise from low actual yields of each crop in each location (i.e., low y_{ji}^c), from not producing in the highest yielding locations across space, or from the low yielding crop mix in each location.

3.3 Counterfactuals

I construct three counterfactual aggregate potential yields for each administrative unit i, by exploiting the set of potential yields by crop at the cell level j and the spatial distribution of production by crop across cells. The counterfactuals incorporate the three potential channels of productivity variation connected with land quality: production potential, spatial potential, and total potential.

Production potential The main counterfactual assesses the impact of producing at the potential yield for each crop and each location. This counterfactual can be mapped in equation (1) by simply replacing the actual yield y_{ji}^c for each crop for each cell by its potential counterpart $\hat{y}_{ji}^c$. Hence, in this counterfactual only the crop-cell yields change, while the weights represented by the shares of cultivated land of crops across locations are kept constant ℓ_{ji}^c/L_i to their actual ones. The aggregate yield in this counterfactual is defined as,

$$Y_i^{pp} = \sum_{c \in \mathcal{C}} \sum_{j \in J_i} p^c \hat{y}_{ji}^c \frac{\ell_{ji}^c}{L_i}.$$

If the variation in actual yields is not related to the variation in the production potential counterfactual, then geography and land quality are not important determinants of actual yield gaps across administrative units.

Spatial potential Here I assess the extent to which reallocation of agricultural production of the different crops to the most productive locations across space within an administrative unit can raise aggregate output. This counterfactual combines the production potential with a reallocation of crops across space to the most suitable locations. In particular, I allow production to be reallocated so that each crop is produced in the cells where it realizes the highest potential yields, keeping constant the amount of cultivated land for that crop in the country to the actual level, i.e., $L_i^c = \sum_{j \in J_i} \ell_{ji}^c$. This allocation problem is non-trivial, as 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 as is the amount of land of a cell. I reallocate the production of crops to cells according to *comparative advantage* in potential yields of the different crops, i.e., where the relative potential return for each crop is the highest. Formally, this involves solving a large-scale linear programming problem for each administrative unit, given by,

$$\max_{\{\ell_{ji}^c\}} \sum_{c \in \mathcal{C}} \sum_{j \in J_u} p^c \hat{y}_{ji}^c \ell_{ji}^c, \tag{2}$$

subject to

$$\sum_{c \in \mathcal{C}} \ell_{ji}^c \leq L_{ji}, \quad j = 1, 2, ...J_i; \tag{3}$$

$$\sum_{j \in J_i} \ell_{ji}^c \leq L_i^c, \quad c = 1, 2, ...C; \tag{4}$$

$$\ell_{ji}^c \geq 0, \quad j = 1, 2, ...J_i; \quad c = 1, 2, ...C. \tag{5}$$

The objective is to maximize the total amount 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.

Total potential The last counterfactual is to assess the extent to which administrative units may not be producing the highest yielding mix of crops in each location given their land endowment characteristics. This counterfactual involves computing the aggregate yield in each country by picking the crop in each location that maximizes output. Formally, I solve for ℓ_{ji}^c in equation (2) subject to only the first and third set of constraints, that is equations (3) and (5). This counterfactual involves production potential, reallocation of crops across space, and changes in crop choices in order to maximize aggregate output. 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.

This decomposition allows the empirical analysis to isolate the relative contribution of land quality versus production organization, first under current climate conditions and later under projected future ones.

4 Cross-Country Results

I first present the production-potential results under low inputs in Section 4.1, that capture the natural suitability of the land. Section 4.2 presents the production-potential yields under the mixed input scenario, to illustrate the role of complementary inputs, and Section 4.3 shows the gains from reallocation across space and crops. Section 4.4 illustrates the aggregate implications for structural change of the production-potential yields under mixed inputs. These results establish the geography–production relationship under current climate conditions. In Section 6, I show how projected climate change reshapes these production possibilities and alters the value of spatial reallocation.

4.1 Natural Land Suitability

I begin by comparing actual agricultural productivity with the biophysical production potential implied by land suitability under low-input conditions. This quantifies the extent to which countries in the region are currently translating land quality into output.

I calculate for each country aggregate output per hectare (actual yield) for the year 2000, using output and harvested land data by crop and cell within countries, and FAO international crop prices (Geary-Khamis international dollars, GK$ henceforth). In the first column of Table 2, I report the actual yield for individual Latin American and Caribbean countries along with Portugal and Spain, as well as the average across these countries (LAC). In addition, to facilitate comparisons with other countries, I report values for the two other North American economies, Canada and the United States, as well as the average over the 10 percent richest and 10 percent poorest across all countries in Adamopoulos and Restuccia (2022). The second column in Table 2 reports the ratio of each country's actual yield to that of the 10 percent richest economies in the world, as higher income countries tend to have higher agricultural productivity. On average, LAC countries are closer in actual yield to the richest rather than the poorest set of countries. Nevertheless, the average actual yield across LAC countries exhibits an 18 percent deficit relative to the richest countries. This average masks considerable variation across LAC countries. Chile, Colombia, Costa Rica, Jamaica, Guyana and Peru are all more productive than the high income countries. However, Antigua and Barbuda, Nicaragua, Honduras have a yield at 50 percent or less than the richest group.

In the third column of Table 2, I report the value in GK$ of the counterfactual production potential yield under the low input scenario. The aggregate production potential yield is constructed by replacing the observed yields by crop in each cell with the potential yields estimated by GAEZ under rainfed and low farming inputs. As noted above, the low input production potential captures more

Table 2: Actual and Production-Potential (low inputs) Yields

	Actual Yield	Act Rel to Rich	Potential Yield	Pot Rel to Rich
North America				
Canada	441.2	0.60	166.1	0.70
Mexico	415.8	0.56	170.2	0.72
United States	814.4	1.10	284.6	1.20
Central America				
Belize	639.8	0.87	276.5	1.17
Costa Rica	960.6	1.30	322.9	1.36
El Salvador	435.4	0.59	275.8	1.16
Guatemala	560.8	0.76	326.2	1.38
Honduras	371.4	0.50	301.9	1.27
Nicaragua	343.8	0.46	265.4	1.12
Panama	520.9	0.70	292.7	1.23
Caribbean				
Antigua and Barbuda	165.1	0.22	353.4	1.49
Bahamas	497.2	0.67	224.6	0.95
Cuba	605.3	0.82	406.1	1.71
Dominican Republic	684.9	0.93	430.5	1.81
Jamaica	1152.8	1.56	187.2	0.79
South America				
Argentina	563.8	0.76	314.9	1.33
Bolivia	404.8	0.55	300.6	1.27
Brazil	637.6	0.86	213.3	0.90
Chile	825.0	1.12	285.7	1.20
Colombia	901.7	1.22	312.5	1.32
Ecuador	504.7	0.68	245.9	1.04
French Guiana	547.2	0.74	170.5	0.72
Guyana	858.0	1.16	220.9	0.93
Paraguay	650.6	0.88	204.9	0.86
Peru	759.1	1.03	176.6	0.74
Uruguay	607.7	0.82	366.8	1.55
Venezuela	653.4	0.88	262.6	1.11
Europe				
Portugal	455.8	0.62	345.3	1.46
Spain	654.6	0.89	288.4	1.22
LAC countries	606.6	0.82	279.3	1.18
Rich 10% of all countries	739.5	1.00	237.2	1.00
Poor 10% of all countries	235.5	0.32	225.7	0.95

Notes: Actual and potential yields are measured as total value output per hectare in international prices (GK$/ha). Low inputs assumes rainfed water supply and low-input cultivation practices.

closely the natural suitability of the land for the production of different crops cell-by-cell, because it involves the least human intervention and input application in natural endowment conditions. This however also means that the potential yields under the low input scenario will typically be lower than the actual yields, given that all countries have at least some input application, cultivation practices, and possibly irrigation.

In levels, the production potential yield does not differ systematically across rich and poor countries in the world. It is about 230 GK$. In the LAC countries the potential yield ranges between 170 GK$ in Mexico (just above what it is in Canada) and 430 GK$ in the Dominican Republic. The average potential yield across all LAC countries is 279 GK$, which is about the value in the United States. In other words, in terms of natural suitability of the land the LAC are on average above the rest of the world, with some countries like the Dominican Republic and Uruguay considerably above.

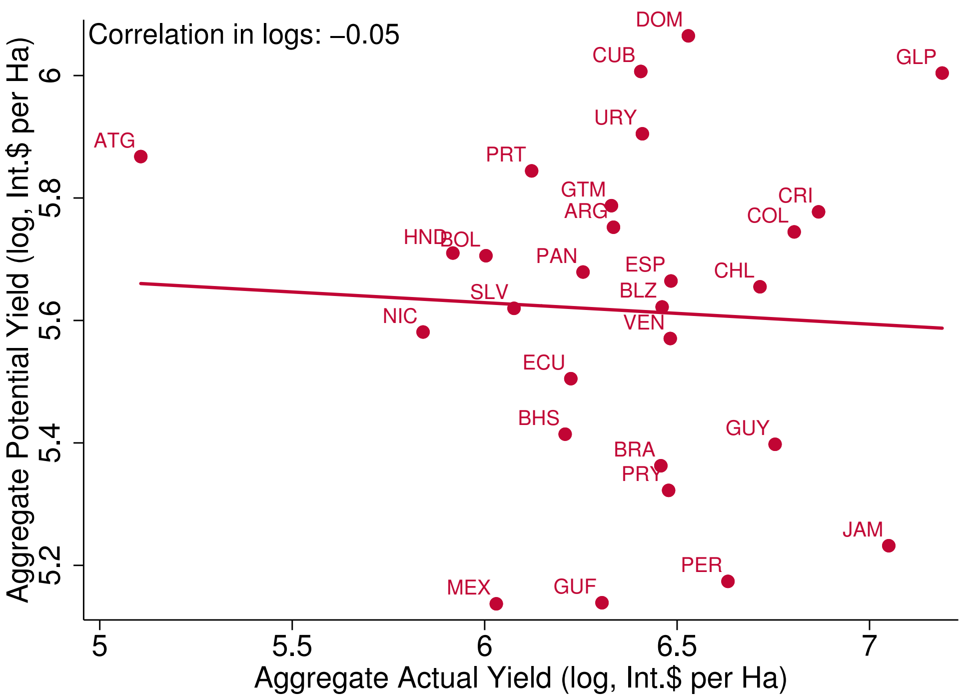
The fourth column reports the aggregate potential yield relative to the rich group of countries. If countries produced the crops they are producing in the locations they are actually producing them but according to the their potential yields, the aggregate yield deficit between LAC countries and the rich group of countries would be reversed. With no complementary inputs and rainfed water conditions, LAC countries would attain an 18 percent higher aggregate yield. In other words, the agricultural productivity shortfall of LAC countries is not due to poor land quality and unfavorable geography. There is considerable variation across LAC countries, with Portugal, Uruguay having 46 and 55 percent higher potential yields relative to rich countries, and several countries like Peru and Paraguay considerably below. Comparing the second and third column the relative position of Chile and Colombia in actual yields is closest to that in potential yields.

To what extent are the actual yield differences across LAC countries the result of differences in land quality and geography, captured by the low-input aggregate potential yields, across them? In Figure 1, I plot (in logs) the aggregate production-potential yield for the rainfed low-input scenario against the aggregate actual yield. If aggregate potential yields were driving the actual yields then we would expect countries to roughly fall on a 45 degree line. Instead, country-level actual and production potential yields are completely uncorrelated across LAC countries, with a correlation coefficient of -0.05. This implies that current land quality and geographic conditions play a weak role in accounting for the observed agricultural productivity differences.[6]

In order to picture the geography of the cross-country variation in the natural suitability of the land, in Figure 2 I draw a map of the average country-level production potential yield under the

[6]In Appendix A, I show that this finding is robust to the inclusion of coffee, tea, cocoa in the set of crops considered.

Figure 1: Aggregate low-input production-potential versus actual yield across countries



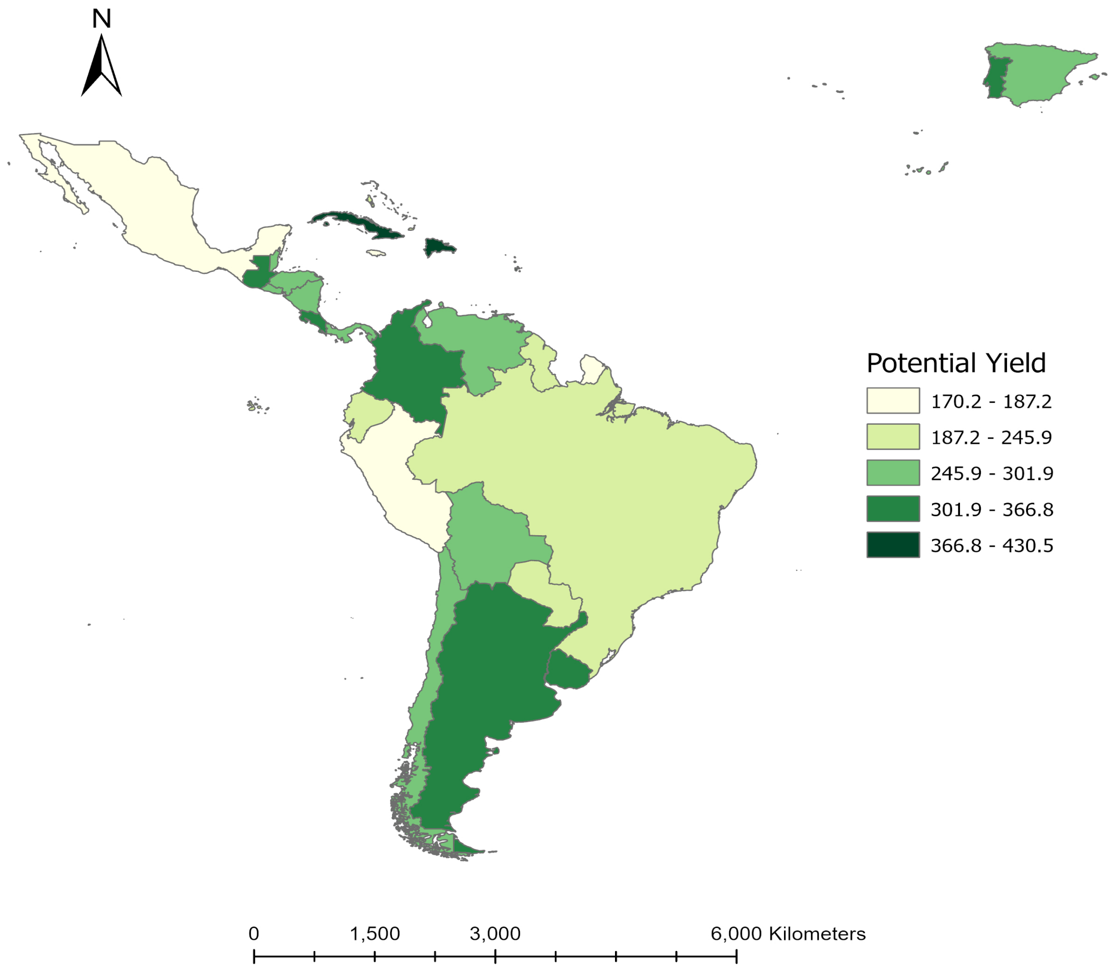
Notes: Aggregate production-potential yield under rainfed low-input scenario.

rainfed - low input scenario. The darker shading indicates a higher potential yield. Geographically potential yields appear to be better in the Central America region, with countries like Guatemala and the Dominican Republic standing out, as well in the Southern Cone region with countries like Argentina and Uruguay being distinguishable.

4.2 Land Quality with Input Application

While the production potential counterfactual yield under the rainfed - low input scenario, captures a country's raw natural land quality endowments, it is typically below countries' actual yields, as all farmers tend to apply some form of inputs, management, and cultivation practices. I now estimate the average production potential counterfactual yield across countries under the mixed input scenario, which includes irrigation (in addition to rainfed water supply) and an intermediate level of input application. The mixed input scenario is a more reasonable approximation of current production conditions across many countries. The crop-cell potential yields capture how the natural land quality and geographic endowments of a location can be combined with reasonable application of appropriate inputs to achieve the highest attainable yield for that crop in that location.

Figure 2: Country-Level Potential Yields (low inputs)



Notes: "Potential Yield (low)" refers to the country-level potential yield from the Production Potential experiment, that replaces actual yields in each cell and for each produced crop with the corresponding potential yield, under rainfed conditions and low level of inputs. The potential yield is expressed in Geary-Khamis international \$. In the map darker shades reflect higher potential yields.

The second column of Table 3 reports the counterfactual production potential yield for individual LAC countries, their average, as well as for Canada, the United States, and the averages of the richest and poorest countries of the world. The production potential yield maintains the observed distribution of harvested land across all crops and all cells within countries, but production for each crop-cell takes places according to the mixed input potential yields rather than the actual. The first column repeats the actual yield. Across LAC countries the level of the mixed input potential yields ranges from a low of 836 GK$ in the Bahamas to a high of 2136 GK$ in Chile, with an average of 1477 GK$, well above the averages of rich and poor countries.[7]

The third column of Table 3 reports the ratio of the mixed input production potential yield for each country relative to the rich group of countries. Similar to the conclusion under the low input scenario, on average LAC would be 21 percent more productive than the richest countries in the world if they exploited their raw land endowments and all countries applied the same reasonable set of inputs. The implication is that LAC countries are not taking advantage of their land and geographic endowments enough. There is however considerable variation in potential yields relative to the rich countries, with Chile, Colombia, Peru and Portugal exhibiting much higher potential productivity, and Bahamas, Mexico, Nicaragua lower.

The aggregate potential yields under the mixed input scenario are typically higher than the aggregate actual yields across all countries, because they assume efficient use of appropriate cultivation practices. The yield gap, that is the ratio of the mixed production potential yield to the actual represents the potential yield gains countries could attain if they combined their land quality endowments with a mix of inputs. Across all countries, while the level of the potential yield with mixed inputs is very similar, the yield gap is substantially higher in poor countries at 4.9, relative to rich at 1.7. This implies that on average poor countries are much further away from their production potential than rich countries. Across LAC countries the yield gap ranges between 1.08 in Jamaica to 4 in Portugal, with an average of 2.4 across all LAC countries (excluding the outlier of Antigua and Barbuda). In other words, LAC countries produce closer to their potential than the typical country, and exploit their natural conditions at a level more similar to that in rich countries, than poor countries.

To put the range of yield gaps across LAC countries into geographic perspective, Figure 3, displays the average yield gap for each LAC country, with the darker shades of orange reflecting a higher gap. Brazil stands out as a country with a fairly low yield gap, implying smaller potential gains from better input application. Bolivia, Honduras and Cuba are the furthest away from their production potential with a yield gap of over 3. Interestingly, there is no specific geographic

[7] Antigua and Barbuda is an outlier, but is very small and has relatively little agricultural land.

Table 3: Actual and Production-Potential (mixed inputs) Yields

	Actual Yield	Potential Yield	Pot Rel to Rich	Potential/Actual
North America				
Canada	441.2	648.3	0.53	1.47
Mexico	415.8	1003.4	0.82	2.41
United States	814.4	1457.3	1.19	1.79
Central America				
Belize	639.8	1275.5	1.05	1.99
Costa Rica	960.6	1610.5	1.32	1.68
El Salvador	435.4	1128.5	0.92	2.59
Guatemala	560.8	1243.2	1.02	2.22
Honduras	371.4	1180.3	0.97	3.18
Nicaragua	343.8	985.0	0.81	2.87
Panama	520.9	1294.8	1.06	2.49
Caribbean				
Antigua and Barbuda	165.1	2878.9	2.36	17.44
Bahamas	497.2	835.6	0.68	1.68
Cuba	605.3	1923.9	1.58	3.18
Dominican Republic	684.9	1918.4	1.57	2.80
Jamaica	1152.8	1241.7	1.02	1.08
South America				
Argentina	563.8	1210.1	0.99	2.15
Bolivia	404.8	1419.9	1.16	3.51
Brazil	637.6	1108.0	0.91	1.74
Chile	825.0	2135.8	1.75	2.59
Colombia	901.7	1693.0	1.39	1.88
Ecuador	504.7	1296.4	1.06	2.57
French Guiana	547.2	1561.9	1.28	2.85
Guyana	858.0	1482.4	1.22	1.73
Paraguay	650.6	1385.7	1.14	2.13
Peru	759.1	1902.5	1.56	2.51
Uruguay	607.7	1545.0	1.27	2.54
Venezuela	653.4	1424.0	1.17	2.18
Europe				
Portugal	455.8	1821.1	1.49	4.00
Spain	654.6	1359.9	1.11	2.08
LAC countries	606.6	1476.5	1.21	3.0
Rich 10% of all countries	739.5	1220.0	1.00	1.65
Poor 10% of all countries	235.5	1160.6	0.95	4.93

Notes: Actual and potential yields are measured as total value output per hectare in international prices (GK$/ha). The production potential yield is calculated under the mixed input scenario.

pattern to the yield gap variation across countries, which is consistent with the idea that economic factors (policies, constraints, frictions) are the drivers of how much countries exploit their natural endowment conditions in producing agricultural goods.

Despite being lower in levels, to what extent can the variation in actual yields be accounted for by the variation in mixed input potential yields across LAC countries? In Figure 4, I plot the mixed input production potential yield against the actual yield (in logs) for LAC countries, excluding the outlier of Antigua and Barbuda.[8] The mixed input production potential and the actual yields are positively correlated, with a correlation coefficient of 0.56. This is different than the virtually flat relationship between the low input production potential and the actual yield. The implication is that while all countries are under-utilizing their natural land endowments, LAC countries with the highest actual agricultural productivity are likely the ones that effectively utilize their land's potential by applying sufficient inputs (such as fertilizers, irrigation, and improved agricultural practices). As a result, inputs play a crucial role in unlocking the potential of land to achieve higher yields, by overcoming environmental and natural limitations.

The mixed-input production potential provides a natural benchmark for evaluating how current production choices depart from attainable yields today. In Section 6, I show that the same benchmark can be constructed for future climate conditions, enabling a consistent comparison of current and future production possibilities.

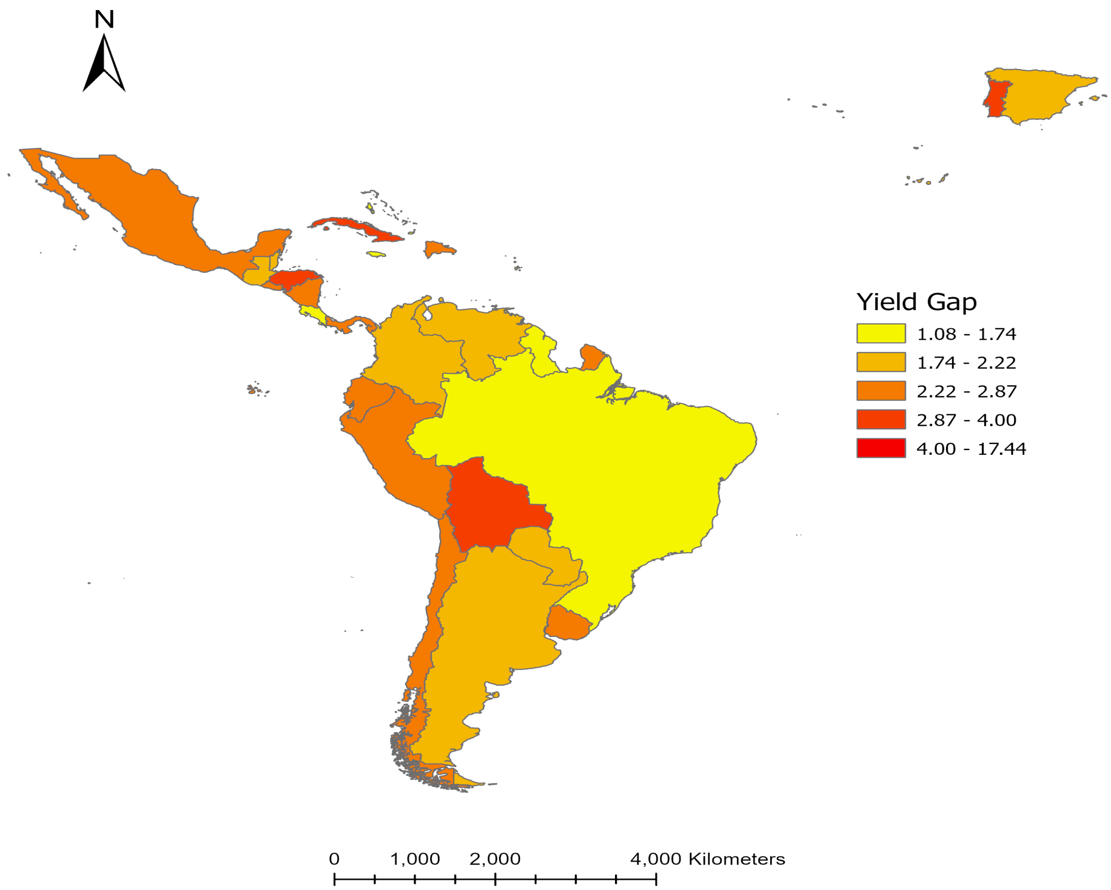
4.3 Gains from Spatial and Crop Reallocation

In many developing countries large segments of the population live in rural areas, operating in the agricultural sector at subsistence levels, with poor connectivity to markets to sell their crops and buy inputs. Insufficient transport infrastructure and other distortions, can be a major constraint for farmers who may end up producing crops that are not necessarily suitable to the geography of the land they farm, see for instance Adamopoulos (2025). These constraints can affect what is produced and where it is produced in the country. Here, I assess the potential for productivity gains from the spatial reallocation of production within a country and gains from the shift in the mix of crops produced towards higher value yielding varieties. To do this, I estimate in turn, the counterfactual spatial potential and total potential yields by country, under the mixed input scenario.

The spatial potential yield captures gains from reallocation across space by asking: how would the aggregate yield change if we reallocated the production of individual crops across cultivated cells according to where they exhibit the highest relative yield in the country, holding the total

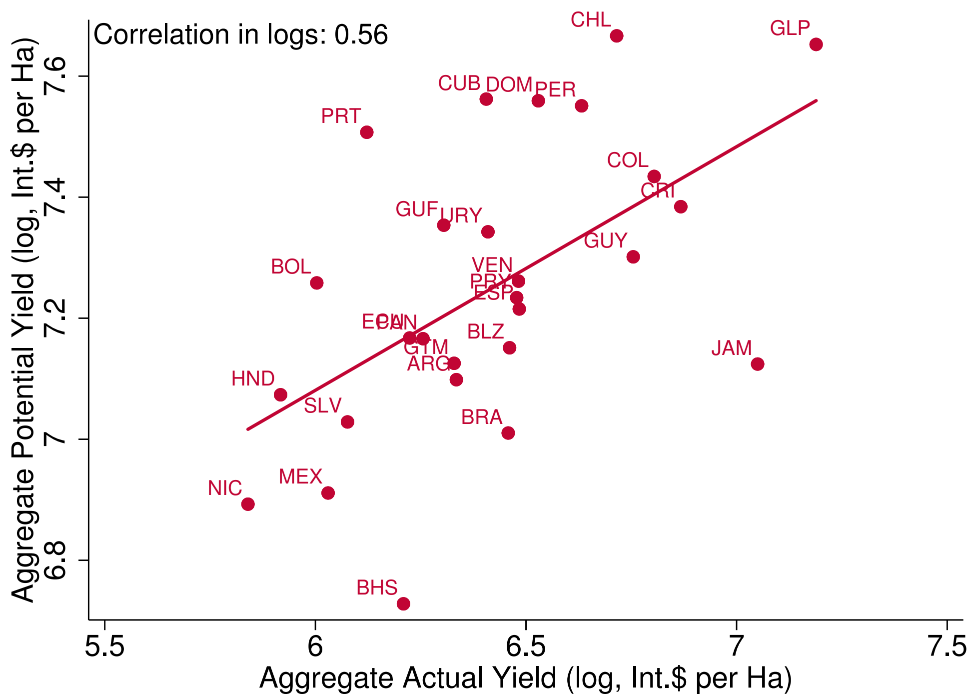
[8]Including Antigua and Barbuda the correlation is positive but much lower at 0.08.

Figure 3: Country-Level Potential Yield Gaps (mixed inputs)



Notes: "Yield Gap (mixed)" refers to the country-level gap in the production potential yield under mixed inputs and the actual yield. Potential and actual yields are expressed in Geary-Khamis international dollars. The map shows yield gaps as ratios. In the map darker shades of orange reflect higher yield gaps, that is opportunities for yield gains.

Figure 4: Aggregate mixed input production-potential versus actual yield across countries



Notes: Aggregate production-potential yield is under the mixed input scenario.

land allocated to each crop in the country at its actual level? Table 4 reports the results of the spatial potential counterfactual in column 2 and the yield gains relative to the production potential (repeated here in column 1), in column 3. In the richest and poorest countries in the world the yield benefits from the spatial reallocation of production is similar, at 19 and 17 percent respectively. Across LAC countries the average yield gain under the production potential is similar, at 14 percent but this ranges from a low 1 percent in French Guiana to a high 33-35 percent additional potential gain in Portugal and Spain. Given that the effect is similar between LAC and other countries, spatial reallocation does not help further increase the productivity advantage of LAC relative to rich, beyond what the production potential does.

The total potential counterfactual asks, how would the aggregate yield change if in each cell the highest value yielding crop was produced, holding the amount of cultivated land in each cell to its actual level? This counterfactual captures the maximum potential yield that can be achieved from a shift in the set of produced crops to the highest return ones, above the spatial and production potential. The results of the total potential counterfactual are reported in column 4 of Table 4, with the last column reporting the additional yield gains from the total potential relative to the spatial potential. Across the world the additional total potential gains are 1.7 for rich countries and 2.4 for poor countries. Across the LAC countries the average additional yields gains from the total potential are in between at 2.1, but range from 1.1 (Bahamas) to 3.6 (Argentina). The higher the additional potential gains from the total potential counterfactual experiment, the stronger the misalignment between the highest yielding value crops and the actual crops produced.[9]

To visualize the effects of all the counterfactuals relative to the actual yields by country, Figure 5 displays in stacked bar format the additional yield gain from each counterfactual relative to the previous one from the bottom up, production potential relative to actual, spatial potential relative to production potential, and total potential relative to spatial potential. To facilitate exposition I display the results in three separate panels: South America in Panel (a); Central America in Panel (b); Caribbean and Europe in Panel (c). In all cases, the actual yield is lower than the production potential, which in turn is lower than the spatial potential and the total potential. As can be seen, while there is variation in the magnitude of the different components across countries, the largest yield gains are observed when moving from the actual to the production potential and from the spatial potential to the total potential. The additional yield gains from the spatial potential are fairly small in comparison. The countries with the highest total potential yields are Chile, Uruguay and Argentina.

These findings under current biophysical conditions are informative for understanding future adaptation pressures. Because climate change alters the spatial pattern of potential yields, the value of spatial reallocation itself may rise or fall. Section 6 quantifies how these gains evolve under projected climate scenarios for the 2050s.

4.4 Implications for Structural Change

In order to put into perspective the yield gains implied by the production potential counterfactual, I study their implications for structural change and aggregate GDP per capita gains through the lens of a simple two sector model of agriculture and non-agriculture. The model features non-homothetic preferences with a subsistence constraint for agricultural consumption. The structure of the model follows Adamopoulos and Restuccia (2022), and I provide a brief description of the model in Appendix 2. A key implication of the model is that when agricultural productivity is low, a country devotes a disproportionate amount of labor to producing agricultural goods, taking away resources from the rest of the economy. As agricultural productivity improves, subsistence needs are met with fewer resources allocated to agriculture, which releases labor to the rest of the

[9] I note here that because this is an accounting exercise, the total potential counterfactual does not take into account changes in the cost structure, the demand side, and relative prices.

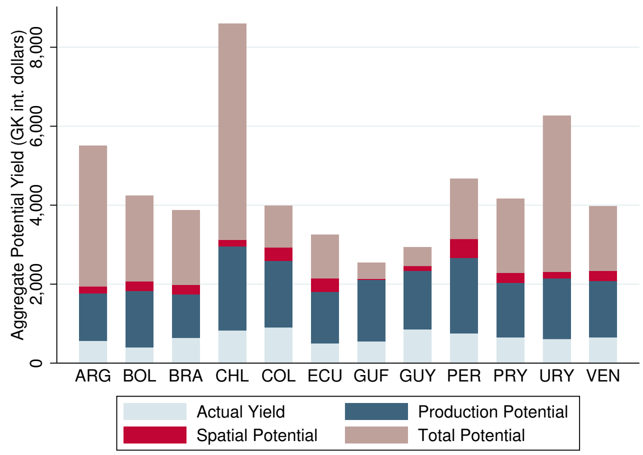
Table 4: Counterfactual Spatial and Total Potential Yields (mixed inputs)

	Aggregate potential yield with mixed inputs				
	Production	Spatial	Spatial/ Production	Total	Total/ Spatial
North America					
Canada	648.3	763.4	1.18	1596.9	2.09
Mexico	1003.4	1197.1	1.19	3100.2	2.59
United States	1457.3	1725.7	1.18	2610.9	1.51
Central America					
Belize	1275.5	1383.8	1.08	2363.2	1.71
Costa Rica	1610.5	1869.6	1.16	3128.6	1.67
El Salvador	1128.5	1232.6	1.09	3736.4	3.03
Guatemala	1243.2	1417.4	1.14	3828.2	2.70
Honduras	1180.3	1334.4	1.13	3884.7	2.91
Nicaragua	985.0	1223.2	1.24	3414.2	2.79
Panama	1294.8	1415.4	1.09	2823.3	1.99
Caribbean					
Antigua and Barbuda	2878.9	2909.1	1.01	3844.4	1.32
Bahamas	835.6	876.8	1.05	952.2	1.09
Cuba	1923.9	2120.6	1.10	3415.5	1.61
Dominican Republic	1918.4	2096.6	1.09	3048.6	1.45
Jamaica	1241.7	1368.2	1.10	1901.8	1.39
South America					
Argentina	1210.1	1374.9	1.14	4943.8	3.60
Bolivia	1419.9	1669.9	1.18	3842.6	2.30
Brazil	1108.0	1346.1	1.21	3238.8	2.41
Chile	2135.8	2300.7	1.08	7777.9	3.38
Colombia	1693.0	2024.0	1.20	3086.0	1.52
Ecuador	1296.4	1643.1	1.27	2745.5	1.67
French Guiana	1561.9	1585.3	1.01	1994.1	1.26
Guyana	1482.4	1599.7	1.08	2074.9	1.30
Paraguay	1385.7	1631.9	1.18	3518.1	2.16
Peru	1902.5	2381.6	1.25	3908.8	1.64
Uruguay	1545.0	1702.9	1.10	5655.1	3.32
Venezuela	1424.0	1684.1	1.18	3323.9	1.97
Europe					
Portugal	1821.1	2414.2	1.33	4203.8	1.74
Spain	1359.9	1834.6	1.35	3814.0	2.08
LAC countries	1476.5	1690.3	1.14	3465.5	2.05
Rich 10% of all countries	1220.0	1446.0	1.19	2498.3	1.73
Poor 10% of all countries	1160.6	1361.1	1.17	3254.7	2.39

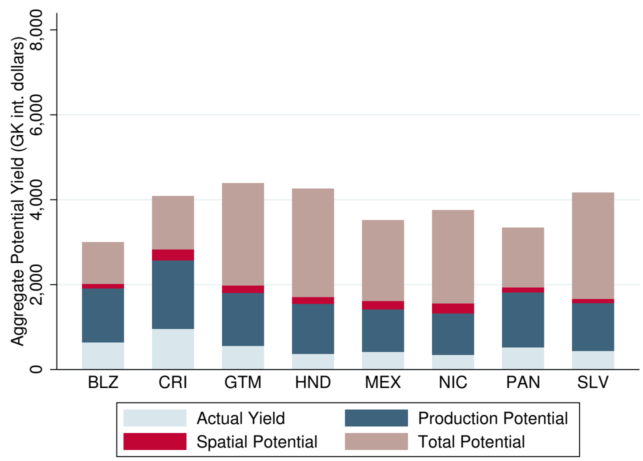
Notes: "Production," "spatial," "total" refer to the production-potential, spatial-potential, and total-potential counterfactual yields (GK$/ha) under mixed inputs.

Figure 5: Yield Gains by Production, Spatial, Total Potentials

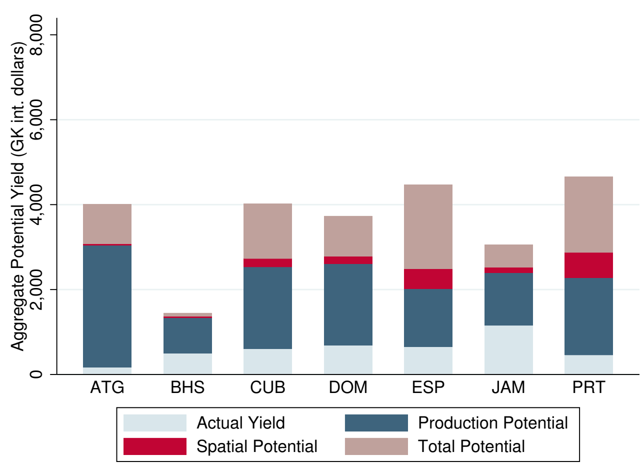
(a) South America



(b) Central America



(c) Caribbean and Europe



Notes: Different colors show the change in GK$/ha relative to the yield below it in the stacked bar.

economy.

I calibrate the model to the United States, with a share of labor in agriculture of 1.7 percent, as per Table 1. I choose TFP in agriculture for every economy in Table 1 (i.e., all LAC countries and Canada) to exactly match the share of labor in agriculture, keeping all other parameters the same as in the benchmark US economy. Then I examine what the effect would be on structural change (the share of labor in agriculture) and real GDP per capita if all countries produced in agriculture according to their production-potential yield under mixed inputs rather than their actual one. Specifically, I increase the calibrated TFP in agriculture in each country by a factor equal to the ratio of the actual to the production potential yield (including the United States). The results of this experiment are presented in Table 5. In calculating real GDP per capita I keep the relative price of agriculture constant to the benchmark economy, thus evaluating GDP at a common set of prices across all countries as is done by statistical agencies.

The first column of Table 5 repeats the share of labor in agriculture for each country from the data, to which I calibrate the baseline economies. The second column shows the percentage point change in the share of labor in agriculture, capturing the implied structural transformation, and the third column the percentage change in real GDP per capita relative to each baseline economy, capturing economic development. Because potential yields with mixed inputs are higher than the actual yields, the model implies substantial structural change and income gains particularly for economies heavily engaged in agriculture and with low income like Bolivia, Guatemala, Honduras and Nicaragua. In other words, if the observed distribution of land quality was complemented with appropriate inputs to fully exploit its potential, LAC countries could see substantial structural change benefits, especially the lower income ones.

5 Sub-National Results

Sub-national variation is central to understanding how land quality interacts with production choices. Using cell-level and province-level potential yields, I document large within-country differences in biophysical potential and examine how closely production aligns with these differences.

The actual and counterfactual yields constructed so far have been at the country level. As a result, they are (weighted) averages across all cells with harvested land in the country. Country averages could mask considerable heterogeneity across space within countries. Here, I consider the role of land quality and geography for agricultural productivity at the sub-national level across LAC countries. Below, I report the results of the production potential counterfactual at the cell-level, as well as the first sub-national administrative boundaries level, i.e., states or provinces. I also report

Table 5: Aggregate Implication of Potential Yield Gains

	Agr. Empl. Share (%)	p.p. Ch. in Agr. Empl. Share (%)	Perc. Ch. in Real GDP pc
North America			
Canada	1.8	-0.8	+0.8
Mexico	14.6	-10.7	+12.2
United States	1.7	-1.0	+1.0
Central America			
Belize	18.5	-11.9	+14.1
Costa Rica	12.4	-6.7	+7.4
El Salvador	20.8	-15.8	+19.3
Guatemala	33.5	-23.4	+33.8
Honduras	36.5	-30.0	+45.4
Nicaragua	29.6	-23.5	+32.2
Panama	17.4	-13.0	+15.3
Caribbean			
Antigua and Barbuda	21.0	-20.7	+25.4
Bahamas	3.3	-1.8	+1.8
Cuba	18.6	-15.3	+18.2
Dominican Republic	12.4	-9.8	+10.8
Jamaica	17.7	-1.9	+2.3
South America			
Argentina	6.0	-4.1	+4.3
Bolivia	31.7	-26.9	+38.0
Brazil	11.5	-6.5	+7.1
Chile	10.1	-7.7	+8.3
Colombia	18.5	-11.3	+13.5
Ecuador	27.9	-21.1	+28.3
Guyana	21.4	-12.0	+14.8
Paraguay	25.6	-17.4	+22.6
Peru	28.0	-21.0	+28.2
Uruguay	11.6	-8.7	+9.6
Venezuela	8.5	-5.9	+6.3
Europe			
Portugal	11.2	-9.8	+10.7
Spain	4.2	-2.8	+2.8
LAC countries	18.2	-13.1	+16.6

Notes: First column displays data from the World Bank's *World Development Indicators*. The second and third column show model-based aggregate implications of potential yield gains, for structural change and development.

summary statistics at the sub-national level.

5.1 Cell-level estimates

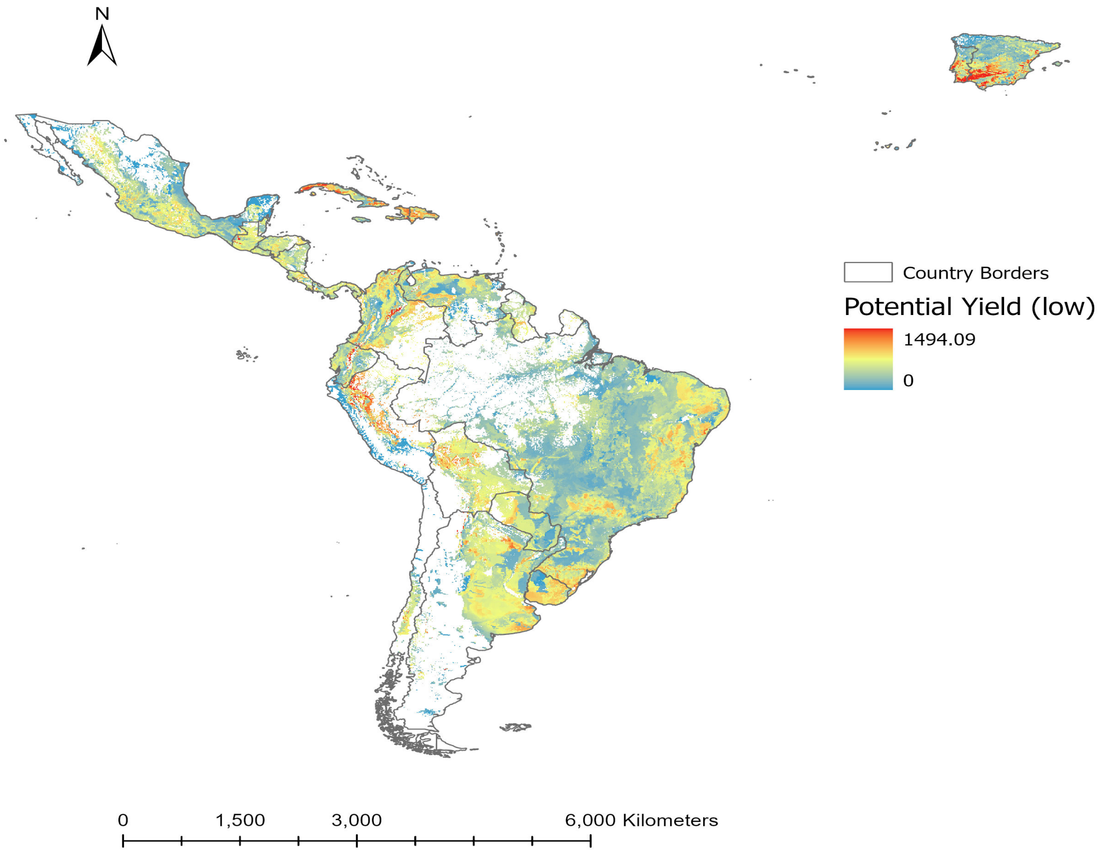
Figure 6 displays the results of the production potential counterfactual under the rainfed low input scenario, at the 5-arc minute resolution. In each cell, of roughly 10×10 kilometers, the same crops actually produced and in the amounts they are produced, takes place according to their potential rather than their actual yields. These cell-level potential yields aggregate across all crops in a cell, and capture the natural suitability of the land for agricultural production at a high spatial resolution. The map coloring is continuous, with bluish shades reflecting low potential yields, yellowish shades intermediate potential yields, and darker orange shades high potential yields. No coloring means zero yields or missing data.

It is clear that the coloring within countries is not homogeneous and that the continuity of land quality characteristics transcends country borders. For example, the Rio de la Plata part of Argentina is highly productive compared to the southern part of the country where productivity is spotty. In contrast Uruguay and southern Brazil are more similar in land quality to northern Argentina even though they are different countries. Peru, Ecuador and Colombia also have patches of very productive land.

5.2 Province-Level Results

The results in Section 4 are all at the country-level. However, there is considerable variation within countries, as to where production takes place, the actual yield observed, and the attainable potential yield achieved. In order, to examine within country variation in geography and land quality, in this section, I expand the analysis to the first administrative sub-national level, typically provinces or states. The sub-national administrative boundaries for each LAC country are obtained from GADM. I provide four figures with two sets of maps for each of the largest four LAC countries, Argentina in Figure 7, Brazil in Figure 8, Colombia in Figure 9 and Mexico in Figure 10. The first map in each figure, Panel (a), shows the intensity of crop production by sub-national unit, as measured by the total sum of harvested hectares of land allocated to all crops in that unit. The coloring in this map is from yellow to red with darker shades indicating more hectares allocated to crop production. The second map in each figure, Panel (b), shows the average potential yield at the sub-national unit level, under the production potential counterfactual with the low input level scenario. Panel (b) captures the natural suitability of the land for agricultural production. The map coloring is from light yellow to green, with darker shades of green reflecting higher average

Figure 6: Cell-Level Potential Yields (low inputs)



Notes: "Potential Yield (low)" refers to the country-level potential yield from the Production Potential experiment, that replaces actual yields in each cell and for each produced crop with the corresponding potential yield, under rainfed conditions and low level of inputs. The potential yield is expressed in Geary-Khamis international dollars. Map shading is continuous.

potential yields.

There is considerable heterogeneity within countries in terms of both location of crop production and potential yields. In Argentina most agricultural production takes place in the Buenos Aires and Cordoba regions which are indeed among the most productive in the country. However, the provinces of Santiago del Estero and Chaco which have similarly high potential yields see less agricultural production.

In Brazil the provinces in the western part of the country have the highest potential yields, whereas a lot of agricultural production takes place in the central southwestern part of the country. For example, in the provinces of Goias and Minas Gerais one finds the most hectares of harvested land in the country, which do not have the highest potential yields.

In Colombia most agricultural production takes place in the northeast of the country, especially Cordoba, Antioquia, Tolima and Santiago de Cali. However, the western part of the country has the highest potential yields.

In Mexico production is concentrated in the south part of the country, which is the most productive as well. Large concentration of harvested hectares are observed in the provinces of Chiapas and Veracruz, whereas Guerrero and Oaxaca have the highest potential yields.

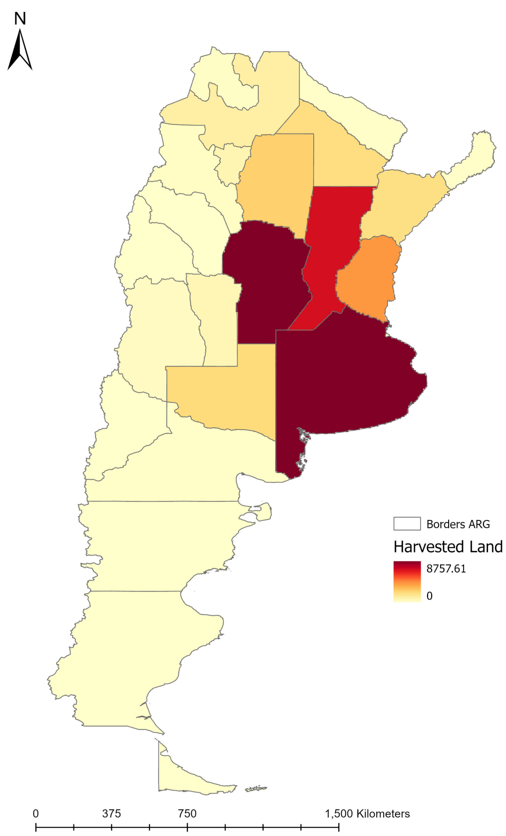
5.2.1 Sub-National Summary Results

Here I examine more systematically the relationship between agricultural production, potential yield, and actual yield across provinces/states within LAC countries.

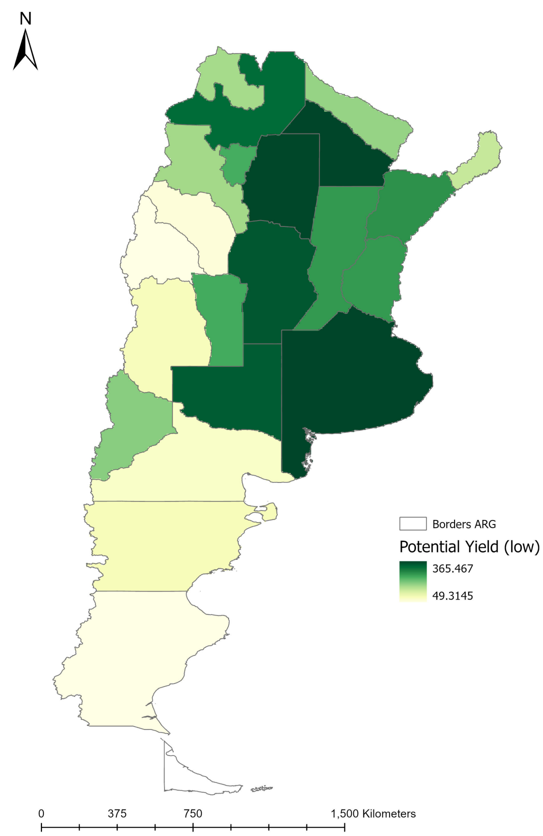
In Figure 11, I plot the average potential yield at the province level against the actual yield, for all provinces within LAC countries. In the scatter plot countries vary by color shading, with the observations corresponding to provinces of the same country all having the same color. Interestingly, across all provinces of all LAC countries taken together there is no correlation between actual and potential yields, just as at the cross-country level under the low input scenario.

However, this masks considerable heterogeneity across countries. In Table 6, I report for each country the correlation across provinces/states of harvested land and potential yield in logs, as well as the correlation between the potential yield and the actual yield in logs. The first correlation is a metric of whether agricultural production takes place primarily where the highest quality land is. The second correlation captures whether actual yields are closely related to the productive potential yields across provinces. There is a lot of variation across countries. The correlation of production and potential yield ranges from -0.20 across provinces in Jamaica to 0.83 across provinces in Argentina. The median correlation across these countries is 0.06. The correlation of actual and

Figure 7: Argentina



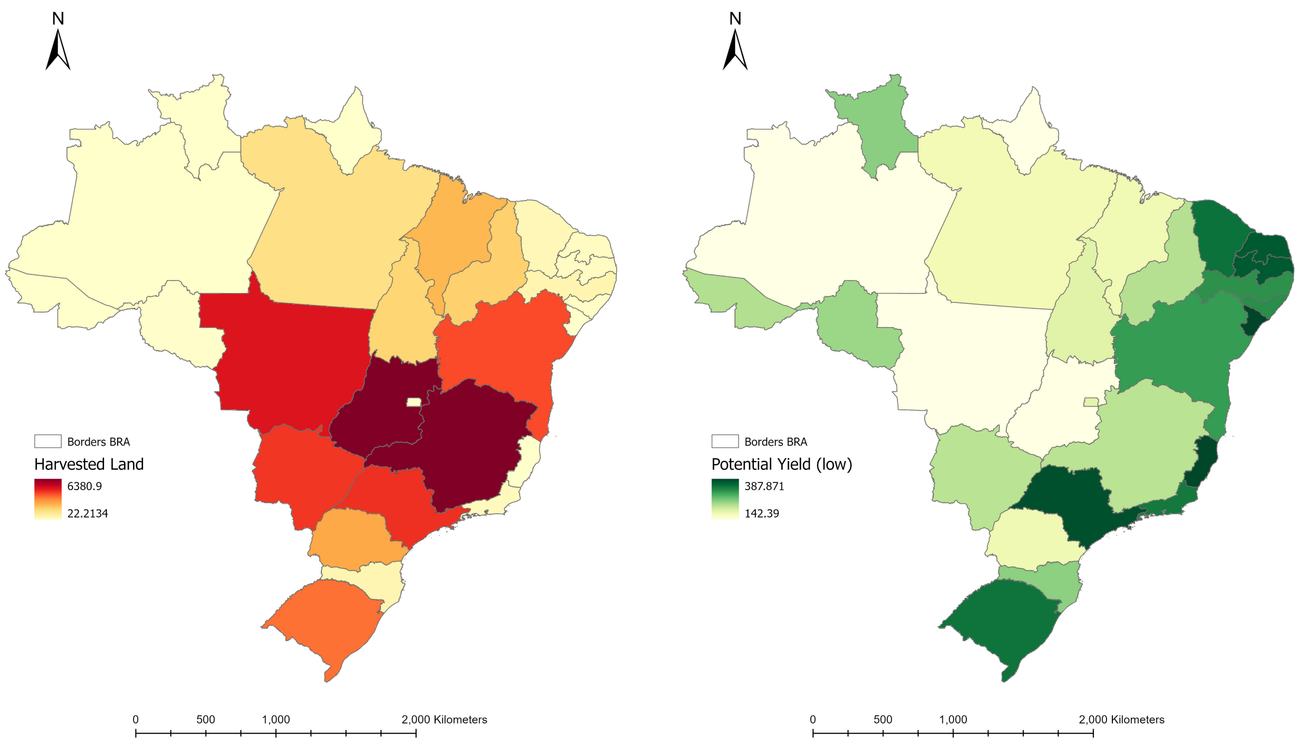
Harvested Land



Potential Yield

Notes: "Harvested Land" is the total amount of harvested land over all crops in hectares. "Potential Yield" from the Production Potential experiment, replaces actual yields in each cell and for each produced crop with the corresponding potential yield, under rainfed conditions and low level of inputs. The potential yield is expressed in Geary-Khamis international dollars. Map shading is continuous.

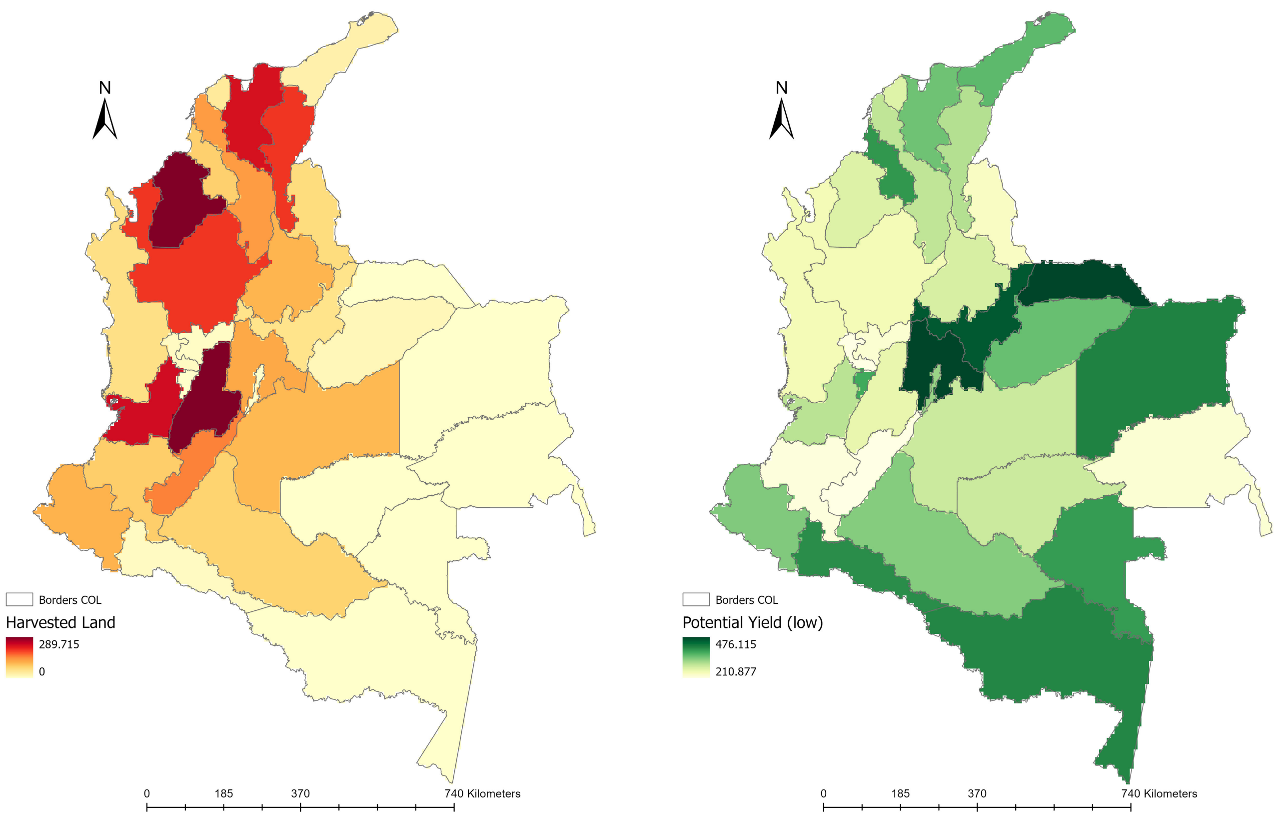
Figure 8: Brazil



Harvested Land Potential Yield

Notes: "Harvested Land" is the total amount of harvested land over all crops in hectares. "Potential Yield" from the Production Potential experiment, replaces actual yields in each cell and for each produced crop with the corresponding potential yield, under rainfed conditions and low level of inputs. The potential yield is expressed in Geary-Khamis international dollars. Map shading is continuous.

Figure 9: Colombia

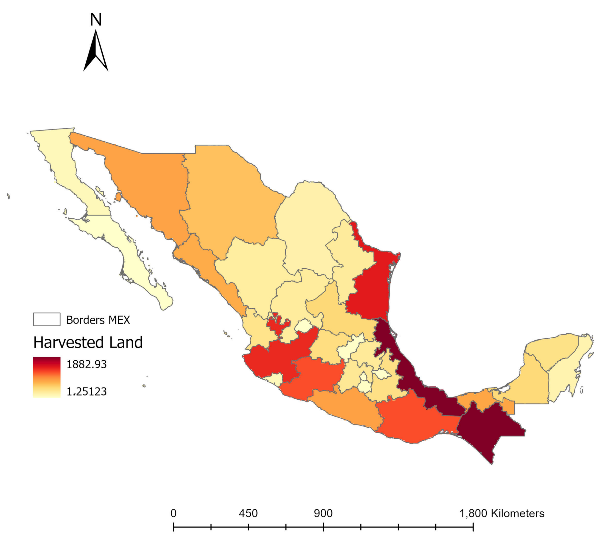


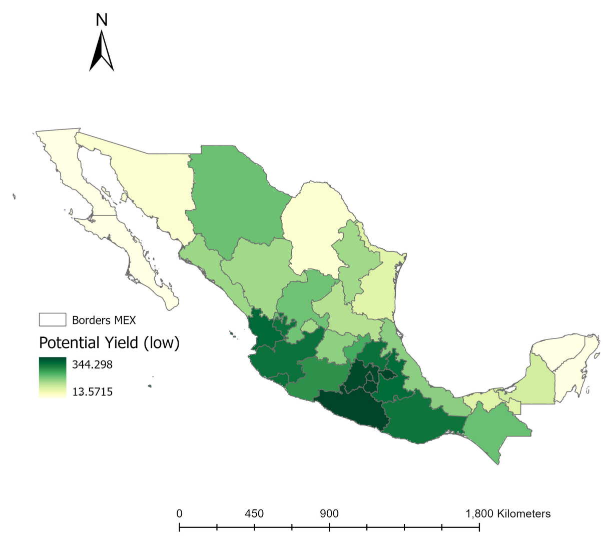
Harvested Land

Potential Yield

Notes: "Harvested Land" is the total amount of harvested land over all crops in hectares. "Potential Yield" from the Production Potential experiment, replaces actual yields in each cell and for each produced crop with the corresponding potential yield, under rainfed conditions and low level of inputs. The potential yield is expressed in Geary-Khamis international dollars. Map shading is continuous.

Figure 10: Mexico



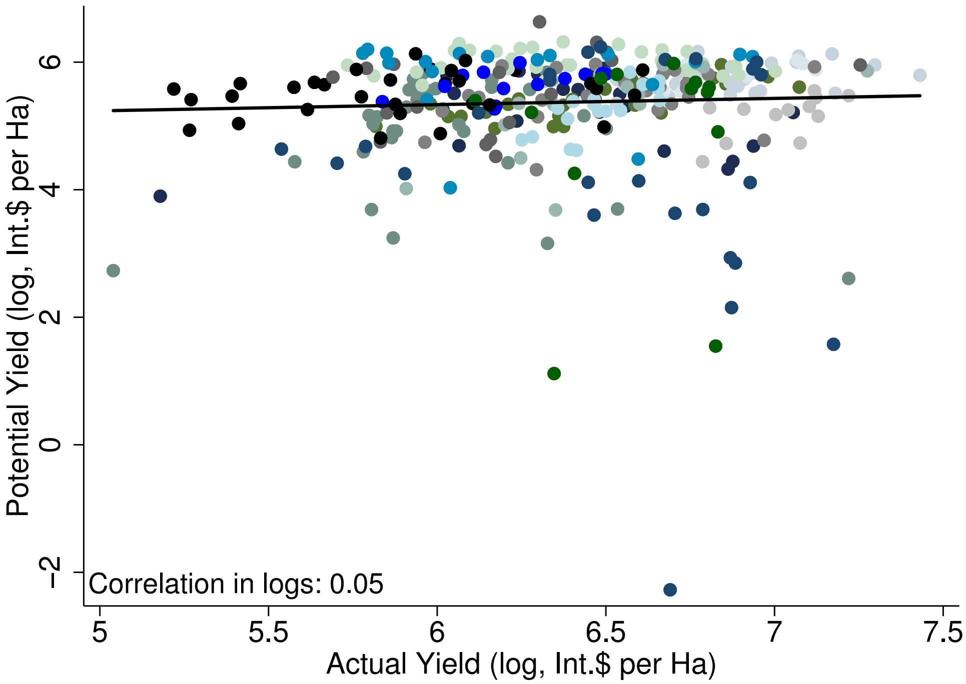


Harvested Land

Potential Yield

Notes: "Harvested Land" is the total amount of harvested land over all crops in hectares. "Potential Yield" from the Production Potential experiment, replaces actual yields in each cell and for each produced crop with the corresponding potential yield, under rainfed conditions and low level of inputs. The potential yield is expressed in Geary-Khamis international dollars. Map shading is continuous.

Figure 11: Aggregate production-potential versus actual yield across provinces



Notes: Figure displays all sub-national units (states/provinces) for all LAC countries, with the units of the same country having the same color shading. Production-potential yield is under rainfed low-input scenario.

potential yields ranges from a low of -0.20 across provinces in Peru, to a high of 0.80 in Bolivia, and a median of 0.30 across all countries. These results indicate an imperfect alignment of production and natural land suitability at the sub-national level, a source of potential productivity gains.

6 Climate Change and Future Geography of Agriculture

The spatial accounting framework is designed to evaluate how geography shapes agricultural production under any set of biophysical conditions. In this section, I apply the same framework to projected climate conditions for the 2050s. This allows me to assess not only how climate change alters average potential yields, but also how it reshapes the spatial heterogeneity of land suitability, and therefore the scope for productivity gains through spatial reallocation.

The projected rise in global temperatures and other climatic phenomena are expected to affect future economic outcomes across several sectors. Agriculture, which uses location-specific natural inputs such as rainfall, humidity and temperature will be affected directly the most. Here, I ex-

Table 6: Within Country Cross-Province Correlations

	Correlation in logs Pot. Yield & Land	Correlation in logs Pot. Yield & Act. Yield
Argentina	0.83	0.06
Bolivia	0.45	0.80
Brazil	-0.03	0.73
Chile	0.43	0.09
Colombia	-0.19	0.30
Cost Rica	-0.11	0.71
Dominican Republic	0.13	0.01
Ecuador	-0.10	0.25
Spain	0.45	0.66
Jamaica	-0.20	0.60
Mexico	-0.04	-0.01
Panama	0.15	0.49
Peru	0.06	-0.20
Portugal	0.51	0.32
Paraguay	-0.05	0.77
Uruguay	-0.12	-0.03
Venezuela	0.12	0.30

Notes: Actual and potential yields (low inputs) are measured as total value output per hectare in international prices (GK$/ha). Harvested land is measured in hectares.

amine the effects of expected climate change on future agricultural productivity, using my spatial accounting framework and the potential yields by crop and cell that GAEZ v4.0 estimates, with its agronomic models factoring in climate change from the most updated climate models. Importantly, given that climate change is expected to have heterogeneous effects across locations, even within countries, these potential yields account for climate change at the high spatial resolution level of roughly 10×10 kilometers. I use the crop-cell future projected yields to estimate for each LAC country (along with Canada and the United States) expected aggregate potential yields from the production-potential, spatial-potential, total-potential counterfactuals.

I consider two moderate, intermediate climate change scenarios, that in turn use climate models GFLD-ESM2M (climate model "M1" below) and IPSL-CM5A-LR (climate model "M2" below). I focus on climate change projections for the period 2041-2070. In both cases I use the cell-crop potential yields under rainfed water conditions, and high level of inputs, with CO_2 fertilization, and RCP 4.5 which corresponds to a middle path warming scenario.[10] For aggregation across crops I use the same set of FAO international prices

In Table 7, I report by country the aggregate potential yields from the production-potential counterfactual under climate model M1 (second column) and model M2 (third column). For comparability, in column 1, I repeat the production-potential yield under the mixed input scenario, which captures a realistic potential attainable yield today under current climate conditions and a reasonable input application. Columns 4 and 5 display the ratio of the potential yield under climate model M1 and M2 respectively to the current potential yield. The picture painted by the two climate change models is similar, even though there are variations for individual countries. In most countries the level of potential agricultural productivity is expected to fall relative to current potential productivity, but not everywhere and not by the same amount, capturing the heterogeneity of projected effects across countries. For example, Canada with its cold climate today is expected to benefit in terms of crop productivity. Among LAC countries Nicaragua, Bahamas, Jamaica, are expected to see a rise in their productivity. The countries expected to see the largest drops in their potential yield from climate change are Antigua and Barbuda, Chile, and Peru, Portugal and Spain. The average, across LAC countries, of the climate based potential yield relative to the current potential yield is 0.78 under model M1 and 0.77 under model M2.

Next, I ask whether in the face of climate change, there is scope to achieve yield gains from the spatial reallocation of crop production across locations in a country, and changes in the composition of produced crops? To answer this question, I conduct the spatial-potential and total-potential

[10]The projected cell-crop level potential yields are available from GAEZ v.4 only under the high level of inputs. The implicit assumption in this estimation is that all countries would be using a level of inputs by this point that corresponds to the high level of inputs today.

Table 7: Production Potential Yields under Climate Change

	Current Pot Yield	Clima Pot Yield (M1)	Clima Pot Yield (M2)	Ratio M1/Current	Ratio M2/Current
North America					
Canada	648.3	887.6	829.0	1.37	1.28
Mexico	1003.4	719.0	735.9	0.72	0.73
United States	1457.3	1308.8	1183.2	0.90	0.81
Central America					
Belize	1275.5	1241.2	1065.1	0.97	0.83
Costa Rica	1610.5	1502.7	1472.9	0.93	0.91
El Salvador	1128.5	1105.7	1167.4	0.98	1.03
Guatemala	1243.2	1060.6	1087.3	0.85	0.87
Honduras	1180.3	1012.1	1207.1	0.86	1.02
Nicaragua	985.0	1096.7	1033.5	1.11	1.05
Panama	1294.8	1354.9	1377.2	1.05	1.06
Caribbean					
Antigua and Barbuda	2878.9	994.5	1284.6	0.35	0.45
Bahamas	835.6	956.2	804.4	1.14	0.96
Cuba	1923.9	1636.2	1371.6	0.85	0.71
Dominican Republic	1918.4	1543.5	1170.2	0.80	0.61
Jamaica	1241.7	1782.7	1762.5	1.44	1.42
South America					
Argentina	1210.1	1116.6	1137.6	0.92	0.94
Bolivia	1419.9	1321.0	1241.3	0.93	0.87
Brazil	1108.0	942.1	953.3	0.85	0.86
Chile	2135.8	993.6	1171.1	0.47	0.55
Colombia	1693.0	1356.2	1390.0	0.80	0.82
Ecuador	1296.4	1061.3	1116.2	0.82	0.86
French Guiana	1561.9	1445.5	1420.7	0.93	0.91
Guyana	1482.4	1395.6	1383.8	0.94	0.93
Paraguay	1385.7	1258.7	1170.5	0.91	0.84
Peru	1902.5	755.7	731.4	0.40	0.38
Uruguay	1545.0	933.6	1172.6	0.60	0.76
Venezuela	1424.0	1086.3	1035.3	0.76	0.73
Europe					
Portugal	1821.1	640.9	625.0	0.35	0.34
Spain	1359.9	644.8	702.1	0.47	0.52
LAC countries	1476.5	1146.6	1140.4	0.78	0.77

Notes: "Current Pot Yield" refers to the production-potential counterfactual under the mixed input scenario. "Clima Pot Yield" refers to the production-potential counterfactual under the climate change yield projections of climate models M1 and M2.

counterfactuals under each of the two climate models. The results of these counterfactuals are provided in Tables 8 for climate model M1 and 9 for climate model M2. The first column in each table repeats the production-potential under the respective climate model. The tables also report the ratios of the spatial to production potentials, and total to spatial potential, capturing in turn the additional yield gains coming from spatial reallocation and crop mix changes. One key takeaway under both climate models is that the scope for yield gains from the spatial reallocation of crop production on average doubles across LAC relative to current conditions, from 14 percent to 29 percent. This implies that in the face of heterogeneous climate change across locations, countries can exploit the spatial misalignment of challenges and opportunities. In turn, the potential for further gains from changing the crop mix is lower under climate change than under current conditions, from 108 percent to 68 percent under M1 and to 70 percent under M2. There is however considerable variation of these gains across countries. Peru, Portugal, Spain especially but also Mexico, Chile and Nicaragua are expected to benefit the most from the spatial reshuffling of production. Argentina and Uruguay as well as the countries in Central America are expected to benefit the most from changing the set of crops they produce in each location.

To visualize the variation in yield gains from climate change under the production, spatial and total potential, in Figure 12 I show the contribution of each counterfactual in stacked bar format for climate model M1. Panel (a) displays South American countries, Panel (b) Central America, and Panel (c) Caribbean and European countries. The larger contribution of the spatial reallocation to overall yield gains under climate change is seen from the longer stacked bar for the spatial-potential yield in several of the countries.

7 Conclusions

This paper provides a unified assessment of how geography and climate shape agricultural productivity in Latin America. Using high-resolution geospatial data on potential yields combined with a spatial accounting framework, I decompose agricultural productivity into components reflecting natural land suitability, input use, the spatial organization of production, and crop choice. I find that, despite possessing some of the most naturally productive agricultural land in the world, Latin American countries exhibit large productivity differences across and within national borders. These differences are not related to geography: actual yields are essentially uncorrelated with natural land potential at both the country and sub-national levels. This implies that the key constraint to agricultural productivity in the region is not land quality but economic choices in how production is organized.

Table 8: Spatial and Total Potential under Climate Change (M1)

	Aggregate potential yield with climate change				
	Production	Spatial	Spatial/ Production	Total	Total/ Spatial
North America					
Canada	887.6	971.7	1.09	1778.8	1.83
Mexico	719.0	987.6	1.37	1715.3	1.74
United States	1308.8	1512.4	1.16	1956.4	1.29
Central America					
Belize	1241.2	1375.2	1.11	2062.5	1.50
Costa Rica	1502.7	1864.2	1.24	2567.5	1.38
El Salvador	1105.7	1193.3	1.08	2859.1	2.40
Guatemala	1060.6	1374.7	1.30	2808.1	2.04
Honduras	1012.1	1174.8	1.16	3056.2	2.60
Nicaragua	1096.7	1376.7	1.26	3150.3	2.29
Panama	1354.9	1623.9	1.20	2906.1	1.79
Caribbean					
Antigua and Barbuda	994.5	1016.8	1.02	2973.3	2.92
Bahamas	956.2	1143.8	1.20	1321.9	1.16
Cuba	1636.2	1851.2	1.13	2570.8	1.39
Dominican Republic	1543.5	1821.5	1.18	2455.0	1.35
Jamaica	1782.7	1930.9	1.08	2405.0	1.25
South America					
Argentina	1116.6	1335.0	1.20	3229.5	2.42
Bolivia	1321.0	1666.2	1.26	3123.6	1.87
Brazil	942.1	1240.8	1.32	2458.7	1.98
Chile	993.6	1463.8	1.47	3221.1	2.20
Colombia	1356.2	1741.7	1.28	2160.0	1.24
Ecuador	1061.3	1469.7	1.38	2280.3	1.55
French Guiana	1445.5	2045.1	1.41	1603.2	0.78
Guyana	1395.6	1563.0	1.12	1967.6	1.26
Paraguay	1258.7	1557.2	1.24	2689.1	1.73
Peru	755.7	1843.6	2.44	1333.6	0.72
Uruguay	933.6	1437.3	1.54	3705.9	2.58
Venezuela	1086.3	1392.8	1.28	2532.1	1.82
Europe					
Portugal	640.9	1220.3	1.90	2111.0	1.73
Spain	644.8	1169.5	1.81	1832.1	1.57
LAC countries	1146.6	1477.1	1.29	2485.1	1.68

Notes: "Production," "spatial," "total" refer to the production-potential, spatial-potential, and total-potential counterfactual yields with climate change. "M1" uses climate model GFLD-ESM2M.

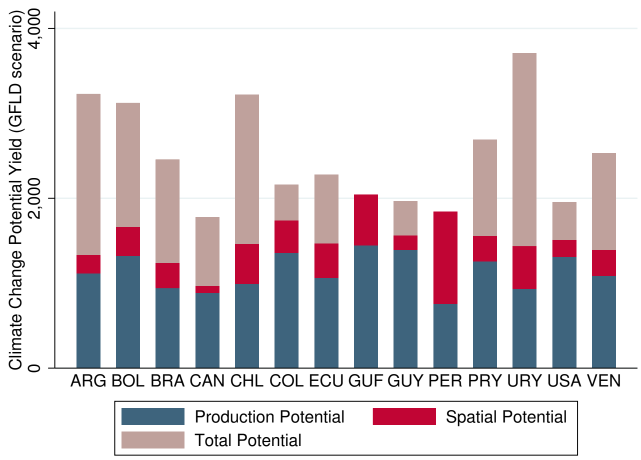
Table 9: Spatial and Total Potential under Climate Change (M2)

	Aggregate potential yield with climate change				
	Production	Spatial	Spatial/ Production	Total	Total/ Spatial
North America					
Canada	829.0	948.1	1.14	1618.2	1.71
Mexico	735.9	1031.5	1.40	1603.6	1.55
United States	1183.2	1410.0	1.19	1728.2	1.23
Central America					
Belize	1065.1	1191.7	1.12	2155.7	1.81
Costa Rica	1472.9	1826.1	1.24	2681.9	1.47
El Salvador	1167.4	1251.4	1.07	3250.0	2.60
Guatemala	1087.3	1372.4	1.26	2815.1	2.05
Honduras	1207.1	1395.0	1.16	3142.3	2.25
Nicaragua	1033.5	1442.8	1.40	2994.8	2.08
Panama	1377.2	1691.0	1.23	2987.3	1.77
Caribbean					
Antigua and Barbuda	1284.6	1309.9	1.02	3454.2	2.64
Bahamas	804.4	957.1	1.19	1278.9	1.34
Cuba	1371.6	1588.3	1.16	2345.7	1.48
Dominican Republic	1170.2	1578.2	1.35	2150.3	1.36
Jamaica	1762.5	1924.2	1.09	2364.3	1.23
South America					
Argentina	1137.6	1340.8	1.18	3136.0	2.34
Bolivia	1241.3	1581.3	1.27	2850.1	1.80
Brazil	953.3	1232.2	1.29	2357.7	1.91
Chile	1171.1	1671.8	1.43	3819.0	2.28
Colombia	1390.0	1775.5	1.28	2277.0	1.28
Ecuador	1116.2	1496.8	1.34	2322.0	1.55
French Guiana	1420.7	2008.7	1.41	1579.6	0.79
Guyana	1383.8	1542.6	1.11	1937.0	1.26
Paraguay	1170.5	1478.3	1.26	2500.0	1.69
Peru	731.4	1755.1	2.40	1261.5	0.72
Uruguay	1172.6	1340.9	1.14	3755.4	2.80
Venezuela	1035.3	1369.2	1.32	2358.6	1.72
Europe					
Portugal	625.0	1254.5	2.01	1832.3	1.46
Spain	702.1	1247.8	1.78	2103.1	1.69
LAC countries	1140.4	1468.7	1.29	2493.1	1.70

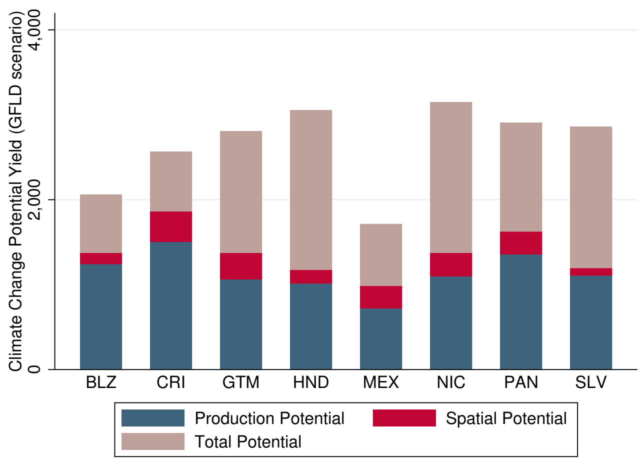
Notes: "Production," "spatial," "total" refer to the production-potential, spatial-potential, and total-potential counterfactual yields with climate change. "M2" uses climate model IPSL-CM5A-LR.

Figure 12: Yield Gains under Climate Change

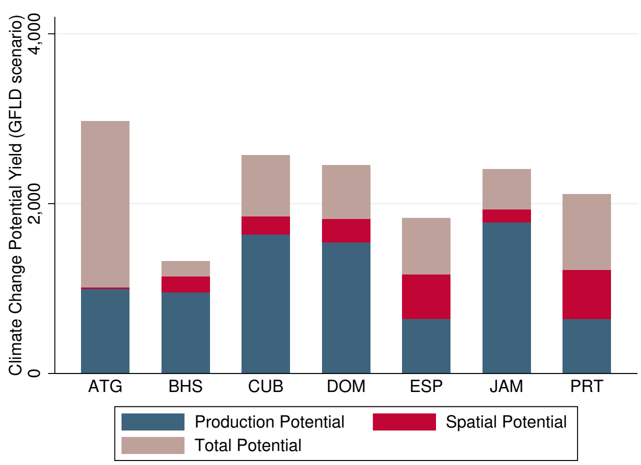
(a) South America



(b) Central America



(c) Caribbean and Europe



Notes: Different coloring captures the yield change relative to the previous counterfactual yield in the stacked bars. Assumes climate change scenario M1.

I find considerable potential gains from the raw suitability of the land if complemented with inputs application and adoption of more modern cultivation practices, doubling productivity in many Latin American countries. I also find additional, but smaller gains from the spatial reallocation of crop production across locations within countries, and the switch to higher return crops cell-by-cell on the grid.

I examine the effect of climate change on the future of agricultural productivity in Latin America, and potential adaptation strategies. Incorporating the 2050s projected effects on crop-cell yields as predicted by natural scientists into the same framework reveals that climate change will reshape agricultural production possibilities and thus comparative advantage within countries. While average potential yields decline in most countries, climate change will induce changes in yields that are heterogeneous across crops and space even within national borders. This amplified variation nearly doubles the gains from reallocating production across space relative to current conditions, which can partially mitigate the pitfalls of global warming.

If land quality and geography are not the drivers of actual agricultural productivity, then it is important to understand the role of policies, constraints, institutions shaping the economic decisions of farmers about where to produce and how to produce, i.e., production and management practices, input application, mechanization and technologies used. The literature has made considerable headway in understanding the role of these factors at the micro and macro level, but understanding how these economic choices interact with land quality and climate could yield benefits. More research on the role of climate change and its implications for future agricultural productivity is sure to provide important insights, in the face of food security and sustainability challenges, as well as environmental and other risks.

References

Adamopoulos, T. (2025). Spatial integration and agricultural productivity: Quantifying the impact of new roads. *American Economic Journal: Macroeconomics*, 17(1):343–378.

Adamopoulos, T., Brandt, L., Chen, C., Restuccia, D., and Wei, X. (2024). Land security and mobility frictions. *The Quarterly Journal of Economics*, 139(3):1941–1987.

Adamopoulos, T., Brandt, L., Leight, J., and Restuccia, D. (2022). Misallocation, selection, and productivity: A quantitative analysis with panel data from china. *Econometrica*, 90(3):1261–1282.

Adamopoulos, T. and Leibovici, F. (2025). *Trade Risk and Food Security.* Federal Reserve Bank of St. Louis, Research Division.

Adamopoulos, T. and Restuccia, D. (2014). The size distribution of farms and international productivity differences. *American Economic Review*, 104(6):1667–97.

Adamopoulos, T. and Restuccia, D. (2022). Geography and agricultural productivity: Cross-country evidence from micro plot-level data. *The Review of Economic Studies*, 89(4):1629–1653.

Burke, M. and Emerick, K. (2016). Adaptation to climate change: Evidence from us agriculture. *American Economic Journal: Economic Policy*, 8(3):106–140.

Burke, M., Hsiang, S. M., and Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, 527(7577):235–239.

Calzadilla, A., Zhu, T., Rehdanz, K., Tol, R. S., and Ringler, C. (2013). Economywide impacts of climate change on agriculture in sub-saharan africa. *Ecological Economics*, 93:150–165.

Caselli, F. (2005). Accounting for cross-country income differences. *Handbook of Economic Growth*, 1:679–741.

Cassman, K. G. (1999). Ecological intensification of cereal production systems: yield potential, soil quality, and precision agriculture. *Proceedings of the National Academy of Sciences*, 96(11):5952–5959.

Caunedo, J. and Keller, E. (2021). Capital obsolescence and agricultural productivity. *The Quarterly Journal of Economics*, 136(1):505–561.

Chen, C. (2020). Technology adoption, capital deepening, and international productivity differences. *Journal of Development Economics*, 143:102388.

Conte, B. (2022). Climate change and migration: the case of africa.

Costinot, A., Donaldson, D., and Smith, C. (2016). Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world. *Journal of Political Economy*, 124(1):205–248.

Cruz, J.-L. (2024). Global warming and labor market reallocation. *Available at SSRN 4946752.*

de Vries, G., Arfelt, L., Drees, D., Godemann, M., Hamilton, C., Jessen-Thiessen, B., Kaya, A. I., Kruse, H., Mensahm, E., and Woltjer, P. (2021). The economic transformation database (etd): Content, sources, and methods. *WIDER Technical Note 2/2021. DOI: 10.35188/UNU-WIDER/WTN/2021-2.* https://www.wider.unu.edu/project/etd-\OT1\textendash-economic-transformation-database.

Dell, M., Jones, B. F., and Olken, B. A. (2009). Temperature and income: reconciling new cross-sectional and panel estimates. *American Economic Review*, 99(2):198–204.

Dell, M., Jones, B. F., and Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3):66–95.

Desmet, K. and Rossi-Hansberg, E. (2024). Climate change economics over time and space. *Annual Review of Economics*, 16.

Donovan, K. (2021). The equilibrium impact of agricultural risk on intermediate inputs and aggregate productivity. *The Review of Economic Studies*, 88(5):2275–2307.

FAO (2015). Country profile - antigua and barbuda. Technical report, AQUASTAT Reports, Food and Agricultural Organization, United Nations.

GAEZv3.0 (2012). Global agro-ecological zones, version 3.0. *Food and Agricultural Organization (FAO) and International Institute for Applied Systems Analysis (IIASA).* https://www.gaez.iiasa.ac.at/ (accessed March 11, 2018).

GAEZv4.0 (2021). Global agro-ecological zones, version 4.0. *Food and Agricultural Organization (FAO) and International Institute for Applied Systems Analysis (IIASA).* https://gaez.fao.org/pages/data-access-download (accessed February 3, 2025).

Gallup, J. L., Sachs, J. D., and Mellinger, A. D. (1999). Geography and economic development. *International regional science review*, 22(2):179–232.

Gollin, D., Parente, S. L., and Rogerson, R. (2007). The food problem and the evolution of international income levels. *Journal of Monetary Economics*, 54(4):1230–1255.

Gouel, C. and Laborde, D. (2021). The crucial role of domestic and international market-mediated adaptation to climate change. *Journal of Environmental Economics and Management*, 106:102408.

Gröger, A. and Zylberberg, Y. (2016). Internal labor migration as a shock coping strategy: Evidence from a typhoon. *American Economic Journal: Applied Economics*, 8(2):123–153.

Hsiang, S., Kopp, R., Jina, A., Rising, J., Delgado, M., Mohan, S., Rasmussen, D. J., Muir-Wood, R., Wilson, P., Oppenheimer, M., et al. (2017). Estimating economic damage from climate change in the united states. *Science*, 356(6345):1362–1369.

Jagnani, M., Barrett, C. B., Liu, Y., and You, L. (2021). Within-season producer response to warmer temperatures: Defensive investments by kenyan farmers. *The Economic Journal*, 131(633):392–419.

Kravchenko, A. N. and Bullock, D. G. (2000). Correlation of corn and soybean grain yield with topography and soil properties. *Agronomy Journal*, 92(1):75–83.

Kuznets, S. S. (1966). *Modern economic growth*. Yale University Press.

Lagakos, D. and Waugh, M. E. (2013). Selection, agriculture, and cross-country productivity differences. *The American Economic Review*, 103(2):948–980.

Levine, D. I. and Yang, D. (2014). The impact of rainfall on rice output in indonesia. Technical report, National Bureau of Economic Research.

Moscona, J. and Sastry, K. A. (2023). Does directed innovation mitigate climate damage? evidence from us agriculture. *The Quarterly Journal of Economics*, 138(2):637–701.

Nath, I. (2025). Climate change, the food problem, and the challenge of adaptation through sectoral reallocation. *Journal of Political Economy*, 133(6):1705–1756.

Nordhaus, W. D. (2006). Geography and macroeconomics: New data and new findings. *Proceedings of the National Academy of Sciences*, 103(10):3510–3517.

Restuccia, D., Yang, D. T., and Zhu, X. (2008). Agriculture and aggregate productivity: A quantitative cross-country analysis. *Journal of Monetary Economics*, 55(2):234–250.

Sachs, J. D. (2003). Institutions don't rule: direct effects of geography on per capita income. Technical report, National Bureau of Economic Research.

Schlenker, W. and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to us crop yields under climate change. *Proceedings of the National Academy of sciences*, 106(37):15594–15598.

Somanathan, E., Somanathan, R., Sudarshan, A., and Tewari, M. (2021). The impact of temperature on productivity and labor supply: Evidence from indian manufacturing. *Journal of Political Economy*, 129(6):1797–1827.

Sotelo, S. (2020). Domestic trade frictions and agriculture. *Journal of Political Economy*, 128(7):2690–2738.

Wiebe, K. D. (2003). *Land quality, agricultural productivity, and food security: Biophysical processes and economic choices at local, regional, and global levels*. Edward Elgar Publishing.

Zhao, C., Liu, B., Piao, S., Wang, X., Lobell, D. B., Huang, Y., Huang, M., Yao, Y., Bassu, S., Ciais, P., et al. (2017). Temperature increase reduces global yields of major crops in four independent estimates. *Proceedings of the National Academy of Sciences*, 114(35):9326–9331.

Appendix

A Robustness: including coffee, cocoa, tea

The main analysis has focused on 18 major crops produced across the world. I have abstracted from high value cash crops such as coffee, tea and cocoa as these crops have high relative prices compared to other crops and can have a disproportionate effect on aggregate values. However, LAC countries are known to be large producers and exporters of coffee, tea and cocoa. Here, I examine the robustness of the baseline results of the production potential counterfactual, under the low input scenario, when coffee, tea, and cocoa are included in the analysis.

Table 10 displays the aggregate actual yield (column 1) and the production potential yield with low inputs (column 3) for each LAC country. Columns 2 and 4 show the actual yield and the potential yield relative to the richest group of countries for comparison. This table reproduces Table 2 but with coffee, cocoa and tea. Interestingly, when focusing on actual yields there is no significant change between the baseline set of crops and the set that includes the additional cash crops, in relative terms, except for individual countries like Costa Rica. When taken together, all LAC countries are still at 82 percent of the richest countries. However, there are larger differences in the potential yield when coffee, cocoa, tea are included. The potential yield for all LAC countries is now 42 percent higher than the richest countries (as opposed to 18 percent above without coffee, cocoa, tea). This is driven by the fact that relative potential yield with coffee, cocoa, tea of some LAC countries is considerably higher, such as Colombia, Dominican Republic and the Central America countries of Costa Rica, Honduras and Guatemala.

Figure 13 shows that the earlier conclusion with the 18 crops is robust to the inclusion of coffee, cocoa, tea. The variation in actual yields across LAC is completely uncorrelated with the variation in the production potential yields across these countries. The map in Figure 14 shows the production potential yield (low inputs) including coffee, cocoa, tea, at the pixel level. This allows to see the continuity of variation across LAC countries, transcending country borders. Relative to the baseline case (without coffee, tea, cocoa), the potential yield now shows patches of higher intensity (darker orange) in Brazil, Colombia and Central America. The takeaway is that the baseline findings are robust to the inclusion of coffee, tea, cocoa and that LAC countries have a natural comparative advantage in the production of these crops.

B Simple Model of Structural Change

The economy produces an agricultural and a non-agricultural good, in separate sectors. Agricultural production Y_a takes place according to a Cobb-Douglas technology,

$$Y_a = A_a L^{\theta} N_a^{1-\theta}$$

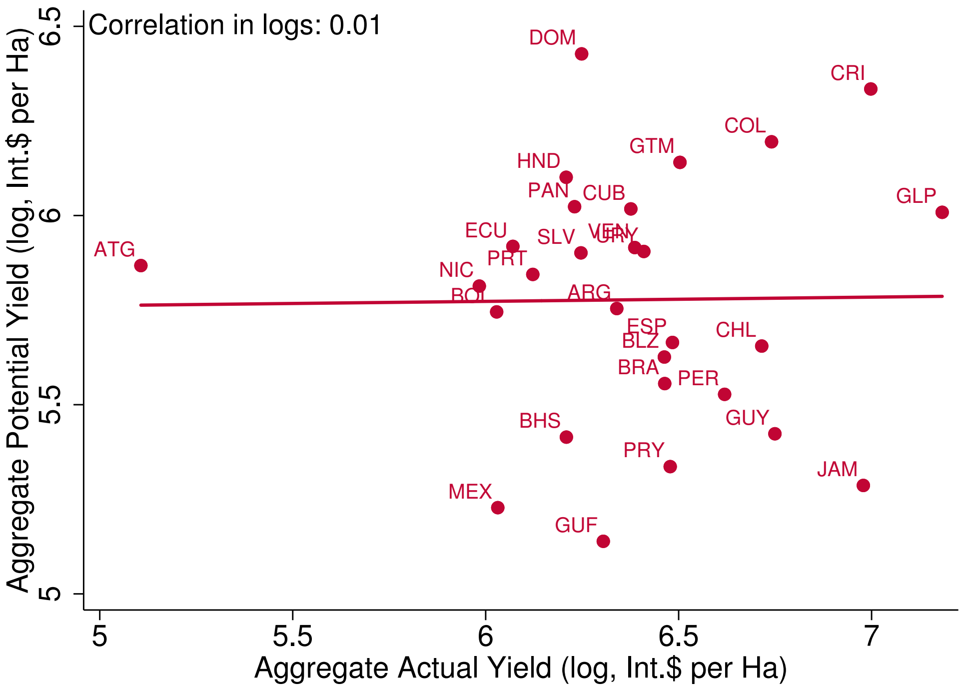
where L is land (in fixed supply), N_a is labor input, and A_a is TFP in agriculture. For simplicity, I abstract from capital and intermediate inputs. Output in non-agriculture takes place according to

Table 10: Actual and Production-Potential (low inputs) Yields with coffee, cocoa, tea

	Actual Yield	Act Rel to Rich	Potential Yield	Pot Rel to Rich
North America				
Canada	441.2	0.60	166.1	0.70
Mexico	416.3	0.56	186.4	0.79
United States	814.4	1.10	284.6	1.20
Central America				
Belize	641.0	0.87	277.5	1.17
Costa Rica	1094.4	1.48	563.7	2.38
El Salvador	516.4	0.70	365.5	1.54
Guatemala	667.5	0.90	464.2	1.96
Honduras	497.0	0.67	446.3	1.88
Nicaragua	396.8	0.54	334.8	1.41
Panama	507.9	0.69	412.9	1.74
Caribbean				
Antigua and Barbuda	165.1	0.22	353.4	1.49
Bahamas	497.2	0.67	224.6	0.95
Cuba	587.7	0.79	410.5	1.73
Dominican Republic	517.3	0.70	618.4	2.61
Jamaica	1073.5	1.45	197.7	0.83
South America				
Argentina	566.6	0.77	315.5	1.33
Bolivia	415.1	0.56	312.7	1.32
Brazil	641.6	0.87	258.7	1.09
Chile	825.0	1.12	285.7	1.20
Colombia	846.2	1.14	490.2	2.07
Ecuador	432.9	0.59	371.8	1.57
French Guiana	547.2	0.74	170.5	0.72
Guyana	853.6	1.15	226.6	0.96
Paraguay	650.8	0.88	207.7	0.88
Peru	749.3	1.01	251.5	1.06
Uruguay	607.8	0.82	366.8	1.55
Venezuela	593.7	0.80	370.7	1.56
Europe				
Portugal	455.8	0.62	345.3	1.46
Spain	654.6	0.89	288.4	1.22
LAC countries	608.1	0.82	337.7	1.42
Rich 10% of all countries	739.5	1.00	237.2	1.00
Poor 10% of all countries	244.0	0.33	239.5	1.01

Notes: Actual and potential yields are measured as total value output per hectare in international prices (GK$/ha). Low inputs assumes rainfed water supply and low-input cultivation practices.

Figure 13: Aggregate low-input production-potential versus actual yield across countries



Notes: Aggregate production-potential yield is under rainfed low-input scenario, and includes coffee, cocoa, tea.

a constant returns to scale technology that is linear in labor input N_n,

$$Y_n = A_n N_n$$

where A_n is non-agricultural TFP. There is a fixed amount of labor N which can be allocated to these two sectors. Thus the market clearing condition for labor is,

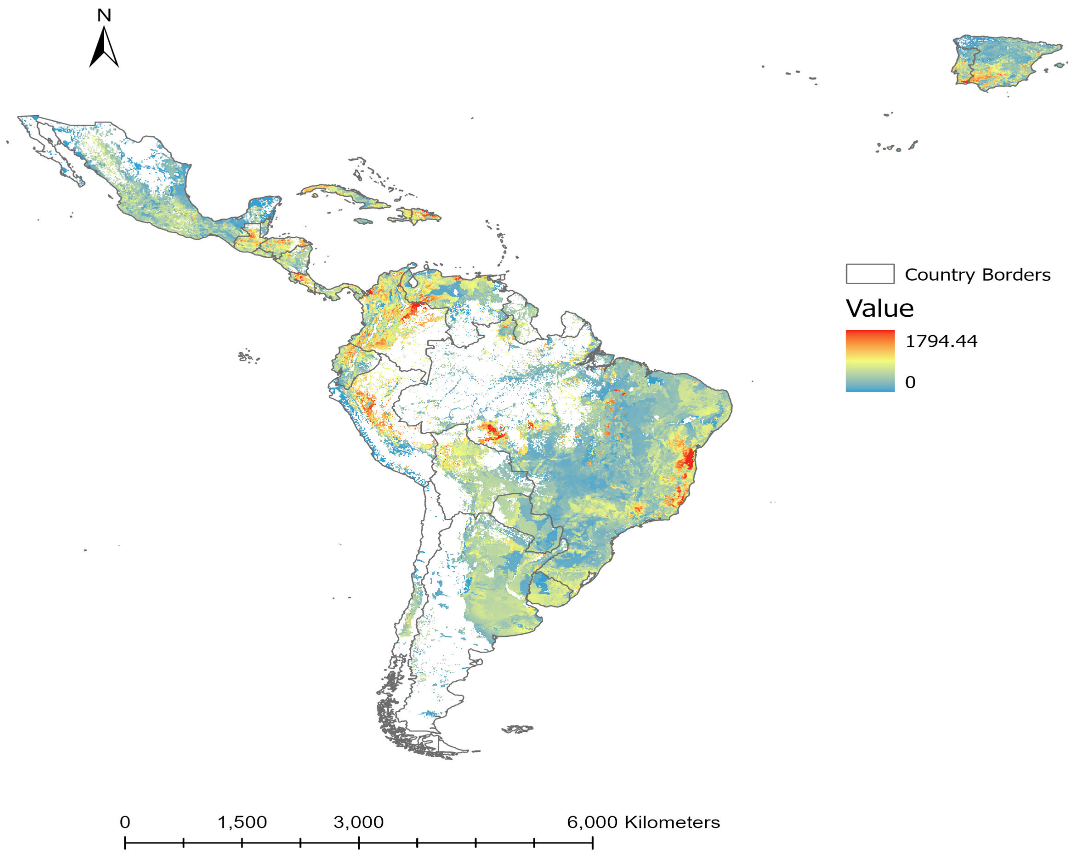
$$N = N_a + N_n$$

There are non-homothetic preferences with a subsistence constraint for food consumption. These preferences take a simple form, whereby individuals consume a minimum amount of agricultural consumption goods per person $\bar{a}$. Once this minimum is met individuals allocate the rest of their income to the consumption of non-agricultural goods. The market clearing condition for agricultural goods is thus,

$$Y_a = N\bar{a}$$

Denoting per-capita labor in agriculture and land as n_a and l respectively, and combining the agricultural market clearing condition with the agricultural production function, the share of employment

Figure 14: Cell-Level Potential Yields including Coffee, Cocoa, Tea (low inputs)



Notes: "Potential Yield (low)" refers to the country-level potential yield from the Production Potential experiment, that replaces actual yields in each cell and for each produced crop with the corresponding potential yield, under rainfed conditions and low level of inputs. Coffee, cocoa, and tea are included. The potential yield is expressed in Geary-Khamis international dollars. Map shading is continuous.

in agriculture is,

$$n_a = \left(\frac{\bar{a}}{A_a l^\theta} \right)^{1/(1-\theta)}. \tag{6}$$

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

I calibrate the benchmark economy to the United States. Productivity parameters are normalized, $A_a = A_n = 1$. $\bar{a}$ is calibrated to match the share of employment in agriculture in the United States of 1.7 percent (see Table 1). This procedure implies $\bar{a} = 0.07$, and a benchmark economy relative price of $p = 0.39$.