AGRICULTURAL PRODUCTIVITY IN LATIN AMERICA AND THE CARIBBEAN: WHAT WE KNOW AND WHERE WE ARE HEADING

Edited by:

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Maja Schling
Carmine Paolo de Salvo
Pedro Martel

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TABLE OF CONTENTS

INTRODUCTION:

UNDERSTANDING AGRICULTURAL PRODUCTIVITY IN LATIN AMERICA AND THE CARIBBEAN: EVIDENCE FOR SUSTAINABLE GROWTH

AUTHORS: LINA SALAZAR, PEDRO MARTEL

The agricultural sector in Latin America and the Caribbean (LAC) currently faces complex and unprecedented challenges: producing enough nutritious food to feed a growing population, providing prosperous livelihoods, and protecting natural resources by reducing greenhouse gas emissions and pollution.

First, population growth is placing increasing pressure on the sector to ensure a sufficient and stable supply of nutritious food. In 2024, about 28% of the LAC population—approximately 187.6 million people— experienced food insecurity, while 27% could not afford a healthy diet (FAO et al., 2025). Ensuring access to affordable, nutritious food must therefore remain a top priority for the region's agricultural sector.

Second, rural areas in LAC are disproportionately affected by poverty: an estimated 39% of the rural population lives in poverty, compared with 24.6% in urban areas (ECLAC, 2024). As the vast majority of rural livelihoods depend on agriculture, reducing rural poverty requires strengthening the sector's capacity to provide prosperous and economically viable employment opportunities.

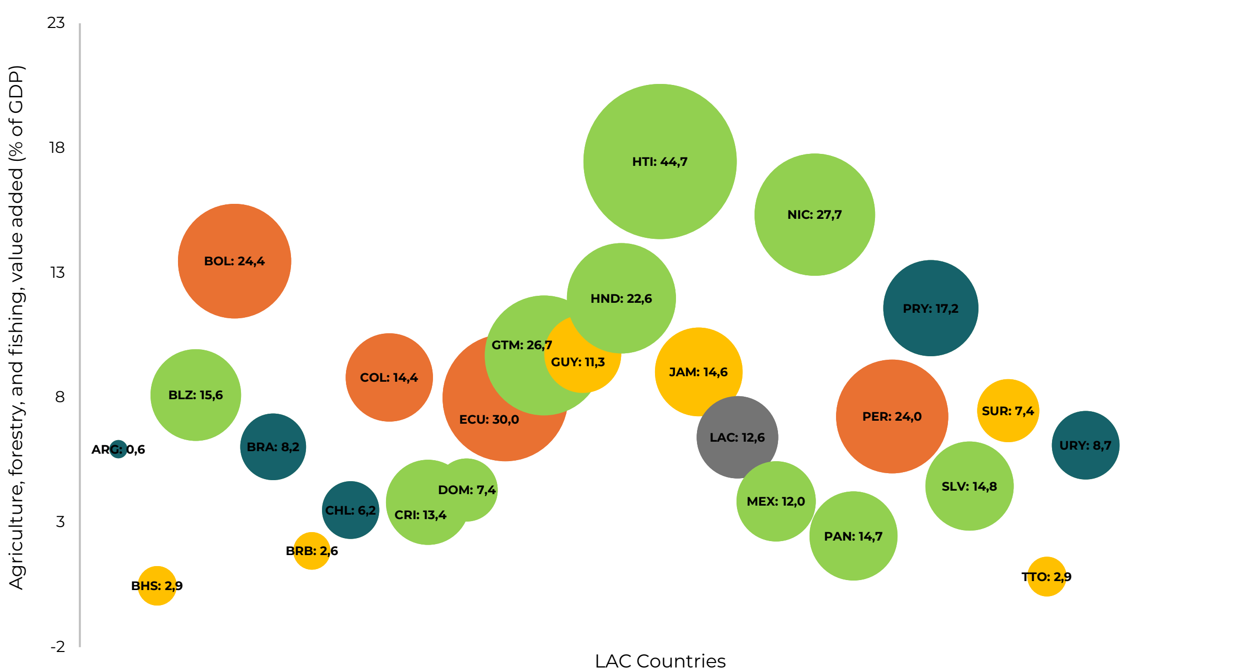
Third, LAC contributes approximately 8% of global greenhouse gas emissions (ECLAC, 2017; WB, 2021; WRI, 2023), with the agriculture, forestry, and land use (AFOLU) sector as the main contributor—accounting for 43% of total regional emissions (IDB, 2022; WRI, 2023). Hence, addressing agriculture's negative environmental impacts is becoming a pressing issue to ensure the sector's long-term sustainability and profitability.

These challenges are amplified by the sector's exposure to climate risks. Because agriculture depends heavily on weather conditions, it is highly sensitive to climate variability and the rising frequency of extreme weather events.

Addressing these challenges requires prioritizing sustainable productivity growth. First, improving food security depends on stable agricultural production to ensure the year-round availability of nutritious food. Second, rural livelihoods are closely tied to the profitability of agricultural activities. Increasing production without expanding input use is thus essential to enhance the purchasing power of rural households. Finally, reducing pressure on natural resources requires limiting the expansion of the agricultural frontier and eliminating reliance on environmentally harmful inputs. These goals can only be achieved through sustainable improvements in agricultural productivity.

The agricultural sector is a pillar of the economy in LAC, accounting for approximately 6% of GDP, generating 15% of total employment, and contributing 13% of global agricultural output, 24% of total LAC exports, and 16% of global agricultural exports (WDI, 2023; FAOSTAT, 2023). However, these aggregate figures mask significant heterogeneity across countries. For example, agricultural GDP exceeds 10% in Paraguay, Bolivia, Honduras and Nicaragua, while it falls below 4% in Chile and Mexico. Similarly, the share of agricultural employment varies widely: over 25% of the labor force in Haiti and Guatemala is engaged in agriculture, compared to less than 10% in Brazil and Uruguay. **Figure 1** illustrates this diversity in output and employment in the agricultural sector across LAC.

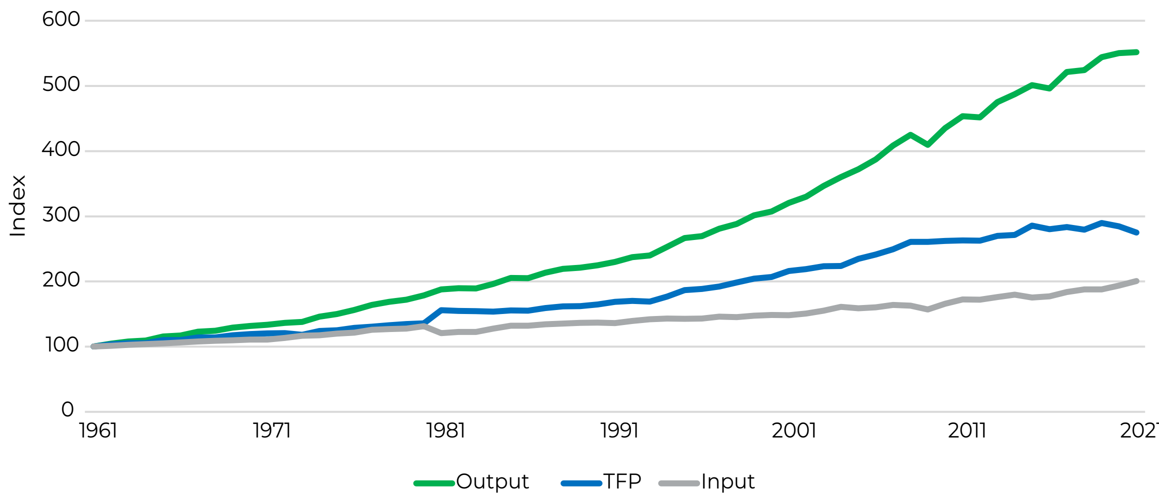
FIGURE 1. AGRICULTURAL GDP AND EMPLOYMENT IN THE AGRICULTURE SECTOR BY COUNTRY (2023)



Note: The size of the bubble is proportional to employment in agriculture (% of total employment).
Source: Author's calculations based on World Development Indicators.

LAC has experienced remarkable growth in agricultural production over the past 60 years, increasing nearly sixfold. Improving agricultural output can be achieved through increases in total factor productivity (TFP) and/or input utilization. In turn, TFP can be enhanced by technological changes or by improving technical efficiency. Recent analysis reveals that, from 1961 to 2021, the region's output grew by an average of 2.9% per year. These gains were driven primarily by improvements in total factor productivity (TFP), which expanded at an annual average of 1.7%, above the world average (Salazar et al., 2025). However, between 2010 and 2020, TFP in LAC decelerated at around 0.9% per year, leading to a slowdown in the growth of agricultural production. During this period, TFP accounted for only 40% of agricultural output growth, compared to 60% from input growth (Salazar et al., 2025).

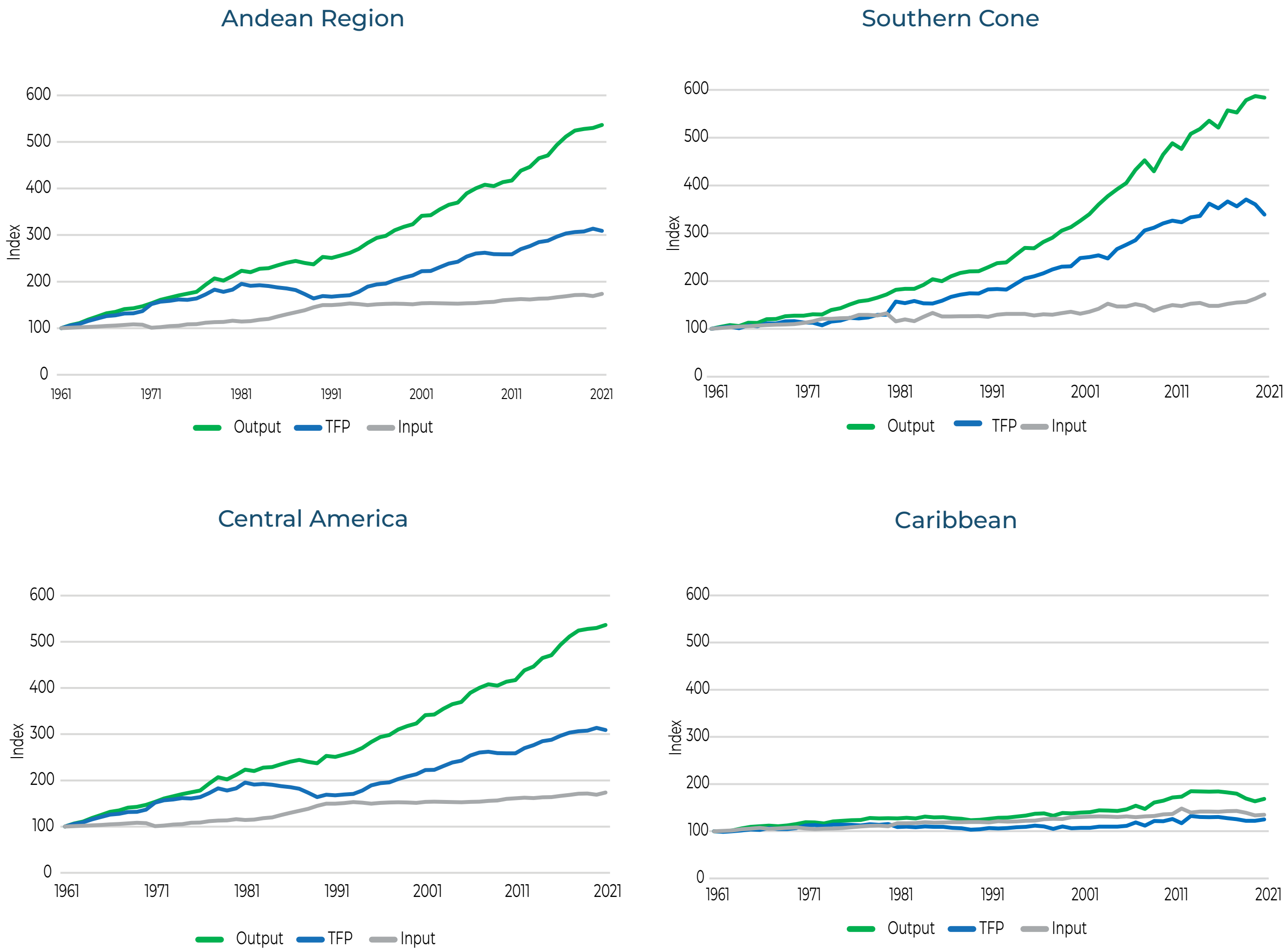
Figure 2. Growth in agricultural output, inputs, and TFP in LAC (1961–2021)



Source: Salazar et al. (2025)

Across LAC, agricultural production has grown at varying rates, driven by differing contributions from TFP and input use. The Southern Cone experienced the highest average annual growth in agricultural output (3.0%), primarily due to TFP gains (2.1%), although in recent years productivity shows signs of stagnation. Central America follows, with a 2.8% growth rate, also driven by TFP (1.9%), despite periods of stagnation and contraction. The Andean region shows a slightly lower growth rate of 2.7%, with TFP contributing 1.5% and inputs 1.2%. The subregion with the slowest growth was the Caribbean, with 0.9%, driven mainly by increased input use (0.5%) and modest TFP gains (0.4%) (Salazar et al., 2025). Trends highlight significant subregional disparities in the drivers of agricultural performance and underscore the importance of tailored strategies to enhance sustainable productivity. If left unaddressed, the current challenges facing agrifood systems—combined with a slowdown in productivity growth—could undermine food security and agricultural competitiveness in LAC.

Figure 3. Growth in agricultural output, inputs, and TFP by subregion (1961–2021)



Source: Salazar et al. (2025)

In contrast, proactive measures grounded in robust evidence have the potential to unlock new opportunities for sustainable and inclusive growth. The central objective of this publication is to contribute to such evidence-based policy design and implementation by exploring the determinants of agricultural productivity through regional, subregional, and national perspectives. To this end, this report focuses on assessing the determinants of agricultural total factor productivity measured through productivity indexes in the case of the regional analyses and stochastic production frontiers in the case of country specific studies.

The Agricultural Productivity Flagship Report brings together a series of studies examining the drivers of agricultural productivity across LAC over recent decades. It addresses multiple dimensions, including national and subnational heterogeneity; reviews existing research to identify knowledge gaps and set priorities for future inquiry; analyzes projections under climate variability; and assesses the role of environmental sustainability in shaping productivity dynamics. The report complements the regional analysis with national studies that address factors such as trade, investment, and human capital, recognizing their strong influence on the determinants of agricultural production—particularly TFP and input use. Existing evidence shows that international trade can foster the adoption of modern technologies through the importation of machinery and integration into global markets (Caunedo & Kala, 2022; Farrokhi & Pellegrina, 2023). Similarly, foreign direct investment can enhance agricultural productivity, especially when supported by local capacities to absorb and adapt new technologies (Han, Smith, & Wu, 2023).

The document aims to guide countries in developing and implementing policies that promote higher productivity, environmental sustainability, and climate resilience.

This study is organized into four sections. The first section, “Transforming Challenges into Opportunities,” outlines the key agricultural productivity challenges and opportunities in the LAC region, focusing on climate variability and agricultural policy. The second section, “Agricultural Productivity in Focus,” presents nine country case studies that analyze agricultural productivity at the national and subnational levels to provide a more detailed understanding of productivity determinants across different geographic areas. The third section, “Productivity with Purpose,” introduces one of the region’s pioneering efforts to develop a sustainable productivity index that integrates both the positive and negative environmental impacts of agricultural production into productivity measurement. Finally, the fourth section, “Generating Impact through Evidence,” synthesizes lessons from IDB-led impact evaluations in the agricultural sector and compiles insights from an evidence synthesis, highlighting key findings and identifying knowledge gaps in agricultural productivity across LAC.

The analysis presented in this report leads to six general findings:

I. Bridge the technological adoption gap in agriculture

Technological innovation continues to drive significant gains in TFP across the agricultural sector. However, the evidence presented in this report suggests that farmers face persistent challenges in keeping pace with these advancements. The spread of new technologies has not been matched by sufficient investment in technical assistance, managerial training, and advisory services. These support mechanisms are essential for strengthening farmers’ managerial capacities and enabling the effective adoption and use of innovative tools and practices. To ensure inclusive and sustainable productivity growth, agricultural policies must prioritize the development and delivery of comprehensive support systems that empower farmers to harness the full potential of technological progress.

II. Integrate environmental outcomes into productivity measurements to secure long-term sustainability

Analyses indicate that overlooking the environmental impacts of agricultural production can lead to long-term productivity gains being overestimated. Ignoring these hidden costs may also prompt countries to overexploit natural resources essential to future food production, thereby threatening the sector's viability. Strengthening environmental accountability within the agriculture sector is therefore critical to ensuring its long-term sustainability.

III. Pursue climate adaptation policies as a driver of agricultural competitiveness

Climate variability is increasingly reshaping global agricultural landscapes, redefining comparative advantages, and creating both challenges and new opportunities for countries that can effectively adapt. While climate variability presents significant challenges to agricultural productivity in LAC, it also offers a strategic opportunity to build new sources of competitiveness. Harnessing this potential requires proactive adaptation strategies and appropriate incentive structures to promote the adoption of new technologies that enhance the long-term resilience of productive systems. Policies should make climate adaptation a core component of competitiveness, ensuring that investments and innovations align with emerging environmental realities.

IV. Tackle inter- and intraregional disparities

National-level analyses indicate that the factors shaping agricultural performance within countries are highly heterogeneous. For example, changes in temperature or rainfall patterns do not affect all local contexts in the same way. These differences underscore the need for context-specific analyses based on disaggregated and representative data to guide targeted, evidence-based interventions. Agricultural policies should account for local determinants of performance, including agronomic conditions, social dynamics, climate variability, and market structures. Moreover, there remains a significant gap in research assessing how interventions affect diverse groups are vital to sustaining food systems and rural economies but often lag behind, including women farmers, Indigenous producers, and farmers of African descent. Closing these gaps requires developing and evaluating targeted interventions, while systematically including data disaggregated by gender and ethnicity in agricultural policy design.

V. Balance direct support with public goods to foster sustainable agricultural growth

The complexity of the agricultural sector calls for a strategic mix of direct support and public goods to achieve both short- and long-term gains. Targeted, nondistortive, market-based direct support—such as smart subsidies—can address immediate market failures, especially for smallholder farmers facing shocks like climate-induced liquidity constraints or information gaps. At the same time, sustained investment in public goods—including research, sanitary and phytosanitary services, infrastructure, and data systems—is essential for long-term, sustainable productivity growth.

VI. Strengthen agricultural data systems to support evidence-based decision-making

Robust agricultural data systems are foundational for designing effective productivity-enhancing policies. Evidence mapping reveals that research on agricultural productivity is concentrated in a limited number of countries and crops. Notably, countries with larger bodies of evidence tend to have well-established farm-level information systems and repeated data collection rounds. This correlation underscores the importance of investing in comprehensive, high-quality agricultural data infrastructure. To promote inclusive, context-specific policy development, governments and development partners should prioritize expanding and modernizing agricultural data systems to ensure broader geographic and crop coverage.

I. TRANSFORMING CHALLENGES INTO OPPORTUNITIES

CHAPTER 1.

RETHINKING AGRICULTURAL SUPPORT: THE ROLE OF PUBLIC POLICY IN PRODUCTIVITY GROWTH

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SUMMARY

This chapter examines the relationship between total factor productivity (TFP) and various types of agricultural policies in 17 countries in Latin America and the Caribbean (LAC) from 1995 to 2021. The analysis relies on the producer support estimate (PSE) methodology developed by the OECD and applied in LAC[1] through the IDB's Agrimonitor initiative since 2014. Specifically, the objective is to assess the relationship between TFP and different agricultural support policies: market price support (MPS), direct payments, and general services support (GSSE). To address potential endogeneity, a System GMM estimator is applied using rural voter turnout as an exogenous instrument.

The results reveal that different policy instruments have heterogeneous effects on TFP. Budgetary transfers (direct support and GSSE) have a positive effect, while MPS and PSE show negative correlations. Although GSSE shows no short-term effect, agricultural research and development (R&D), a key component of general services, is positively linked to TFP over time. Overall, the findings suggest that shifting from market-distorting support toward investment-oriented policies can enhance agricultural productivity. Strengthening the stock of agricultural knowledge through sustained investments in R&D also plays an important role in fostering productivity growth. The chapter also incorporates a new dimension by using rural voter turnout as an external instrument and provides practical recommendations to improve the design and effectiveness of agricultural support in the region.

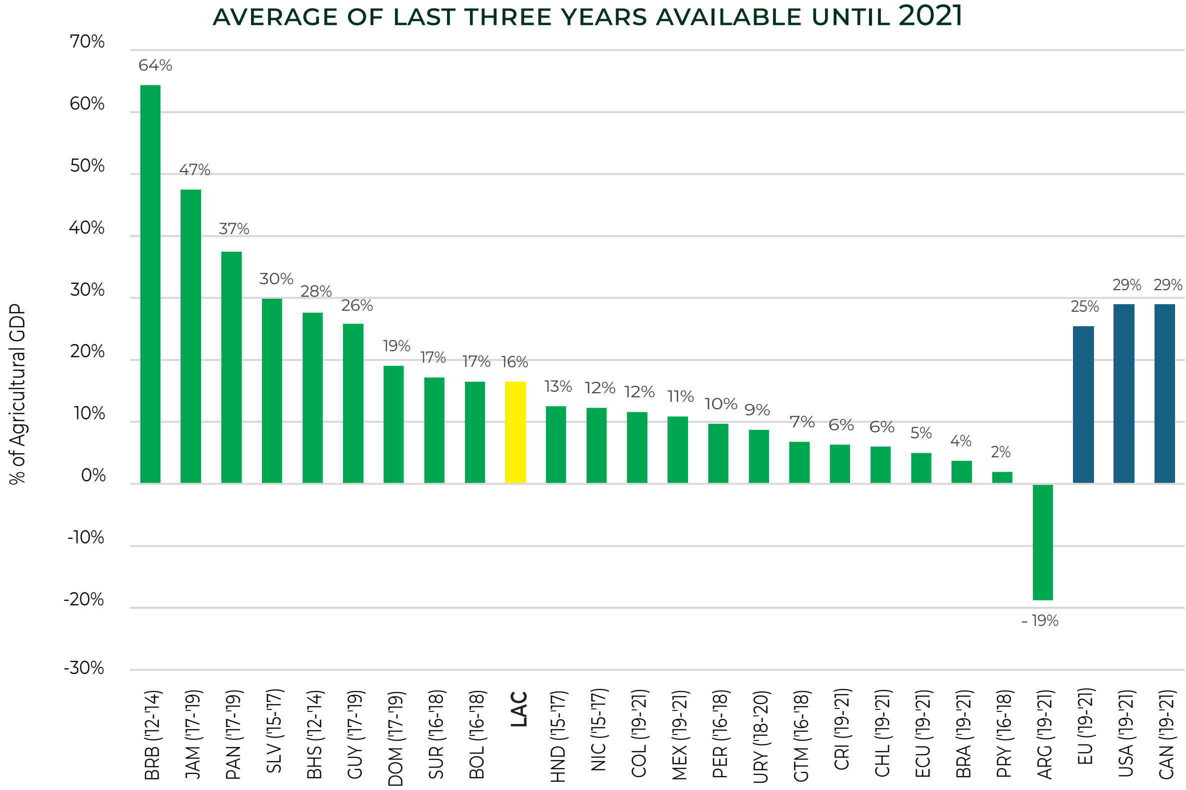
[1] Since the OECD already produces official PSE estimates for five LAC countries—Brazil, Chile, Colombia, Costa Rica, and Mexico—the IDB's Agrimonitor initiative applies the methodology to the rest of the region.

I. INTRODUCTION

Agricultural support policies encompass the different instruments governments implement to enhance the sector's performance. These policies are designed to improve agricultural outcomes and support producers. A wide range of such policies exists across LAC countries, yet productivity challenges persist. A well-established method for quantifying the magnitude and composition of these policies is the producer support estimate (PSE) methodology, developed by the OECD and applied in LAC through the IDB's Agrimonitor initiative since 2014.[2] This framework measures agricultural support through market price (MPS), direct transfers to producers (DT), general services support estimates (GSSE), and consumer support estimates (CSE). The objective of this chapter is to use different TFP indices to assess whether these different types of agricultural support policies enhance agricultural productivity.

Figure 1 shows the total support estimate (TSE) as a percentage of agricultural GDP for countries included in the Agrimonitor dataset, which captures the level of government support for each country relative to the size of its agricultural sector. Most LAC countries present positive levels of total agricultural support relative to their agricultural GDP. Argentina, however, shows a negative percentage, indicating that producers are transferring resources to consumers, through the application of policy mechanisms that reduce prices for their products (Conroy et al., 2024). In LAC as a whole, total support to the agricultural sector represents less than 20% of agricultural GDP—well below levels in the EU, Canada, and the United States, where support reaches about 30%.

FIGURE 1. TSE AS A PERCENTAGE OF AGRICULTURAL GDP, AVERAGE OF LAST THREE YEARS AVAILABLE UNTIL 2021



Source: Conroy et al. (2024).

[2] More information is available on the Agrimonitor website: https://agrimonitor.iadb.org/home

A growing body of literature finds that the composition of agricultural support is more important than its total magnitude in improving sector performance. For instance, Anríquez et al. (2016) find that reallocating 10% of support from private to public goods in LAC could increase per capita agricultural value added by 5%. Further evidence from the region suggests that MPS and input subsidies might distort incentives, misallocate resources, and hinder innovation, while GSSE might foster TFP through infrastructure, education, and R&D. Ludeña (2010) uses a stochastic frontier model to estimate TFP growth across LAC, finding that the region achieved some of the world's highest agricultural TFP growth rates between 1980 and 2007, largely driven by technical change.

The paper explains that policies that reduce price distortions and enhance input efficiency have been key enablers of this progress. Similarly, using a cross-country panel analysis, Bravo-Ortega and Lederman (2004) find that public investments in infrastructure and education significantly enhance agricultural TFP, whereas agricultural credit and direct subsidies are either weakly associated or negatively correlated with this. López and Galinato (2007) find that subsidies to private agricultural inputs (e.g., fertilizers) often have no significant effect on long-term productivity growth, while support through public goods improves productivity growth, reduces poverty, and mitigates negative environmental effects related to increases in agricultural output.

More recently, Anríquez et al. (2016) have shown that countries with heavier reliance on support for private goods, such as Mexico and the Dominican Republic, tend to have lower per capita agricultural value added than countries like Chile or Paraguay, which spend a greater share on public goods. Piñeiro et al. (2020) also argue that policy incentives linked to public infrastructure and R&D are more effective in promoting sustainable productivity improvements than price-based mechanisms.

The composition and magnitude of agricultural support are influenced by a combination of factors, including the sector's contribution to the economy, its importance in determining socioeconomic outcomes, the environmental costs of agricultural activities, institutional capacity, and political economy dynamics such as political bargaining. Swinnen (2018) argues that in developing countries, which experience significant budget constraints and political pressures, policymakers tend to prioritize high-profile, immediate transfers over less visible, longer-term public investments such as R&D or extension services. Additionally, government support tends to benefit economic groups with higher bargaining power, even if these are not the most efficient, productive, or sustainable producers. For instance, by mobilizing resources to lobby legislators, shaping regulatory details, and sustaining protection over time despite its broader social costs (Krueger, 1974; Olson, 1982).

This chapter provides valuable insights for policymakers and other stakeholders navigating the complexities of designing effective agricultural policies, given the diversity of conditions, institutional capacities, and policy instruments in place across LAC countries. Additionally, the analysis contributes to the existing literature by incorporating a political economy perspective incorporating it as an instrument in the model.

II. METHODOLOGY AND DATA

Research questions

This chapter investigates the extent to which public support for agriculture, as captured by the TSE, is associated with TFP in LAC. It also explores whether different types of support—including MPS, DT, GSSE, and R&D—have heterogeneous effects on productivity.

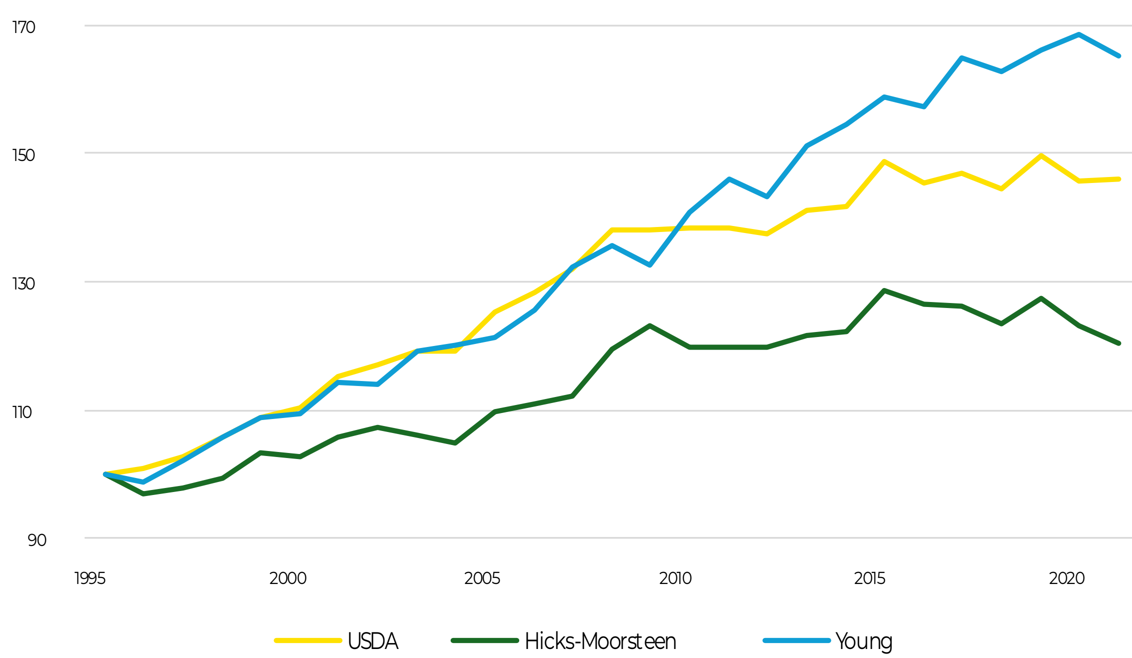
Data and methods

The analysis uses national-level panel data for 17 LAC countries from 1995 to 2021: Argentina, Belize, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Jamaica, Mexico, Panama, Peru, Paraguay, and Uruguay. A variety of TFP indices are used, each constructed under different assumptions regarding prices and weights.

TFP metrics aim to capture the portion of output growth that cannot be attributed to increases in inputs, thus reflecting how efficiently resources such as land, labor, or capital are used in agriculture (Salazar et al., 2024). Specifically, we employ three TFP indices: the USDA index, the Hicks-Moorsteen index, and the geometric Young index.[3]

Figure 2 shows the trend for each TFP index between 1995 and 2020. All three confirm significant TFP growth between 1995 and 2010. After this point, the Hicks-Moorsteen and USDA indices suggest that productivity growth slowed from 2010 to 2015, then stagnated between 2015 and 2020. In contrast, the Young index shows continuous growth from 1995 to 2015, followed by a slowdown thereafter.

Figure 2. Evolution of TFP indices for Latin America and the Caribbean (1995-2021)

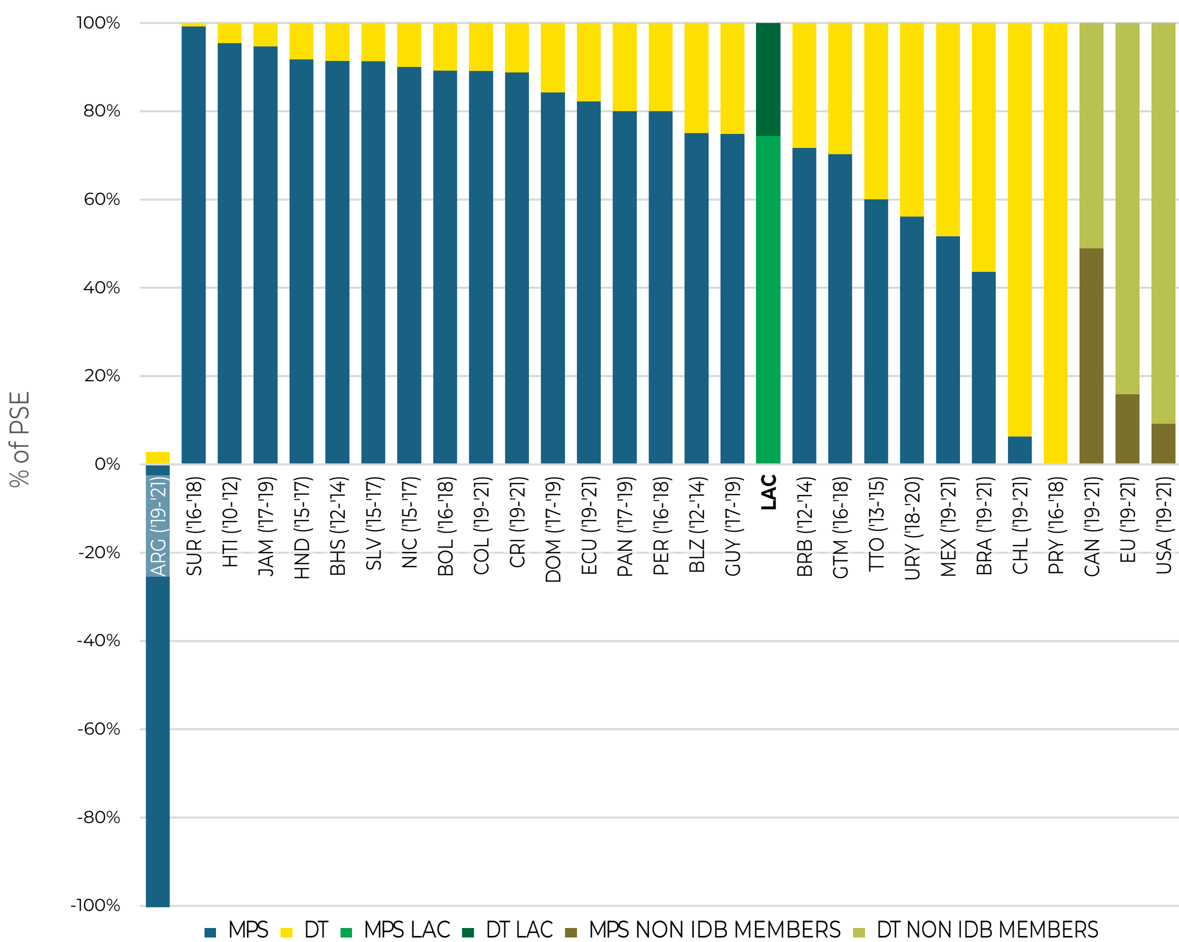


Source: Authors' calculations using USDA-ERS (2024)

[3] The extended analysis includes the Fair-Primont and Lowe indices and the sustainability productivity index (SPI), which are used as robustness checks.

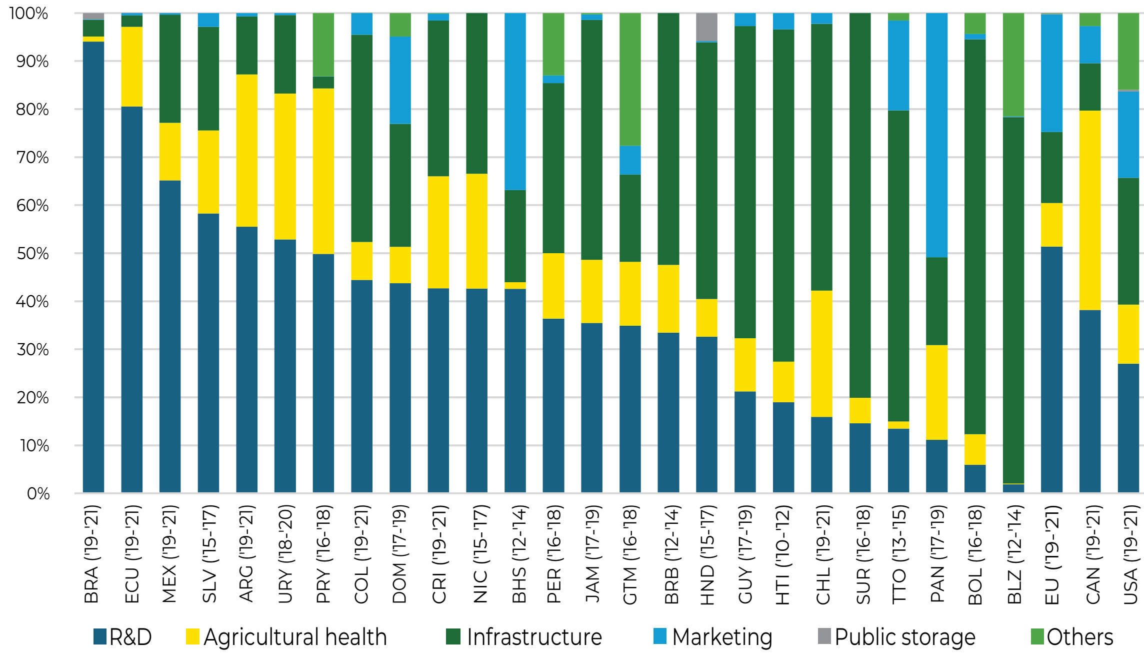
The variables of interest are different measures of agricultural support obtained from the Agrimonitor database. **Figure 3** presents MPS and DT as a share of PSE. At the regional level, LAC allocates 74% of PSE to MPS and 26% to DT. These proportions contrast with countries such as Canada, the European Union, and the United States, where MPS accounts for a smaller share of PSE. **Figure 4** illustrates the composition of GSSE, which encompasses R&D, agricultural health, infrastructure, marketing, public storage, and others. The data show that Brazil and Ecuador devote more than 80% of their GSSE to R&D, a markedly higher share in Canada, the European Union, and the United States. Given that R&D is a central component of GSSE, it can serve as a key mechanism through which GSSE influences productivity. Public research may generate immediate technological improvements or, alternatively, accumulate as a stock of knowledge that produces gains only over the longer term. To capture this dual dynamic, the analysis distinguishes between short- and long-term effects, testing the robustness of the main GSSE results while clarifying the potential transmission channel from R&D to TFP.

Figure 3. PSE components (MPS and DT)



Source: Conroy et al. (2024)

Figure 4: GSSE components (R&D, agricultural health, infrastructure, marketing, public storage and others)



Source: Conroy et al. (2024)

The analysis also includes weather variables, such as annual precipitation and the number of extreme heat days, derived from satellite-based sources. Macroeconomic and institutional controls are also included to account for country-specific conditions. Key data sources and variables are summarized in **Tables 1, 2,** and **3.**

Table 1. Main outcome variables[4]

Variable	Description	Source
USDA	TFP index based on four inputs (land, labor, capital, and materials), with weights that vary by decade	USDA (September 2023)
Hicks-Moorsteen	TFP index calculated using nonparametric methods (DEA[5]), with variable weights, based on six inputs	USDA (September 2023), FAOSTAT (August 2024)
Young	TFP index calculated following an economic approach, based on ten inputs and multiple outputs, using fixed prices	IFRPI and IDB (2025)

[4] Multiple productivity indices are used to triangulate results and strengthen the interpretation of trends by combining complementary properties and reducing reliance on a single methodological approach.
[5] Data Envelopment Analysis (DEA) is a non-parametric linear programming method that evaluates the relative efficiency of comparable units based on multiple inputs and outputs (Charnes, Cooper, & Rhodes, 1978).

Table 2. Main variables of interest

Variable	Description	Source
Total support estimate (TSE)	Total support to agriculture (PSE + GSSE + CSE), in millions of US$	Agrimonitor dataset
Producer support estimate (PSE)	Support to agricultural producers (MPS + direct support), in millions of US$	Agrimonitor dataset
Market price support (MPS)	Gap between domestic and international prices for commodities, multiplied by production levels, reflecting implicit support via prices, in millions of US$	Agrimonitor dataset
Direct transfers (DT)	Budgetary transfers provided directly to producers, including payments based on output, area, animals, income, or input use, in millions of US$	Agrimonitor dataset
General services support estimate (GSSE)	Public expenditures benefiting the agricultural sector (e.g., R&D, inspection, oversight, marketing, infrastructure), in millions of US$	Agrimonitor dataset
Budget support	National budget allocated to agriculture (GSSE + direct support), in millions of US$	Agrimonitor dataset
Stock of agricultural public knowledge	Weighted sum of public R&D spending on agriculture over the past 14 years, representing the cumulative effect of research investment on the sector's productivity	Van Dijk et al. (2025)

Table 3. Set of control variables

Variable	Description	Source
Rural voter turnout (external exogenous instrument)	Interaction of rural population and voter turnout in parliamentary elections	IDEA International, World Bank—World Development Indicators (WDI)
Trade openness	Ratio of total exports and imports of goods and services to GDP (% of current US$)	CEPALSTAT
Control of corruption	Country percentile rank of political institutions	World Bank—Worldwide Governance Indicators (WGI)
Inflation	Annual consumer price inflation (%)	WDI
Annual precipitation	Total annual precipitation (mm)	Copernicus
Extreme heat days	Number of days per year with temperature shocks (≥2 SD above historical mean)	Copernicus
Share of agricultural GDP	Agricultural value added (% of total GDP)	WDI
Agricultural GDP	Agricultural value added (current US$)	WDI

The study relies on country-level aggregates, which allows capturing broad patterns of how agricultural support relates to TFP. However, this approach may conceal important micro-level dynamics, such as intra-firm innovation and learning, resource reallocation across firms, or competitive pressures.

The econometric strategy employs panel data methods to estimate the association between agricultural support and productivity. A key concern is endogeneity, which may arise from omitted variables or reverse causality. On the one hand, unobserved factors could simultaneously affect both productivity and agricultural support allocation. On the other hand, productivity outcomes might influence policy decisions, creating simultaneity bias. To address these issues, the analysis applies the System GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998). This approach is well-suited for dynamic panel data for several countries and relatively short time periods (Islam, 2003; Rehman & Nunziante, 2023). The model is specified as follows:

$$TFP_{i,t} = \alpha TFP_{i,t-1} + X'_{i,t}\beta + \gamma SE_{i,t} + \eta_i + \varepsilon_{i,t}$$

where $TFP_{i,t}$ is the TFP of country i in year t, measured using the different indices, and $TFP_{i,t-1}$ is the dependent variable lagged by one period, which is included to capture the dynamic nature of agricultural productivity.

$SE_{i,t}$ is the level of agricultural support for country i in year t, using PSE methodology to capture different types of support. $X_{i,t}$ is a vector of control variables that capture socioeconomic and climate characteristics, including both endogenous and exogenous regressors. η_i captures unobserved country-specific fixed effects. Finally, $\varepsilon_{i,t}$ is the idiosyncratic error term.

Due to the inclusion of the lagged dependent variable and potentially endogenous controls, we use both internal instruments (the lags of the variables themselves) and an external instrument (rural voter turnout) to achieve valid identification of the parameter of interest, γ.

All control variables are treated as exogenous, except for inflation, which is considered endogenous in the estimations of MPS, TSE, and PSE, given the central role of prices in their composition. Agricultural GDP is not included as a control variable because it is used to normalize all variables except for the stock of agricultural public knowledge. In the latter case, the share of agriculture in GDP is included as a control variable.

To address model endogeneity, two equations are estimated simultaneously. First, the equation in first differences is estimated to eliminate unobserved fixed effects:

$$\Delta TFP_{i,t} = \alpha \Delta TFP_{i,t-1} + \Delta X'_{i,t}\beta + \gamma \Delta SE_{i,t} + \Delta\varepsilon_{i,t}$$

In this equation, endogenous controls are instrumented internally using their own lags (specifically, second-order lags, $t-2$, and third-order lags, $t-3$), while exogenous controls are included directly as they are uncorrelated with the error term[6].

The level equation is estimated simultaneously, providing additional moment conditions under stronger exogeneity assumptions[7]:

$$TFP_{i,t} = \alpha TFP_{i,t-1} + X'_{i,t}\beta + \gamma SE_{i,t} + \eta_i + \varepsilon_{i,t}$$

Here, endogenous controls are instrumented using their lagged first differences, and an external instrumental variable in levels (rural voter turnout) is included. This variable is assumed to be correlated with agricultural support but exogenous to the model's error term. The rationale for this is that rural voter turnout is linked to agricultural support, as higher political participation in rural areas may lead to greater political pressure on policymakers to implement or maintain such programs. However, voter turnout is considered exogenous to the model's error term because it is unlikely to be directly affected by short-term shocks or unobserved factors that affect national TFP. Nevertheless, the exogeneity assumption could be questioned if rural turnout co-varies with long-term structural changes such as socio-economic shifts or patterns of social conflict that also influence TFP. Crucially, however, the selected instrument (rural voter turnout) is designed to be orthogonal to both these slow-moving structural forces and contemporaneous productivity shocks, ensuring that this potential concern does not compromise its validity.[8]

[6] Richer fixed-effects structures, such as country-specific trends, were explored but discarded as they absorb much of the relevant variation, limiting identification. Instead, we rely on first differencing with comprehensive controls to account for structural changes while preserving the variation needed to identify the causal effect.

[7] All two-step GMM estimates apply the Windmeijer finite-sample correction, which adjusts standard errors to account for potential bias in small samples.

[8] To transform the data and eliminate individual fixed effects, we apply the orthogonal transformation proposed by Arellano and Bover (1995), also known as forward orthogonal deviations. This method consists of subtracting from each observation a weighted average of future observations for the same unit, thereby preserving the initial observations of the panel. Unlike first differences, this transformation maintains orthogonality with respect to fixed effects, improving the validity of moment conditions and estimation efficiency.

III. FINDINGS

Separate dynamic panel regressions were estimated to assess the relationship between agricultural policy support and TFP in the agricultural sector. As noted above, the analysis used three different TFP indices (USDA, Hicks-Moorsteen, and Young) and five categories of support (TSE, PSE, MPS, DT, and budget support), each expressed as a percentage of agricultural GDP.[9]

The results of the effects associated with the different types of support across TFP indices are presented in **Table 4**. The results show that TSE is negatively associated with TFP, confirming that productivity gains are not linked to the overall level of support provided to the sector. In particular, a 1-percentage-point increase in TSE as a share of agricultural GDP is associated with a reduction of about 0.1 points in TFP. Since TSE aggregates all forms of support (PSE, GSSE, and CSE), we analyze each component separately to explore their different effects.

For PSE, the results show coefficients with very similar signs and magnitudes to those for TSE. A 1-percentage-point increase in PSE as a share of agricultural GDP reduces TFP by about 0.1 points. PSE captures the overall support provided directly to producers through either MPS or direct subsidies. The estimations suggest that MPS is associated with lower productivity, highlighting how market distortions can jeopardize agricultural performance. By contrast, DT is positively associated with productivity, although the significance of this relationship is not consistent across estimations.

For budget support, which comprises actual fiscal expenditures (GSSE and DT), the results suggest a positive correlation with agricultural productivity. Specifically, a 1-percentage-point increase in budget support corresponds to increases in TFP of 0.337 units under the USDA index and 0.503 units under the Hicks-Moorsteen index. These results suggest that less distortionary forms of policy support are more conducive to productivity improvements.

The GSSE, which includes nontransfer expenditures such as R&D, infrastructure, and inspection services, does not exhibit a statistically significant effect on TFP. This finding contrasts with much of the existing literature, which generally reports that public services have a positive and significant impact on agricultural productivity (Ludeña, 2010; Bravo-Ortega et al., 2004; Anríquez et al., 2016).

This difference may be due to the nature of GSSE investments, which generally target public goods that benefit agricultural performance in the long term. In this sense, productivity gains are likely to materialize only after a time lag, a pattern consistent with the literature emphasizing the delayed returns of public expenditures (van Dijk et al., 2025).

In summary, the results suggest that agricultural support per se might not be fostering productivity growth. This could depend on the composition of support policies. In fact, policies that create market distortions could harm agricultural performance. In contrast, targeted support to producers may foster productivity gains, while the benefits of investments in public goods (GSSE) are likely to emerge only over time.

[9] Across all models, we find evidence of first-order autocorrelation but no second-order autocorrelation. In addition, the Hansen test does not reject the validity of the instruments, suggesting that both the internal and external instruments are appropriate.

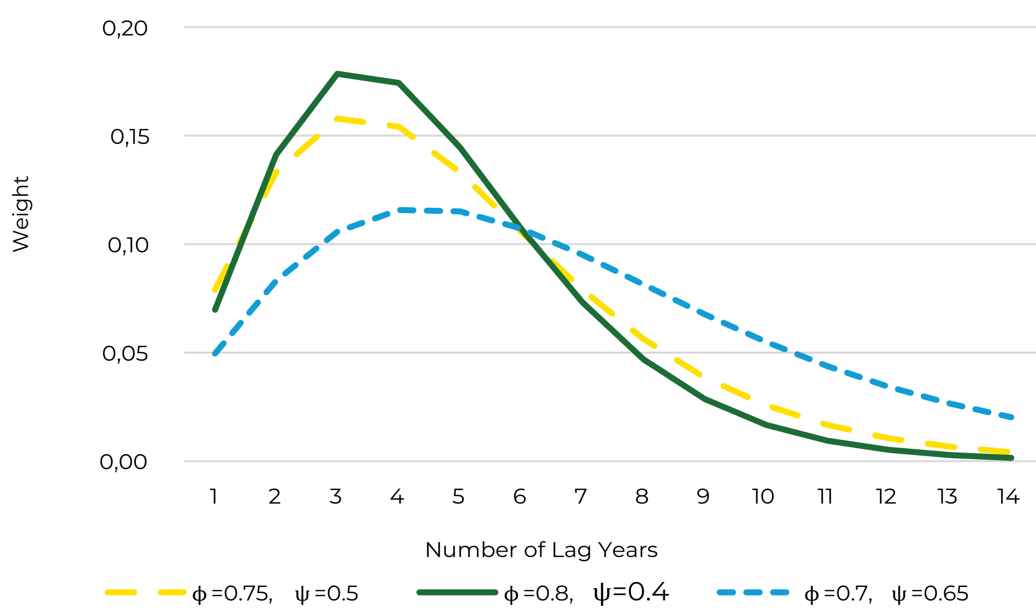
Table 4. Effect of agricultural policy support on TFP

Type of support variable	Outcome variable (TFP indices)		
	USDA	Hicks-Moorsteen	Young
TSE (PSE+GSSE+CSE)	-0.092*	-0.131**	-0.103*
(% of agricultural GDP)	(0.049)	(0.062)	(0.058)
No. instruments	15	15	15
AR (1)	0.011	0.033	0.010
AR (2)	0.113	0.167	0.341
Hansen test	0.836	0.334	0.531
Difference-in-Hansen test	0.732	0.426	0.158
PSE (DT+MPS)	-0.096**	-0.131**	-0.110*
(% of agricultural GDP)	(0.045)	(0.055)	(0.059)
No. instruments	15	15	15
AR (1)	0.011	0.020	0.010
AR (2)	0.106	0.140	0.339
Hansen test	0.876	0.370	0.559
Difference-in-Hansen test	0.908	0.495	0.164
MPS	-0.097**	-0.184***	-0.139**
(% of agricultural GDP)	(0.046)	(0.056)	(0.070)
No. instruments	12	12	12
AR (1)	0.009	0.008	0.010
AR (2)	0.099	0.100	0.375
Hansen test	0.730	0.303	0.780
Difference-in-Hansen test	0.490	0.699	0.318
Direct support	0.507**	0.754	0.058
(% of agricultural GDP)	(0.231)	(0.519)	(0.530)
No. instruments	15	15	15
AR (1)	0.013	0.006	0.013
AR (2)	0.143	0.145	0.464
Hansen test	0.475	0.666	0.915
Difference-in-Hansen test	0.622	0.912	0.404
GSSE	0.320	0.563	-0.738
(% of agricultural GDP)	(0.843)	(0.438)	(0.665)
No. instruments	15	15	15
AR (1)	0.010	0.003	0.011
AR (2)	0.172	0.158	0.400
Hansen test	0.313	0.873	0.508
Difference-in-Hansen test	0.270	0.466	0.697
Budget support (DT+GSSE)	0.337**	0.503*	0.194
(% of agricultural GDP)	(0.163)	(0.273)	(0.272)
No. instruments	15	15	15
AR (1)	0.014	0.003	0.011
AR (2)	0.156	0.127	0.457
Hansen test	0.491	0.858	0.524
Difference-in-Hansen test	0.718	0.734	0.157
No. countries	**17**	**17**	**17**
No. observations	**279**	**279**	**279**

Notes: Coefficients for the control variables included in each regression are omitted for convenience. Robust standard errors shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The table also reports standard diagnostic tests for System GMM estimations. The Hansen test assesses the validity of overidentifying restrictions, while the Difference-in-Hansen test evaluates the exogeneity of the external instrument. p-values for AR(1) and AR(2) correspond to the Arellano–Bond tests for first- and second-order serial correlation in the residuals.

While our estimations did not present evidence of GSSE having a significant effect on productivity, there is a broad consensus regarding the positive and significant impact of public goods on agricultural outcomes (Ludeña, 2010; Bravo-Ortega et al., 2004; Anríquez et al., 2016). As mentioned, a possible explanation for this result is that investments in public goods do not bring short-term results. To confirm this premise, a complementary analysis was conducted, focusing on public agricultural R&D—a core component of GSSE. To construct the stock of agricultural public knowledge, we applied a modified gamma-weighted distribution to past R&D expenditures (Alston, 2009; Fuglie, 2018). Next, we used an auto-regressive distributed lag (ARDL) approach to select a 14-year lag.[10] The resulting stock variable, expressed in logarithmic form, captures the cumulative effect of public R&D investments and was used as the main explanatory variable. To capture this relationship, we employ the main GMM specification used throughout the analysis. We drew on a different data source for this exercise, enabling us to work with longer time series and more consistent R&D expenditure data across countries.[11] **Figure 5** shows the gamma lag distribution, and **Table 5** reports the effect of the stock of agricultural public knowledge on TFP.

FIGURE 5. GAMMA LAG DISTRIBUTION FOR THE CONSTRUCTION OF THE STOCK OF AGRICULTURAL PUBLIC KNOWLEDGE



Source: Authors' calculations using van Dijk et al. (2025)

10 To determine the optimal lag length, we first applied an ARDL approach, which indicated a 14 year lag. We then conducted a grid search over 81 combinations of shape and scale parameters (Ø and ψ) to calibrate the gamma distribution (Alston, 2009; Lachaud & Bravo-Ureta, 2021). The final parameter values, Ø = 0.8 and ψ = 0.4, were chosen based on the statistical significance of the regression coefficients and the strength and validity of both internal and external instruments in the full model specification.

11 As with the previous specifications, we found evidence of first-order but not second-order serial correlation, and the Hansen test did not reject the null hypothesis, supporting the validity of the instruments.

Table 5. Effect of the stock of agricultural public knowledge on TFP

R&D variable	USDA	Hicks-Moorsteen	Young
Log. stock of agricultural public knowledge	0.011 **	0.012	-0.015
	(0.005)	(0.012)	(0.011)
No. instruments	15	15	15
AR (1)	0.027	0.008	0.009
AR (2)	0.238	0.150	0.475
Hansen test	0.529	0.656	0.841
Difference-in-Hansen test	0.349	0.866	0.634
No. countries	**17**	**17**	**17**
No. observations	**388**	**388**	**388**

Notes: Coefficients for the control variables included in each of the three separate regressions were omitted for convenience. All three TFP indices were transformed into logarithmic form, enabling the elasticities of the coefficients to be interpreted. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The table also reports standard diagnostic tests for System GMM estimations. The Hansen test assesses the validity of overidentifying restrictions, while the Difference-in-Hansen test evaluates the exogeneity of the external instrument. p-values for AR(1) and AR(2) correspond to the Arellano–Bond tests for first- and second-order serial correlation in the residuals.

The results in **Table 5** provide some evidence of a positive effect of agricultural R&D on TFP. A 1% increase in the stock of agricultural public knowledge is associated with a 0.011% increase in TFP according to the USDA index, a statistically significant result. Although the coefficients for the Hicks-Moorsteen and Young indices are not statistically significant, the positive sign in the former supports the notion that R&D makes a potential long-term contribution to productivity growth.

Overall, these findings highlight the potential importance of sustained investment in agricultural research and the need for a long-term perspective when assessing its impact. Knowledge accumulation generates gradual and cumulative rather than immediate returns, a pattern consistent with the literature on R&D lags and gradual effects, and conditional on the specific model specification and control set used in the analysis.

The findings reported in this chapter should be interpreted with caution, as each estimate reflects the impact of a single type of support on TFP, without accounting for the effects of the other forms of sectorial assistance. Nevertheless, the approach adopted here provides clear insights into the relationship between each policy instrument and productivity outcomes.

IV. CONCLUSIONS AND POLICY RECOMMENDATIONS

Building on the findings outlined above, the following recommendations can help guide policymakers in designing more effective agricultural support strategies in LAC:

I. Gradually reduce distortive MPS policies.

The findings in this chapter suggest that agricultural support policies should shift away from broad transfers and MPS interventions, which tend to hinder productivity growth. In most LAC countries, these represent an average 74% of producer support. Only Brazil, Chile, and Paraguay report MPS levels below half of their PSE, with Chile at 6% and Paraguay effectively at 0%. Argentina exhibits negative MPS, translating into support for consumers rather than producers (Agrimonitor, 2025). In light of these findings, governments should aim to gradually reduce this type of support while increasing more targeted assistance to the sector.

II. Combine direct support and GSSE to achieve both short- and long-term benefits

The complexities of the agricultural sector may require a balanced mix of approaches. Nondistortive direct support could help address market failures or unexpected shocks that demand immediate solutions, such as liquidity constraints caused by climate events or information asymmetries in agronomic practices. In parallel, long-term investments in public goods are essential, as they deliver sustainable long-term productivity gains, even though these may take time to materialize.

III. Strengthen productivity-oriented agricultural R&D policies

We find some evidence that R&D is positively associated with productivity, but public expenditure varies significantly across LAC countries. Ecuador allocates 50% of its GSSE to R&D as a percentage of its public agricultural expenditure, and Brazil and Bahamas also show relatively high shares, at 44% and 36%, respectively. In Belize, in contrast, the share is just 1% (Conroy et al., 2024). These disparities suggest that LAC countries have substantial room to improve the scale and focus of agricultural R&D investment.

IV. Establish long-term funding mechanisms for public agricultural research that are linked to sustainable productivity outcomes

Because the benefits of R&D often take years to emerge, institutional continuity beyond electoral cycles is essential. Countries should establish or strengthen autonomous agricultural research funds, such as EMBRAPA in Brazil or INIA in Uruguay. Funding should be tied to measurable productivity indicators and subject to regular, independent evaluations that measure causal effects to ensure efficiency and impact.

V. Complement policy support measurement and analysis with rigorous, systematic impact assessments of agricultural interventions

While PSE indicators are indispensable for monitoring the allocation of public resources, they are insufficient to assess policy effectiveness. Incorporating counterfactual-based evaluations is essential to identify which interventions deliver results, thereby strengthening evidence-based decision-making and supporting the scaling up of interventions that enhance sustainable improvements in agricultural productivity.

CHAPTER 2.

ADAPTING TO A CHANGING CLIMATE: STRATEGIES FOR PRODUCTIVE AND RESILIENT AGRIFOOD SYSTEMS

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SUMMARY

Latin America and the Caribbean (LAC) stand at a pivotal juncture for advancing the sustainability and resilience of the region's agrifood systems. As both a net agricultural exporter and a global biodiversity hotspot, the region faces the challenge of enhancing productivity while safeguarding long-term environmental and social resilience. This chapter offers a forward-looking assessment of how climate variability may affect agricultural productivity and land use through 2050, drawing on climate-adjusted projections to explore potential shifts in yields and crop distribution under mounting climate pressures. Results indicate that climate change could alter comparative advantages, depress yields in certain areas, and lead to significant reconfigurations of cultivation patterns. Nevertheless, substantial opportunities lie in strategic investments in climate-smart practices, resilient infrastructure, and inclusive policies. Outcomes will vary widely across countries and producer types, underscoring the need for tailored, context-specific strategies. Ultimately, LAC's capacity to anticipate and adapt—through foresight, robust data, and scenario planning—will determine the productivity, sustainability, and resilience of its agrifood systems, and enable the region to remain a central actor in global food systems despite a changing climate.

Some highlights:

- LAC is predicted to experience a greater decline in the production of all crops analyzed in than the world average. However, these findings vary at the sub-regional level.
- Two of Central America's most important crops, maize and coffee, are likely to experience greater negative impacts than the rest of LAC under a scenario of climate variability.
- In Mexico, maize is the dominant crop by area. While cultivated area is projected to expand, declining yields are expected to reduce overall output.
- For Caribbean countries, where sugar-cane is the most important crop by area, the predictions indicate a decline in yields and production, despite an increase in harvested areas.
- In the Andean Region, yields and harvested areas are projected to increase for beans and soybeans, leading to increases in total production. However, rice yields and harvested areas are projected to decline, leading to lower production. Coffee production is expected to increase slightly, driven by the expansion of harvested areas.
- In the Southern Cone, soybeans are by far the leading crop by cultivated areas. Both yields and total production are predicted to decline.

I. INTRODUCTION

Agriculture remains a cornerstone of food security, rural livelihoods, and economic development in Latin America and the Caribbean (LAC), while also positioning the region as a vital supplier to the global food system through exports of key crops and livestock. However, shifts in rainfall patterns, rising temperatures, and changing agroecological zones are already disrupting crop yields, water availability, and soil quality. These pressures are projected to intensify by 2050, triggering complex and uneven changes across the region, redefining what can be grown and where, how resources are used, and which countries or subregions retain comparative advantages.

This chapter presents forward-looking projections from the International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT) model, a partial equilibrium bioeconomic tool that integrates climate, economic, and agricultural data. It explores how climate dynamics will affect yields, land use, and production across LAC, emphasizing the importance of strategic responses tailored to local conditions. The findings demonstrate that outcomes in 2050 will be shaped not only by climate dynamics but also by the strategic decisions and policy choices made today. Investments in innovation, infrastructure, and inclusive adaptation strategies will be essential to safeguard and reshape agricultural competitiveness.

II. ABOUT THE STUDY

Research questions

The interplay of GDP growth, population increases, and evolving dietary preferences naturally drives transformations in supply chains, pricing, and land use. However, when analyses factor in climate impacts—particularly yield shocks, water constraints, and heat stress—the picture becomes far more complex.

Climate dynamics introduces new push-and-pull forces that alter incentives, crop viability, and regional advantages in ways that are not necessarily evenly distributed.

Data/methods

This chapter presents findings from the IMPACT partial equilibrium bioeconomic model of global food and agriculture for subregions in LAC (Robinson et al. 2024). The analysis uses IMPACT version 3.4, which integrates climate, hydrology, and crop modules to simulate. IMPACT relies on projections by the OECD at the country level for GDP (Dellink et al. 2017) and for population (Samir and Lutz, 2017) through 2050, as well as expert-based assumptions on the most probable yield growth trajectories by crop and country. IMPACT is informed by integrated climate, water, and crop models operating at a 0.5° spatial resolution to assess the effects of climate change on agricultural productivity. Climate impacts on yields are derived from five general circulation models (GFDL, IPSL, MPI, MRI, and UK) under three Representative Concentration Pathways (RCP2.6, RCP7.0, and RCP8.5) and three Shared Socioeconomic Pathways (SSP1–3), simulated using the DSSAT crop model. IMPACT also incorporates exogenous projections of cropland expansion, accounting for both the growth of physical cropland and increases in cropping intensity.

III. FINDINGS

As a result of a steadily warming climate, global temperatures are now approximately 1°C higher than pre-industrial levels. Despite rising temperatures, LAC has managed impressive agricultural growth thus far, with productivity increasing fourfold since the 1970s (USDA, 2024). However, productivity gains have been unequal, with heterogeneous dynamics emerging among subregions and countries. Looking ahead, yields are expected to continue rising due to investments in agricultural research, improved inputs, and infrastructure. But at a slower rate under climate variability. More importantly, growth will be distributed unevenly across crops, countries, and agroecological zones. Leading to shifts in comparative advantages. Some regions and commodities will emerge as relative winners, while others will become less competitive.

Projected climate impacts on LAC as a whole

Table 1 presents the projected impacts of climate on yields, harvested area, and total production for LAC's seven most important crops by area, using 2020 as the base year. Specifically, the effects on soybeans, maize, sugar cane, wheat, beans, coffee and rice are shown; figures are provided for LAC and the world.

Under a scenario with climate change, the results show that yields of all crops (shown in orange in Table 1) will decrease across LAC, and in every case, regional losses exceed global averages. Coffee and soybeans, two critical exports shown; figures are provided for the region, are projected to experience yield losses of over 10% due to climate change, which is 4 to 5 percentage points higher than the average global decline. Maize yields are expected to fall by 9.6% in LAC, compared to 8.5% globally. Rice, wheat, and beans face smaller yield reductions (less than 5%), but still perform worse in LAC than the rest of the world. These findings are especially relevant considering the vital contribution of these crops to the region's food security.

Table 1. Projected impact of climate on yield, harvested area, and production relative to a scenario without climate change for the top seven crops in LAC in 2050 (with base year 2020)

Crop	*Cultivated area in 2020 (thousands of hectares)*	Climate impact on YIELDS by 2050 (%)		Climate impact on HARVESTED AREA by 2050 (%)		Climate impact on PRODUCTION by 2050 (%)	
		LAC	World	LAC	World	LAC	World
Soybeans	*58,542*	-10.1	-5.4	3.8	4.1	-4.7	-1.4
Maize	*35,703*	-9.6	-8.5	1.6	1.9	-8.2	-6.3
Sugarcane	*14,212*	-7.9	-6.1	3.9	3.9	-4.6	-2.4
Wheat	*9,686*	-4.4	4.3	-7.1	-0.1	-10.4	4.4
Beans	*6,62*	-4.8	-0.2	-5.7	-0.5	-9.7	-0.7
Coffee	*5,243*	-10.3	-5.9	-0.1	1.7	-9.5	-4.1
Rice	*4,933*	-3.7	-2.1	-1.0	0.4	-5.1	-1.7

Source: Projections are from IMPACT v3.4 (Rosegrant et al., 2024).

Notes: Results are shown without the CO2 fertilization effect and are based on emissions under RCP8.5 and economic and demographic changes based on SSP2. The results are based on the median outcome for five climate models. The values in the table reflect changes in global supply and demand that include population, GDP, and technological change.

While yields of nearly all crops are expected to decline in LAC and the world, one striking exception is wheat, Global yields are projected to increase by 4%, driven by rising temperatures benefiting cold-climate wheat producers. However, in a scenario with climate change, LAC's wheat yields are expected to fall by 4.4%. This is an example of shifting comparative advantage, and one that has implications for trade policy, research priorities, and land-use planning.

Climate dynamics will also affect harvested areas (shown in blue in **Table 1**). Under a scenario with climate variability, the harvested areas for wheat, beans, coffee and rice in LAC are expected to decrease, with wheat experiencing the sharpest decline. On the other hand, harvested areas for soybeans, maize, and sugarcane are predicted to increase moderately (2%-4%). Globally, harvested areas are projected to increase for most of the crops analyzed, except for wheat and beans, which show small declines.

The findings suggest that total production of all seven crops (shown in green in **Table 1**) is expected to fall sharply across LAC by 2050. This drop could be particularly pronounced for wheat (-10%), beans and rice (<-9%), and maize (-8%). A more moderate decline is projected for rice, soybeans, and sugarcane between 4.5% and 5.1%. Globally, with the exception of wheat, the model predicts a decline in production and yields of all seven crops under climate change, with decreases of between -0.7% and -6.3%.

In sum, projections for 2050 under climate change show that LAC could experience significantly lower crop yields because of climate variability compared to the baseline. These relative declines would be accompanied by shifts in harvested areas, as farmers adapt their land use to new climate realities. Across the seven most important crops in the region, yields are expected to decrease more sharply than the global average, highlighting LAC's particular vulnerability.

Projected impacts on LAC, by subregion

The subregional breakdown paints even more nuanced stories. **Table 2** shows the projected impact of climate change on crop yields in LAC and its subregions, alongside global trends. The predictions suggest declining yields for all seven crops in Central America and the Southern Cone.

The Andean countries would perceive a slight increase in the yields of soybeans (1.2 percent) and beans (1.4 percent), while the same applies for the Caribbean in the case of soybeans (.6 percent) and maize (3.8 percent). Both subregions would experience yield declines for the remaining crops.

In the case of soybeans, Mexico and Central America face particularly severe yield losses at 17.5% and 11.9%, respectively. In contrast, the Andes and the Caribbean are expected to experience slight increases of 1.2% and 0.6%, respectively. Similar trends are observed for maize, with LAC as a whole expected to see a decline of 9.6%, while reductions in Central America are more severe (18.2%). Yields for sugarcane, coffee, and beans are also expected to decline sharply in most subregions, often exceeding global averages.

Table 2. Projected impact of climate on yield relative to a scenario without climate change for the top seven crops in LAC in 2050 (base year 2020, percent change)

Crop	*World*	*LAC*	Southern Cone	Andes	Mexico	Central America	Caribbean
Soybeans	*-5.4*	*-10.1*	-10.3	1.2	-17.5	-11.9	0.6
Maize	*-8.5*	*-9.6*	-10.2	-6.8	-7.1	-18.2	3.8
Sugarcane	*-6.1*	*-7.9*	-8.4	-4.9	-7.1	-16.8	-12.1
Wheat	*4.3*	*-4.4*	-4.7	-2.9	1.4	-5.9	NA
Beans	*-0.2*	*-4.8*	-6.1	1.4	-8.1	-5.2	-3.2
Coffee	*-5.9*	*-10.3*	-8.9	-2.3	-5.6	-15.2	-6.6
Rice	*-2.1*	*-3.7*	-5.2	-2.5	-1.8	-6.7	-8.8

Source: Projections are from IMPACT v3.4 (Rosegrant et al., 2024).

Notes: Results are shown without the CO2 fertilization effect and are based on emissions under RCP8.5 and economic and demographic changes based on SSP2. The results are based on the median outcome for five climate models. The values in table reflect changes in global supply and demand that include population, GDP, and technological change.

Table 3 presents the predicted impact on harvested areas in each subregion under climate change by 2050. The results show an expected increase in the harvested area of soybeans across all subregions, particularly in Central America (9.5%), Mexico (5.8%), and the Caribbean (5.2%). This suggests that demand and market conditions may still support soybean production, despite productivity challenges. The area planted with maize is also projected to increase in Mexico (4.0%), the Caribbean (4.3%), and the Andean Region (2.7%) but to decline in Central America (-1.1%), where yield losses are expected to be greatest (-18.2%, see **Table 1**).

Sugarcane shows positive harvested area growth across all subregions, even ranging from 1.7 percent in the Andean Region to 6.3 percent in Central America. Notably, harvested area for sugarcane increases even, where yields decline significantly. In contrast, the harvested area of wheat and beans is projected to decline under climate change across most of LAC. The largest reductions in cultivated area for beans occurs in Mexico, where beans lose more than 11 percent of harvested area. The outlook for coffee is mixed: the harvested area may expand slightly under climate change in Mexico (2.9%) and the Andean Region (2.6%), but will decrease in the Southern Cone (-2.2%) and Central America, (-0.6%) possibly reflecting shift to higher altitudes.

Table 3. Projected impact of climate on harvested area relative to a scenario without climate change for the top seven crops in LAC in 2050 (base year 2020, percent change)

Crop	World	LAC	Southern Cone	Andean Region	Mexico	Central America	Caribbean
Soybeans	4.1	3.8	3.9	2.4	5.8	9.5	5.2
Maize	1.9	1.6	0.9	2.7	4.0	-1.1	4.3
Sugarcane	3.9	3.9	3.9	1.7	4.8	6.3	4.8
Wheat	-0.1	-7.1	-7.5	-2.3	-2.6	-2.9	NA
Beans	-0.5	-5.7	-5.1	0.5	-11.9	-1.7	-2.7
Coffee	1.7	-0.1	-2.2	2.6	2.9	-0.6	0.8
Rice	0.4	-1.0	-1.0	-1.0	0.9	-2.6	-2.2

Source: Projections are from IMPACT v3.4 (Rosegrant et al., 2024).

Notes: Results are shown without the CO2 fertilization effect and are based on emissions under RCP8.5 and economic and demographic changes based on SSP2. The results are based on the median outcome for five climate models. The values in table reflect changes in global supply and demand that include population, GDP, and technological change.

Ultimately, the combination of lower yields under climate change and shifting land use results in substantial variation in crop production across the region. **Table 4** summarizes the projected climate impact on production levels for LAC and its subregions. Overall, the predictions suggest a possible decline in the production of all crops analyzed in Central America, Mexico, and the Southern Cone.

The Andean region could experience an increase in the production of soybeans (4.2%), beans (1.9%), and coffee (0.1%) while the Caribbean is predicted to increase production of soybeans (5.8%) and maize. (8.4%). The breakdown by crop suggests that soybean production is expected to be 4.7% lower across LAC as a whole, with severe losses in Mexico (11.6%) and the Southern Cone (4.8%). However, the Andean and Caribbean regions are expected to see increases in soybean production (4.2% and 5.8%, respectively), which are explained by the increases in both yields and harvested area (see **Table 1** and **Table 2**).

Central America is expected to face the most severe impacts on maize production, with a 19.7% drop, while the Caribbean is projected to show an 8.4% increase. Wheat is a particularly stark case: LAC's production is projected to decline by 10.4% relative to a scenario without climate change, even as global production increases. Coffee, beans, and rice will also steep and widespread declines in production, although the Andes region shows modest increases in coffee and bean production, suggesting emerging comparative advantages in certain highland regions.

Table 4. Projected impact of climate on Production relative to a scenario without climate change for the top seven crops in LAC in 2050 (base year 2020, percentage change)

Crop	World	LAC	Southern Cone	Andean Region	Mexico	Central America	Caribbean
Soybeans	-1.4	-4.7	-4.8	4.2	-11.6	-3.6	5.8
Maize	-6.3	-8.2	-9.4	-5.5	-3.2	-19.7	8.4
Sugarcane	-2.4	-4.6	-4.1	-3.8	-2.1	-11.5	-7.9
Wheat	4.4	-10.4	-10.9	-4.6	-1.3	-7.2	NA
Beans	-0.7	-9.7	-11.3	1.9	-18.7	-8.5	-6.1
Coffee	-4.1	-9.5	-11.9	0.1	-1.3	-15.1	-6.9
Rice	-1.7	-5.1	-7.2	-3.5	-0.9	-9.2	-10.8

Source: Projections are from IMPACT v3.4 (Rosegrant et al., 2024).

Notes: Results are shown without the CO2 fertilization effect and are based on emissions under RCP8.5 and economic and demographic changes based on SSP2. The results are based on the median outcome for five climate models. The values in table reflect changes in global supply and demand which include population, GDP, and technological change.

Key Lessons

I. Without significant intervention, yields for all crops analyzed are expected to decrease for LAC as a whole, and the vast majority of crops may experience yield reductions within LAC's subregions. Across LAC as a whole, yields for all crops analyzed are expected to decline. This holds true for the vast majority of LAC's subregions, where the yields of nearly all crops are expected to decline. The only cases where yield increases are observed are beans in the Andean region (1.4%), soybeans in the Andean region, wheat in Mexico (1.4%), soybeans in the Caribbean (0.6%) and maize in the Caribbean (3.8%).

II. Increasing harvested area will not offset production losses when yield reductions are present. As shown in **Table 2**, many subregions are projected to expand the harvested area of crops experiencing yield declines, suggesting an effort to sustain production despite lower yields (as reported in **Table 1**). However, in most cases, the model indicates that such area expansion will not be sufficient to offset yield losses or even maintain current production levels. Even substantial land increases fail to counterbalance the impact of declining yields: in Central America, for instance, the harvested area for soybeans is projected to grow significantly (9.8%), yet production is expected to fall by 3.7%. The only exception to this trend is coffee in the Andean Region, where production is projected to rise modestly (0.1%) despite a 2.3% decline in yields—likely explained by a 2.6% expansion in harvested area.

III. At the subregional level, crops that are expected to experience yield increases will also experience production increases. As shown in **Table 4**, at the regional level, all analyzed crops are projected to experience declines in production. At the subregional level, most crops follow the same downward trend, with only a few exceptions. Production increases are expected for soybeans, beans, and coffee in the Andean Region, and for soybeans and maize in the Caribbean. Notably, with the exception of beans in the Andean Region—where yields are projected to fall—the crops showing production growth are the same ones exhibiting yield gains. This indicates that yield improvements, rather than area expansion, will be the key driver of higher production levels across LAC's subregions. The only case where rising yields did not translate into higher production is maize in Mexico, where output declines by 3.2% despite yield gains, likely due to a 2.6% reduction in harvested area. Nevertheless, maize production in Mexico shows the smallest decline among subregions with negative results, suggesting that yield improvements may partially offset production losses.

IV. CONCLUSIONS AND POLICY RECOMMENDATIONS

Based on these findings, this chapter proposes the following policy interventions to prepare LAC's agriculture sector for future climate scenarios.

I. Design proactive and adaptive strategies to mitigate socioeconomic disparities under changing agroecological conditions

As the model shows, climate variability is expected to shift the viability of certain crops and regions by altering agroecological conditions, which is likely to intensify and reshape existing regional disparities. Policymakers should take a long-term view and proactively develop mechanisms and programs that help vulnerable agricultural sectors and value chain actors adapt to changing conditions. Adaptation policies for the following value chains may be especially critical given their importance in terms of harvested area and vulnerability to climate-driven yield and production reductions, according to the model: maize and coffee in Central America, maize in Mexico, sugarcane in the Caribbean, soybeans in the Caribbean, and rice in the Andean Region. Policymakers should consider an array of adaptive policy actions, such as investing in resource-efficient economic activities that can provide a viable alternative for actors in these vulnerable value chains and establishing social protection programs and reskilling programs for value chain actors with high barriers to transitioning to new economic activities.

I. Prioritize yield-enhancing interventions to sustain production under changing climatic conditions

The model predicts that increasing yields, rather than increasing harvested area, will be the key lever for increasing production across LAC's subregions under a climate change scenario. Without significant intervention, key crops such as maize, coffee, and rice will face production declines in many regions, even despite large increases in harvested area. While the model is clear in its prediction that climate impacts could strain yield growth, targeted interventions directed at increasing yields under changing climate conditions could avert this scenario and protect these markets. Countries that invest early in climate-smart technologies, sustainable infrastructure, and inclusive support systems could maintain or even expand their agricultural potential.

II. Make strategic investments adapt to rapidly changing comparative advantages

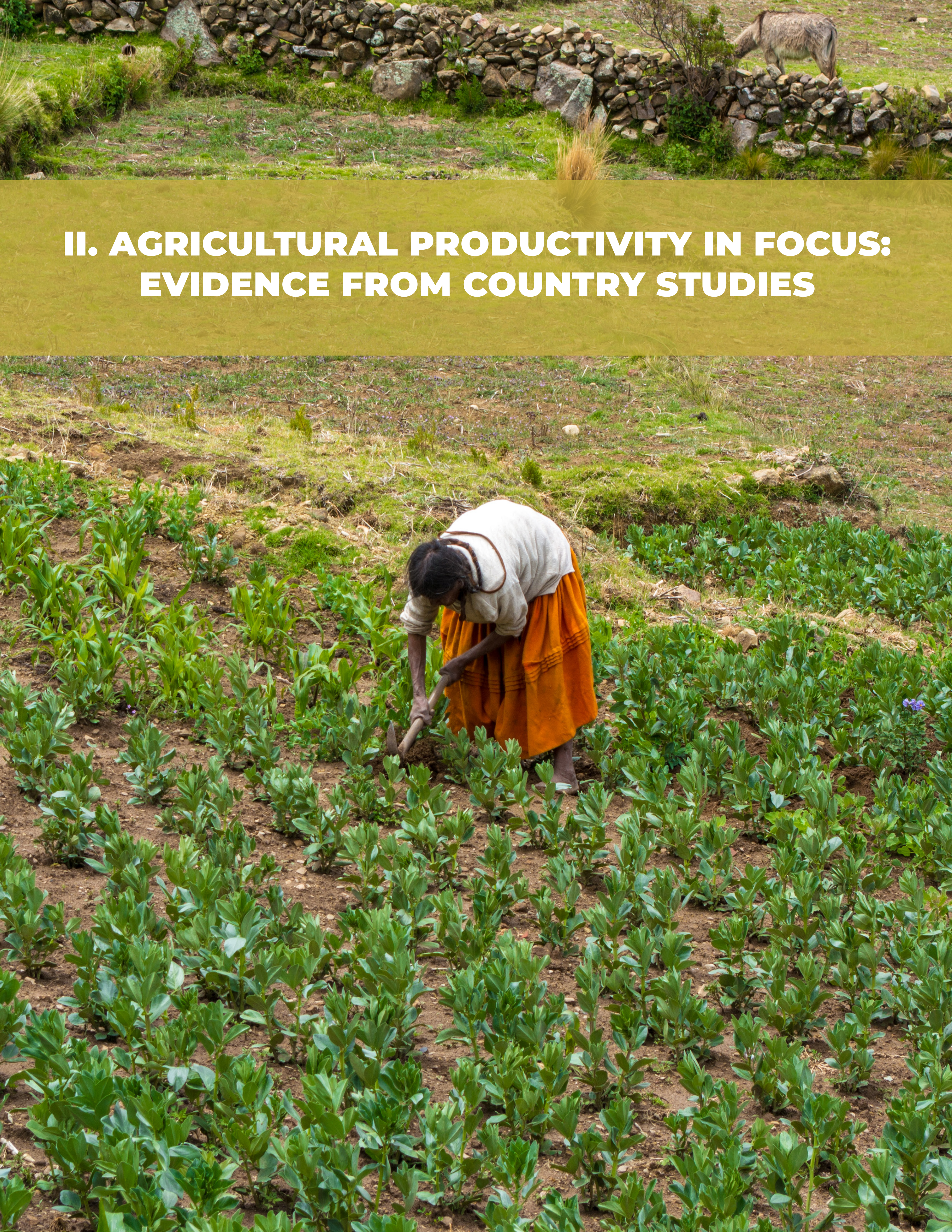
To achieve gains in productivity and sustainability, LAC countries will need to take coordinated action to build an enabling environment that supports innovation, adaptation, and inclusion. Technological advances alone will not be sufficient-the success of such initiatives depends on strong institutions, inclusive policies, and equitable access to resources and support, particularly for smallholders, who face significant barriers. Strategic investments are needed in new markets, diversified production systems, and innovation that reaches all types of producers. Without a coordinated, forward-looking approach, the region risks environmental degradation and missed economic opportunities. By acting strategically, LAC has the potential to become a global leader in building resilient, competitive, and sustainable agrifood systems.

IV. Strengthen regional integration and collaboration to build cost-effective climate resilience strategies

As the model shows, production patterns and markets may shift significantly across LAC's subregions. Climate change, evolving trade patterns, and environmental pressures transcend national borders. Aligning strategies, sharing knowledge, and coordinating actions across countries can improve the region's capacity to respond to expected changes. Greater cooperation can enhance the effectiveness of climate adaptation, research efforts, and market integration, ensuring that no country is left behind in the transition toward more resilient and inclusive food systems.

In sum, the future of agriculture in LAC will depend on the region's ability to apply lessons from the past while anticipating the challenges and opportunities ahead. Maintaining competitiveness in a changing global context will require a deliberate shift toward sustainability, resilience, and inclusive development. By embedding foresight into decision-making and aligning policies with long-term objectives, countries in the region can support the transition to agrifood systems that are both productive and climate resilient.

II. AGRICULTURAL PRODUCTIVITY IN FOCUS: EVIDENCE FROM COUNTRY STUDIES



CHAPTER 3. **MEXICO**

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SUMMARY

This chapter estimates potential production, technical efficiency, technological change, and total factor productivity (TFP) in Mexico between 2007 and 2022, using stochastic production frontier methods and data from recent agricultural censuses. The findings confirm that productive potential increased in 85.8% of municipalities, but technical efficiency declined in 84%. While TFP growth was positive in 88.9% of municipalities, the average increase was less than 1% per year. This growth was driven by technological progress, which averaged 1.37% annually, counteracted by technical efficiency decreased by -0.32%. Weather conditions had a negative effect, reducing TFP growth by 0.016% per year, suggesting the importance of strengthening climate resilience in the agriculture sector. The main factors contributing to TFP growth during this period are irrigation (5.3%), land tenure (11.3%), and investments in infrastructure (3%).

I. INTRODUCTION

This chapter analyzes the main determinants of agricultural production and productivity in Mexico between 2007 and 2022, with the aim of identifying potential policies to improve sector performance sustainably.

To capture sector heterogeneity, the analysis reports estimations at both the national and municipal levels, where the disaggregation by municipality captures within-country differences in agricultural performance, enabling policymakers to target interventions more effectively.

In 2025, agriculture accounted for less than 3.3% of Mexico's GDP, down from a peak of 4.09% in 1986, with an average share of 3.39% during the study period. Despite its relatively modest contribution to GDP, the sector remains a key source of employment, providing jobs for approximately 6.4 million people, representing 10.8% of the country's workforce (INEGI, 2024). In 2023, total agricultural production included 298.9 million tons of food,[1] approximately 85% of which was for domestic consumption (basic food commodities, the national food industry, and animal feed), while 13% was exported, and the remaining 2% was accounted for by losses or informal markets (SADER, 2024).

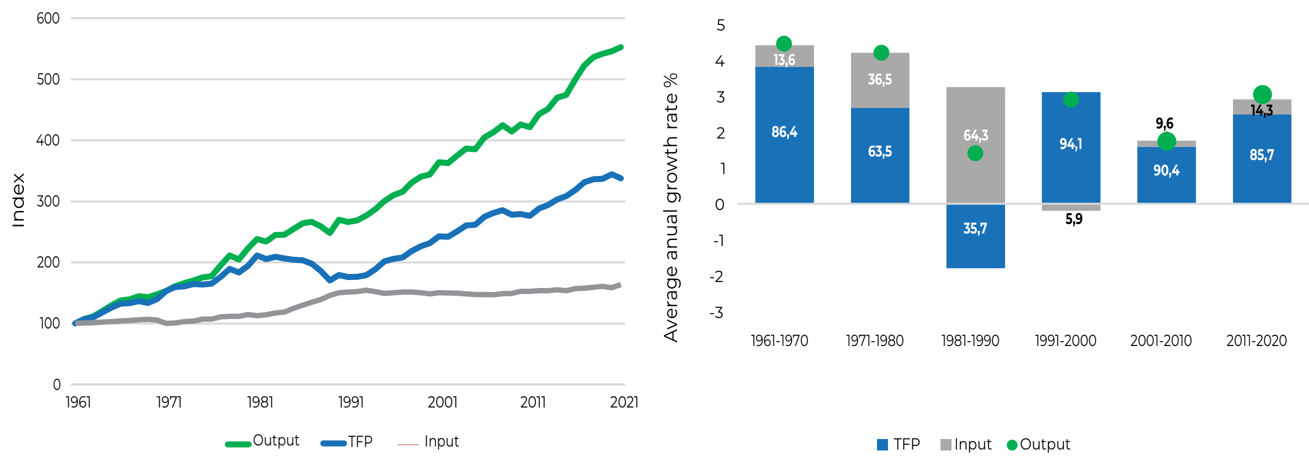
According to the World Trade Organization (WTO), Mexico has consolidated its position as the seventh largest food exporter in 2023, supported by its extensive network of free trade agreements and a recognized sanitary status that allows exports to over 190 countries (Secretaría de Agricultura y Desarrollo Rural, 2023). Although foreign direct investment (FDI) in the agricultural sector has increased in recent decades, it still accounts for less than 1% of total FDI inflows to Mexico (Canales et al., 2019). While FDI contributes to economic growth in the agricultural sector, the development of the sector is largely driven by domestic factors, particularly investment in infrastructure, machinery, and equipment, as well as the capacity of producers to manage challenges such as exchange rate fluctuations (Valdez-Cornejo et al., 2025). The adoption of innovative agricultural practices, often certified under international standards such as organic, fair trade, or Tipo Inspección Federal (TIF), has allowed a portion of Mexican producers to access demanding international markets, enhancing their competitiveness and promoting sustainability.

Mexico's agricultural sector is highly heterogeneous, characterized by sharp contrasts in farm size, production orientation, and access to resources. Most producers are small-scale and subsistence farmers, often living in vulnerable conditions marked by food insecurity and poverty (FAO, 2016), whereas a smaller group of large-scale farms operate using cutting-edge technologies (INEGI, 2023). The productivity of traditional farmers has been estimated at just 15-20% of that of commercial producers (UNCTAD, 2014), underscoring deep structural disparities. These gaps are compounded by social challenges: in 2022, 36.3% of the Mexican population lived in poverty and 7.1% in extreme poverty, rising to 48.8% and 14.9% in rural areas (CONEVAL, 2023). Food insecurity affected 18.2% of the population nationwide, compared with 23.9% in rural areas. In this context, strategies to boost productivity in the agricultural sector are crucial to improve rural livelihoods while promoting environmental sustainability.

Over the past 60 years, Mexico's agricultural output has grown nearly sixfold (**Figure 1**). USDA-ERS data shows that production expanded at an average annual growth rate of 2.9%, driven mainly by increases in TFP, especially since the 1990s. On average, TFP grew by 2.1% per year, while input growth averaged 0.8% annually. Between 2010 and 2020, TFP continued to improve, translating into higher agricultural output. A decade-by-decade breakdown reveals that Mexico outperformed the average Central American countries in both agricultural production and TFP, except during the 1980s and the first decade of the 2000s. During the latter period, Mexico's TFP grew at 1.6% annually, slightly below the regional average of 1.7%. In the 1980s, TFP declined, mirroring trends observed in Central American countries. Most notably, between 2010 and 2020, agricultural production grew at an average annual rate of 2.9%, 86% of which was explained by TFP gains of 2.5% per year, with the remaining 14% explained by increased input use (Salazar et al., 2025).

[1] This figure includes 271.8 million tons of agricultural products, 25.1 million tons of livestock products, and 2 million tons of fishery and aquaculture products.

Figure 1. Changes in TFP, output, and inputs in Mexico (1961–2020)



Note: Figure extracted from Salazar et al. (2025).

The Mexican agricultural sector is highly vulnerable to climate variability, as nearly 60% of cropland depends on rainfall, making it sensitive to extreme weather, while agricultural activities contribute 19% of the country's greenhouse gas and other greenhouse-effect compounds (GyCEI) (Secretaría de Agricultura y Desarrollo Rural, 2022). This dual challenge highlights both the sector's exposure to climate risks and its potential role in mitigation.

To account for the environmental impacts generated by the production process, IFRPI and IDB (2025) also estimated Sustainable Productivity Indexes (SPI) for 1995–2020. When environmental costs are penalized using a 10% weighting scheme for undesirable by-products, productivity growth decreases from 1.5% to 1.3%.

Productivity analyses of Mexico's agricultural sector using recent methodologies, such as stochastic frontier approaches, remain scarce. Existing studies are often limited to specific commodities or programs, and many are outdated. At the national level, a World Bank study found that productivity growth in agriculture, forestry, fishing, and hunting was stagnant in Mexico between 1991 and 2018 (Iacovone et al., 2021).

In contrast, Bravo-Ortega (2021), using a translog production function, estimated average annual TFP growth of 1.7% for the agricultural sector between 1961 and 2017. Some early studies examined the efficiency of the Mexican agricultural sector. For example, Yúnez-Naude et al. (2006) analyzed determinants of inefficiency, finding that subsistence and indigenous farmers tend to be less productive and that natural disasters are also a source of inefficiency. Conversely, Kagin et al. (2016) reported that large farms had lower output per hectare and were less efficient than smallholder farms.

Evaluations of agricultural interventions present mixed findings. Analyses of the largest agricultural transfer program in Mexico, previously known as ***Procampo***, revealed limited impacts on productivity (Dyer Leal et al., 2017; "Valentín-Garrido et al. 2016"). A recent study of the same program, renamed ***Producción para el Bienestar*** in 2019, found no significant productivity gains among program beneficiaries in the sugarcane and maize production (Ortega Díaz & Guerrero, 2024). By contrast, Todd et al. (2010) found the program had positive effects on agricultural outcomes such as land use, livestock ownership, and agricultural expenditures.

Studies of interventions that aim to mitigate the effects of weather shocks showed mixed results. Fuchs and Wolff (2016) found that a rainfall-indexed weather insurance program increased maize yield by 6%. Extension and technical assistance programs also present positive and significant outcomes. For instance, Donnet et al. (2017) conducted a metafrontier analysis and reported technical efficiency scores between 70% and 100% among the beneficiaries of the Sustainable Modernization of Traditional Agriculture *(MasAgro)* program, a government–CIMMYT initiative launched in 2010 that aimed to increase maize and wheat productivity while promoting sustainable practices among smallholder farmers. Finally, Guerrero Ortiz et al. (2023) found that a guaranteed price support program *(Precios de Garantía)* moderated the decline in cultivated maize area by 5%.

The contribution of this chapter lies in the multilevel analysis conducted at the farm and municipality levels, which complements previous studies that rely solely on aggregate data (ERS-USDA, 2024; Fernandez-Cornejo & Shumway, 1997; Iacovone et al., 2021), those analyzing specific agricultural commodities (Díaz et al., 2025; Ortega et al., 2023), or explicit interventions (Corral et al., 2016). In contrast, this study leverages microlevel data aggregated at the municipal level to provide a view of overall agricultural production. This approach allows us to analyze key agricultural variables, including technical efficiency, technological change, and TFP growth, while identifying localized challenges and opportunities. Given the diversity of conditions within Mexico's agriculture sector, policymakers and other stakeholders could use the disaggregated findings in this chapter to target specific policies by region.

II. Methodology and data

TFP growth is explained by changes in technological progress or technical efficiency. This analysis relies on a production frontier analysis methodology to identify the factors that drive TFP. For this purpose, potential production is estimated by including traditional agricultural inputs and weather-related variables, whereas technical efficiency is estimated through managerial factors (Asravor et al., 2024). Uncertainty is captured through climate and other factors beyond producers' control (Battese and Coelli, 1995).

Data sources

For the estimation of agricultural production, technical efficiency, and TFP, this chapter relies on agricultural census microdata from the National Institute of Statistics and Geography of Mexico (INEGI) for 2007 and 2022. A total of 3,885,353 farms were analyzed for 2007 and 3,543,030 for 2022[2]. To calculate the value of production, the agricultural census data were complemented with agricultural prices from the Ministry of Agriculture's price system (SIAP). Additional information on climate, land suitability, and location was drawn from INEGI, the US Geological Survey, and Google Earth Engine. **Table 1** summarizes these data sources.

[2] The 2022 census records 4,613,004 agricultural production units, compared to 4,072,729 in the 2007 census, though complete data is not available for all units. Of the units recorded in 2022, 103,150 are classified as large enterprises and 4,509,854 as medium- or small-scale enterprises. No official classifications were included in 2007.

Table 1. Data and sources

Data	Description	Source
Agricultural production aggregated by municipality	Data from farms is aggregated at the municipal level for across-time comparisons: land, inputs, and socioeconomic variables (2007, 2022)	INEGI: Agricultural Census (2007 and 2022)
Prices of agricultural products	Municipal-level agricultural product prices (2007, 2022, constant 2022 MXN)	Ministry of Agriculture: SIAP - SADER (2007 and 2022)
Agricultural suitability	Land use and vegetation by municipality (2003, 2018)	INEGI: Land Use and Vegetation Map, Series II (2003) and Series VII (2018)
Precipitation	Satellite data on daily precipitation by municipality (1997–2007, 2012–2022)	Google Earth Engine: Climate Hazards Center InfraRed Precipitation with Station data (CHIRPS)
Temperature	Satellite data on 8-day composite land surface temperature by municipality (2003–2007, 2010–2020)	Google Earth Engine: Aqua Moderate Resolution Imaging Spectroradiometer (MODIS, MYD11A2)
Public finance	Annual municipal revenues and expenditures (2007, 2022)	INEGI: municipal public finances (EFIPEM) (2007 and 2022)
Land tenure	Area by type of land tenure at municipal level (2007, 2022)	INEGI: Agricultural Census (2007 and 2022)
Irrigation system	Share or production units using irrigation systems (sprinkler, drip, microsprinkler, lined and unlined canals)	INEGI: Agricultural Census (2007 and 2022)
Poverty	Wellbeing and poverty (2010, 2020)	CONEVAL Poverty Maps 2022

Source: Authors.

Table 2 presents the variables used to estimate the production function and potential production—that is, the maximum output that can be obtained with current inputs. **Table 3** lists the variables used to estimate technical efficiency.

Table 2. Control variables in the production function

Variables of interest	Description
Capital	Number of tractors, trucks, machines, facilities, and technologies used on each farm, aggregated by municipality
Labor	Number of employees on farms, by municipality
Inputs	Number of farms using fertilizers, herbicides, and insecticides by farm, or number of farms using each agrochemical input, by municipality
Land	Hectares of land sown, used for pasture, rented, or irrigated, by municipality
Weather variables	Ten-year averages of precipitation and temperature, by municipality

Note: Authors' elaboration based on agricultural census data (2007 and 2022). Weather variables are derived from satellite data aggregated at the municipal level, using period averages for 2003–2007 and 2010–2020.

Table 3. Management variables in technical efficiency

Variables of interest	Description
Socioeconomic variables	Number of male producers, average age, number of Indigenous producers, average years of schooling, by municipality
Credit	Number of producers that received credit, by municipality
Certified seed	Number of farms using certified seed, by municipality
Other activities	Number of farms engaged in nonagricultural activities, by municipality

Note: Authors' elaboration based on agricultural census data (2007 and 2022).

Table 4 presents the factors that affect short-term uncertainty.

TABLE 4. VARIABLES BEYOND PRODUCERS' CONTROL

Variables of interest	Description
Climate variables	Standard deviation from average precipitation and temperatures
Competition	Number of farms, by municipality
Land size	Hectares of agricultural land, by municipality

Note: Authors' elaboration based on agricultural census data (2007 and 2022). Weather variables are derived from satellite data aggregated at the municipal level.

Finally, the decomposition method of Lachaud et al. (2022) is used to calculate the TFP index and growth. Next, TFP is linked to policy variables including public finance, land tenure type, and irrigation techniques, presented in **Table 5**.

TABLE 5. MAIN POLICY VARIABLES

Variables of interest	Description
Irrigation	Percentage of irrigated land by method (sprinkler, drip, microsprinkler, and canals), by municipality
Land tenure	Hectares by land tenure type (ejidal, communal, agricultural neighborhood, private, public), by municipality
Public finance	Municipal public finance data, including public debt, investment expenditures, taxes, and federal transfers, covering revenues and expenditures of local governments

Source: Authors' elaboration using INEGI data (2007).

STOCHASTIC PRODUCTION FUNCTION

Agricultural productivity changes can result from technical efficiency (the mix of inputs and technologies used to achieve maximum potential output, with 100% efficiency representing the frontier) and / or technological change (technologies and innovations that shift the production frontier outward, allowing higher output with the same inputs).[3] Potential production and technical efficiency are estimated using stochastic frontier analysis.[4]

TFP DECOMPOSITION

To estimate TFP growth, we adapted the approach of Lachaud et al. (2022) by estimating the stochastic production frontier specified as follows:

$$y_{it} = \alpha_i + \sum_{k=1}^{K} \beta_k\, x_{k,it} + \tau t + \sum_{j=1}^{J} \eta_j\, z_{j,it} + v_{it} - u_{it}^{5} \quad (1)$$

All variables are aggregated at the municipal level and expressed in inverse hyperbolic sine (IHS) form for continuous variables. y_{it} represents the aggregate value of production by municipality i in time t; x_{it} denotes the aggregate inputs variables; t is a time trend; z_{it} includes long-term weather variables; v_{it} and μ_{it} are symmetric random errors. The estimated coefficients from equation 1 are used to compute the TFP index (TFPI), which compares two locations (e.g., municipalities) (m,i) in two periods of time (s,t), as expressed in the following equation:

$$TFPI_{it} = e^{(\alpha_i - \alpha_m)} \times \left[\prod_{k=1}^{K}\left(\frac{X_{kit}}{X_{kms}}\right)^{\beta_{ki}-b_i}\right] \times e^{(T_i - T_m)} \times \left[\prod_{j=2}^{J}\left(\frac{z_{jit}}{z_{jms}}\right)^{nj}\right] \times e^{-(u_{it}-u_{ms})} \times e^{(v_{it}-v_{ms})} \quad (2)$$

Where the first term, $e^{(\alpha_i - \alpha_m)}$, captures country time-invariant unobserved heterogeneity (UH); the second term $\left[\prod_{k=1}^{K}\left(\frac{x_{kit}}{x_{kms}}\right)^{\beta_{ki}-b_i}\right]$, measures relative change in scale efficiency (SE), where $b_k = \widehat{\beta_k} / \sum_{k=1} \widehat{\beta_k^K}$, and $\widehat{\beta_k}$ is an estimator of β_k; the third term, $e^{(T_i - T_m)}$, is the relative change in technological progress (TP); the fourth term, $\left[\prod_{j=2}^{J}\left(\frac{z_{jit}}{z_{jms}}\right)^{nj}\right]$, accounts for weather effects (WE) given by variations in climatic conditions; the fifth component, $e^{-(u_{it}-u_{ms})}$, measures relative changes in technical efficiency (TE) calculated based on Battese and Coelli (1995).

The last term, $e^{(v_{it}-v_{ms})}$, is statistical noise (SN) attributable to functional form and other errors that cannot be identified.
In summary, TFP for municipality i at time t is estimated as follows:

$$TFP_{it} \equiv TP_{it} \times TE_{it} \times SE_{it} \times CE_{it} \times UH_i \quad (3)$$

III. FINDINGS

TFP DECOMPOSITION

Table 6 reports national averages of TFP growth between 2007 and 2023 and its determinants. The results show that TFP grew by less than 1% per year in the study period. This growth was driven by technological progress (+1.37%), but was offset by a decrease in technical efficiency (-0.317%) and adverse weather effects (-0.016%).

Finally, the negative value of the scale efficiency index (SEI) suggests that larger farmers have reduced efficiency (-0.013%). These results are consistent with those reported by Lachaud et al. (2022), who reported TFP growth of 1.43% for Mexico between 1961 and 2014, along with TPI growth of 1.58%, a SEI of -0.06%, and a CEI of -0.205%.

[3] In analyses of the agricultural sector in developing countries, heteroscedasticity across farms is the principal component to control for in the inefficiency term, so we use the model of Battese and Coelli (1995), which separates the error term from technical efficiency term, modeling each according to their own determinants.

[4] Following Battese and Coelli (1995) and Maruyama et al. (2018), we estimate a Cobb-Douglas stochastic frontier function defined as: $y_i = f(x_i;\beta)\exp(v_i - u_i)$, with $v_i \sim N(0,\sigma^2)$ and $u_i \sim N^+(0,\sigma_u^2)$, where y_i is the inverse hyperbolic sine of production for farmer, representing the value of producion for producer i; β are the elasticities; v_i is a random error with zero mean associated with random factors outside the producer's control; and u_i is a nonnegative random variable associated with the producer's efficiency in management.

[5] $u_{it} = \delta \sum_{l=1}^{L} w_{l,it} + \mu_{it}$ where $w_{l,it}$ represents management-related characteristics, including sex, age, ethnicity, family size, education level, and access to credit certification. The term v_i is a random error with zero mean, associated with random factors beyond the producer's control, including the number of plots, agricultural land area, and climate conditions.

Table 6. Annual growth rates of Mexico's TFP and its components (2007–2022)

TFP index	Scale efficiency index (SEI)	Weather effects index (WEI)	Technical efficiency index (TEI)	Technol. progress index (TPI)	Statistical noise (SN)
0.955%	-0.013%	-0.016%	-0.317%	1.370%	-0.069%

Note: Authors' calculations based on agricultural censuses (2007 and 2022). Annual TFP growth rates and their components are derived from a stochastic frontier analysis (SFA)-based multiplicative index. Municipal-level annual growth rates are aggregated to the national level using an arithmetic mean.

At the municipal level, 11% of municipalities experienced negative TFP growth, 37% showed growth below 1%, 44.5% saw growth between 1% and 2%, and only 6.6% exceeded 2% growth (see **Table 7**).

Table 7. Municipal-level TFP growth (2007-2022) and growth categories, by federal entity

(continued on next page)

Federal entity	Average TFP growth (p.a.)	TFP category			
		Negative	Between 0 and 1%	Greater than 1%	Total
Aguascalientes (Ags)	1,56%	9,09%	18,18%	72,73%	100%
Baja California (BC)	1,45%			100,00%	100%
Baja California Sur (BCS)	0,58%	20,00%	60,00%	20,00%	100%
Campeche (Camp)	1,16%		36,36%	63,64%	100%
Chiapas (Chis)	1,09%	3,39%	43,22%	53,39%	100%
Chihuahua (Chih)	1,13%	14,93%	22,39%	62,69%	100%
Ciudad de México (CDMX)	0,81%		75,00%	25,00%	100%
Coahuila de Zaragoza (Coah)	0,91%	18,42%	36,84%	44,74%	100%
Colima (Col)	1,25%	10,00%	10,00%	80,00%	100%
Durango (Dgo)	0,95%	28,21%	5,13%	66,67%	100%
Guanajuato (Gto)	1,69%	4,35%	17,39%	78,26%	100%
Guerrero (Gro)	0,88%	12,35%	37,04%	50,62%	100%
Hidalgo (Hgo)	1,14%	5,95%	27,38%	66,67%	100%
Jalisco (Jal)	1,40%	6,45%	13,71%	79,84%	100%
Michoacán de Ocampo (Mich)	1,11%	8,85%	24,78%	66,37%	100%
Morelos (Mor)	0,89%	9,09%	33,33%	57,58%	100%

Note: Authors' calculations based on agricultural censuses (2007 and 2022). Federal entity-level annual growth rates are obtained as the arithmetic average of municipal growth rates.

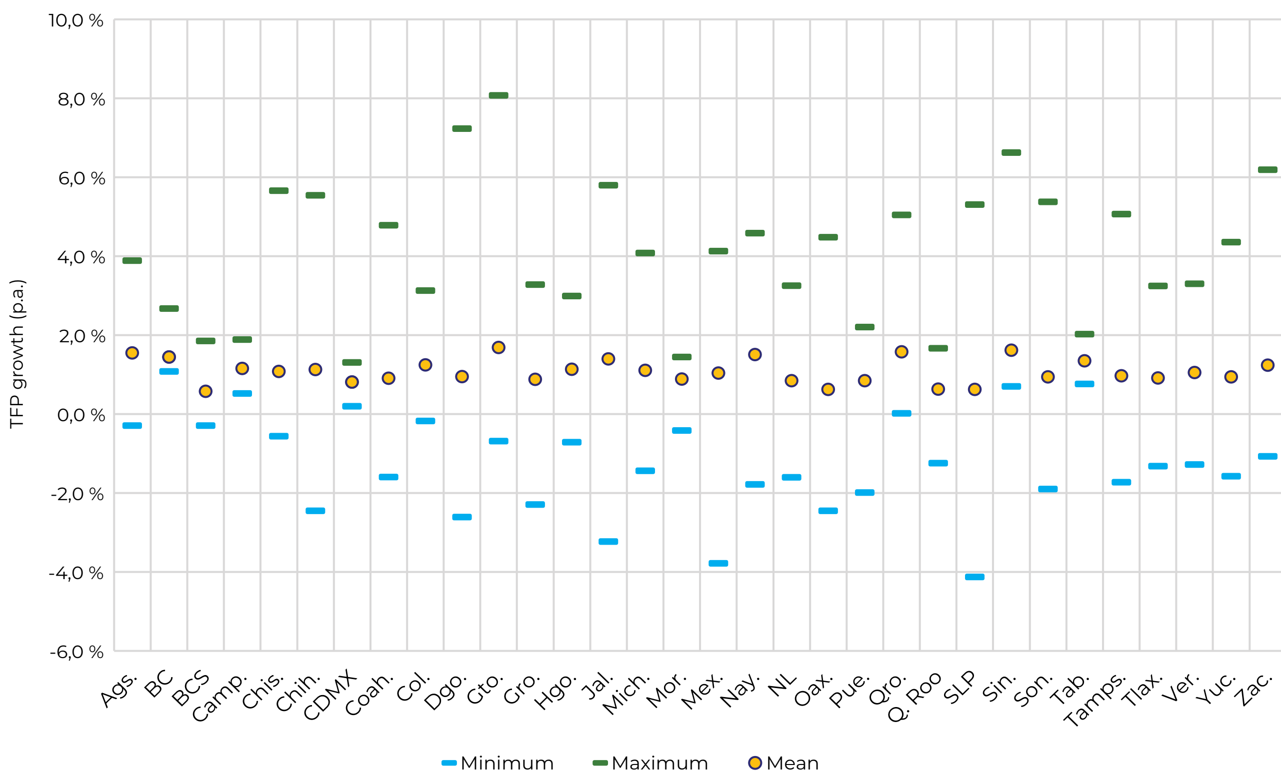
Table 7. Municipal-level TFP growth (2007-2022) and growth categories, by federal entity
(continued)

Federal entity	Average TFP growth (p.a.)	TFP category			
		Negative	Between 0 and 1%	Greater than 1%	Total
México (Mex)	1,04%	9,68%	29,03%	61,29%	100%
Nayarit (Nay)	1,51%	5,00%		95,00%	100%
Nuevo León (NL)	0,85%	22,92%	27,08%	50,00%	100%
Oaxaca (Oax)	0,63%	14,08%	62,68%	23,24%	100%
Puebla (Pue)	0,85%	8,29%	48,85%	42,86%	100%
Querétaro (Qro)	1,58%		22,22%	77,78%	100%
Quintana Roo (Q. Roo)	0,63%	25,00%	25,00%	50,00%	100%
San Luis Potosí (SLP)	0,63%	29,31%	29,31%	41,38%	100%
Sinaloa (Sin)	1,62%		16,67%	83,33%	100%
Sonora (Son)	0,94%	16,67%	26,39%	56,94%	100%
Tabasco (Tab)	1,35%		11,76%	88,24%	100%
Tamaulipas (Tamps)	0,97%	21,43%	26,19%	52,38%	100%
Tlaxcala (Tlax)	0,92%	6,67%	40,00%	53,33%	100%
Veracruz (Ver)	1,06%	5,19%	27,83%	66,98%	100%
Yucatán (Yuc)	0,95%	9,43%	46,23%	44,34%	100%
Zacatecas (Zac)	1,24%	17,24%	12,07%	70,69%	100%
Mexico	**0,96%**	**11,07%**	**37,84%**	**51,09%**	**100,00%**

Note: Authors' calculations based on agricultural censuses (2007 and 2022). Federal entity-level annual growth rates are obtained as the arithmetic average of municipal growth rates.

The results also suggest substantial variability in TFP growth across municipalities within each state, as shown in **Figure 2**. The analysis reveals states with very low variability—such as Tabasco, Morelos, or Campeche—and others with high variability—such as San Luis Potosí, Durango, or Guanajuato.

FIGURE 2. AVERAGE TFP GROWTH ACROSS MUNICIPALITIES BY STATE (2007–2022)

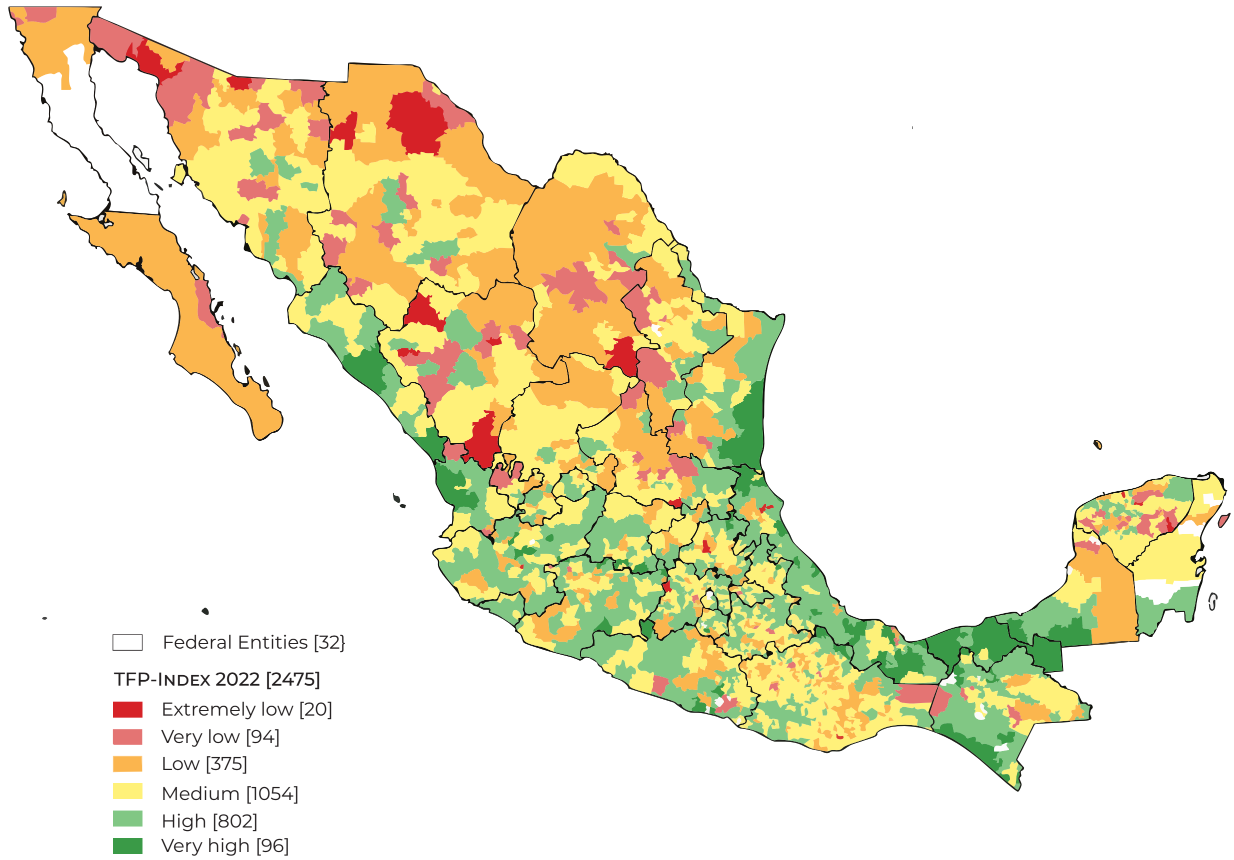


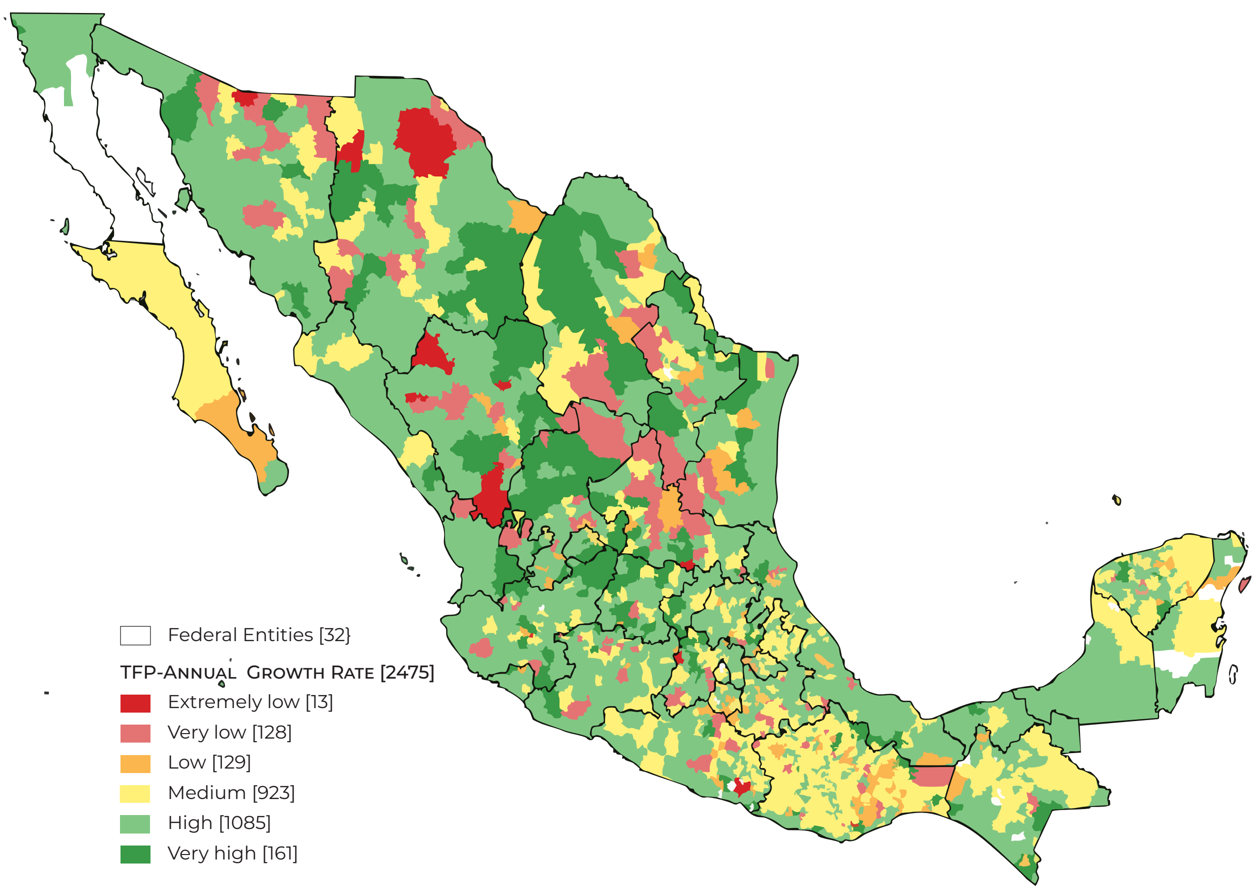
Note: The figure shows annual TFP growth (p.a.) for each state from 2007 to 2022. The green lines represent the maximum municipal TFP growth within each state, the blue lines the minimum, and the yellow circles the average across all municipalities in the state.

TFP for 2022 and TFP growth for 2,475 municipalities are shown in **Figure 3.** Sinaloa ranks among the top states in average municipal TFP growth, second only to Guanajuato. Sinaloa's municipal annual TFP growth rates range from 0.70% to 6.62%, for an average of 1.62%. Notably, 83.33% of the state's municipalities experienced growth above 1%, while 16.67% registered levels below 1%. In contrast, Guanajuato, despite having the highest average municipal TFP growth, shows more variation: 4.35% of its municipalities registered negative growth, 17.39% grew by less than 1%, and 78.26% exceeded 1%.

States with no municipalities experiencing negative TFP growth include Querétaro, Ciudad de México, Campeche, Sinaloa, Tabasco, and Baja California. At the other end of the spectrum, Oaxaca and Baja California Sur rank lowest in average municipal TFP growth. Oaxaca's municipalities show a wide range of outcomes, from -2.4% to 4.4%, with an average of 0.62%. However, 14.08% experienced negative growth, 62.68% grew by less than 1%, and only 23.24% exceeded 1%. In Baja California Sur, municipal TFP growth ranged from -0.29% to 1.85%, with 20% of municipalities showing negative growth.

Figure 3. Municipal TFP index (2022) and TFP growth (2007–2022)



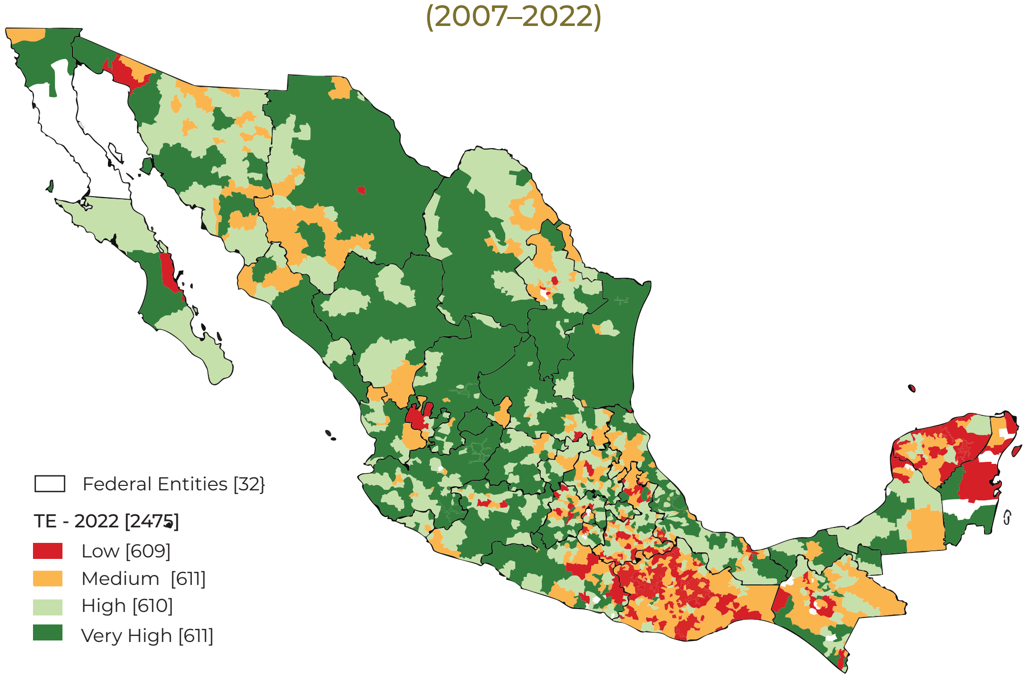


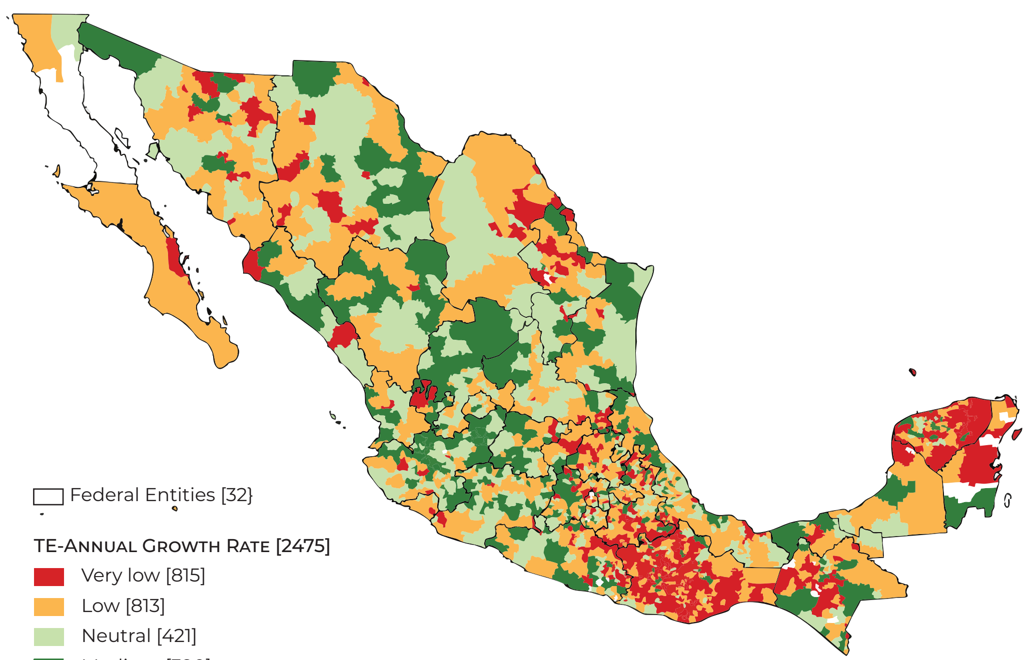
Note: Authors' elaboration based on agricultural censuses (2007 and 2022).

Technical efficiency

At the national level, the results confirm that average technical efficiency decreased from 90% in 2007 to 85% in 2022. Specifically, 84% of municipalities experienced a decline, while only 16% recorded an improvement (see **Figure 4**). In 2022, 25% of municipalities achieved high technical efficiency levels (91.9%–97.6%), primarily concentrated in the central region of the country. In contrast, municipalities in the southeast and southwest exhibited low to medium levels, with only a few showing positive growth during the study period.

Figure 4. Municipal technical efficiency levels (2022) and growth in technical efficiency (2007–2022)





Note: Authors' elaboration based on agricultural censuses (2007 and 2022).

Specific determinants of agricultural production

Findings. Results derived from the stochastic production frontier described in equation 1 reveal the factors influencing agricultural production and technical efficiency across municipalities. The estimations suggest that capital, land, and labor increase agricultural production while inputs have mixed effects. Precipitation, temperature, and soil water content also favor agricultural output, as do climate-smart practices such as land recovery and irrigation. Furthermore, average education levels and the share of male producers are associated with higher technical efficiency at the municipal level, while economic diversification away from agriculture is linked to higher inefficiency (see **Table 8**).

Table 8. Factors that affect production and technical efficiency at the municipal level (continued on next page)

Factors	Effect on production
Capital	The use of tractors, vehicles, and technologies in the production chain increases output by around 13%, on average, while machinery does so by 3%.
Fertilizer, herbicides, and insecticides	The use of chemical fertilizers decreases production by 8.7%. Herbicides have a small but positive effect (2.7%).
Labor	Higher average numbers of workers in each municipality raise production by 8.5%.
Land	Each additional unit of harvested land increases production by 26%. Rented land increases output by 6.4%, land recovery by 15%, and irrigated land by 8.8%.
Weather conditions	At the municipal level, a 1% increase in average precipitation over the past 10 years raises output by 18%. Average temperature has a large impact (82%), while soil water content increases production by 8.8%.
Factors	**Effect on technical efficiency**
Age	Producer age is negatively related to efficiency but is not statistically significant.
Credit	No effect, likely due to farmers having low access: only 3.8% to 6.4% of farms per municipality receive credit.
Schooling	Positive effect: each additional year of schooling decreases inefficiency variance by 87%.
Indigenous producers	No effect on inefficiency.
Male producer	A higher share of male producers reduces inefficiency variance by 138% compared to female producers. Male producers tend to have more assets than female producers, facilitating access to collateral, credit, and investments.
GMO seed	No significant effect.
Diversity in activities	A higher share of farmers engaged in agricultural activities increases inefficiency by 42% at the municipal level.

Table 8. Factors that affect production and technical efficiency at the municipal level (continued)

Factors	Effects of short-term exogenous variables
Number of plots	More plots per municipality reduces variance in production uncertainty by 24%.
Agricultural land area	Larger agricultural areas increase production uncertainty by 21%.
Climate conditions	Variance in precipitation at the municipal level increases production uncertainty by 52%, whereas variance in temperatures increases it by 18%.

Note: Estimated coefficients from the stochastic production frontier (equation 1) at the municipal level, using data aggregated from the 2007 and 2022 Agricultural Censuses.

Finally, we explore the determinants of the estimated levels of agricultural TFP growth, including irrigation systems, land tenure type, and public finance at the municipal level. The estimated coefficients are reported in **Table 9**, with the corresponding effects summarized in **Table 10**. The findings confirm that access to irrigation, public investment, and federal transfers increase TFP growth.

Table 9. Effect of 2007 policy variables on TFP growth, 2007–2022

	Irrigation	Land tenure	Public finance (expenditure)	Public finance (revenue)
Share of farms using dripping irrigation	0.050***			
	(0.018)			
Share of farms using lined canal	0.038**			
	(0.016)			
Communal land are (ha)		-0.014**		
		(0.006)		
Ejidal land area (ha)		0.043***		
		(0.011)		
Public land area (ha)		0.024**		
		(0.010)		
Public debt ($)			0.044***	
			(0.012)	
Public investment ($)			0.053*	
			(0.027)	
Taxes ($)				0.030*
				(0.016)
Federal transfers ($)				0.113***
				(0.04)
Observations	**1,633**	**1,982**	**1,325**	**1,875**

Note: All variables are expressed in IHS form. Explanatory variables correspond to their 2007 values, based on EFIPEM data. The dependent variable is TFP growth from 2007 to 2022, estimated through the SFA. Monetary variables are expressed in Mexican pesos for 2007. Standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table 10. Results of policy variables

Variables of interest	Description
Irrigation	A 1% increase in drip irrigation area increases TFP growth by 5%; traditional irrigation canals increase it by 3.8%.
Land tenure	A 1% increase in communal land tenure decreases TFP growth by 1.4%, the ejido tenure model increases it by 4.3%, and public land tenure by 2.4%. Other tenure types had no significant effect.
Public resources for investment	A 1% increase in public debt raises TFP growth by 4.4%, while public investment does so by 5.3%. Higher municipal income also boosts TFP growth: a 1% increase in federal transfers increases growth by 11.3%, while local tax revenue raises it by 3%.

Source: Authors.

IV. CONCLUSIONS AND POLICY RECOMMENDATIONS

This chapter has analyzed the dynamics of TFP growth in Mexico between 2007 and 2022 using stochastic frontier analysis. The objective was to provide policymakers and stakeholders with evidence to design and implement context-specific interventions that address the needs of underperforming municipalities and improve the impact and efficiency of public resources. The main policy recommendations that emerged from the analysis are as follows:

I. Invest in technical efficiency to unlock productivity Gains

The decomposition shows that TFP growth has been driven mainly by technological progress, while low technical efficiency has constrained productivity. Farmers have not fully capitalized on the productive capacity generated by technological change. Moreover, the positive effect of schooling on technical efficiency underscores the need for targeted investments in training, extension, and education. Expanding technical assistance and knowledge transfer could yield significant productivity improvements, especially in underperforming municipalities.

II. Strengthen climate resilience as a driver of productivity

Climate variability has reduced productivity gains during the period analyzed. At the same time, positive results associated with investments in irrigation and technologies that mitigate climate vulnerability highlight the importance of adapting agriculture to changing weather patterns. Expanding access to efficient irrigation systems and climate-smart practices will be critical to sustaining productivity growth.

III. Target women farmers to close efficiency gaps

The analysis shows that municipalities with a higher share of male producers are associated with a 138% lower variance in technical inefficiency, suggesting that male farmers operate more efficiently on average. Tailored interventions—such as training, technical assistance, and education programs specifically designed for women—could enhance their productivity without requiring additional input use, thereby improving overall sector performance.

IV. Leverage public resource transfers to municipalities

Transfers of public resources are positively associated with TFP growth. Public investment (5.3%), federal transfers (11.3%), and municipal tax revenues (3%) are all linked to higher productivity. Strengthening the design and targeting of such transfers can further enhance their impact on agricultural performance.

V. Promote targeted, context-specific agricultural investments tailored to the challenges of each municipality

The wide variability in municipal TFP performance—both within and across states—highlights substantial productivity disparities, while a small share of municipalities achieved growth rates above 6%, a significant proportion experienced negative growth or growth below 1%. These patterns reveal widening municipal productivity and efficiency gaps, underscoring that place-based agricultural investments could help narrow disparities in performance and foster more equitable growth.

CHAPTER 4. **COLOMBIA**

Authors: Rachid Laajaj, María Camila Ortiz Álvarez, Margarita Gáfaro, Lina Salazar

SUMMARY

Improving agricultural productivity is essential for rural development, food security, and inclusive growth in Colombia. The country has fertile land and favorable geographic conditions, yet low productivity remains the main obstacle preventing the agricultural sector from reaching its full potential (Valdivia Zelaya et al., 2023). This study analyzes recent productivity trends and the effects of climate shocks, credit access, violence, and public investment, using household- and municipal-level panel data.

The findings confirm that agricultural output growth is mainly driven by increased input use rather than productivity gains, with total factor productivity (TFP) growing at less than 1% annually between 2015 and 2023. The analysis also shows that Colombian agriculture is highly vulnerable to climate shocks. Regarding specific policies, access to credit and rural road infrastructure are consistently associated with productivity gains, whereas the direct provision of agricultural inputs is not statistically significant. These findings underscore the need to prioritize investments that expand financial inclusion and strengthen rural connectivity. They also support shifting input transfers toward public goods while promoting climate-resilient practices and more efficient land use to sustain agricultural productivity growth.

I. INTRODUCTION

Historically, agriculture has been a cornerstone of Colombia's socioeconomic development. The sector contributes 9% of GDP, employs 14% of the workforce, and supports millions of rural households, which comprise about 17% of the population (World Bank, 2024). Colombia is a net food exporter, so the sector plays a fundamental role in the country's trade balance: in 2024, agricultural products were its second-largest export group.

Colombia, one of the most biodiverse countries in the world, has 42.9 million hectares of agricultural frontier, equivalent to 37.6% of its national territory (UPRA, 2024). It produces a wide variety of crops, the most significant of which include livestock, coffee, flowers, cocoa, bananas, rice, and palm oil. These factors position the agricultural sector as a strategic driver of growth and rural development.

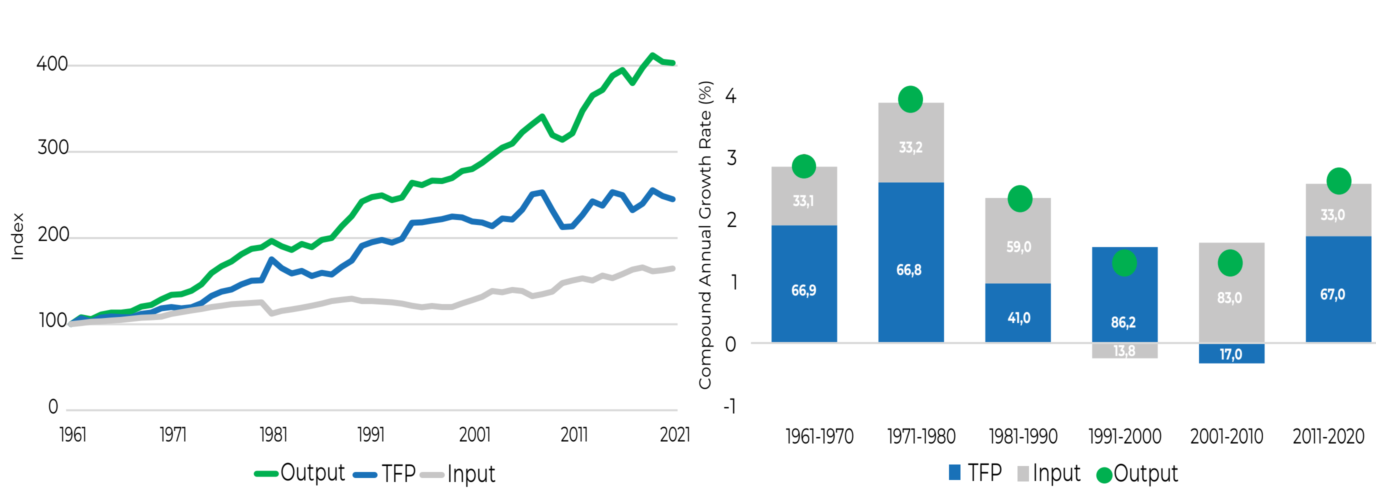
Over time, the sector's share of the national economy has declined. This downturn is partly explained by Colombia's development process and the growing importance of services (OECD, 2022) but is also due to low productivity growth. Most evidence on long-term productivity comes from multi-country studies using aggregated data. For instance, Nin-Pratt et al. (2015) estimate that Colombia's annual TFP growth was 1% between 1981 and 2012, slightly below the regional average. Country-specific evidence is limited, although Jiménez et al. (2018) find annual TFP growth rates between 0.8% and 1.3% between 1975 and 2013.

According to Salazar et al. (2025), between 1961 and 2021 agricultural output in Colombia grew at an average annual rate of 2.4%, below the regional average of 2.9%.

Figure 1 shows that this growth was largely driven by improvements in TFP, which increased at an average annual rate of 1.5%, a pace similar to that recorded by the Andean Community, rather than by increased use of inputs. To offer an accurate picture of sustainable growth, IFRPI and IDB (2025) estimated Sustainable Productivity Indexes (SPI) for 1995-2020. When environmental costs are included under a 10% weighting scheme, productivity growth is reduced by half, reflecting the negative environmental impact of agricultural production.

Taken together, these studies suggest that Colombia's agricultural productivity has increased modestly in recent decades. This slow progress has limited the sector's ability to drive sustained economic growth. Strengthening TFP is therefore essential, not only to boost economic performance but also to reduce pressure on natural resources. With appropriate safeguards and sustainable land-use policies, higher productivity could help curb land expansion and mitigate deforestation.

Figure 1. Growth in TFP, outputs, and inputs in Colombia, 1961–2021



Note: Figure extracted from Salazar et al. (2025).

Low productivity is associated with a range of structural barriers. Land concentration reduces productivity by preventing smallholders from achieving economies of scale (Deininger et al., 2013), by limiting their ability to use land as collateral to access credit (Rajan & Ramcharan, 2011) and by leading to inefficient land use (Castagnini et al., 2004). Other persistent barriers include informal land tenure, the legacy of armed conflict, deficient rural infrastructure, limited access to finance and extension services, and persistent underinvestment in public goods (Jiménez et al., 2019; OECD, 2022).

Since 1990, Colombia has embarked on a process of trade liberalization, that has promoted foreign direct investment (FDI). However, in the agricultural sector, FDI participation has historically been low, accounting for only 2.3% of the total between 2019 and 2024 (Banco de la República, 2025), largely constrained by land ownership issues, legal restrictions on public lands, and the ongoing armed conflict. In recent years, efforts have focused on promoting agro-industry and diversifying agricultural value chains. In this context, although still marginal, FDI in the sector has been increasing, which could contribute to enhancing productivity, especially through technology transfer (Khan et al., 2018). However, high tariffs and the widespread use of non-tariff measures continue to hinder the development of competitive value chains (Parra-Peña & Puyana, 2021).

Climate shocks further constrain agricultural performance. According to the methodology of the Third National Communication on Climate Change (TCNCC), which evaluates impacts and vulnerabilities using 66 indicators across biodiversity, ecosystem services, water resources, and food security, almost half of the municipalities are classified as highly vulnerable to climate events, particularly those linked to the El Niño–Southern Oscillation (ENSO) where recurrent droughts and floods have caused significant agricultural losses (FAO & Ministry of Agriculture, 2021).

Agricultural policies in Colombia have primarily focused on market interventions and direct subsidies for production, inputs, and capital. Additional measures include the provision of agricultural credit with subsidized interest rates, co-financed agricultural insurance, and tax exemptions (OECD, 2015). Moreover, as a strategy to address climate vulnerability and promote sustainable production systems, Colombia is advancing the agroecological transition through initiatives such as the *Plan Integral de Gestión del Cambio Climático del Sector Agropecuario*, which guides adaptation and mitigation actions across agricultural activities. In line with these guidelines, efforts have begun to promote the production and use of bio-inputs, organic fertilizers, and soil conditioners nationwide, and to implement programs that foster climate-resilient practices through genetic improvement, crop management, efficient water use and low-emission technologies.

More recently, as part of the 2016 Peace Agreement, the government committed to implementing the *Reforma Rural Integral* [Comprehensive Rural Reform], which seeks to address structural barriers in rural areas by democratizing land access, improving infrastructure, boosting productivity and targeting conflict-affected regions. Its main instruments include the redistribution of 3 million hectares through the Land Fund—of which less than 1% had been achieved by early 2024—the formalization of 7 million hectares, with progress reaching about 36%, and the multipurpose cadaster, which by early 2024 had updated only 12% of the national territory (PGN, 2024). Overall, implementation remains limited, constrained by institutional weaknesses, the rearmament of dissident groups, the expansion of coca cultivation, and the state's limited capacity to establish territorial control, all of which have reignited conflict in rural areas and undermined reform efforts.

While the main factors influencing productivity in the agricultural sector have been identified, rigorous estimates of their effectiveness are still lacking.

Robust measures of the evolution of TFP over time are also needed to support evidence-based decision-making. Progress on this agenda and developing empirical literature has been constrained by the limited availability of high-quality, regularly collected data. Existing studies have relied on national aggregates, which mask local heterogeneity and often exclude key variables such as climate conditions.

This study addresses these gaps by using municipal- and household-level data, to estimate and disaggregate TFP growth and examine the effectiveness of different agricultural policies on output. It provides new evidence to guide policy decisions at both the national and subregional levels.

II. METHODOLOGY AND DATA

This chapter addresses the following research questions:

I. How has agricultural productivity evolved in Colombia over 2015-2023?
II. Has productivity growth been driven mainly by technical efficiency, technological progress, or other factors?
III. What roles have access to credit, the signing of the Peace Agreement, public investment, and climate variability played in shaping productivity outcomes?

To address these questions, this analysis combines two agricultural datasets. The first is the Evaluaciones Agropecuarias Municipales (Municipal Agricultural Evaluations; EVA), an annual municipal-level dataset covering 2007–2023. The second is the *Encuesta Longitudinal Colombiana de la Universidad de los Andes* (Colombian Longitudinal Survey; ELCA), a household -level dataset, covering the years 2010, 2013, and 2016. **Table 1** contains a brief description of the data sources employed.

TABLE 1. DESCRIPTION OF DATA SOURCES

(CONTINUED ON NEXT PAGE)

Data	Description	Level	Source
Agricultural data			
Household-level agricultural production	Crop and livestock production, land area by use, production costs, use of inputs and machinery, access to credit, and exposure to violence (years: 2010, 2013, 2016)	Household	*Encuesta Longitudinal Colombiana de la Universidad de los Andes (ELCA)*[1]
Municipal-level agricultural production	Crop production and cultivated area for temporary and permanent crops (annual: 2007–2023)	Municipal	*Evaluaciones Agropecuarias Municipales (EVA)*[2]
Agricultural Inputs	Volumes transported of fertilizers, seeds, and tractors (annual: 2015–2023)	Municipal	Ministry of Transportation

[1] https://datoscede.uniandes.edu.co/elca/
[2] https://www.agronet.gov.co/estadistica/paginas/home.aspx?cod=59

TABLE 1. DESCRIPTION OF DATA SOURCES
(CONTINUED)

Data	Description	Level	Source
Policy drivers			
Postconflict	Violent acts carried out by armed groups (annual: 1988–2019)	Municipal	Violent Presence of Armed Actors in Colombia (ViPAA)[3]
	Presence of armed groups in the community (years: 2010, 2013, 2016)	Household	ELCA
Credit	Value of disbursed agricultural credits (annual: 2007–2023)	Municipal	*Fondo para el Financiamiento del Sector Agropecuario* (FINAGRO)
Public Investments	Value and number of public contracts to finance road infrastructure, agricultural services, input delivery, and machinery provision (annual: 2015–2023)	Municipal	*Sistema Electrónico para la Contratación Pública* (SECOP)[4]
Climate data			
Temperature	Monthly average temperature (1901–2023)	Municipal	*Climate Research Unit* (CRU)[5]
Precipitation	Monthly total precipitation (1901–2023)	Municipal	CRU

TFP DECOMPOSITION: STOCHASTIC PRODUCTION FUNCTION

This chapter uses a stochastic production frontier model at the municipal level to estimate agricultural TFP growth between 2015 and 2023. The decomposition analysis provides a deeper understanding of how different mechanisms contribute to TFP growth. The following stochastic production function is estimated to assess TFP performance and its components:

$$\ln y_{it} = \alpha_i + \sum_{k=1}^{K} \beta_k \ln x_{kit} + \sum_{j=1}^{J} \eta_j z_{jit} + \sum_{r=1}^{R} \lambda_r R_{ri} t + v_{it} - u_{it} \quad (1)$$

where y_{it} denotes the value of agricultural production for municipality i at time t; x_{kit} includes the input variables presented in **Table 2**; and z_{jit} is the vector of climate variables. R_{ri} is a vector of regional dummies (i.e., the Caribbean, the Coffee Region, the Pacific, South-Central Amazonia, the Central-Eastern Region, the Eastern Plains)[6] that allows technological progress to vary across regions when it is interacted with the time trend. Finally, u_{it} is the inefficiency term and v_{it} is the error term.

[3] https://www.colombiaarmedactors.org
[4] https://www.contratos.gov.co/consultas/inicioConsulta.do
[5] https://crudata.uea.ac.uk/cru/data/hrg/
[6] The Caribbean Region includes the departments of Atlántico, Bolívar, Cesar, Córdoba, La Guajira, Magdalena, San Andrés, and Sucre. The Coffee Region comprises Antioquia, Caldas, Quindío, and Risaralda. The Pacific includes Cauca, Chocó, Nariño, and Valle del Cauca. South-Central Amazonia includes Amazonas, Caquetá, Huila, Putumayo, and Tolima. The Central-Eastern Region comprises Bogotá, Boyacá, Cundinamarca, Norte de Santander, and Santander. The Eastern Plains Region includes Arauca, Casanare, Guainía, Guaviare, Meta, Vaupés, and Vichada.

Table 2. Variables included in the production function (household and municipal levels)

Level	Output	Inputs	Climate variables
Household	Production value (crops + livestock)	Cultivated area, family labor, cost of purchased inputs, hired labor, capital stock of animals, machinery rental value	Monthly average temperature, total precipitation, temperature anomaly, precipitation anomaly
Municipal	Production value (crops)	Cultivated area, rural population, volumes of seeds and fertilizer, tractors	

Note: Output and inputs are included in the production function in logarithmic form, while climate variables are included in levels.

III. FINDINGS

TFP decomposition

Table 3 presents the estimated coefficients from equation 1. The decomposition reveals that between 2015 and 2023, agricultural productivity in Colombia grew modestly, increasing by about 0.65% per year.[7] This growth was mainly driven by favorable climate conditions (61%), followed by technical efficiency (28%) and technological progress (20%).[8] Scale efficiency growth was virtually negligible across all regions between 2015 and 2023, since scale efficiency is a farm-level concept, estimates at the municipality level do not reflect farm-scale effects. The value of agricultural output grew at an annual average rate of 2.46%. However, 72% of this growth resulted from an increase in input use, while less than one-third was due to productivity improvements.

While informative, national averages mask considerable regional variation. The Caribbean Region—where 10 million hectares are dedicated to agricultural and livestock activities and which produces bananas, cotton, maize, and rice—recorded the highest output growth and the largest TFP increase as shown in **Table 3** . Average TFP growth in the region was 2% annually, driven primarily by technological progress. While agricultural output was mainly driven by input use, TFP accounted for about 36% of total growth. The Pacific Region also recorded above-average TFP growth, albeit significantly lower than in the Caribbean. In this case, technical efficiency and weather conditions were the main drivers. In contrast, the Coffee Region, the Central-Eastern Region, and the Eastern Plains all experienced productivity growth below the national average, reflecting a decline in technological progress. Finally, South-Central Amazonia was the only region where productivity declined (-0.12%), driven by a drop in technical efficiency.

Climate conditions also played a key role in shaping regional heterogeneity in productivity. At the national level, climate variations were the largest contributor to TFP, accounting for 62% of growth. In the Central-Eastern Region and the Coffee Region, favorable weather conditions partly offset the negative effects of declining technological progress. Similarly, in the South-Central Amazonia, climate conditions partially offset the decline in technical efficiency, though not enough to produce positive TFP growth.

[7] The difference between this growth rate and that reported in figure 1 is due to variations in the period, methodology, and level of aggregation. This analysis uses municipal-level data for 2015–2023, estimated using Stochastic Frontier Analysis (SFA) with inputs derived from administrative records, whereas figure 1 is based on nationally aggregated USDA-ERS data for 1961-2021, using index numbers for six different inputs.
[8] The contributions are obtained by dividing the annual growth rate of each component by the national TFP growth rate, as reported in Table 3.

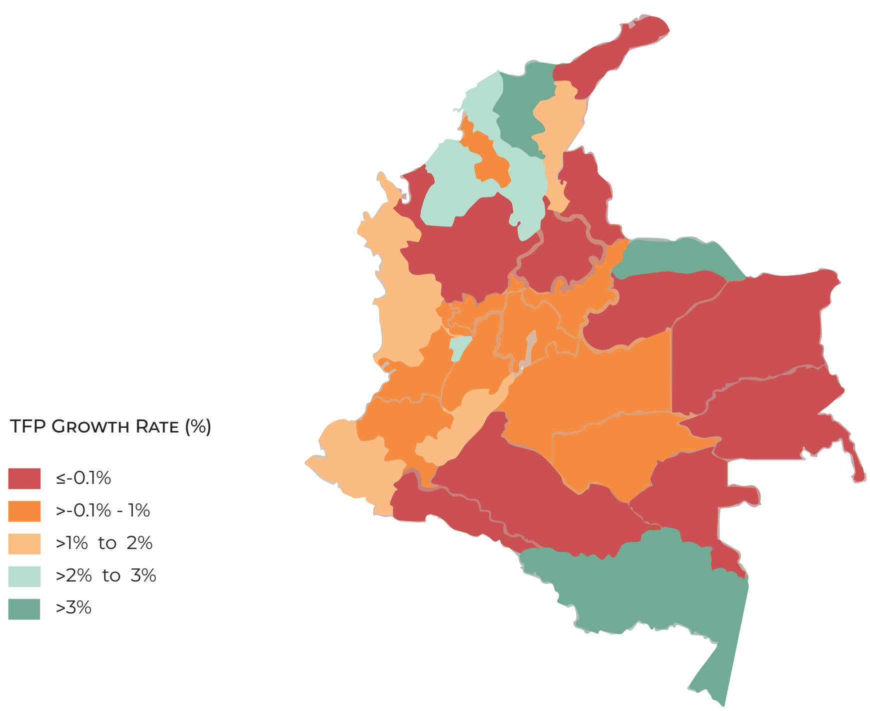
Table 3. Annual growth rates of output, inputs, TFP, and TFP components by region, using municipality-level data (%) (2015–2023)

Region	Output index	Input index	TFP index	Scale efficiency index	Technical efficiency index	Technological progress index	Weather effects	Statistical noise
Caribbean	5.84	3.62	2.14	0.12	0.47	1.56	0.22	-0.23
Coffee Region	1.22	0.97	0.25	0.03	0.15	-0.55	0.45	0.17
Pacific	2.63	1.62	0.99	0.05	0.33	0.16	0.33	0.12
South-Central Amazonia	1.04	1.15	-0.12	0.04	-0.06	0.02	0.42	-0.54
Central-Eastern Region	1.36	1.12	0.23	0.04	0.05	-0.2	0.53	-0.19
Eastern Plains	4.15	3.96	0.18	0.13	0.06	-0.18	0.3	-0.12
National	**2.46**	**1.79**	**0.65**	**0.06**	**0.18**	**0.13**	**0.4**	**-0.12**

Note: Author's calculations using municipal data from EVA, 2015-2023. Annual growth rates of TFP and its components are obtained through a stochastic frontier analysis (SFA)-based multiplicative index, following Njuki et al. (2018) and O'Donnell (2018). Municipal indexes are computed first and then aggregated at regional and national levels using a geometric mean.

Map 1 illustrates TFP changes at the department level. Specifically, departments such as Magdalena, Arauca, and Amazonas recorded annual TFP growth rates above 3%, while Vichada, Vaupés, Caquetá, Putumayo, Guainía, Casanare, Santander, Antioquia, and La Guajira experienced the largest productivity losses.

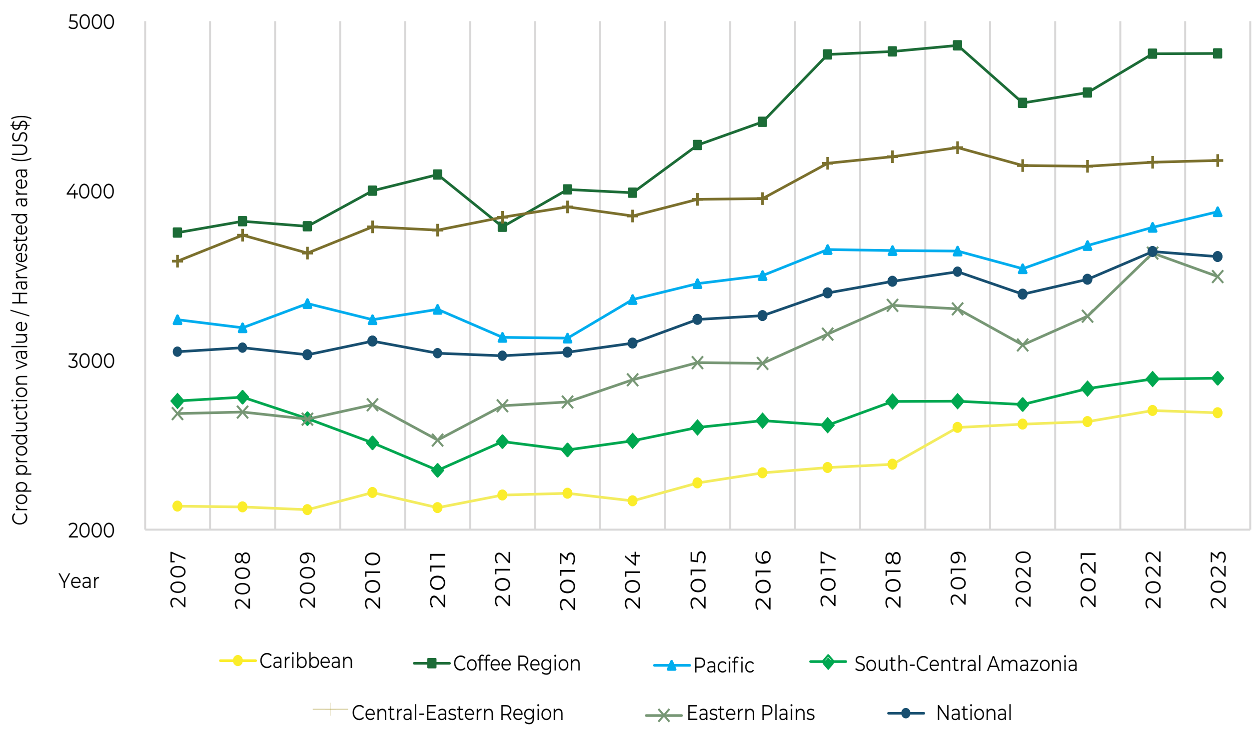
Map 1. Annual department-level TFP growth rates



Note: Author's calculations using municipal data from EVA, 2015-2023. Departmental indexes are constructed by taking the geometric mean of municipal values, which are then used to compute compound annual growth rates.

While TFP provides a comprehensive measure of agricultural productivity, regional differences in the value of crop production per hectare offer insights into geographical disparities in land productivity. **Figure 2** illustrates these differences over time: while the national average increased steadily, regional trends diverged. The Coffee Region, Central-Eastern Region, and Pacific consistently maintained land productivity levels above the national average. The Eastern Plains recorded the highest growth in crop value per hectare (1.66% annually), followed by the Coffee Region, as both surpassed the national average of 1.06%. In contrast, South-Central Amazonia had the weakest performance, with growth of just 0.3% annually.

FIGURE 2. CROP PRODUCTION VALUE PER HECTARE, BY REGION



Note: Author's calculations using municipal data from EVA, 2007-2023. Regional and national series are obtained by aggregating municipal-level production value and harvested area by year and computing their ratio.

IMPACT OF POLICY DRIVERS ON AGRICULTURAL PRODUCTIVITY

In addition to the TFP decomposition, this analysis examines the impacts of key agricultural interventions using both household-level data from the ELCA survey and municipal-level data from the EVA.

The effects of these policy drivers are estimated using an ordinary least squares (OLS) regression, as specified below:

$$\ln y_{it} = \alpha_i + \delta D_{it} + \sum_{n=1}^{N} \beta_n \ln x_{nit} + \sum_{j=1}^{J} \eta_j z_{jit} + \lambda_t + v_{it} \quad (2)$$

Where δ captures the average effect of key policy drivers; λ_t and α_i represent time and municipality or household fixed effects, respectively, controlling for common shocks and for unobserved, time-invariant characteristics; and v_{it} is the idiosyncratic error term.

The remaining parameters are defined as in equation 1.

Table 4 summarizes the policy drivers analyzed and the variables used to capture their effects on productivity and production.

Table 4. Overview of policy drivers and estimated effects

Policy driver	Variable
Post-conflict	Dummy variable capturing the impact of the 2014 ceasefire with the largest armed group in the country (FARC) on municipalities and households affected by the conflict
Credit	Value of agricultural credit disbursed at the municipal level (US$), and a household-level dummy indicating access to credit
Road infrastructure	Monetary value of public contracts for road infrastructure at the municipal level (US$)
Agricultural services	Monetary value of public contracts for agricultural services at the municipal level, including technical assistance, value-chain strengthening, and related programs (US$)
Input delivery	Monetary value of public contracts for agricultural inputs (e.g., seeds, fertilizers, agrochemicals) at the municipal level (US$)
Machinery provision	Monetary value of public contracts for the delivery or rental of agricultural machinery at the municipal level (US$)

The results of the estimations are presented in **Table 5**. Coefficients reflect the effect for each policy driver, based on municipal-level and/or household-level estimations, depending on data availability.

Table 5. Estimated coefficients from municipal- and household-level regressions

	Credit value (US$, per capita)	Credit access (dummy)	Road infrastructure (US$1,000 /farm)	Input delivery (US$1,000/farm)	Agricultural services (US$1,000/farm)	Machinery provision (US$1,000/farm)	Postconflict
Municipal level	0.014** (0.006)		0.007*** (0.002)	-0.007 (0.009)	0.003 (0.002)	-0.004 (0.004)	-0.041* (0.022)
Household level		0.406 (0.85)					0.389* (0.214)
Observations	9,885	8,957	3,420	3,420	3,420	3,420	8,483 (mun) / 1,903 (hh)
Number of municipalities	1,101	-	380	380	380	380	499
Number of households	-	2,988	-	-	-	-	635
Time period	2015–2023	2010, 2013, 2016	2015–2023	2015–2023	2015–2023	2015–2023	2007–2023 (municipal) 2010, 2013, 2016 (household)
Methodology	**TWFE**	**IV**	**TWFE**	**TWFE**	**TWFE**	**TWFE**	**DiD**

Note: Author's calculations using data from EVA and ELCA. All estimations include year and unit fixed effects (municipality or household) and controls for inputs and climate conditions. Dependent variable is the logarithm of agricultural production value. Credit value is measured as the value of agricultural loans per capita (IHS transformed). Road infrastructure, Input delivery, Agricultural services, and Machinery provision are measured as the cumulative value of public contracts per farm in thousands of USD. Postconflict is a dummy equal to one for municipalities with prior FARC presence after 2016. Standard errors clustered at the municipal level (in parentheses) **p<0.01, *p<0.05, p<0.1

Table 6 highlights several important findings:

1. The effects of the ceasefire with the FARC differ depending on the scale of analysis

At the household level, communities affected by FARC presence experienced a significant increase in productivity after the ceasefire. In contrast, municipal-level analysis shows a decline in average productivity, driven by an expansion of cultivated area, possibly into lower-yielding lands, and the entry of new, potentially less productive producers.

2. Credit is positively associated with gains in agricultural productivity [9]

A 1% increase in per capita credit is linked to a 0.014% rise in productivity at the municipal level. This finding underscores the potential for financial inclusion to enhance agricultural development by boosting long-term productivity growth. By easing liquidity constraints, credit enables farmers to invest more efficiently in capital and

[9] The study does not find a significant effect of credit access on household-level agricultural productivity. The small sample (17 municipalities) limits statistical power and increases noise, underscoring the need for broader data and further household-level analysis before definitive conclusions.

strengthens their ability to deal with shocks and uncertainty.

3. Investments in rural road infrastructure improve agricultural performance

An additional US$1,000 in infrastructure investment per farm is associated with a 0.75% increase in agricultural productivity. These effects emerge three years after the contract is completed. By reducing transaction costs, improving access to input and output markets, and facilitating the adoption of new technologies, rural roads play a fundamental role in driving productivity growth (Kebede, 2024; Parada et al., 2015; Shamdasani, 2018).

4. Agricultural input and machinery provision at the municipal level shows no significant effects

Although a substantial share of support is allocated to input transfers, the evidence suggests these contracts have not translated into meaningful productivity gains, on average.

Several factors may explain this limited impact, including the absence of complementary investments or enabling conditions (such as access to credit, technical assistance, phytosanitary measures, or land titling), inefficiencies in program targeting, constraints in the adoption and effective use of machinery, and potential production distortions.

5. No evidence is found on the effects of agricultural services

While the low contribution of technical efficiency to productivity growth suggests a need for improved managerial capacities among farmers through technical assistance, the municipal-level results indicate that such services have not been effective at improving productivity. The lack of measurable impact may stem from the low quality of such services, insufficient intensity, or outdated or inadequate technical recommendations, among other factors. Moreover, the heterogeneous nature of contracts grouped under this category likely introduces measurement noise.

These findings underscore the need for further research to identify the drivers that determine the effectiveness of agricultural services.

Table 6. Estimated effects of policy drivers on agricultural performance

Policy driver	Estimated effect
Postconflict	Production decreased by 4% in municipalities with FARC presence after the ceasefire.
	Productivity increased by 46% in households located in regions with FARC presence after the ceasefire.
Credit	A 1% increase in per capita credit (US$) is associated with a 0.014% increase in productivity at the municipal level.
Road infrastructure	An additional US$1,000 investment in rural roads per farm is associated with a 0.7% increase in productivity.

Note: Author's elaboration based on regression results in Table 5, using data from EVA and ELCA.

IV. CONCLUSIONS AND POLICY RECOMMENDATIONS

The results of the analysis point to priority areas for promoting sustained agricultural productivity growth in Colombia. The following recommendations are intended to support the design of geographically targeted, efficient, and climate-resilient policies:

I. Strengthening agricultural research and extension services could help promote the development and adoption of context-specific technologies

While our results do not show a clear effect on productivity, this points to the need for improving their design and implementation rather than dismissing them as policy tools. The small contribution of technological change to productivity highlights the importance of generating and disseminating context-specific, cutting-edge technologies. These should enhance agricultural potential while accounting for agroecological conditions, climate vulnerability, and socioeconomic diversity across regions. Attention could be focused on areas where technological progress or technical efficiency has been low, such as the Coffee Region, the Central-Eastern Region, and the Eastern Plains. Well-designed extension services and technical assistance may support the adoption of better-adapted technologies and practices, potentially improving both agronomic and managerial performance, particularly in South-Central Amazonia, the Central-Eastern Region, and the Eastern Plains, where the contribution of technical efficiency has had a negative or negligible effect on productivity growth.

II. Expand access to agricultural credit

Strengthening and scaling up rural financing programs is essential. Strategies to reach producers in the most remote areas should include simplifying access requirements, addressing information asymmetries, and implementing innovative financial inclusion mechanisms, including access to digital banking. Public rural finance institutions require stronger institutional capacity, while private-sector participation should be encouraged through incentives that mitigate the risks associated with agricultural lending, such as seasonality and weather shocks. One final priority should be expanding access to financial services for vulnerable communities—such as women, Indigenous peoples, and Afro-Colombian populations—that have been historically excluded from financial markets.

III. Ensure efficient land use in post-conflict rural recovery processes

Policies on land restitution, formalization, or productive reactivation in post-conflict areas must be accompanied by technical assessments of soil productivity and include technical assistance and access to appropriate technologies. Mechanisms should also be implemented to limit land expansion and incentivize efficient, sustainable use of land resources within the agricultural frontier.

IV. Investments in public goods are more effective in driving long-term gains in agricultural productivity than programs focused on input transfers

Persistent rural infrastructure gaps limit connectivity, hinder market access, and reduce the returns from agricultural activity. While input provision can ease short-term constraints, its long-term effects are more limited. Input subsidies may substitute for private purchases that would have occurred anyway or incentivize the use of inputs even when they are not profitable, increasing environmental costs. In contrast, infrastructure investments address structural barriers that cannot be overcome individually and generate broader spillover effects across value chains. From a policy perspective, strengthening rural transportation networks should therefore be a central component of Colombia's rural development strategy, as it reduces transaction costs and enhances market access.

V. Reassess the structure, delivery, and quality of agricultural input and service programs

Policies should move away from isolated transfers and instead provide integrated packages that combine access to improved technologies, credit, extension, and market linkages, alongside infrastructure investments, particularly in contexts where those enabling conditions are currently weak. Programs should ensure appropriate targeting and promote the sustainable use and maintenance of machinery. Moreover, given the sector's high vulnerability to climate factors, programs should prioritize access to bio-inputs and climate-smart technologies that enhance soil conservation, water efficiency, and climate resilience. Facilitating international trade and promoting foreign investment could create important channels for productivity growth through technology transfer, compliance with international standards, and stronger value chain linkages. By strengthening production systems, these interventions help farmers withstand climate shocks, improve resource-use efficiency, and preserve the natural resource base (Bhatnagar et al., 2024).

VI. Design adaptive policies in response to climate change

Given that climate variability accounted for more than one-third of national TFP growth, a gradual structural transformation is required to delink agricultural production from climate variability. This includes promoting adaptive practices that incorporate sustainability, efficient resource use, productive diversification, ecosystem restoration, and integrated landscape management. It also requires developing and disseminating strategic agroclimate information systems that prevent crop losses by supporting decision-making through improved planting calendars, early warning systems, and climate forecasting.

In sum, the analysis underscores the importance of prioritizing investments in public goods that strengthen both technical efficiency and technological progress. Enhancing agricultural research, extension services, and rural infrastructure can create the enabling conditions for long-term productivity gains, while expanding access to financial services ensures that producers have the necessary resources to invest, innovate, and adapt. Together, these measures can support a more inclusive, competitive, and climate-resilient agricultural sector.

CHAPTER 5. **BRAZIL**

Authors: Steven M. Helfand, Francisco Lima Cavalcanti, Carlos Otávio de Freitas, Ajax R. B. Moreira, Maja Schling

SUMMARY

Brazil ranks among the world's top four agricultural producers and exporters, and continued output growth can significantly impact both domestic and global food security. Sustained productivity growth is essential to support this expansion. The agricultural sector also contributes to poverty reduction by generating income and lowering food prices, and it supports broader economic growth via export earnings. This study calculates total factor productivity (TFP) growth in Brazilian agriculture and decomposes it into components related to technology, weather, policy (education and agricultural R&D), and other factors. The analysis draws on municipal-level data from four waves of the Agricultural Census between 1985 and 2017. The results provide a novel characterization of TFP growth during this period and carry important policy implications. TFP increased at an average annual rate of 1.56%, accounting for roughly 60% of output growth. The decomposition highlights the slowing effect of climatic factors on productivity growth, alongside the accelerating influence of investments in agricultural R&D and farmers' education. A key finding is the pronounced divergence in outcomes across various dimensions. Output and TFP grew fastest in the Cerrado biome, characterized by large farms, and slowest in the Caatinga, where many of the smallest farms are located. Output has become increasingly concentrated in a small number of municipalities, which tend to exhibit faster TFP growth and specialization in annual crops such as soybeans. Conversely, about one-third of municipalities experienced declines in both output and TFP, with higher shares in the Amazon and Caatinga, in areas specialized in perennial crops, and in lower-production locations. The study's findings have significant policy implications for addressing climate change, guiding investments in agricultural R&D, and managing the growing divergence of outcomes.

I. INTRODUCTION

Studying agricultural productivity growth in Brazil is of considerable importance for both the country itself and the international community. Brazil is among the world's top four agricultural producers and exporters by value (FAO, 2023), and the continued growth of its production has major implications for domestic and international food security. Agriculture accounted for only 7% of GDP and close to 10% of employment in 2021; however, by generating income for a large share of producers and keeping food prices low, the sector is an essential component of Brazil's poverty reduction strategy.[1] It also plays a strategic role in the generation of foreign exchange, which can be critical for economic development. Between 2000 and 2020, the share of agrifood in Brazil's total exports rose from 23% to 37%, highlighting the sector's growing importance. Its integration to global markets and the expanding participation of foreign agribusiness investors are linked to productivity advances through the adoption of modern technologies, the dissemination of quality and sustainability standards, and stronger connections with high value chains. The agricultural sector was also responsible for over 40% of the country's greenhouse gas emissions around 2021, giving it a potentially significant role in efforts to combat climate change.

Public policies have been instrumental in stimulating agricultural production and productivity since the 1970s (Teixeira et al., 2014; Buainain, 2025). Among the most significant interventions were investments in R&D, which accelerated with the creation of the public-sector Brazilian Corporation for Agricultural Research (Embrapa) (Vieira Filho, 2018). Embrapa's investments, which were part of a broader research effort, contributed to a dramatic technological transformation during this period. Buainain (2014) emphasizes the role of credit and technical assistance in the adoption and diffusion of new technologies. Indeed, subsidized agricultural credit has been one of Brazil's most important agricultural output, using highly disaggregated data over a longer time span. This extended horizon is particularly valuable for studying the effects of climate change.policies since the creation of the National System of Rural Credit (SNCR) in 1965.

In recent decades, specific lines of credit were created for family farms (PRONAF); medium-sized farms (Pronamp); investment in tractors, harvesters, and other machines (Moderfrota); investment in infrastructure and irrigation (Moderinfra); and others. Policies have also been created that seek to reduce greenhouse gas emissions, such as the Low-Carbon Agriculture program (ABC).

Research on TFP growth in Brazilian agriculture is rich in some ways and lacking in others. There are many papers on TFP growth at the national level since the 1970s. Gasques et al. (2020), for example, estimate average annual TFP growth in Brazil at about 1.82% between 1985 and 2017, while Salazar et al. (2025) show that TFP growth in Brazil was considerably slower when negative environmental impacts are accounted for in a Sustainably Productivity Index (SPI).[2] Few studies, however, utilize econometric techniques with rich panel data that allow analysis below the state level. One exception is Rada et al. (2019), who estimate TFP growth with municipal-level data for different farm size groups, but their study ends in 2006. Another is Spolador and Danelon (2024), who use microregional data from 1996 to 2017, but focus exclusively on crop production. We fill this gap by

[1] The data in this paragraph come from OECD (2023).
[2] The results are sensitive to the choice of weight assigned to negative environmental impacts, with the reduction in TFP growth in 1995-2017 ranging between 16% and 49% in the scenarios that they analyze.

presenting a novel analysis of TFP growth using more than 30 years of municipal-level data. Our study differs from earlier research in that it encompasses all agricultural output, using highly disaggregated data over a longer time span. This extended horizon is particularly valuable for studying the effects of climate change.

A notable feature of output growth during this period is that it occurred on less agricultural land, reflecting, in part, productivity gains. While deforestation remains a critical issue in Brazil, and the agricultural frontier expanded first in the Center-West and later north through the Cerrado biome, total area in crop and pasture actually declined by approximately 4% between 1985 and 2017 (IBGE). This reduction corresponds to a decline of nearly 60 million hectares of natural pasture, which was partially offset by about 40 million hectares of planted pasture and 13.5 million hectares of annual crops. Land devoted to perennial crops also declined by 20% or roughly 2 million hectares.

Building on this context, this study estimates the heterogeneity of TFP growth across Brazilian municipalities and decomposes it into components that are relevant for public policy.

II. METHODOLOGY AND DATA

This chapter is guided by the following questions:

I. What has been the rate of growth of production and TFP growth for Brazil, its major biomes, and its municipalities?

II. What factors explain the heterogeneous pattern of productivity growth, including differences across:

a. biomes,
b. specialization in animal production, annual, or perennial crops, and municipal scale of production?

III. What factors are driving or constraining TFP growth? In particular:

a. Have climatic factors —especially extreme heat— slowed productivity growth?
b. Which policies —such as investments in R&D and farmers' education— have accelerated productivity growth?

IV. Are productivity levels converging over time, or are some municipalities trapped in persistently low levels of TFP?

To address these questions, we estimate a stochastic frontier production function to calculate TFP growth. We then apply a decomposition method, following O'Donnell (2018) and related work.

The decomposition first distinguishes the contributions of input growth and TFP growth to output growth, and then further disaggregates TFP growth into components associated with (a) technology, (b) weather, (c) returns to scale, (d) policy (education and agricultural R&D), (e) technical efficiency, and (f) statistical noise.

The model is estimated using municipal-level data from the Agricultural Census for 1985 to 2017. The dataset includes approximately 3,800 municipalities—defined as consistent geographical units across time[3] —and four census waves (1985, 1995–96, 2006, 2017), yielding around 14,000 observations. Definitions and data sources for the main variables are provided in **Table 1**.

[3]The number of municipalities increased from around 4,000 to over 5,500 between 1985 and 2017. We construct consistent geographical units so that we are analyzing municipalities—or aggregations of them—that do not change over time. For simplicity, we continue to refer to them as "municipalities."

Table 1. Data, main variables, and sources

Data	Description	Sources
Municipal-level agricultural output and inputs	Outputs representing over 98% of value of output. Inputs: Land , family labor, purchased inputs, measures of capital stock in machines, animals, and perennial trees	Agricultural Censuses of 1985, 1995-96, 2006, 2017 (IBGE)
Temperature	Satellite data on daily max and min temperatures. Used to construct Growing Degree Days in nine-month growing season from Oct. to June aggregated into three intervals: 8-28°C, 28-32°C, >32°C	Copernicus Climate Change Service, ERA5: Essential climate variables for water sector applications derived from climate projections
Precipitation	Monthly data on total precipitation	Climate Research Unit, University of East Anglia
Public knowledge stock	Proxy for public knowledge stock based on Embrapa expenditures in about 15 ecoregions and 15 product lines	Embrapa
Producer education	Years of schooling of agricultural producers	Demographic Censuses (IBGE)

Stochastic frontier production function

We estimate a Cobb-Douglas stochastic frontier production function with an output quantity index expressed in constant 2017 prices:

$$y_{it} = \alpha_i + \sum_{k=1}^{K} \beta_k x_{kit} + \tau T + \sum_{j=1}^{J} \eta_j z_{jit} + v_{it} - u_{it} \quad (1)$$

where y_{it} is the natural log of the output quantity index in municipality i at time t; α_i are municipal fixed effects; x_{kit} denotes the log of production inputs k; T is a time trend that captures technological progress; z_{jit} are climatic variables as well as other determinants of TFP;[4]

[4] To be more precise, z_{jit} represents determinants of output. Once we control for inputs x_{kit}, these can be interpreted as determinants of TFP.

v_{it} is a symmetric random error; u_{it} is an asymmetric half-normal error term that captures inefficiency; and β_k, τ, and η_j are coefficients to be estimated.The climatic variables in z_{jit} include extreme heat, annual precipitation, and the latter's square. Other determinants proxy agricultural producers' lagged human capital and the public knowledge stock resulting from federal investments in agricultural R&D. We also model the variance of inefficiency as a function of technical assistance, credit, and irrigation, and heteroskedasticity in v_{it} as a function of scale, proxied by total agricultural land.

Production function results

The production function exhibits a moderate degree of increasing returns to scale: a 10% increase in all production inputs raises output by 10.6%. This implies that municipalities with higher production scales are likely to be more productive. Among individual inputs, land and purchased inputs are the most influential: a 10% increase in either raises output by about 3.5%, holding other factors constant.

Climatic effects

Climatic effects are strongly negative. We measure extreme heat using growing degree days (GDD), defining the growing season as the nine months excluding winter (the third quarter of the year).[5] To capture a range of product-specific temperature thresholds, we adopt a more flexible approach than has been common in the literature by using three GDD intervals: normal (8–28°C), harmful (28–32°C), and very harmful (>32°C). Unexpectedly, additional degree days within the normal range reduce output, although effects vary across biomes. The impact in the harmful interval is roughly twice as large as in the normal interval, and the effect in the very harmful interval is also nearly double that of the harmful range. These results suggest that climate change has had a substantial negative impact on TFP growth over the 32-year study period, an effect that we quantify below.

Public agricultural R&D and education

Public investments in the stock of knowledge and farmer education can help counteract adverse climatic effects. We construct knowledge stock variables based on federal spending on agricultural R&D by Embrapa between 1973 and 2016, disaggregated into about 15 different product groups and 15 geographical areas (called ecoregions).[6]

Each line of spending is extrapolated back to 1950 and aggregated using weights over the 35 years preceding each census. These stocks are then allocated to municipalities according to their location within ecoregions and production composition. Embrapa spending serves as a proxy for the broader public-sector effort through the National System of Agricultural Research (SNPA). Farmer education is measured as lagged years of schooling among agricultural producers. Both the public knowledge stock and farmer education have positive and statistically significant effects on TFP. In the results section below, we quantify their contribution to TFP growth in 1985–2017.

III. FINDINGS

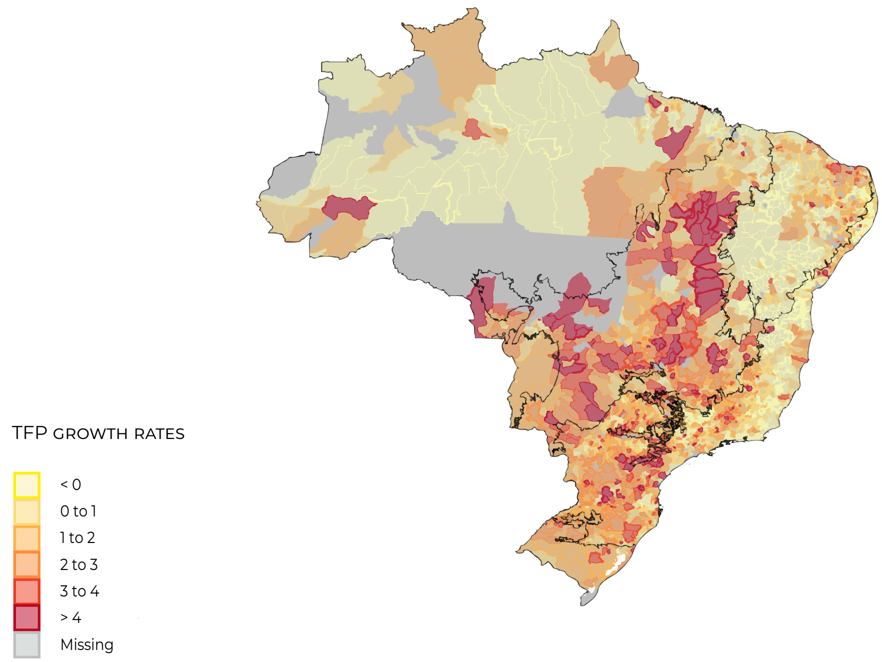
TFP growth and its heterogeneity

A. National. Agricultural TFP grew by an average of 1.56% per year between 1985 and 2017, a period marked by considerable heterogeneity across municipalities (Figure 1).

[5] The approach follows Schlenker and Roberts (2009), Burke and Emerick (2016), and Aragón et al. (2021). Because our analysis is based on decadal census data, rather than an annual panel, our estimates fall somewhere between the effects of weather and of climate change. We use the term "climatic effects" because they are closer to long difference estimates, as in Burke and Emerick (2016), than to annual weather shocks.
[6] Our approach follows the methods described in Alston et al. (2010), Alston and Pardey (2021), Avila and Evenson (1995), and Rada and Valdes (2012).

During this time, TFP growth accounted for around 60% of output growth, which averaged 2.59% per year (**Table 2**). Overall, Brazil stands out as an exceptionally successful case in Latin America and the Caribbean (LAC) in this period, particularly given its position as the region's largest producer and exporter.

Figure 1. Total factor productivity growth by municipality: 1985-2017



Source: Authors' calculations based on the model and data described above.

Table 2. Average annual growth in output, inputs, TFP, and its components: Brazil and biomes (1985–2017)

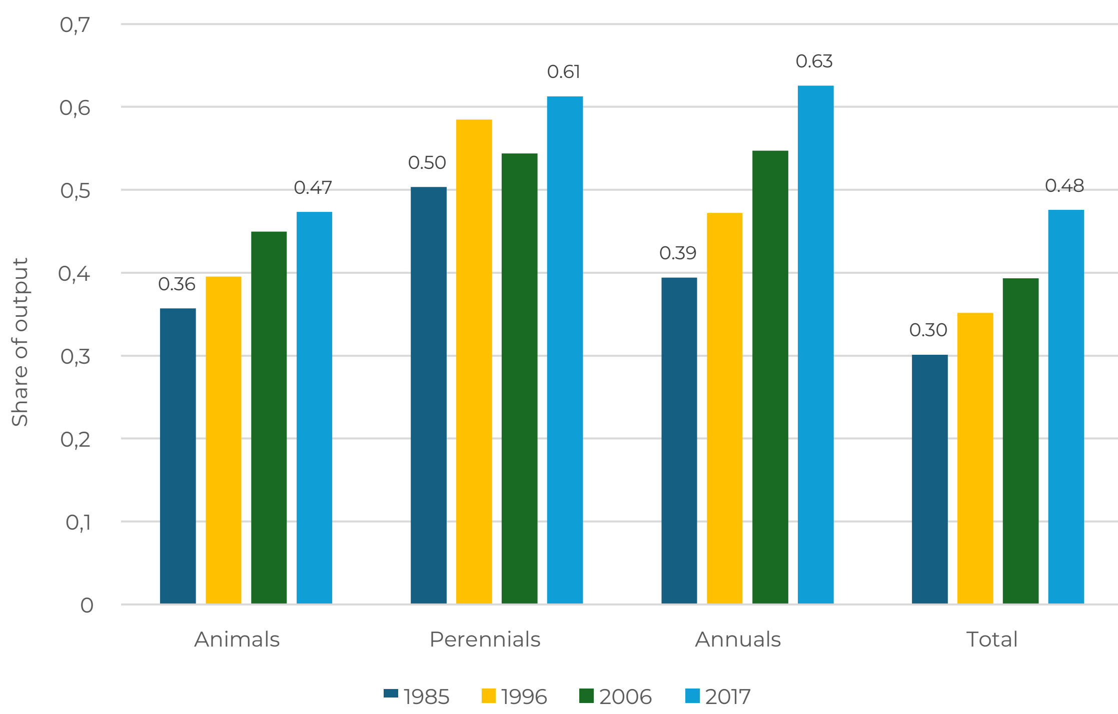
				TFP components						
Biome	**Output (1)**	**Inputs (2)**	**TFP (3)**	**Climatic (4)**	**Education (5)**	**R&D (6)**	**Technology (7)**	**Scale (8)**	**Efficiency (9)**	**Stat. Noise (10)**
Amazon	3.56	2.47	1.02	-0.80	0.17	0.97	0.56	0.15	-0.05	0.01
Caatinga	0.51	0.39	0.07	-1.36	0.16	0.70	0.56	0.02	-0.01	0.01
Cerrado	4.29	1.61	2.43	-0.59	0.30	0.76	0.56	0.10	-0.08	1.36
Atl. Forest	1.70	0.51	1.25	-0.43	0.27	0.57	0.56	0.03	0.04	0.21
Brazil	**2.59**	**0.97**	**1.56**	**-0.56**	**0.27**	**0.67**	**0.56**	**0.06**	**-0.01**	**0.57**

Source: Authors' calculations based on the model and data described above. More details can be found in the working paper that supports this Policy Brief.

B. Biomes and decades. TFP growth varied considerably across biomes and decades. Table 2 shows that the Cerrado experienced the fastest growth at 2.43% per annum (p.a.), while the Caatinga nearly stagnated (0.07% p.a.). Although not shown in Table 2, TFP growth accelerated sharply, doubling from about 1% p.a. between 1985 and 1996 to over 2% p.a. in the following two decades. Sluggish growth in the first decade reflected macroeconomic instability and substantial policy reforms at the end of the import substitution era. The subsequent acceleration is striking in the LAC context.

C. Scale of output. TFP growth was closely linked to output scale. The 75% of municipalities with the lowest output saw average TFP growth of just 0.6% p.a., while the top 10% grew well above the national average. These large-scale producers were far more likely to specialize in annual crops, particularly soybeans, reflecting the boom of recent decades. The effect of scale matters given the growing concentration of output in Brazil. Figure 2 shows that the top 5% of municipalities expanded their share of total output from 30% to almost 50% between 1985 and 2017. In 2017, the top 5% for annual and perennial crop output produced over 60%.

Figure 2. Share of output produced by top 200 municipalities (~5%)



Source: Authors' calculations based on Agricultural Census data.

D. Municipalities with declining TFP. Rapid TFP growth was far from universal. About one-third municipalities experienced declining TFP and output over the three decades—an astonishing finding for a country with rapid TFP growth. Negative TFP growth was more likely in the Amazonia and Caatinga biomes (over 45% of municipalities), in municipalities specializing in perennial crops (65%), and among the municipalities with the lowest output (38%). By contrast, among the 5% of municipalities that produced the most, fewer than 10% had declining TFP.

Decomposition of TFP growth: The roles of climate, policy, and other factors

A. Climatic effects. One of the most important results in Table 2 is the large negative effect of climatic variables, which slowed TFP growth by 0.56 percentage points (p.p.) per year. These effects were more than twice as large in the Caatinga biome. They reflect the combined influence of the three temperature variables, along with precipitation, whose effect is close to zero. The impact arises from the interaction of the regression coefficients (which become increasingly negative across GDD intervals) and the observed changes in these variables between 1985 and 2017. The share of GDDs between 28°C and 32°C rose from 13% to 17% during the period, and the share over 32°C doubled from 4% to 8%. As Brazil continues to warm, the negative impact on TFP growth is likely to intensify, presenting a growing challenge to agricultural production and productivity.

B. Technological change and public investments in research and education. Technological change accounts for the majority of TFP growth, and the model captures this effect in three ways—two with important policy implications. First, public investments in agricultural R&D are the largest contributor, adding 0.67 p.p. of TFP growth annually. This reflects sustained public sector efforts over decades to develop and adapt new technologies. Second, changes in producer human capital—driven by public education—contributed an additional 0.27 p.p. per year. Farmer education accelerates the adoption of technology and enhances its efficient use. Finally, a time trend captures residual technological progress, adding 0.56 p.p. per year. This component reflects unobserved factors such as private sector R&D, improved seeds, feed, pasture, and input quality.

C. Other factors. The rising scale of production had a modest positive effect, while changes in technical efficiency had virtually none, likely due to challenges in measuring inefficiency. A relatively large positive residual, categorized as statistical noise, represents unexplained components of TFP growth.

Additional evidence on divergence: TFP levels and transitions

TFP transition matrix. To assess mobility and persistence in TFP levels, we ranked municipalities by TFP in 1985 and 2017, divided each year's ranking into quintiles, and constructed a transition matrix. Over half (56%) of municipalities in the bottom quintile in 1985 remained there in 2017, and nearly a quarter (23%) of those in the second quintile moved down to the first. As a result, 79% of the bottom quintile in 2017 came from the bottom two quintiles in 1985. This reflects a high degree of persistence, akin to a "TFP trap." At the other end, 42% of the top quintile in 1985 remained there, and 30% of the fourth quintile moved up, meaning that 72% of the top quintile in 2017 originated in the top two quintiles in 1985. The top quintile also pulled further ahead: its TFP grew more rapidly than all of the others, again suggesting deeply divergent dynamics. Geography and specialization help explain this divergence: more than 70% of municipalities that remained in the bottom quintile were located in the Caatinga biome, while 40% of those consistently in the top quintile specialized in annual crops such as soybeans and corn. This share is more than double the national average.

Farm size and the productivity of land and family labor

We conclude with evidence on farm size and partial measures of productivity. In the Cerrado biome, where TFP growth was fastest, average farm size is more than twice the national average, and many farms are very large. Around two-thirds of land is in farms over 500 hectares, and in the Center-West (largely overlapping the Cerrado biome), more than half is in farms over 2,500 hectares. Land and family labor productivity—measured with the output quantity index—grew about 40% faster in the Cerrado biome than the national average. In contrast, the Caatinga biome, where poverty is high, has an average farm size of about one-third of the national average. Over half (55%) of farms are under 5 hectares, and another 23% between 5 and 20 hectares. Land productivity is only 40% of the national average, and family labor productivity is just 15%. Despite starting from such a low base, growth in both measures was well below the national average. Finally, in the area of the Mata Atlântica located in the South of Brazil, where family farms are common and successful, land and family labor productivity are around twice the national average, and grew slightly faster. Average farm size is around half the national average in this portion of the biome, but only a quarter of farms are under 5 hectares, while 44% range between 5 and 20 hectares—a stark contrast to the Caatinga.

IV. CONCLUSIONS AND POLICY RECOMMENDATIONS

Based on the analysis in this chapter, several important policy recommendations follow:

I. Address the challenges of climate change

Global warming poses a major threat to Brazilian agriculture. Our estimates show that rising temperatures slowed TFP growth by over 0.5 p.p. per year in these three decades. Public policy and private innovation and adaptation must address these challenges, which include extreme events like drought. Strategies include investment in heat- and drought-resistant seeds, broader and more efficient use of irrigation, and policy support for the evolving geography of production in response to climate change.

II. Sustain and improve agricultural R&D and education

Public investments in R&D and education were crucial drivers of TFP growth in this period, but past achievements do not guarantee future success. The contribution of R&D diminished in the final decade, and the expansion of public education is unlikely to be repeated. At the same time, debates continue within (and outside of) Embrapa about how to remain relevant and impactful in the context of growing private-sector R&D. Productivity growth depends on the continued generation of new knowledge and technologies, and their adoption by producers. Embrapa plays a central role in the Brazilian research ecosystem by coordinating research efforts at the federal, state, and university levels, as well as through partnerships with the private sector. Ensuring adequate budgets, highly trained researchers, and strategic initiatives are essential to this. Targeted training programs for farmers could further support the adoption and efficient use of technologies. Credit and technical assistance, while not a main focus of this study, also play an important role.

III. Target policies to address diverging outcomes across biomes, product specialization, scale of output, and farm size

Concentrated, large-scale production boosts food security, incomes, and exports, and should be supported. Brazil has a relatively neutral policy environment, having moved away from discrimination of the agricultural sector as of the late 1980s. However, general support services are still small relative to the size of the sector (OECD, 2023), and infrastructure is precarious. This is an area where policy could be improved. Further concentrating production in a small share of municipalities also implies increasing inequalities between areas, with implications for employment and poverty. Family labor use declined by 30% during this period, and younger generations are increasingly leaving agriculture and rural areas. Average farmer age has risen, and many family farmers have difficulty finding a child who wants to take over the farm. Policies must improve the accessibility and quality of schooling for the children of farmers, as this benefits both the productivity and income of those who remain as well as the likelihood of a nonpoor adulthood for those who migrate.

IV. Prioritize a multi-faceted approach to the Caatinga biome

This biome in northeast Brazil concentrates many of the most acute challenges discussed above: small farms, high poverty, low output, and widespread negative TFP growth. Climatic impacts were most severe here, with negative TFP growth in both the first and last decades. Policy for this biome requires an "all-of-the-above" strategy, including investments in infrastructure (especially irrigation), the development of heat- and drought-resistant crop varieties, and crop insurance and social safety nets to mitigate the effect of shocks. Improving access to quality education is also critical—both for those who stay in farming and for the youth who seek opportunities elsewhere.

CHAPTER 6. **ECUADOR**

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SUMMARY

This chapter assesses the performance of total factor productivity (TFP) in Ecuador's agricultural sector over the last 10 years and identifies its main drivers. The findings from this analysis are critical to boosting agricultural sector performance, reducing poverty, increasing food security, and addressing the effects of climate variability. As Ecuador faces rising input costs and unpredictable extreme weather events, understanding the key variables that drive agricultural growth is essential to making well-informed decisions.

The analysis uses official data from the country's 23 provinces between 2014 and 2023, combining farm production information with climate data. A stochastic production frontier approach was applied to account for differences between provinces and regions, allowing the contribution of new technologies, better management, and environmental factors to growth to be quantified. The results show that farm productivity in Ecuador grew by 4.5% per year, mostly due to improved technological progress. However, the results indicate that farmers are not using the available technologies efficiently, as managerial performance has declined over time. Regional disparities are notable: the Coast region saw the largest productivity gains, while the Mountain region lagged, which might reflect the challenges imposed by climatic conditions.

To improve productivity outcomes, the results point to the importance of strengthening managerial performance, which in turn implies a focus on human capital formation through farmer training, education, and technical assistance. The results show that technological progress has played a key role in productivity growth, but growth varies considerably across provinces and regions.

This uneven performance across regions points to the need for targeted research and development efforts to support and equip farmers with tools suited to their specific climate and geographical conditions. It is equally important to expand farmer education and climate-smart training, develop gender-sensitive extension programs, and strengthen provincial-level productivity monitoring systems.

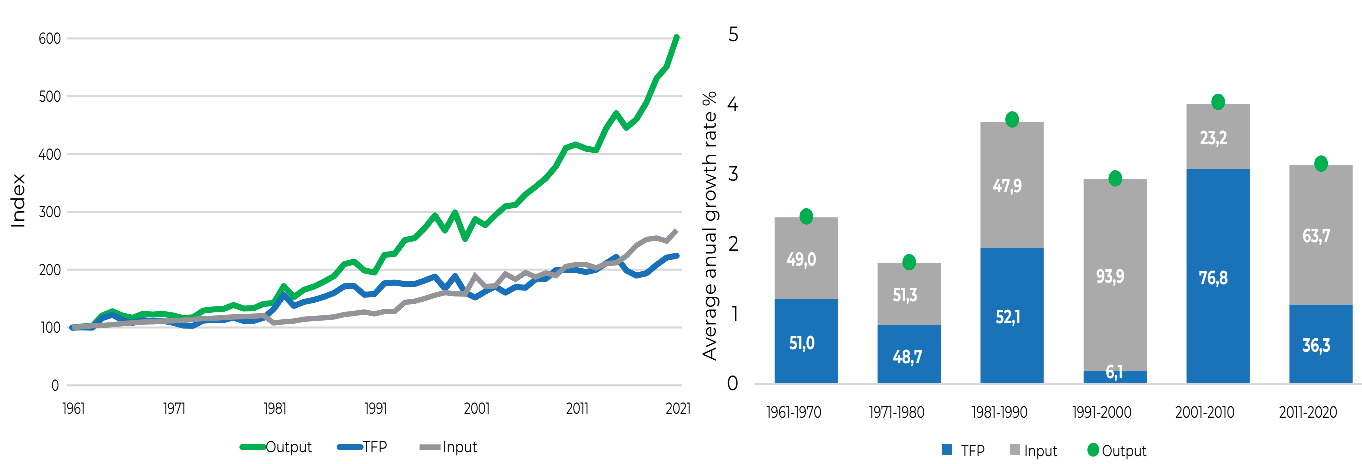
I. INTRODUCTION

The agricultural sector in Ecuador plays a fundamental role in the national economy, accounting for 7.7% of GDP (INEC, 2024). According to the National Institute of Statistics (INEC), in 2023, it employed 29.8% of the total workforce (2.6 million people). In terms of international trade, Ecuador increased the value of its agricultural exports by 41% over the past 10 years, compared to a 44% increase across South America (FAO, 2024). The agricultural sector contributes 27% of the country's total exports (INEC, 2024). Its growing integration into international markets, combined with the presence of foreign investment in agro-industrial value chains, offers opportunities to strengthen productivity through technology adoption, compliance with export standards, and improved organizational practices.

In 2024, Ecuador had 4.8 million hectares dedicated to agricultural production (INEC, 2025).Two distinct production models coexist. According to FAO (2024), commercial agriculture, which comprises 15% of agricultural production units (APUs), controls 80% of agricultural land and is primarily export-oriented, relying heavily on agrochemicals and energy inputs. By contrast, family farming represents 85% of APUs, uses 20% of agricultural land, and focuses on subsistence production and meeting basic needs.

As shown in **Figure 1**, agricultural production in Ecuador expanded significantly at the aggregate level over the past decade. According to an Inter-American Development Bank study using data from the USDA-ERS (Salazar et al., 2025), agricultural output grew at an annual average of 3.15% between 2011 and 2020. This expansion was primarily driven by increased use of inputs, while total factor productivity (TFP) stagnated at just 1.14%; a notable decline compared to the 3.08% growth observed between 2001 and 2010. Over the longer term, Ecuador's agricultural output has increased sixfold between 1961 and 2021, averaging 3% per year. This growth was driven mainly by input accumulation (1.7%) and, to a lesser extent, by TFP improvements (1.4%). Productivity gains were strongest in the 1980s and early 2000s, whereas the most recent decade reflects a shift toward input-driven growth.

FIGURE 1. CHANGES IN TFP, OUTPUT, AND INPUTS IN ECUADOR, 1961–2020



Source: Salazar et al. (2025)

Agricultural productivity is critical to food security: it influences food availability at both the national and local levels, household access through higher rural incomes, and the stability of food supply. Ecuador has seen a rise in food insecurity in recent years. In 2022, 36.9% of the population—6.6 million people—experienced food insecurity, up from 20% in 2015 (FAO, 2024). Additionally, an estimated 25.9% of the population, approximately 4.6 million people, cannot afford a healthy diet (FAO, 2024).

Several factors highlight the significance of analyzing agricultural productivity growth in Ecuador. First, after years of performing well, the country's agricultural sector has lost momentum, leading to severe challenges in rural areas, including mounting poverty, unemployment, and high susceptibility to weather shocks (Toledo et al., 2023; Yerovi et al., 2018). Second, Ecuador's wide range of microclimates and landscapes provides rich marine and terrestrial environments (World Bank Group, 2021). However, overlaps between high-biodiversity zones and densely populated areas with good farming conditions have led to growing tensions across communities and interest groups. Quintana et al. (2019) contend that promoting agricultural productivity is imperative to balance farming with conservation and prevent social conflicts. Third, in the past decade, 63% of agricultural output growth has been driven by increased input use, which could have detrimental effects on the environment and public health. Fourth, a dynamic agricultural sector could ease Ecuador's reliance on income from oil exports, which would be crucial to decarbonization while also lessening deforestation pressures (González Amador et al., 2024). Finally, TFP growth is essential to meet rising food demand driven by population growth, the shift in consumption preferences toward more complex diets, and rising incomes. For all these reasons, a solid understanding of the drivers of agricultural productivity in Ecuador is needed.

In light of these issues, the primary objective of this chapter is to analyze current trends in TFP growth and assess its determinants in relation to major annual crops in Ecuador. Quantifying the evolution of the key productivity components is critical for designing effective rural development and food security strategies. Specifically, the study addresses the following five research questions:

I. What is the rate of TFP growth for annual crops in Ecuador?

II. What is the relative importance of different components in driving TFP growth?

III. What is the connection between major socioeconomic factors and productivity levels?

IV. What key policy implications can be derived from this analysis?

V. What critical issues remain to be explore by future research on agricultural productivity in Ecuador that could complement this study?

Addressing these questions will shed light on the drivers of productivity growth and provide evidence for policymakers seeking actionable interventions to enhance agricultural efficiency, productivity, and resilience in Ecuador.

II. METHODOLOGY AND DATA

This analysis relies on a balanced panel dataset comprising 230 observations across 23 provinces in Ecuador between 2013 and 2023. The dataset integrates agricultural input-output and socioeconomic information from Ecuador's *Encuesta de Superficie Agrícola y Producción Agropecuaria* (ESPAC) conducted by INEC (2023), combined with climatic data from the University of East Anglia's Climatic Research Unit (CRU TS versions 4.08 and 4.09).

Table 1. Data and sources

Data	Description	Source
Provincial-level agricultural output, inputs, and socioeconomic variables	Data from agricultural households on land, labor, fertilizer, production value, gender, education, and age (2014–2023)	*2014–2023 Encuesta de Superficie Agrícola y Producción Agropecuaria (INEC)*
Temperature and precipitation variables	High-resolution gridded daily temperature and precipitation data (1901–2023)	Gridded weather data covering Earth's land areas for 1901–2023, Climatic Research Unit, University of East Anglia

Source: Authors' calculations.

The socioeconomic characteristics of farm managers listed in **Table 2** are sourced directly from ESPAC. To measure output, we construct a Geometric Young (GY) output quantity index following O'Donnell (2012, 2018). This index aggregates data for 23 economically significant annual crops grown in Ecuador.[1] The output value for each crop is calculated as production volume (thousands of tons) multiplied by the national average market price received by producers. The GY index uses revenue-based weights and takes 2015–2017 as the base period, consistent with Norton (1988) guidelines.[2]

Table 2. Socioeconomic variables

Variables	Description
Education[3]	Number of farm managers who attained low, medium, or high levels of education
Age	Proxy for experience, measured as the average age of farm managers
Gender	Number of men and women farm managers

Source: Authors' calculations.

[1]Aggregate output includes the following annual crops: barley, broad beans (unshelled), broccoli, cassava (bitter), cassava (Bolona Blanca variety), maize (dried), maize (fresh), onions, pearl barley (dried and cleaned), potatoes (China variety), potatoes (Superchola variety), quinoa, red beans (dried), red beans (unshelled), red onions (dried and cleaned), rice (milled), rice (paddy), soybeans, strawberries, tomatoes (greenhouse), tomatoes (open field), wheat, and yellow beans (dried).
[2]Revenue shares are calculated as: $S_{it}=\frac{1}{2}\left[\frac{P_{i0}y_{i0}}{\sum_j P_{j0}y_{j0}}+\frac{P_{it}y_{it}}{\sum_j P_{jt}y_{jt}}\right]$. The Geometric Young quantity index is calculated as follows: $Y_t^{GY}=e\left(\sum_i s_i \ln\left(\frac{y_{it}}{y_{i0}}\right)\right)$
[3]Low education includes no education, basic, and primary levels; medium education refers to secondary and upper-secondary; and high education corresponds to university and postgraduate levels.

The methodology applied is a true random parameters stochastic production frontier (TRP-SPF) model, which allows the estimated parameters to be random while accounting for both time-invariant and time-varying unobserved heterogeneity at the provincial level (Tsionas, 2002; Greene, 2005, 2008; Lachaud et al., 2022). This modeling framework allows the estimated production parameters to differ across provinces (Lachaud et al., 2017; Njuki et al., 2019; Lachaud & Bravo-Ureta, 2021) and separates technical efficiency from time-invariant unobserved heterogeneity.[4]

TFP is calculated by dividing the output index by an index of inputs, which is built using results from the production frontier model. TFP is then broken down into different components: improvements in managerial performance, advances in technology, and changes in climatic conditions. This decomposition helps identify the factors driving productivity growth, as per Lachaud et al. (2017) and O'Donnell (2018). Finally, a nonparametric method—Spearman's rank correlation coefficients (ρ)— is employed to examine monotonic associations between TFP and key farm manager characteristics.[5]

Stochastic production frontier model

The study uses a panel data stochastic production frontier (SPF) approach, an area in production economics that has experienced substantial methodological development and diverse applications, including policy analysis in agriculture (Lovell, 1995; Fried et al., 2008; O'Donnell, 2018). Specifically, the Cobb-Douglas TRP-SPF model is expressed as follows:

$$\ln y_{it} = \alpha_i + \sum_{k=1}^{K} \beta_{ki} \ln x_{kit} + \sum_{j=1}^{J} \eta_{ij} z_{jit} + \gamma_i T + v_{it} - u_{it} \quad (1)$$

where y_{it} is the value of aggregate output; x_{kit} is a vector of agricultural inputs (land, labor, and fertilizer); z_{jit} is a vector of climatic variables; T is a time trend that captures technological progress; u_{it} is output-oriented technical inefficiency, which provides a measure of managerial performance;[6] vit is a statistical noise term; and αi captures provincial time-invariant heterogeneity.

This model accounts for unobserved heterogeneity in inputs and for technological differences across provinces.

Table 3 describes the key variables of interest included in the empirical analysis.

[4] Although the model accounts for cross-province technological differences via random slopes, its time invariance parameter may pose challenges for periods with structural shifts in technology or input elasticities (Lachaud, 2025).
[5] This approach is robust to nonnormality, heteroscedasticity, ordinal scaling, and outliers (Hollander, Wolfe, & Chicken, 2013).
[6] In this study, managerial performance can be interpreted as the component technical efficiency (TE). According to O'Donnell (2018), output-oriented measures of efficiency are relevant measures of managerial performance in situations where managers have placed nonnegative values on outputs and inputs have been predetermined.

Table 3. Key variables included in the random parameters model[7]

Variables of interest	Description
Output index	Aggregate for annual crops
Land	Total harvested land for annual crops
Fertilizer	Total fertilizer applied to annual crops
Labor	Number of hired and family labor involved in the production of annual crops—the labor variable is derived as a proportion of the share of the total land used for these crops
Climatic anomalies	Deviations from a long-term average (1902–2023) of climate variables (e.g., temperature and precipitation)

Source: Authors' calculations.

III. FINDINGS

Table 4 reports the average elasticities of conventional inputs and shows that agricultural output is most responsive to changes in land use. Technological progress, proxied by a time trend, is statistically significant, suggesting an average annual output increase of 7.7% between 2014 and 2023, which is relatively high. Climate anomalies do not exhibit a statistically significant effect on production. However, higher temperatures are associated with a decline in agricultural output, while precipitation may have a negative influence.[8] The analysis reveals no statistically significant regional fixed effects.

Table 4. Estimates for the random parameter SPF models (2014–2023)

(continued on next page)

Variable	Coefficients
Constant	2.256*** (0.485)
Land	0.490*** (0.126)
Fertilizer	0.035 (0.059)
Labor	0.104** (0.042)
Time	0.077*** (0.028)
Temperature anomaly	0.311 (0.330)
Temperature	-0.099*** (0.021)
Temperature squared	-0.049*** (0.007)
Precipitation anomaly	0.001 (0.005)

[7] Capital is not included in the analysis due to the lack of data at the provincial level. As a result, the findings should be interpreted with caution.
[8] Considering the signs of the linear and quadratic precipitation terms, the estimated turning point is approximately 809 mm per year, while the maximum provincial annual average in the sample is 429 mm. Therefore, within the observed range, the practical effect of precipitation is negative.

Table 4. Estimates for the random parameter SPF models (2014–2023) (continued)

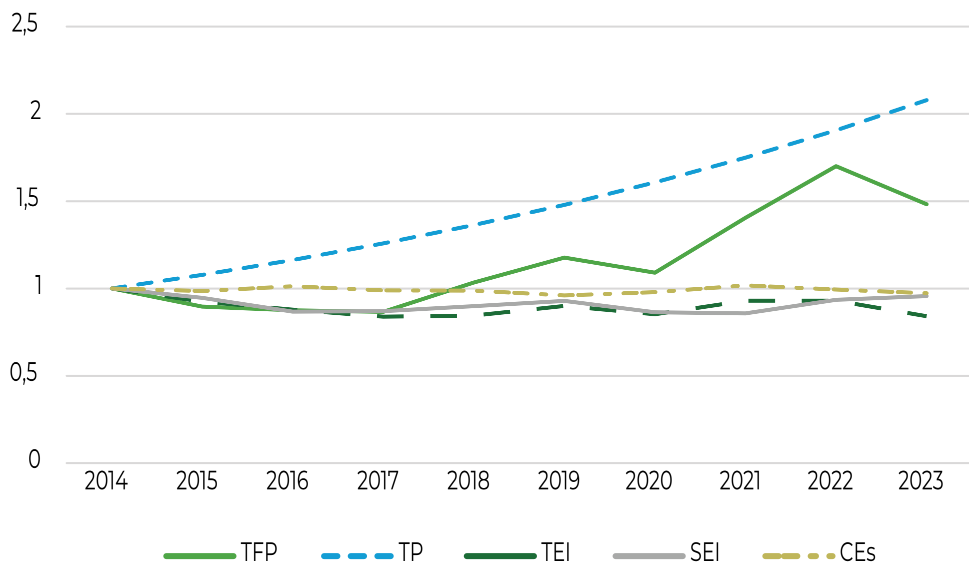
Variable	Coefficients
Precipitation	-0.005*** (0.002)
Precipitation squared	0.000 (0.000)
Coast #	0.013 (0.278)
Mountains	-0.180 (0.309)
λ	2.306*** (0.392)
σ	1.670*** (0.105)
σ_u	1532
σ_v	0.664
Technical Efficiency Estimates	
Mean	0.359
SD	0.171
Min	0.017
Max	0.861
Log-likelihood	-419.7
Observations	**230**

Notes: Authors' calculations. The dependent variable is agricultural production. ***, **, * are 1%, 5%, and 10% level of significance, respectively. Standard errors in parentheses. Variables are measured in natural log. # Amazonia is the excluded category.

Figure 2 shows the dynamics of agricultural output and TFP components. The chronological evolution of TFP growth reveals marked divergence among its drivers. Technological progress shows steady, strong growth, suggesting that advances in technology or production methods have been the dominant source of productivity gains. In contrast, the technical efficiency index (TEI) and scale efficiency index (SEI) remain relatively flat and show minimal variation from the baseline (2014), indicating little progress in resource-use efficiency or production scale optimization.

As a result, productivity gains from technological progress have not fully translated into realized TFP growth. The TFP index exhibits a more uneven pattern: after modest gains in the early years, it accelerates significantly after 2019, peaks around 2022, then declines slightly.

Figure 2. Key drivers of TFP growth (2014–2023)



Source: Authors' calculations using INEC data.

Climatic effects (CEs) remain relatively stable over the period, hovering around the baseline with slight fluctuations. This stability indicates that climatic effects have not acted as a persistent driver of aggregate productivity changes. However, year-to-year deviations still matter at the provincial and regional levels, as discussed below.

Table 5 shows the drivers of TFP growth for each of the 23 regions. At the national level, productivity decomposition reveals that TFP has grown at an average annual rate of 4.53% between 2014 and 2023. The provinces with the highest TFP growth rates were Esmeraldas (13.9%) and El Oro (9.2%), while Cañar, Morona Santiago, and Orellana exhibit negative growth. The average technical efficiency score is relatively low (0.359), indicating that improvements in managerial capacity among farmers could significantly increase productivity. In fact, technical efficiency has deteriorated at a rate of 1.76% per year, with persistently low scores across all provinces and regions.

The results reveal that technological progress has been the main engine of TFP growth across Ecuador's agricultural sector, consistent with prior macro-level studies in the region (Lachaud et al., 2017; Lachaud & Bravo-Ureta, 2022; Lachaud, 2025). By contrast, scale efficiency has declined by 0.139% annually, which may reflect decreasing relative productivity among larger farms. Climatic effects have also negatively affected TFP growth by 0.18%, underscoring the potential of agricultural interventions that enhance climate resilience and adaptation in improving the agricultural sector's performance.

Table 5. Annual average growth rate for TFP, its components (%), and technological efficiency in Ecuador, based on the TRP-SPF model (2014–2023)

Province	TFP	TP	SEC	CEs	TEC	SN	TE
Azuay	5.202	6.819	0.252	0.044	-1.805	-0.108	0.317
Bolivar	6.819	11.094	-0.460	-0.285	-3.129	-0.402	0.298
Cañar	-13.180	-10.059	0.751	-0.302	-3.900	0.329	0.319
Carchi	5.851	8.223	-0.796	0.049	-1.455	-0.170	0.371
Chimborazo	5.669	6.388	-0.101	0.281	-0.853	-0.045	0.359
Cotopaxi	0.134	4.311	0.114	-0.189	-3.933	-0.170	0.349
Imbabura	6.408	8.877	-0.033	1.184	-3.380	-0.241	0.346
Loja	8.904	11.214	0.184	-0.167	-2.094	-0.234	0.273
Pichincha	-2.331	5.112	-0.413	-3.894	-2.915	-0.221	0.362
Santo Domingo de los Tsachilas	12.442	12.089	0.512	0.085	-0.280	0.037	0.263
Tungurahua	10.790	9.309	0.016	0.113	1.224	0.128	0.339
Guayas	1.975	4.735	-0.001	0.706	-3.317	-0.148	0.381
El Oro	9.163	9.545	-0.740	-0.605	1.006	-0.042	0.366
Esmeraldas	13.915	11.535	-0.466	-0.296	2.916	0.225	0.346
Los Rios	8.562	9.093	0.446	-0.084	-0.845	-0.048	0.381
Manabi	4.353	7.205	-0.815	-0.751	-1.117	-0.168	0.381
Santa Elena	6.433	8.418	-1.232	0.080	-0.685	-0.147	0.372
Morona Santiago	-3.819	-0.798	1.004	0.099	-4.104	-0.020	0.350
Napo	5.328	8.184	-0.444	-0.146	-2.063	-0.203	0.374
Orellana	-3.391	5.311	-4.946	0.067	-3.555	-0.269	0.372
Pastaza	8.289	9.388	1.389	-0.390	-1.979	-0.119	0.363
Sucumbíos	1.477	2.959	1.892	-0.181	-3.093	-0.099	0.357
Zamora Chinchipe	5.190	5.150	0.703	0.430	-1.085	-0.007	0.353
Ecuador (average)	**4.530**	**6.700**	**-0.139**	**-0.181**	**-1.758**	**-0.093**	**0.348**

Notes: Authors' calculations using INEC data. TFP = total factor productivity; TP = technological progress; CEs = climatic effects; SEC = scale efficiency change; TEC = technical efficiency change; SN = statistical noise; TE = average technical efficiency.

Table 6 presents TFP growth and its decomposition by region. The results highlight considerable disparities across Ecuador's three agricultural regions. The Coast region shows the highest annual rates of TFP growth (7.4%) and technological progress (8.4%). The Mountain region follows, with annual TFP growth of 4.24% and technological progress of 6.67%. Amazonia presents the lowest rates, with TFP growth of 2.18% and technological progress of 5%.

Technical efficiency declined in all regions over the last ten years, particularly in the Mountain region (-2%) and Amazonia (-2.6%). Finally, climatic effects were adverse for all regions, with the Mountain region most affected.

Table 6. Annual average growth rate for TFP and its components (%), by region (2014–2023)

Region	TFP	TP	SEC	CEs	TEC	SN
Mountain	4.24	6.67	0.000	-0.28	-2.05	-0.10
Coast	7.40	8.42	-0.47	-0.16	-0.34	-0.05
Amazonia	2.18	5.03	-0.07	-0.02	-2.65	-0.12

Notes: Authors' calculations using INEC data.

Finally, nonparametric statistical tests were applied to examine whether sociodemographic characteristics of farm managers correlate with productivity levels (**Table 7**). The analysis shows that provinces with higher shares of male farm managers are associated with lower agricultural productivity (**Table 7**). This finding is consistent with broader evidence that male-dominated farm management tends to be linked to lower productivity. No clear relationship emerges between farm managers' average age and productivity levels, possibly because age differences across provinces are minimal and may be masked at the provincial level by aggregation. Importantly, productivity is lower in areas where farm managers have lower formal schooling levels, although this correlation is relatively weak ($\rho = -0.131$). This finding suggests that education is a potential constraint on agricultural performance.

Table 7. Nonparametric Spearman correlation analysis of TFP and sociodemographic characteristics of farm managers

Variable Group	Variable	Spearman's ρ	p-value
Education	Low education	-0.131**	0.047
Education	Medium education	-0.077	0.244
Education	High education	-0.104	0.12
Age	Average age	-0.055	0.405
Gender	Number of male managers	-0.131**	0.047
Gender	Number of female managers	-0.095	0.149

Notes: Authors' calculations using INEC data.

The key findings from the analysis presented above are summarized in **Table 8.**

Table 8. Key findings

Intervention type	Effects on productivity
Education	Encouraging at least secondary and technical education among farm managers could enhance TFP.
Gender	TFP tends to be lower among farms managed by men compared to those managed by women.
Age	No clear relationship is found between TFP and the age of farm managers.
Technological progress	Technological progress—commonly associated with investments in R&D—has been the main driver of TFP growth, contributing substantially at the national and regional levels.
Managerial performance	In contrast to technological progress, managerial performance remains relatively low. It has decreased over time, highlighting the country's potential to improve agricultural output using existing resources or inputs by investing in technical assistance, formal and informal training, and extension services.
Climatic effects	Climatic effects have negatively affected TFP growth in all regions, especially the Mountain and Coast regions. Strengthening climate resilience is critical to improving the agricultural sector's performance, particularly in these two regions.
Scale efficiency	Scale efficiency has declined by 0.139% annually, indicating that larger farms have become relatively less productive.
Geographical variability	Agricultural progress varies across regions in Ecuador. The Coast region has experienced steady growth, helped by better access to technology. In contrast, the Mountain region is struggling with lower productivity and adverse climatic effects. These differences show that a one-size-fits-all approach is not ideal: effective policies should take this geographic heterogeneity into account.

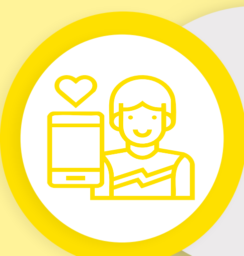
IV. CONCLUSIONS AND POLICY RECOMMENDATIONS

This analysis provides what appear to be the first provincial-level estimates of TFP growth and associated components for annual crops in Ecuador using robust stochastic frontier modeling. The analysis points to five main policy recommendations to help boost TFP growth:

I. Strengthen extension services and technical assistance to improve agronomic and managerial practices

TFP grew at an average annual rate of 4.5% from 2014 to 2023, driven mainly by technological progress. However, technical efficiency decreased sharply at the national and regional levels. Addressing this requires agricultural policies that prioritize education, training, technical assistance, and extension services. In other words, well-targeted human capital development efforts to enhance managerial abilities are essential. Special emphasis should be placed on reaching farmers with low levels of formal education to improve their managerial skills through training programs and technical assistance. Extension programs should be tailored to address literacy gaps so that all farmers can make optimum use of available technologies.

II. Support farmers in adapting to rapid technological change through training programs and technical assistance



Rapid technological change can pose barriers for farmers needing to adopt and adapt to innovations. As new technologies shift the production frontier upward, many farmers struggle to keep up. This gap often shows up as low managerial performance (i.e., low technical efficiency). Because technological change disrupts existing practices, farmers need timely, relevant education and training to stay abreast of emerging technologies.

III. Implement regionally tailored technology transfer programs that account for agroecological diversity, current levels of agricultural performance, and climatic effects

The regional decomposition of TFP growth highlights significant disparities. The Coast region leads in productivity and innovation, while Amazonia and the Mountain region lag behind, with the latter particularly vulnerable to climatic variability.

IV. Adopt gender-sensitive policies to boost productivity growth

Policies aimed at empowering women farmers could help to further boost their productivity, especially in regions where agriculture is predominantly managed by men.

V. Develop and enhance data systems to monitor TFP and efficiency trends at the subnational level

Strengthening agricultural data systems would facilitate the design of effective interventions tailored to specific contexts. Regular productivity monitoring could be institutionalized by supporting INEC's agricultural surveys and integrating geospatial and climatic indicators. Collaboration between INEC, the Ministry of Agriculture, and agricultural economic researchers will be essential to optimizing this data for policy analysis.

CHAPTER 7. **PERU**

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SUMMARY

Agriculture is a fundamental pillar of Peru's economic and social development, playing a crucial role in ensuring food security and improving rural livelihoods (FAO, 2025). The agricultural sector accounts for 5.6% of Peru's GDP and employs approximately 2.07 million farmers. However, agricultural productivity remains a critical concern in Peru, where 88% of farmers belong to subsistence family farming. Drawing on eight rounds of the National Agricultural Survey (ENA) (2015–2023), this study examines Peruvian agricultural productivity, technical efficiency, and the role of weather and public policies. The findings reveal limited agricultural productivity growth and significant volatility in productivity between 2015 and 2023, with annual changes ranging from -11.68% to +8.17%. This instability is primarily driven by fluctuations in technical efficiency and the influence of weather conditions. Land-weighted estimates of productivity at the department level shows that, on average, productivity increased in Peru's Amazonian departments over the eight-year period, while departments with larger amounts of agricultural land experienced productivity decreases. Public policies increasing access to certified seeds and technical assistance are associated with improved productivity, although their effects vary. Additionally, disparities across departments and farm types have a significant influence on the country's total factor productivity (TFP) growth.

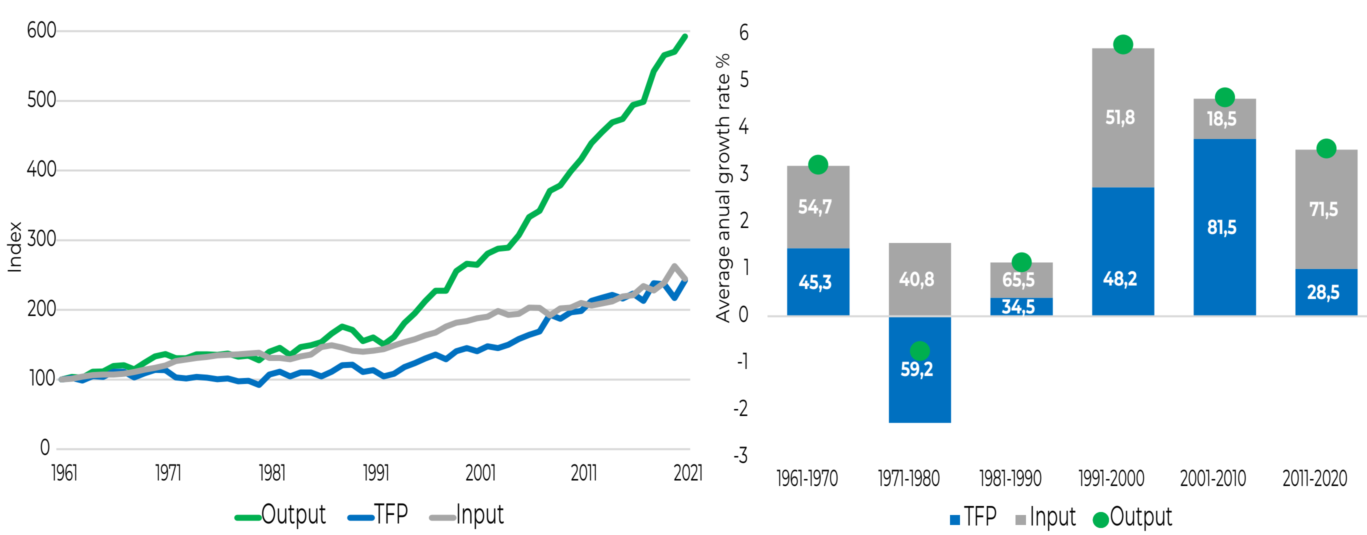
I. INTRODUCTION

The Peruvian agricultural sector accounts for 5.6% of the country's GDP (BCRP, 2025) and employs more than 2.07 million farmers across 2.2 million farms. Recent data shows that 41% of agricultural households live in poverty, nearly twice the rate of nonagricultural households, at 22% (Zegarra, 2024, p. 13). Moreover, according to the 2012 Agricultural Census, 97% of Peruvian farmers are small-scale producers characterized by their heavy reliance on family labor, limited access to land, irrigation, and capital (MIDAGRI, 2015), and whose performances are heterogenous.[1] This segment is marked by particularly low productivity levels, which the literature argues is the result of persistent inefficiencies and constraints in public policy support, access to financial markets, and production resources (Julien, Bravo-Ureta, & Rada, 2019).

Few studies have used the total factor productivity (TFP) approach to estimate agricultural productivity in Peru (World Bank Group, 2017; Galarza & Díaz, 2015; Del Pozo, 2020; and USDA 2024). Among them, only the World Bank Group (2017) uses a stochastic frontier approach (SFA) to compute TFP, showing that TFP growth in Peru has more than doubled since 1990 compared to earlier decades (World Bank Group, 2017). Recent USDA estimates (2024) found that TFP in Peru increased by 10% from 2015 to 2022—an encouraging performance compared to other countries in the region.

A recent analysis published by the Inter-American Development Bank (IDB) also highlights Peru's significant agricultural growth over the past 60 years (1961–2021), during which agricultural output increased sixfold (**Figure 1**) (Salazar et al., 2025). According to USDA-ERS data, this growth was mainly driven by the increased use of inputs (which grew at an average annual rate of 1.5%) alongside a positive, though fluctuating, trend in TFP, which also averaged 1.5% annual growth despite periods of stagnation or contraction. Over the last three decades, the drivers of Peru's agricultural growth have varied: input use expanded in the 1990s, productivity gains dominated in the 2000s, and input use regained prominence in the 2010s. Between 2010 and 2020, agricultural production grew at an average annual rate of 3.6%, with 71% of this growth explained by increased input use and 29% by TFP gains.

Figure 1. Evolution of TPF, output, and input use in Peru (1961–2021)



Source: Salazar et al., (2025), based on USDA-ERS data.

[1] Within the group, 88% belong to subsistence family farming, 10% are classified as transitional family farming, and only 2% are categorized as developed (MIDAGRI 2021).

However, few studies analyze the role of specific interventions or policies in influencing agricultural productivity. Recently, Borrero (2025) found an inverse relationship between farm size and productivity in Peru, estimating that a 1-hectare reduction in average farm size increases agricultural TFP by 0.6%. Regarding irrigation, Del Pozo (2020) finds that access to irrigation increases productivity by 17%. In contrast, there are few studies on technical efficiency in Peruvian agriculture.

One exception is Schling, Sáenz Somarriba, and Mattos (2024), who use a metafrontier[2] approach, estimating national technical efficiency at around 20%, with farmers holding formal land titles experiencing efficiency levels about 5 percentage points higher. Likewise, Kámiche-Zegarra and Bravo-Ureta (2020) use the same approach to find that users of market information are 8 to 20 percentage points more efficient than nonusers (Kámiche-Zegarra & Bravo-Ureta, 2020).

In summary, while previous studies have explored technical efficiency in Peruvian agriculture, there is a lack of comprehensive analyses on its evolution over time and the pronounced disparities across departments. Understanding these subnational differences is critical for informed policy design, as departments face distinct challenges related to productivity, resource allocation, and technology adoption. Addressing these gaps through targeted analysis is essential to developing effective, regionally tailored interventions that promote inclusive and sustainable agricultural development.

This chapter analyzes the evolution and drivers of TFP in Peruvian agriculture between 2015 and 2023, focusing on four questions:

I. How did agricultural TFP vary at the national level between 2015 and 2023?

II. How did departments' TFP and technical efficiency perform during this period?

III. Which departments experienced increases/decreases?

IV. How do public policies contribute to TFP and technical efficiency?

II. METHODOLOGY AND DATA

To answer these research questions, the analysis draws on annual microeconomic data for 2015–2019 and 2021–2023, using the National Agricultural Survey (ENA).[3] This source provides information on variables such as agricultural output, inputs, and farmers' socioeconomic characteristics. Additional data were obtained from Copernicus (2025) for weather variables; the Ministry of Transportation for road infrastructure; the Ministry of Economy and Finance's economic transparency portal for local government agricultural expenditures, and the Superintendency of Banking, Insurance, and Pension Funds (SBS) for banking access information at the district level.

The final dataset comprises data on 181,735 farmers across 24 departments in Peru (MEF, 2015–2023; SBS, 2015–2023). The total value of production, expressed in soles, is the output variable. Inputs include land (hectares), family labor (weighted household members), and expenditures on labor, fertilizer, manure, pesticides, equipment, and maintenance (in soles).[4] Binary indicators equal to 1 identify the use of certified seeds and dependence on drip or gravity irrigation. In addition, the dataset includes weather variables capturing mean temperature and precipitation, as well as their anomalies relative to long-term (30-year) means.

[2] The metafrontier production function model is an approach that allows the calculation of comparable measures of technical efficiency for farms operating under different technologies. It also enables the estimation of technology gaps for firms relative to the potential technology available to the industry as a whole (Battese et al, 2004).
[3] The ENA was not conducted in 2020 due to Covid-19.
[4] All expenses were deflated to 2015 constant soles.

Household characteristics comprise the education (years), age (years), and gender (1 if male) of the household head. Policy-related variables include public agricultural spending (soles per hectare of land), banking access (number of offices and ATMs), paved roads (kilometers divided by surface) and access to technical assistance (as a dummy). Finally, altitude (meters above sea level) is included as a geographic control variable.

The analysis follows a three-step methodology. First, the Stochastic Frontier Analysis True Random Effects model (SFA-TRE), proposed by Greene (2005), as applied at the farmer level, using repeated cross-sectional data. This approach distinguishes between time-invariant unobserved heterogeneity and time-varying technical inefficiency, thereby preventing misattribution and enhancing the accuracy of efficiency estimates. The empirical Cobb-Douglas specification is:

$$ln(Y_{it}) = (\alpha_0 + \tau_i) + \sum_{k=1}^{K} \beta_k lnX_{itk} + \sum_{m=1}^{M} \gamma_i lnW_{itm} + \sum_{s=1}^{S} \vartheta_i HH_{its} + \sum_{r=1}^{R} \varphi_i PP_{itr} + \sum_{n=1}^{N} \eta_i A_{itn} + \delta t_i + \nu_{it} - u_{it}$$

where Y_{it} denotes total production, X represents inputs, W weather variables, HH household characteristics, PP policy variables, and A control factors. The term t_i is a continuous time trend capturing technological change over time; v_{it} represents random noise, and u_{it} measures technical inefficiency.

Second, TFP was calculated at the farmer level, based on the estimated production frontier. Third, the total factor productivity index (TFPI) was constructed and decomposed into technical efficiency, technological change, scale efficiency, weather effects, human capital,[5] infrastructure, and policy indices. This approach allows us to identify and analyze the key drivers of Peru's agricultural productivity dynamics over the period of study.

III. FINDINGS

The results from the main estimations (SFA-TRE) are presented in **Table 1**, which constitutes the first step of the empirical methodology. Partial elasticities are calculated for conventional inputs, public policies or interventions (irrigation, seeds, and technical assistance), infrastructure (roads), and farmers' socioeconomic characteristics.

Table 1. Coefficients for the main model[6]

(continued on next page)

Variables	Model	Standard Errors
Land	0.649***	(0.002)
Family labor	0.076***	(0.005)
Labor expenses	0.033***	(0.000)
Pesticide expenses	0.027***	(0.000)
Fertilizer expenses	0.026***	(0.000)

[5] Constructed with household characteristics.
[6] The difference between the growth rate reported in Figure 1 and the microeconomic analysis is due to variations in the period of analysis, the methodology, and the level of aggregation. The analysis presented in Table 2 uses district-level data for 2015–2023, estimated using SFA-TRE with inputs derived from administrative records, whereas Figure 1 is based on nationally aggregated USDA-ERS data for the period of 1961-2021, using index numbers for six different inputs.

TABLE 1. COEFFICIENTS FOR THE MAIN MODEL[6]
(CONTINUED)

Variables	Model	Standard Errors
Manure expenses	0.014***	(0.000)
Maintenance expenses	0.018***	(0.001)
Equipment expenses	0.013***	(0.003)
Gender	0.135***	(0.005)
Education (years)	0.010***	(0.001)
Age	0.005***	(0.001)
Age square	-0.000***	(0.000)
Temperature (mean)	0.571***	(0.012)
Precipitation (mean)	0.108***	(0.019)
Precipitation square	-0.135***	(0.010)
Temperature anomaly	-0.029***	(0.005)
Precipitation anomaly	-0.023***	(0.007)
Altitude	-0.118***	(0.003)
Drip irrigation	0.378***	(0.017)
Gravity irrigation	0.340***	(0.006)
Certified seeds	0.296***	(0.008)
Technical assistance	0.179***	(0.009)
Paved local road	0.105***	(0.033)
Paved departmental road	0.083*	(0.044)
Banking (ATMs)	0.007***	(0.001)
Public agricultural expenses	0.001	(0.001)
Year	0.001	(0.002)
Constant	8.641***	(0.267)
Department Fixed Effects	Yes	
Observations	**181,735**	

Note: All independent variables are included in levels, while the output variable is expressed in logarithms. Coefficients are therefore interpreted as semi-elasticities. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

EFFICIENCY GAINS IN AGRICULTURAL PRODUCTION

Table 1 presents the agricultural output elasticities for the four variables analyzed: conventional inputs, farmers' socioeconomic characteristics, climate-related variables, and policy interventions. Among the conventional inputs, land exhibits the largest output elasticity: a 10% increase in cultivated area is associated with a 6.5% increase in the total value of agricultural production. This underscores the central role of land in Peru's agricultural output. Labor is another key driver, with family labor exerting a considerably stronger effect than hired labor. In fact, the contribution of family labor (8%) is more than double that of hired labor (3%), underscoring its critical importance in small-scale farming systems. Other inputs and capital—including fertilizers, manure, pesticides, equipment, and maintenance—positively affect output, with elasticities ranging from 1% to 3%. These results suggest there is room to improve efficiency and impact of input use through better access to complementary technologies and technical support.

Among farmer characteristics, education and age show weak associations with agricultural output. Gender has a greater impact: the findings confirm that male-headed farms are, on average, 14% more productive, reflecting gender-based disparities in access to inputs and opportunities. This finding aligns with Julien, Bravo-Ureta, and Rada (2023), who suggest that these gaps are often driven by local conditions that disproportionately disadvantage women, rather than by inherent differences in farm management abilities.

Regarding policy interventions, the results confirm that access to irrigation leads to a one-third increase in agricultural output (38% for drip irrigation and 34% for gravity systems), while access to paved roads is linked to 8%–11% higher agricultural output. Access to technical assistance increases output by 18%, while the use of certified seeds raises it by 30%. These findings confirm that investing in public goods—such as rural infrastructure, R&D, and extension services—yields high efficiency gains. Such investments are implemented primarily by the Ministry of Agrarian Development and Irrigation (MIDAGRI), the National Institute of Agrarian Research (INIA), and the National Agrarian Health Service (SENASA).

Finally, weather conditions and climate variables exert a pronounced influence on the agricultural sector in Peru. While average temperature and precipitation have a positive influence on production, weather anomalies[7] and excessive rainfall diminish agricultural output, as reflected in the negative coefficients for climatic shocks and the squared precipitation term. These results are consistent with the broader literature on the effects of climate variables on agriculture in Latin America and the Caribbean (Lachaud, Bravo-Ureta & Ludeña, 2017).

TFP growth between 2015 and 2023

Annual growth in TFP and its components in Peru was extremely volatile between 2015 and 2023. As shown in **Table 2**, the TFPI growth rate fluctuated sharply, alternating between contractions and expansions. It dropped significantly in 2016 (-8.35%), recovered moderately in 2017 and 2018 (around +3.5% to +3.95%), declined again in 2019 (-3.4%), peaking in 2022 (+8.2%) before collapsing in 2023 (-11.7%). On average, the TFPI growth rate over the period was slightly negative (-0.98%), highlighting the fragility of productivity gains.

The growth rate for technical efficiency (OTEI) largely mirrored these dynamics, with pronounced contractions in 2016 (-4.8%) and 2023 (-4.8%) offset by positive dynamics in 2018 (+1.21%), 2021 (+1.72%), and 2022 (+1.51%). This pattern indicates that productivity improvements are primarily driven by efficiency gains yet remain highly susceptible to reversal.

Weather effects (WEI) also played a critical role, with growth rates alternating between strong positive contributions in 2016 (+5.5%), 2019 (3.5%), and 2022 (+6.0%) and contractions in 2021 (-1.8%) and 2023 (-4.9%). This pattern highlights farmers' vulnerability to climate variability. On average, weather contributed positively (+1.07%) over the period, underscoring both its importance and volatility.

Policy-related factors provided steady but modest positive contributions in most years (0.3%–0.6%), except in 2023, when their growth rate turned slightly negative. In contrast, the infrastructure and human capital indices revealed more structural weaknesses. Infrastructure gains were limited and only became strongly positive in 2023

[7]Anomaly refers to the deviation of an observed value of temperature or precipitation (X_t) from its long term mean ($\overline{X}$), defined as: $Anomaly = Xt - \bar{X}$. In this study, X_t refers to the observed value of temperature or precipitation in year t (from 2015 to 2023), while $\bar{X}$ denotes the 30-year average (1993–2023) of the corresponding variable.

(+4.6%), while human capital was persistently negative from 2019 to 2022 before rebounding sharply in 2023 (+9.2%).

Other components, such as technological change (OTI) and scale efficiency (OSEI), showed only marginal year-to-year variation, rarely exceeding ±1%. This suggests that productivity growth in Peru's agricultural sector has been driven primarily by short-term fluctuations in efficiency and weather, while deeper structural factors such as technology, scale, infrastructure, and human capital have contributed on average little to sustained growth. Their persistently low or neutral growth contributions point to underlying structural limitations that must be addressed over the long term.

Table 2. Annual growth rates of TFPI and associated components in Peru (2015–2023)

Year	TFPI	OTI	OTEI	OSEI	WEI	Policy	Infrastructure	Human capital	Altitude
2016	-8.35	0.66	-4.79	0.03	5.45	0.39	-1.30	0.36	0.93
2017	3.51	-0.25	-0.20	-0.04	-1.11	2.33	-1.26	0.34	2.08
2018	3.95	-0.69	1.21	-0.01	0.38	0.28	-0.30	0.14	-0.45
2019	-3.41	0.35	-1.39	0.03	3.48	0.25	0.55	-1.08	-0.24
2021	0.92	0.37	1.72	-0.03	-1.82	0.56	0.68	-2.14	-1.16
2022	8.17	-0.20	1.51	0.08	6.01	0.52	0.71	-1.04	1.69
2023	-11.68	-0.41	-4.83	-0.20	-4.91	-0.36	4.60	9.21	-4.22
Average*	***-0.98***	***-0.02***	***-0.97***	***-0.02***	***1.07***	***0.57***	***0.53***	***0.82***	***-0.20***

Notes: TFPI = Total Factor Productivity Index; OTI = Technological Change Index; OTEI = Technical Efficiency Index; OSEI = Scale Efficiency Index; WEI = Weather Effects Index

Departmental TFP and drivers of productivity growth

Table 3 presents the geometric average of annual growth rates of TFP and its components across Peruvian departments between 2015 and 2023. The results reveal marked regional disparities in agricultural productivity, driven mainly by differences in technical efficiency. The most striking case is Madre de Dios, which achieved exceptional average TFP growth of 16.25%, supported by strong efficiency gains (+3.57%) and favorable weather (+2.35%), despite adverse technological change. Other high performers include Lambayeque (+6.09%), where efficiency improvements (+1.36%) combined with technological progress (+1.50%) and favorable weather (+1.77%) to boost growth. In Amazonas (+5.89%), efficiency gains (+2.18%) were the primary driver of growth.

By contrast, Ucayali (-7.17%) and Puno (-6.92%) experienced the steepest declines, as efficiency losses (-1.87% and -3.59%, respectively) outweighed modest weather gains. Cusco (-4.46%) and Junín (-3.11%) displayed similar patterns, with efficiency declines compounded by limited positive weather effects. Even dynamic regions such as La Libertad (-1.13%) and Arequipa (-1.67%) recorded negative TFP growth. In La Libertad, a strong contribution from weather (+2.46%) and moderate technological progress (+0.47%) were offset by efficiency losses (-2.39%). Similarly, in Arequipa, favorable weather (+2.21%) and technological gains (+0.71%) did not compensate for the decline in efficiency (-1.83%).

Table 3. Geometric average of TFP growth and its components in Peru, by region (2015–2023)

Departments	TFP	OTI	OTEI	OSEI	WEI	Policy	Infrastructure	Human capital	Altitude
Amazonas	5.89	-0.26	2.18	0.00	0.85	0.33	0.00	-0.26	-0.09
Ancash	-1.24	-0.06	-0.92	0.00	1.59	0.53	0.00	0.25	0.01
Apurimac	-2.47	-0.14	-1.57	0.00	0.70	-0.07	0.00	1.01	-0.01
Arequipa	-1.67	0.71	-1.83	0.00	2.21	0.15	0.00	1.35	0.79
Ayacucho	0.52	0.14	0.13	0.00	0.50	0.00	0.00	1.58	0.02
Cajamarca	2.14	0.27	0.28	0.00	1.64	1.10	0.00	2.15	0.16
Cusco	-4.46	-0.07	-1.32	0.00	0.07	0.13	0.00	1.43	-0.30
Huancavelica	-1.18	-0.02	-1.78	0.00	1.07	0.73	0.00	0.25	0.04
Huánuco	-1.03	0.05	-1.48	0.00	1.51	-0.65	0.00	1.37	0.68
Ica	-1.25	0.36	0.63	0.00	0.84	0.03	0.00	2.58	0.00
Junín	-3.11	0.07	-1.89	0.00	1.29	0.21	0.00	1.92	0.08
La Libertad	-1.13	0.47	-2.39	0.00	2.46	1.52	0.00	2.09	0.71
Lambayeque	6.09	1.50	1.36	0.00	1.77	0.05	0.00	0.46	0.09
Lima	-0.39	-0.16	0.63	0.00	0.73	-0.30	0.00	0.58	-0.89
Loreto	-0.04	0.18	0.12	0.00	0.68	1.27	0.00	0.04	0.16
Madre de Dios	16.25	-0.94	3.57	0.00	2.35	0.18	0.00	1.74	0.23
Moquegua	0.43	0.74	-0.82	-0.25	1.74	0.26	0.00	-0.01	0.22
Pasco	-1.52	0.00	-1.88	0.00	2.29	0.95	0.00	0.98	0.64
Piura	-2.58	0.38	-1.05	0.00	1.61	0.51	0.00	0.93	0.60
Puno	-6.92	-0.08	-3.59	0.00	0.77	0.86	0.00	-0.12	-0.02
San Martín	0.75	0.04	0.22	0.00	0.12	0.24	0.01	-0.44	0.11
Tacna	0.79	0.03	0.66	0.00	1.34	0.30	0.00	0.98	0.21
Tumbes	3.26	-0.10	0.60	0.00	1.12	0.53	0.00	1.32	0.79
Ucayali	-7.17	-0.16	-1.87	0.00	0.79	0.69	0.00	0.15	0.24

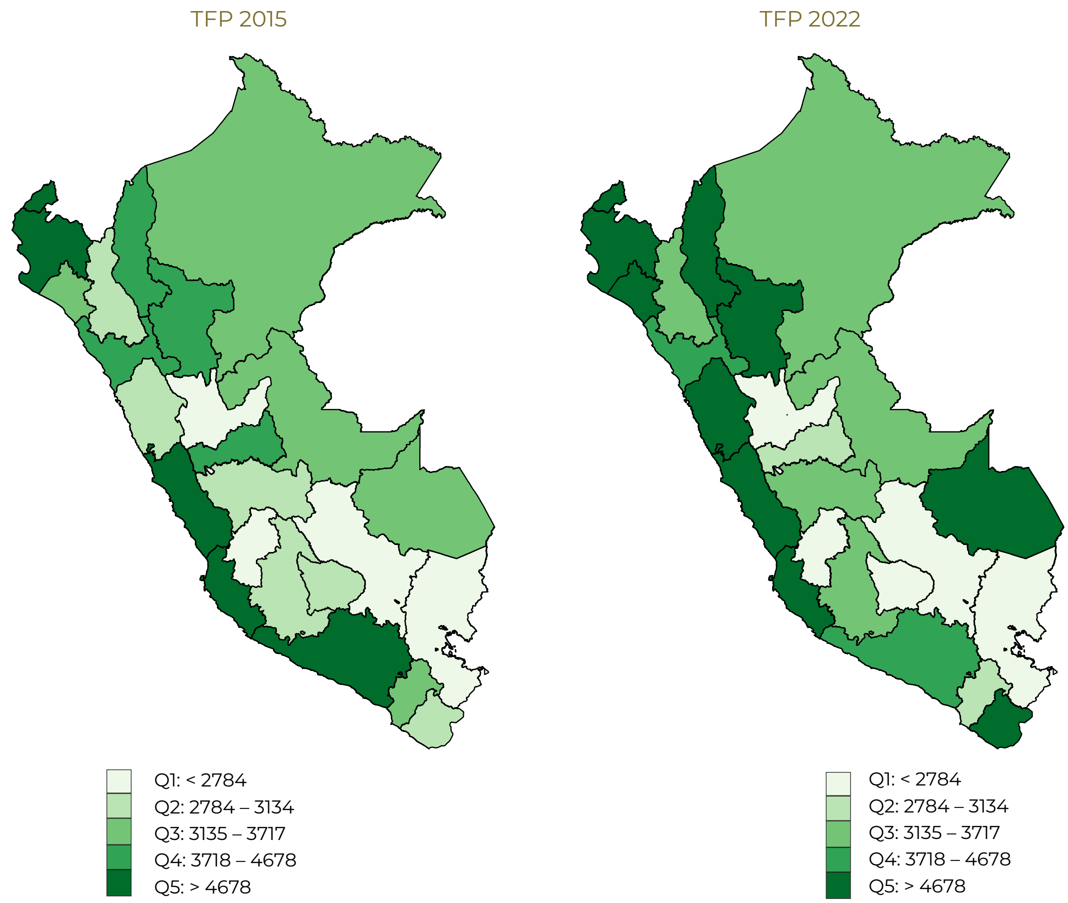
Notes: TFPI = Total Factor Productivity Index; OTI = Technological Change Index; OTEI = Technical Efficiency Index; OSEI = Scale Efficiency Index; WEI = Weather Effects Index.

The persistent lack of growth in both the infrastructure and OSEI indices indicates that TFP gains across departments were not driven by improvements in road connectivity or systematic shifts toward scale-efficient production processes. Nonetheless, Cajamarca achieved growth (+2.14%) through a balance of drivers, namely weather (+1.64%), technical efficiency (+0.28%), and strong policy support (+1.10%). Overall, technological progress in Peru was limited and uneven. Only a few regions saw notable advances, such as Lambayeque and Arequipa, while most areas stagnated or regressed. Weather effects generally provided modest positive contributions but were insufficient to counter technical efficiency losses, underscoring agriculture's vulnerability to climate variability. Policy and institutional effects were localized and inconsistent, as they exceeded 1 percent only in three northern departments located across different regions —coast, highlands, and Amazonia. In contrast, improvements in OTEI emerged as the most critical yet fragile driver of productivity, given the heterogeneity in both the sign and magnitude of growth rate across departments (see **Table 3**).

Geographical dynamics of TFP growth

The analysis of TFP across Peruvian departments in 2015 and 2022[8] reveals substantial geographic disparities and notable shifts in productivity dynamics over time. In 2015, high TFP levels were concentrated in a few coastal departments—Tumbes, Piura, Lima, Ica, and Arequipa. By 2022, the productivity landscape had shifted considerably: the Amazonian regions—including San Martín, Amazonas, and Madre de Dios—moved into the highest productivity quintile, joined by Lambayeque, Ancash, and Tacna. Conversely, several departments in the center and south of the country experienced stagnation or decline, slipping into lower quintiles.

Figure 2. Comparison of departmental TFP between 2015 and 2022[9]



Source: Authors' calculations using ENA's information.

Table 4 illustrates the changes in departments' quintile rankings between 2015 and 2022: 9 improved their ranking, 12 maintained their positions, and 3 experienced a decline. Consequently, 6 regions fall into the first and second quintiles, accounting for approximately 38.1% of the country's total farmers (nearly 800,000) and 43.5% of total agricultural land (MIDAGRI, 2025). These results suggest that more than one-third of Peruvian farmers are obtaining insufficient production returns, implying inefficient input use and consequently lower income and profits.

[8] The negative results for 2023 mentioned in the previous subsection led us to compare TFP for 2015 and 2022, rather than 2023, to show a trend of previous years.
[9] For comparison purposes, 2015 thresholds were used to define each department's position in 2022.

Table 4. Changes in departments' TFP quintile position between 2015 and 2022 (using 2015 thresholds)

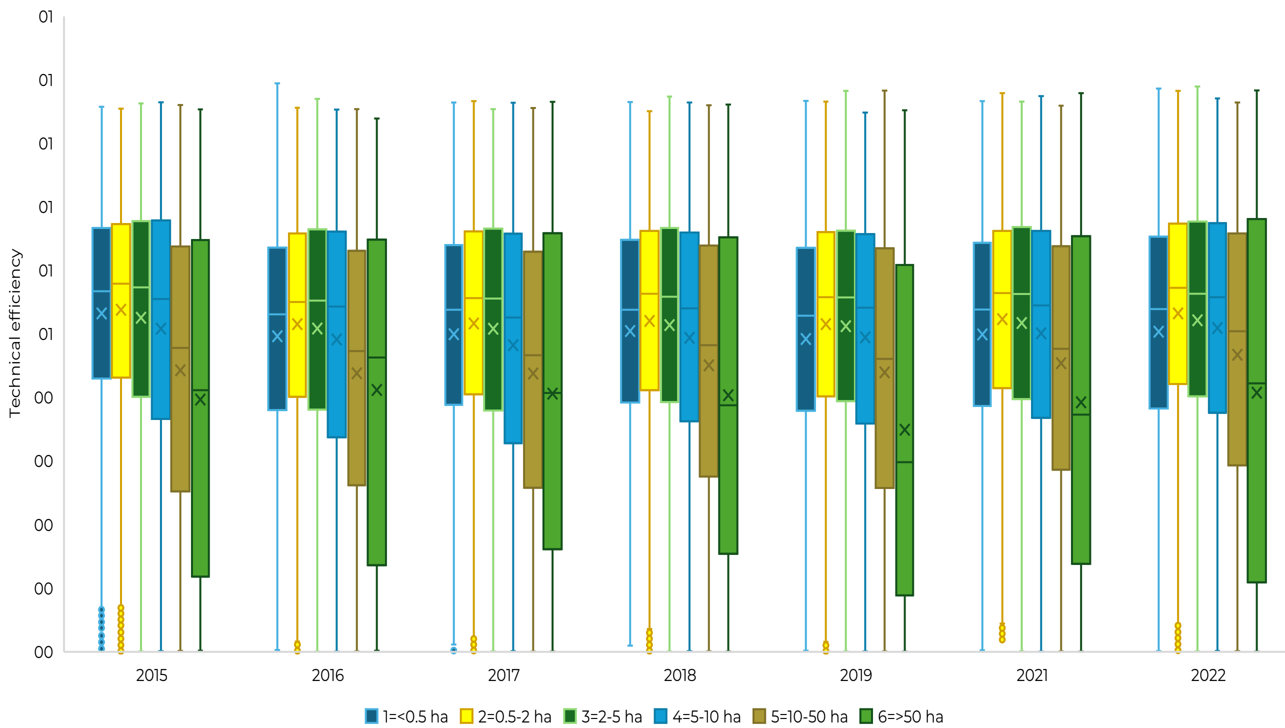
Variation between 2015 and 2022	Quintile position in 2022, using 2015 thresholds				
	Q1	Q2	Q3	Q4	Q5
Increase			Ayacucho Cajamarca Junín		Lambayeque Amazonas Ancash Madre de Dios San Martín Tacna
Stagnation	Huánuco Cusco Huancavelica Puno	Pasco	Loreto Ucayali	La Libertad	Ica Lima Piura Tumbes
Decline	Apurimac	Moquegua		Arequipa	

Source: Authors' calculations using ENA's information.

Relationship between technical efficiency and land size

Figure 3 illustrates the evolution of technical efficiency by farm size category between 2015 and 2022. The results consistently reveal a slightly inverse U-shaped relationship between land size and technical efficiency: small farms (<0.5 ha) and medium-large farms (5–10 ha) have lower levels of technical efficiency, while medium-sized farms (0.5–5 ha) achieve the highest mean and median technical efficiency, generally clustering around 0.5–0.6. However, very large farms (>10 ha) record lower efficiency, with levels around 0.4 and, in some cases, 0.3. Despite minor year-to-year fluctuations, the relative ranking of farm sizes remains stable, with medium-sized farms systematically outperforming both extremes. This persistent pattern indicates that scale advantages are realized only up to a moderate land size, beyond which efficiency tends to decline, likely due to management challenges in larger operations (Julien, Bravo-Ureta, & Rada, 2019).

Figure 3. Department technical efficiency and land size category (2015 and 2022)



Source: Authors' calculations using ENA's information.

IV. CONCLUSIONS AND POLICY RECOMMENDATIONS

Drawing on the empirical findings presented in this chapter, several policy recommendations emerge to strengthen productivity growth in the Peruvian agricultural sector.

I. Prioritize improvements in technical efficiency to reverse recent TFP decline and mitigate volatility

The recent decline in TFP in 2023, largely attributed to a lack of fertilizers and volatile weather conditions, combined with overall instability in the sector between 2015 and 2023, signals the need to strengthen efficient input use. Technical efficiency consistently emerges as the main dynamic driver of both gains and losses in productivity, underscoring the fragility of recent improvements. To consolidate progress, national agricultural policy should focus on strengthening agricultural extension services, improving access to technical training, and promoting farm-level innovations in resource management (i.e., adoption of certified seeds and efficient irrigation techniques). Such interventions directly target the core determinant of TFP performance.

II. Address persistent structural constraints to unlock further productivity growth

While essential, foundational elements such as rural infrastructure and human capital have not been fully harnessed to support TFP growth. Although paved roads have had a significant positive impact on the total value of agricultural production, the overall infrastructure index does not appear to be a major driver of TFP. Public investment should prioritize improving rural connectivity to reduce transaction costs and enhance access to input and output markets. In contrast, although certain human capital variables—such as gender—have positive effects on production in the regression analysis, the human capital index generally exhibits a weak or near-zero impact on TFP growth in most years and remains its weakest contributor. This points to significant untapped potential to boost TFP by addressing persistent limitations in farmer education and skills, which may hinder the adoption of new technologies. Moreover, the results underscore the importance of targeting women farmers in policy interventions, as they continue to lag behind their male counterparts. Addressing market failures and structural barriers faced by women in rural areas could therefore catalyze agricultural productivity growth.

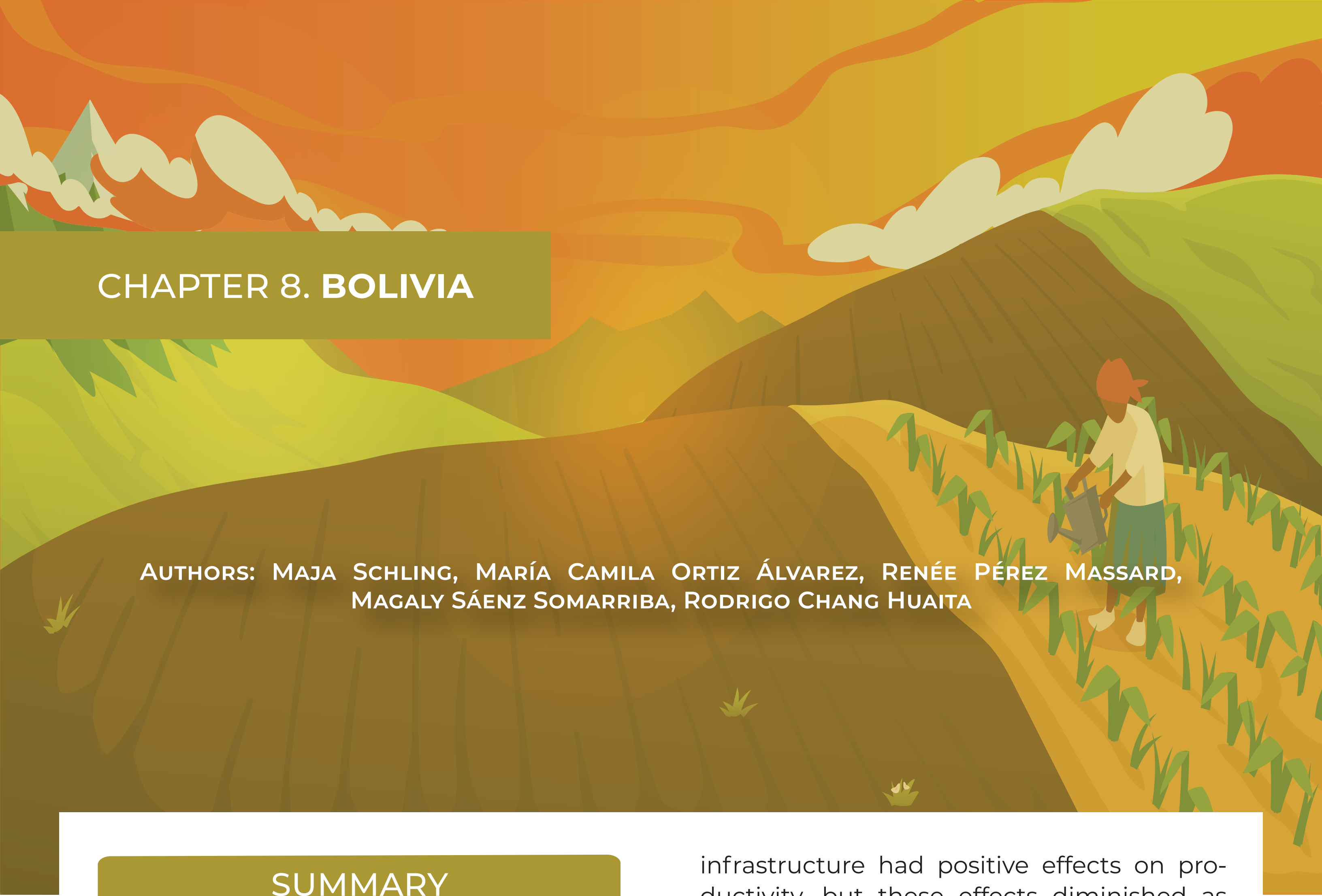
III. Implement differentiated departmental policies to address disparities in TFP and technical efficiency

The persistent and wide variation in TFP and technical efficiency levels across Peruvian departments calls for context-specific policy designs that account for particular geographical features. The contrasting trajectories observed among the departments of Amazonia, coastal areas, and the highlands demonstrate the need for actions tailored to each specific regional context. For instance, the departments of Amazonia have demonstrated notable improvements in both TFP and technical efficiency between 2015 and 2022/2023. These successful pathways could be supported further or used as models and case studies. Likewise, lagging departments in the highlands could benefit from strengthening regional extension services, expanding climate-smart practices, and improving rural infrastructure. Such policies could help narrow the geographic productivity gap and promote more balanced agricultural development across Peru.

IV. Invest in technologies to sustain productivity growth under climate variability

The results highlight the significant influence of the weather index on TFP, which underscores the need to implement technologies that allow for a more efficient use of available water resources. This is particularly important in the context of climate change. The strong positive outcomes associated with drip- or gravity-based irrigation on productivity indicate that investment in these technologies can enhance productivity, especially in departments lagging in both TFP and technical efficiency.

In summary, to promote more stable and sustained productivity gains in Peruvian agriculture, policies should prioritize enhancing technical efficiency through farmer training, improved access to quality inputs (e.g., certified seeds), and agricultural extension programs. At the same time, investments in climate resilience—such as early warning systems, climate-smart practices, and irrigation infrastructure—are essential to mitigating the adverse effects of weather variability on agricultural performance.



CHAPTER 8. **BOLIVIA**

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SUMMARY

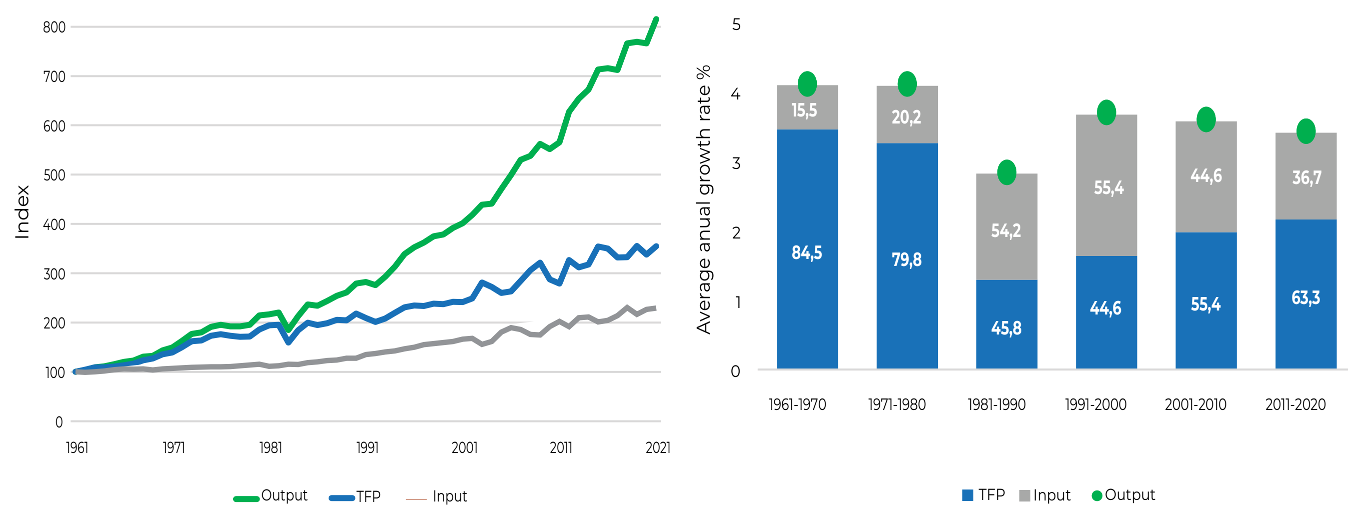
Evidence of the evolution of agricultural productivity and its determinants in Bolivia is scarce and has largely come from studies with a regional focus. This chapter addresses that gap by analyzing changes in agricultural productivity in Bolivia between 2008 and 2015 and the factors driving these changes, using national agricultural surveys and census data. Our findings suggest that agricultural total factor productivity increased by 1.8% annually during this period. Among productive inputs, land had the largest marginal effect on the value of agricultural production. Regarding temperature shocks, we find that each additional harmful degree day during the growing season was associated, on average, with a 9.8% decrease in the value of agricultural output. With regards to policy drivers, short-term cumulative titled agricultural area had no statistically significant effect on productivity. Public irrigation infrastructure had positive effects on productivity, but these effects diminished as precipitation levels rose. Overall, this chapter's findings underscore the importance of continuing to invest public resources efficiently in infrastructure that can boost agricultural productivity, while prioritizing investments in regions with the lowest productivity growth rates and the smallest shares of land and workers.

I. INTRODUCTION

Agriculture is a cornerstone of Bolivia's economy, contributing an average of 12.3% to GDP over the past five years and employing 24% of the workforce in 2023 (World Bank, 2024). Over the last 20 years, the country's agricultural frontier has expanded significantly, increasing from 1.9 million to 4.5 million hectares between 2003 and 2023.

According to Salazar et al. (2024), Bolivia has experienced a significant growth in agricultural production over the past 60 years. Using USDA-ERS data, the authors report average output growth of 3.6% per year between 1961 and 2002 (see **Figure 1**), explained mainly by gains in total factor productivity (TFP), which grew at an average annual rate of 2.1%. Input use also followed a positive, albeit less marked, dynamic during this period, growing at an annual average of 1.4%. Productivity growth began to outpace input use in the 1970s and has continued to do so since.

Figure 1. Agricultural output, inputs, and TFP in Bolivia, 1961–2021



Source: Salazar et al. (2025) using data from USDA-ERS.

At the national level, empirical estimates of TFP growth for Bolivia vary considerably depending on data and methodology. Dias Avila and Evenson (2010) report an annual TFP growth of 2.31% for Bolivia between 1961 and 2001, which, though moderate, is above the regional average of 1.85%. By contrast, most other studies estimate much lower TFP growth for Bolivia, oftentimes below the regional average. For instance, Ludeña (2010) estimates Bolivia's annual TFP growth at just 1.9% between 1961 and 2007. Similarly, Trindade et al.'s (2015) TFP estimates for Bolivia range from 0.7% to 2.22%; the authors highlight Bolivia as one of the lowest-growth countries in South America. Nin-Pratt (2015) finds an average annual TFP growth rate of 1.6%, with negative efficiency growth, between 1980 and 2012. More recent studies incorporate climate variability directly into TFP decomposition. For example, Lachaud et al. (2017) analyze the effect of climatic variability on TFP across 28 Latin American and Caribbean (LAC) countries between 1961 and 2012. They find that climatic variability negatively impacted Bolivia's annual TFP growth rate, which fell from 1.18 to 0.45 after accounting for climatic variables. Other studies emphasize the importance of a range of factors in boosting productivity in Bolivia, including irrigation (Giordano et al., 2023; Salazar and López, 2018), electrification (Lee et al., 2020; Chakravorty et al., 2016), adoption of agricultural technologies (Salazar et al., 2025), and land titling (Besley, 1995; Schling et al., 2024).

Empirical evidence on TFP dynamics within Bolivia remains scarce, as most studies have relied on aggregate national-level data, limiting insight into within-country heterogeneity. This chapter addresses that gap by analyzing municipal-level changes in agricultural productivity in Bolivia between 2008 and 2015, using national agricultural surveys and census data. To examine productivity dynamics across municipalities, farm-level survey data is aggregated to the municipal level. This approach is necessary because Bolivia's data does not allow identification of individual farmers or households, thus precluding a micro-level analysis that tracks the same farmers across survey rounds. As a result, the analysis provides insights into productivity trends across municipalities but cannot capture within-municipality dynamics or heterogeneities.

Despite the rapid growth of the agricultural sector, driven largely by land expansion, estimates from the United States Department of Agriculture (USDA) show that Bolivia's land and labor productivity remain low compared to other countries in the region, and yields of key crops remained below the Latin American average between 2006 and 2018 (Alcaraz Rivero et al., 2020; Díaz Ríos et al., 2019). Therefore, improving productivity is a central goal of Bolivia's agricultural development plans. According to the Comprehensive Development Plan for the Agricultural and Rural Sector (MDRyT, 2024), several factors have hindered productivity growth in the country, including limited innovation, restricted access to financial services, inadequate infrastructure, weak pest and disease prevention and control, ecosystem degradation, and biodiversity loss. In recent decades, public investments in the sector have focused on land titling, irrigation, plant and animal health, food security, and, to a lesser extent, research and innovation. Programs have prioritized expanding irrigation and mechanization, often through direct support to producers, especially in poor and marginalized communities (Díaz Ríos et al., 2019). Productivity is not only influenced by domestic policies, integration into international markets and investment flows also create opportunities for technological upgrading, organizational learning, and the dissemination of best practices across producers.

Key initiatives illustrate this focus. For example, the National Irrigation Plan seeks to enhance food security and rural development through the sustainable use of water for agricultural and forestry production, with a focus on equity, social participation, and institutional strengthening. Improving land tenure security to increase farmers' income and food security has been another focus. In 1996, Bolivia enacted the National Agrarian Reform Service Law, formally tasking the newly created National Agrarian Reform Institute (INRA) with regularizing and titling the rural land in Bolivia. Since 2002, the Inter-American Development Bank (IDB) has supported the Bolivian government with the implementation of the National Plan for Land Regularization and Titling. This initiative has resulted in the regularization and titling of 87% of the country's rural areas and has significantly reduced gaps in land access for smallholders and Indigenous communities (Schling et al., 2024).

Climate change adaptation strategies constitute a major challenge for the country. In recent decades, rising temperatures and increasing variability in rainfall have made climate one of the key factors influencing productivity in Bolivia. For example, declines in agricultural GDP in 2010 and 2016 were driven by adverse weather conditions that severely affected soybean production (UDAPE, 2015). Furthermore, these disruptive effects of climate disasters on the agricultural sector have been shown to increase food insecurity and poverty, especially among women (Escalante & Maisonnave, 2022).

Bolivia exemplifies both the opportunities and challenges of sustainable agricultural productivity growth in LAC. Given the agricultural sector's importance for Bolivia's economic growth, understanding its dynamics and determinants is essential. This chapter analyzes the changes in agricultural productivity in Bolivia between 2008 and 2015 and the factors driving these changes. To do so, it uses nationally representative survey data and the most recent agricultural farm-level census to construct a balanced municipal-level panel. A micro-econometric analysis is then used to estimate the contribution of public investments in irrigation and land titling to productivity growth.

II. METHODOLOGY AND DATA

This chapter addresses four main research questions:

I. How did Bolivia's agricultural productivity change between 2008 and 2015?
II. What were the primary drivers of and barriers to agricultural productivity growth during this period?
III. How did weather shocks impact agricultural productivity?
IV. How did public investment in land titling and irrigation affect agricultural productivity?

To answer these questions, the study combines data from several sources presented in **Table 1.**

Table 1. Data sources

Data	Description	Source
Farm-level agricultural production	Data from agricultural households: input use, land use, crops, livestock, and production levels (2008, 2013, 2015)	2008 National Agricultural Survey (ENA); 2013 National Agricultural Census; 2015 National Agricultural Survey (ENA)
Irrigation	Publicly financed irrigation projects in each municipality, including new construction and improvements of irrigation and micro-irrigation systems (2011–2015)	Administrative data from the Ministry of Environment and Water (MMayA)
Land titling	Land area titled in each municipality (1997–2015)	Administrative data from the National Institute for Agrarian Reform (INRA)
Temperature shocks	Satellite data recording average daily temperature (2008–2015)	USGS Terra Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature/Emissivity Daily (MOD11A1)
Precipitation	Satellite data recording total daily precipitation (2008–2015)	Copernicus: Essential weather variables for water sector applications derived from weather projections

These data allow us to conduct a robust econometric analysis of agricultural productivity changes in Bolivia by employing stochastic frontier analysis (SFA) to measure TFP. SFA is a statistical approach used to estimate a stochastic production function. An SPF is a production function that relates inputs to outputs while explicitly incorporating two additional components: random noise (which captures measurement error and other random shocks) and inefficiency (which captures individual producers' performance relative to the production frontier). Using this methodology with a balanced panel of 231 municipalities and a multiple imputation technique[1] enables us to track fluctuations in overall productivity while also isolating the individual contributions of technological progress, technical efficiency change, scale effects, weather shocks, and statistical noise. Moreover, the models used to derive the TFP decomposition account for the effects of weather variability on productivity.

Table 2. Main policy drivers of interest

Variables of interest	Description
Irrigation investment	Number of hectares in the municipality that received irrigation investment between 2011 and the year before the survey, divided by the municipal agricultural land area. This includes expansions (new construction) and improvements (rehabilitation of existing infrastructure)
Land titling (per capita)	Short-term: Number of hectares titled in the municipality the last two years before each survey, divided by the municipality's rural population
	Long-term: Number of hectares titled between 1997 and the year before each survey, divided by the municipality's rural population

Stochastic production frontier and TFP decomposition

To measure TFP and analyze its sources, this chapter combines a stochastic production frontier approach and a TFP decomposition. The model decomposes TFP into scale effects, technical efficiency change, technological progress, weather effects, and statistical noise. The following stochastic production function is estimated to assess municipal TFP:

$$\ln y_{it} = \beta_0 + \sum_{k=1}^{K} \beta_k \ln x_{kit} + \sum_{j=1}^{J} \eta_j z_{jit} + \sum_{t=1}^{T-1} \delta_t D_t + \sum_{r=1}^{R-1} \gamma_r R_{ri} + \sum_{r=1}^{R-1}\sum_{t=1}^{T-1} \theta_{tr} (R_{ri} \times D_t) + \alpha_i + v_{it} - u_{it} \quad (1)$$

[1] Methodological note: This chapter employs a multiple imputation approach by chained equations, which iteratively imputes missing (null values) values for the variables hired labor, input use, and capital use through conditional univariate models. As predictor variables, the imputation includes values of the same variables reported in the agricultural census 2013, as well as additional relevant information for productive activity: the value of agricultural production, cultivated area, and family labor available for all three rounds, in addition to rural population. 100 imputed datasets are generated, each representing a complete version of the original dataset in which missing values are imputed differently, thereby incorporating the uncertainty associated with the true missing values. From these versions, the average of the imputed values is calculated for each missing observation, and this average is used as the final imputed value in the analysis.

where y_{it} is the value of agricultural production for municipality i at time t; x_{kit} is a vector of inputs; and z_{jit} are weather variables, as defined in **Table 3**. D_t are year dummies; while R_{ri} refers to regional dummies (Lowlands, Valleys, Highlands) to control for structural and geographical differences across the country's agroecological regions. The interaction terms $R_{ri} \times D_t$ allow region-specific technical change to vary over time, while αi is a time-invariant, municipality-specific random term that captures cross-municipality heterogeneity. The composite error term consists of two components: v_{it}, the idiosyncratic component (assumed to follow a standard normal distribution) and u_{it}, representing the technical inefficiency term (assumed to follow a half-normal distribution).

Table 3. Variables included in the municipal-level production function

Level	Output	Inputs	Weather variables
Municipal	Production value (crops)	Land, family labor, labor expenses, capital (farm equipment), fertilizers, and pesticides	Mean daily precipitation; mean squared daily precipitation; mean growing degree days; mean harmful degree days

** All variables correspond to the agricultural season.*

Policy drivers

In addition to the TFP decomposition, we estimate the effects of public policies – specifically, public investments in irrigation and land titling – on agricultural productivity. The effects of these policy drivers are summarized in **Table 5**. To assess the productivity effects of irrigation and land titling on agricultural productivity, we estimate an ordinary least squares (OLS) production function with fixed effects at both the municipality and year level. Municipal fixed effects control for the unobserved, time-invariant characteristics of municipalities that may influence productivity (such as altitude), while year fixed-effects allow us to control for time-variant factors that may have impacted productivity across all municipalities in a given year (such as economic shocks). Our municipal-level production function is defined as follows:

$$\ln y_{it} = \rho\, T_{it} + \sum_{k=1}^{K} \beta_k \ln x_{kit} + \sum_{j=1}^{J} \eta_j z_{jit} + \sum_{t=1}^{T-1} \delta_t D_t + \sum_{r=1}^{R-1} \gamma_r R_{ri} + \sum_{r=1}^{R-1}\sum_{t=1}^{T-1} \theta_{tr} (R_{ri} \times D_t) + \alpha_i + \lambda_t + \varepsilon_{it} \quad (2)$$

where the primary independent variable T_{it} is defined differently depending on whether the analysis focuses on land titling or irrigation. For land titling, T_{it} is defined as the area titled in each municipality over a given timeframe, divided by the municipality's rural population. We examine both short- and long-term effects of titling on productivity, defining T_{it} as the land area titled in each municipality in the two years before each survey round (to capture short-term impacts) or as the cumulative titled area per capita between 1997 and the year before each survey round (to capture long-term impacts). For irrigation, T_{it} is defined as number of hectares covered by new or rehabilitated irrigation infrastructure[2] in each municipality, divided by the municipality's agricultural land area.

[2] The number of hectares covered by irrigation investments includes both expansions in irrigation infrastructure (new construction) and improvements in existing irrigation infrastructure.

III. FINDINGS

The decomposition of national TFP shows a modest annual increase of 1.8% between 2008 and 2015 (Table 4)**.** These gains were largely driven by technological progress, which grew at an annual rate of 1.38%. By contrast, technical efficiency experienced a slight decline over the study period (-0.05%).

Table 4. Decomposition of TFP by natural regions: annual growth rate (%), 2008–2015

Region	Output index	Input index	TFP index	Scale effects index	Technical efficiency change index	Technological progress index	Weather effects index	Statistical noise
National	4.11	2.28	1.80	0.73	-0.05	1.38	-0.27	-0.01
Lowlands	-0.42	1.17	-1.57	0.38	0.61	-1.89	-0.62	-0.05
Valleys	9.11	3.34	5.58	1.07	-0.55	5.03	-0.03	0.04
Highlands	3.39	2.19	1.18	0.70	-0.08	0.81	-0.22	-0.03

Notes: The table decomposes the annual growth rate of each index (expressed as a percentage) between 2008 and 2015, based on the results of the stochastic production function detailed above. The output index measures annual output growth, while the input index measures annual input growth. Any output growth not explained by input growth is attributed to TFP growth. The TFP index is further decomposed into five components: scale effects, changes in technical efficiency, technological progress, weather effects, and statistical noise. The growth rates for each of these indices therefore measures how much each component contributed to TFP growth. Positive values indicate positive impacts on TFP growth, while negative values indicate negative impacts on TFP growth.

Source: Authors' own calculations. Agricultural and output data comes from the 2008 National Agricultural Survey (ENA), the 2013 National Agricultural Census, and the 2015 National Agricultural Survey (ENA). Temperature data comes from MODIS Land Surface Temperature/Emissivity Daily, and precipitation data comes from Copernicus Essential Climate Variables.

Productivity varied significantly across Bolivia's natural regions, which showed the following annual TFP growth rates: 5.58% in the Valleys, 1.18% in the Highlands, and -1.57% in the Lowlands.[3] The Valleys, characterized by diversified crop production and smallholder farming, recorded the strongest TFP growth, with an average annual rate of 5.58%, driven largely by gains in technological progress (5.03%) and scale efficiency. The Highlands achieved more moderate productivity growth (1.18% annually), supported by steady technological progress and scale efficiency, despite limited improvements in technical efficiency. In contrast, despite exhibiting the highest levels of productivity in the country, the Lowlands experienced a 1.57% annual decline in TFP, primarily due to a sharp drop in technological progress and adverse weather effects. Overall, the positive contribution of scale efficiency suggests that the rising scale of production contributed to TFP growth during the study period.

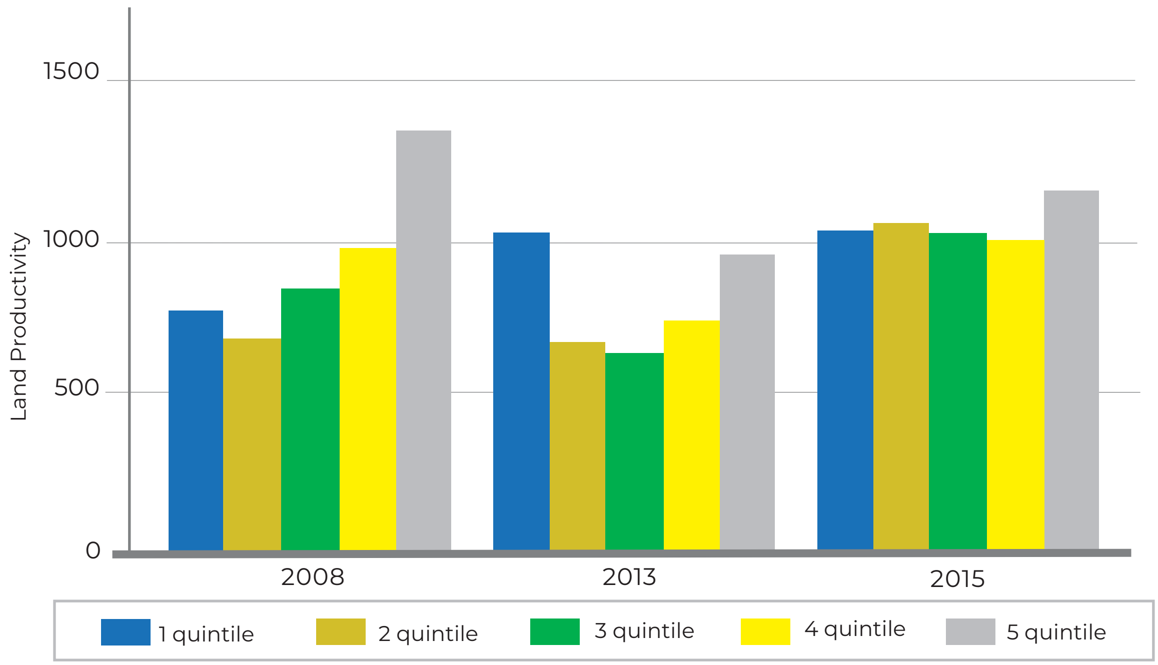
Weather shocks negatively affected TFP growth at both national and regional levels, reducing TFP growth by 0.27% per year on average. The Weather Effects Index in Table 4 shows the impact of precipitation and temperature shocks on TFP across Bolivia and in each of the country's regions. At the national level, weather shocks reduced TFP growth by 0.27% per year on average. At the regional level, the Lowlands were the most affected, with weather shocks

[3] We follow the natural region classifications used in Daga (2020): Lowlands (departments of Beni, Pando, and Santa Cruz); Valleys (departments of Chuquisaca, Cochabamba, and Tarija); and Highlands (departments of La Paz, Oruro, and Potosí).

contributing to a 0.62% annual decline in productivity. The Valleys and Highlands experienced smaller negative impacts of 0.03% and 0.22%, respectively. These results highlight that, despite gains in technological progress and modest improvements in efficiency in some regions, climate variability remains an important constraint on agricultural productivity growth in Bolivia.

BOLIVIA'S LARGEST FARMS (BY LAND SIZE) BECAME LESS PRODUCTIVE OVER TIME, WHILE THE SMALLEST FARMS (BY LAND SIZE) BECAME MORE PRODUCTIVE OVER TIME. While TFP provides a comprehensive measure of productivity by accounting for all inputs, additional insights into disparities in productivity can be offered by examining differences in productivity levels relative to land size and labor availability. Figure 3 illustrates the relationship between farm size and land productivity from 2008 to 2015, showing distinct trends for farms of different sizes.

FIGURE 3. LAND PRODUCTIVITY BY FARM SIZE GROUP, 2008–2015



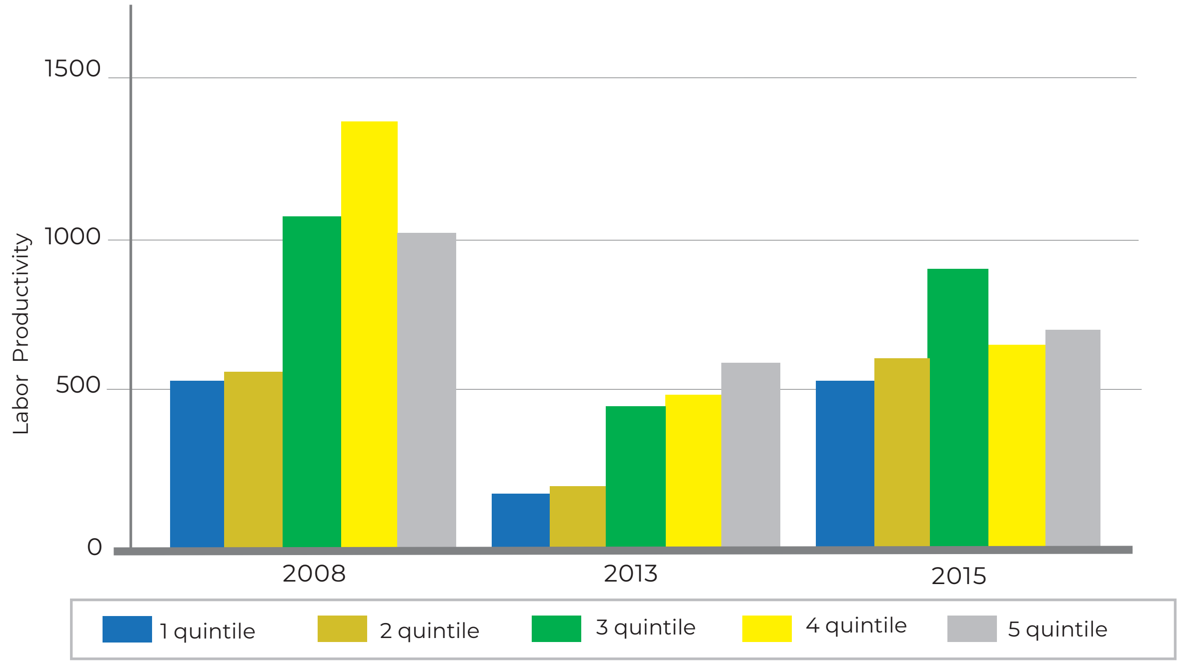
Estimate quintiles using the pooled sample from all years.

Note: Each quintile represents a farm size group, with quintiles arranged from smallest to largest. Quintile 1 represents the smallest 20% of farms by land size, while quintile 5 represents the largest 20% of farms by land size. Land productivity is defined as agricultural output per hectare.

Source: Authors' own calculations, based on the 2008 National Agricultural Survey (ENA), the 2013 National Agricultural Census, and the 2015 National Agricultural Survey (ENA).

Although the largest farms by land area (quintile 5) had the highest levels of land productivity in 2008, their productivity declined by 2015. Meanwhile, land productivity for small and medium-sized farms (quintiles 1, 2, and 3) increased over the same period. These trends point to a convergence in productivity, as the largest farms became considerably less productive per unit of land over time, and small and medium-sized farms became more productive per unit of land over time (see Figure 3).

FIGURE 4. LABOR PRODUCTIVITY BY FARM LABOR-INTENSITY GROUP, 2008–2015



Estimate quintiles using the pooled sample from all years.

Note: Each quintile represents a labor-intensity group, with quintiles arranged from least labor-intensive to most labor-intensive, based on a labor index that combines both family labor and hired labor. Quintile 1 represents the smallest 20% of farms by labor use, while quintile 5 represents the largest 20% of farms by labor use. Labor productivity is defined as output divided by unit of labor (as defined by the labor use index).

Source: Authors' own calculations, based on the 2008 National Agricultural Survey (ENA), the 2013 National Agricultural Census, and the 2015 National Agricultural Survey (ENA).

BOLIVIA'S LARGEST FARMS (BY LABOR USE) BECAME LESS PRODUCTIVE OVER TIME, AND THE SMALLEST FARMS (BY LABOR USE) SAW NEGLIGIBLE INCREASES IN LABOR PRODUCTIVITY.

As Figure 4 shows, labor productivity also shows distinct trends for farms with different levels of labor use. Similar to the land productivity analysis, in 2008, farms that used more labor (quintiles 3-5) had significantly higher labor productivity compared to the least labor-intensive farms (quintiles 1 and 2).

However, by 2015, labor productivity among the most labor-intense farms declined considerably, while farms with the lowest labor use saw a slight increase in labor productivity. Overall, the productivity gap between the more labor-intensive farms and less labor-intensive farms diminished significantly between 2008 and 2015. However, this change was primarily driven by larger-workforce farms becoming less productive over time, as smaller-workforce farms only became slightly more productive over time.

Table 5 details the results of the regression examining the relationship between irrigation, land, titling, and agricultural production value.

Table 5. Impact of irrigated area expansion and land titling on TFP

Dependent Variable: Log Production Value	-1	-2	-3
Irrigated Hectares	6.593** -2737		
Irrigated Hectares x Average daily precipitation	-8.929* -4747		
Irrigated Hectares x Average of squared daily precipitation	0.317 (0.285)		
Titled hectares per capita (last 2 yrs)		-0.002 (0.002)	
Titled hectares per capita (1997- survey year)			-0.003*** (0.000)
Municipality FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes
R-squared	0.959	0.929	0.929
Period	2013-2015	2008-2015	2008-2015
Observations	**424**	**693**	**693**

Notes: All inputs and climatic variables were incorporated into the regression specification as controls. "Irrigated area" refers to cumulative irrigated hectares (2011–pre-survey year), normalized by 2013 cultivated area. Estimates for irrigation exclude the departments of Pando and Beni. "Titled hectares per capita (last 2 yrs)" refers to the sum of hectares titled during the two years prior to each survey round, divided by the municipal rural population. Robust standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' own calculations. Agricultural and output data comes from the 2008 National Agricultural Survey (ENA), the 2013 National Agricultural Census, and the 2015 National Agricultural Survey (ENA). Temperature data comes from MODIS Land Surface Temperature/Emissivity Daily, and precipitation data comes from Copernicus Essential Climate Variables. Irrigation data comes from the Ministry of Environment and Water (MMayA)'s administrative data, and titling data comes from the National Institute for Agrarian Reform (INRA)'s administrative records.

Public investment in irrigation infrastructure has positive effects on agricultural productivity. This finding is consistent with the broader literature linking irrigation to agricultural productivity gains. As expected, when an interaction term is included for irrigation and average precipitation, statistically significant negative effects are observed, suggesting that the positive effect of irrigation diminishes as average precipitation increases.

This finding suggests that the productivity effects of irrigation investments are larger in lower-rainfall municipalities, confirming the need for investments that reduce farmers' vulnerability to weather fluctuations. Along with our finding that extreme temperatures have a negative effect on TFP growth, this result further points to the importance of addressing farmers' resilience to weather shocks.

The productivity effects of public investment in land titling are inconclusive. The results suggest that, in the short term (in the two years before each survey round) changes in land titling are not associated with any statistically significant effect on productivity. Meanwhile, in the long term (from 1997 to the year before each survey round), increases in titled hectares per capita are associated with a negative effect on agricultural productivity.[4] An impact assessment in Bolivia conducted by Schling et al. (2024) confirms that holding a title increased technical farmers' technical efficiency, access to credit, and productive investments. Hence, although the evidence on productivity is mixed, public policy efforts should continue to promote land tenure security as a means of improving rural livelihoods, improving farmers' access to credit,[5] encouraging long-term investment, and increasing productive efficiency. Further research is needed to clarify the mechanisms through which land titling affects tenure security and thus productivity, and to assess whether these effects are more detectable at disaggregated levels of analysis. In the long term, the effectiveness of land titling may depend on complementary policies that help sustain and amplify its benefits.

Table 6 summarizes the effects of public investment in irrigation and land titling on agricultural productivity.

Table 6. Effects of policy drivers on productivity

Intervention type	Effect on productivity
Irrigation	On average, municipal-level investments in irrigation are associated with a positive effect on agricultural productivity at the municipal level. The positive effects of irrigation on productivity diminish as municipal rainfall increases.
Land titling	On average, short-term increases in titled land area at the municipal level were not associated with a statistically significant effect on productivity. Long-term increases in titled land area at the municipal level, on average, were associated with lower productivity.

IV. CONCLUSIONS AND POLICY RECOMMENDATIONS

The findings of this analysis fill significant empirical gaps and provide relevant insights to Bolivian policymakers and stakeholders regarding the effective use of public resources for productivity growth, food security, and rural welfare. The chapter also offers evidence to guide agricultural investments capable of unlocking long-term productivity gains. The main policy recommendations that emerge from the findings are as follows:

[4] A spatiotemporal analysis of Bolivia's land titling rollout reveals that the most productive municipalities had already achieved most of their titling progress before the study period. Consequently, the municipalities that saw the most substantial changes during the analysis were those with lower productivity levels. This sequencing may help explain the negative association observed between long-term titling and productivity, and needs to be address in future research.

[5] Under Bolivian national legislation, farm and ranch lands legally defined as "smallholdings" cannot be used as collateral. This restriction intends to prevent small landowners from selling their land in response to temporary shocks in order to safeguard their source of income and avoid the seizure of their assets (Murguia et al., 2017). However, as Murgia et al. (2017) finds, the legislation may have adverse effects for some smallholders.

I. Prioritize investments in research, development, and innovation (R+D+I) to sustain and accelerate agricultural productivity growth, ensuring strategies are tailored to region-specific contexts

In Bolivia, productivity gains have been driven primarily by technological progress, but these gains have been unevenly distributed across Bolivia's subregions. Technological progress gains have been primarily concentrated in the Valleys region, with the Highlands showing only marginal technological progress. In contrast, the Lowlands have experienced a decline in technological progress. This uneven distribution underscores the need for investments that foster technological development and adoption tailored to the specific socioeconomic, agronomic, and climatic conditions of each region.

II. Integrate climate resilience into agricultural policy agendas

Evidence from the TFP decomposition shows that weather shocks have significantly eroded productivity in Bolivia, reducing TFP by 0.27% per year on average. Agricultural development strategies must therefore prioritize climate resilience through interventions like early warning systems, robust agroclimatic forecasting and information services, widespread adoption of climate-smart technologies, and targeted technical assistance to help farmers anticipate and respond to extreme weather. In light of the sector's vulnerability to weather shocks, these measures are essential to safeguard productivity and ensure long-term sectoral sustainability.

III. Expand irrigation access as a critical climate adaptation measure that enhances productivity growth and resilience while improving water use efficiency

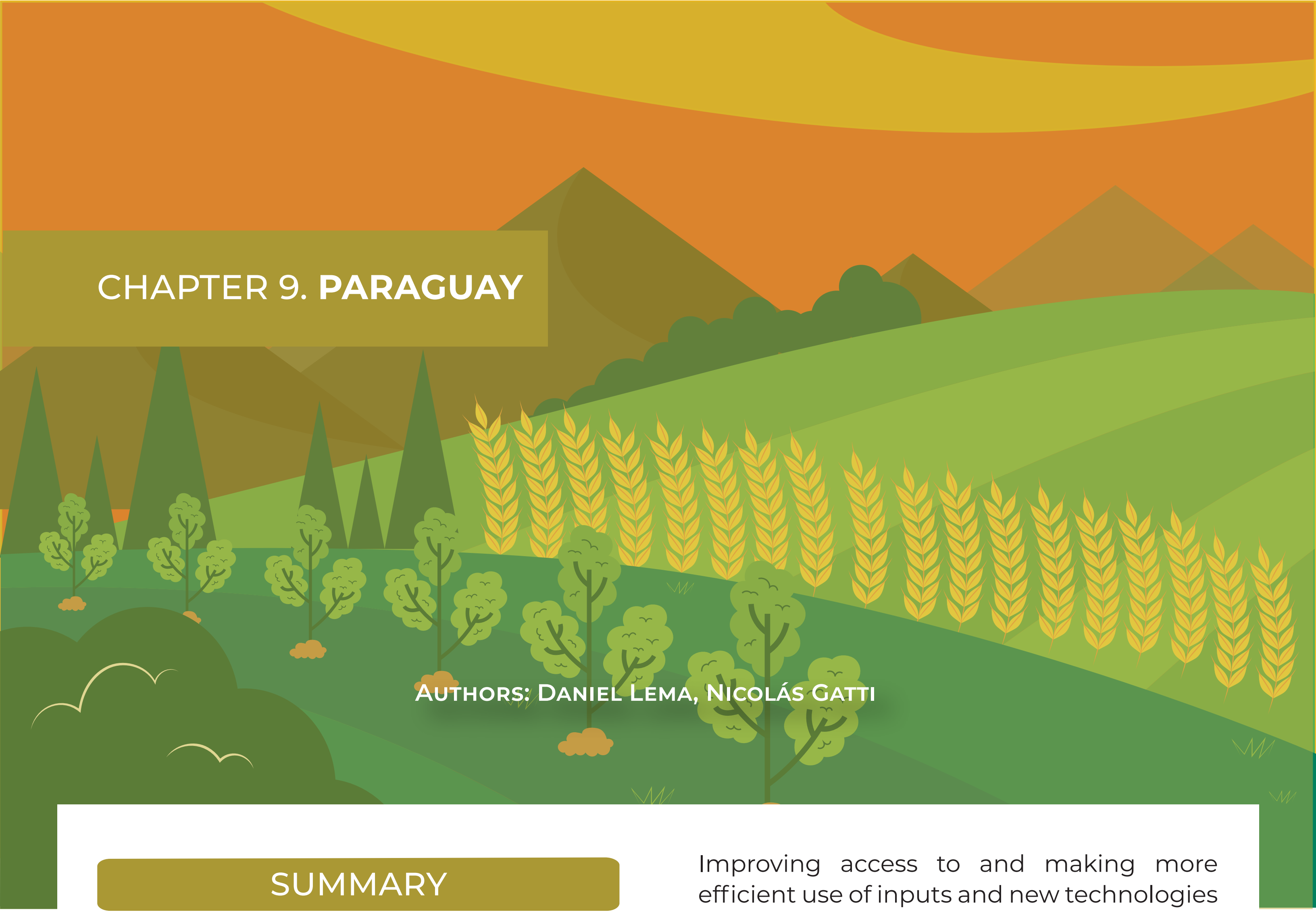
The analysis shows that public investment in irrigation has a statistically significant impact on productivity, particularly in areas with lower rainfall. Future programs should continue to support irrigation access for farmers, investing in irrigation solutions that are tailored to local hydrological conditions. Furthermore, to maximize impact and sustainability, investments in public irrigation infrastructure should be coupled with technical assistance in water use management to promote adoption and ensure efficient water use. Future irrigation programming should be designed with monitoring and evaluation frameworks that permit stakeholders to measure causal effects of irrigation on productivity in the short-, medium- and long-term.

IV. Pair land titling with complementary support services and further study the effects of land titling on productivity over time

This analysis finds inconclusive effects of titling on productivity, and the findings suggest the effects of land titling may vary over time. As aforementioned, the inconclusive results may be due to the aggregate level of this analysis, as previous studies have found positive effects of titling on technical efficiency in Bolivia. Nonetheless, these results suggest that land titling alone may be insufficient to produce productivity gains. To translate tenure security into tangible productivity improvements, titling should be paired with complementary support services, such as legal assistance, access to credit, and regular cadastral updates. Furthermore, to develop a comprehensive understanding of the effect of land titling on productivity, policymakers should collaborate with researchers to implement short-, medium-, and long-term studies that examine productivity dynamics at the level of individual farms.

V. Improve agricultural statistics for evidence-based policy making

The analysis in this chapter was limited by the lack of panel data at the farm level, which prevented us from exploring productive heterogeneity across different types of farmers within a single municipality. This may represent an important factor in determining the dynamics and drivers of productivity. To enable longitudinal evaluations that represent Bolivian farmers and their productive systems more accurately, public investments should focus on generating longitudinal agricultural statistics based on nationally representative farm household surveys. Strengthening data availability in this way would play a critical role in supporting evidence-based decision-making and policy design in the sector.



CHAPTER 9. **PARAGUAY**

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SUMMARY

This chapter uses microdata from the National Agricultural Censuses of 1991, 2008, and 2022 to estimate the evolution of total factor productivity (TFP) and technical efficiency in Paraguay's agricultural sector. The results show that agricultural TFP grew by approximately 2% per year, driven by technological improvements and structural changes in the sector. At the same time, technical efficiency declined, dropping from 52% to 32% of the maximum potential over the last 30 years. Regional differences are also evident: while eastern Paraguay remains more efficient, western departments such as Boquerón have shown relative improvements. The chapter concludes that technological change has played a key role in productivity gains and recommends strengthening agricultural extension services and investments in human capital to increase efficiency levels, especially in relatively less efficient areas. Improving access to and making more efficient use of inputs and new technologies constitutes a tangible opportunity to increase the value of agricultural production without relying solely on greater resource use or expanding the agricultural frontier.

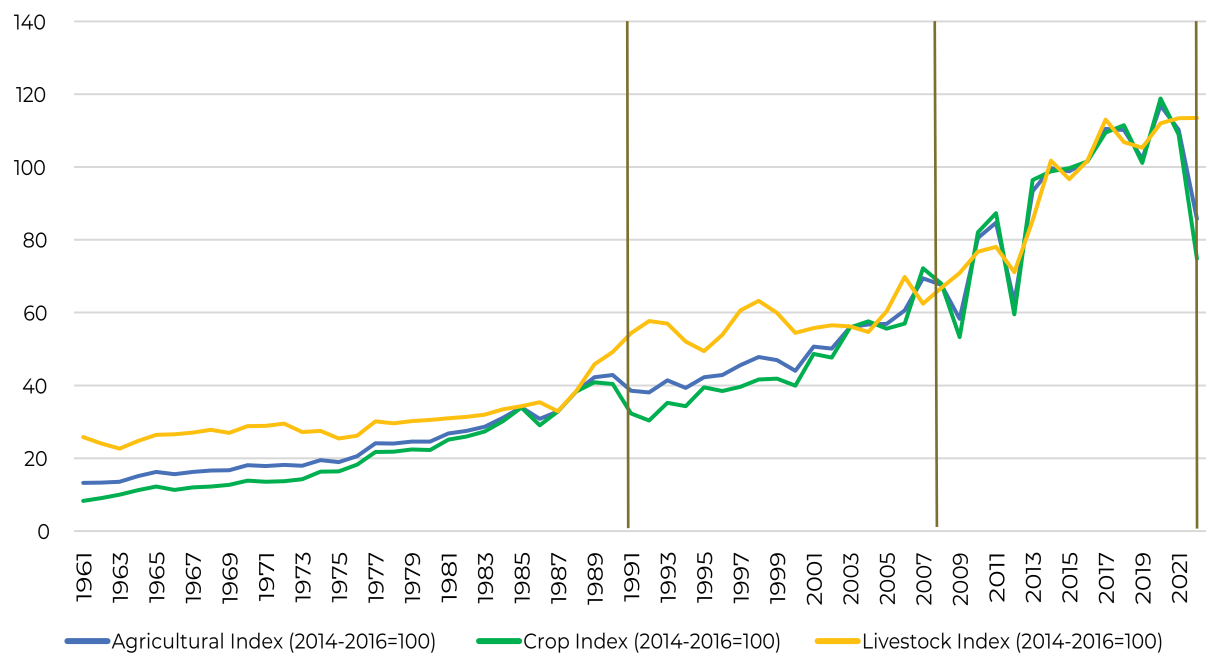
I. INTRODUCTION

Paraguay represents an interesting example of economic transformation in Latin America. Unlike its neighbors, it has remained open to trade for more than 60 years. According to official figures, Paraguay's exports have consistently accounted for more than 20% of GDP, with an average of over 70% during the last 30 years. This high degree of trade openness, together with growing foreign investment in agribusiness, could contribute to productivity growth through technology transfer, adoption of high quality market standards, and deeper integration with international value chains.

Regarding employment in the agriculture sector, the share of the total population working in the sector decreased from 29.6% in 1991 to 17% in 2023 (ILOSTAT, 2025). Over the past 60 years, the agricultural share of GDP declined from 37% in 1962 to 11.2% in 2022, with crops accounting for 7.6% and livestock for 2.8% (Instituto Nacional de Estadísticas, 2022). Despite the sector's importance in the Paraguayan economy, farm-level productivity studies have been scarce, and this chapter aims to help fill that gap.

Figure 1 shows the evolution of Paraguay's agricultural production. The vertical lines indicate the years of the agricultural censuses used in this study, which correspond to periods of significant change in the sector. During the first period (1961–1990), agricultural production showed only modest growth. Between 1991 and 2008, the sector entered a phase of slight expansion, initially driven by growth in livestock production and later reinforced by increases in crop output, particularly of soybeans. From 2008 to 2022, the upward trend persisted across both crops and livestock, with a higher growth rate than in the preceding period.

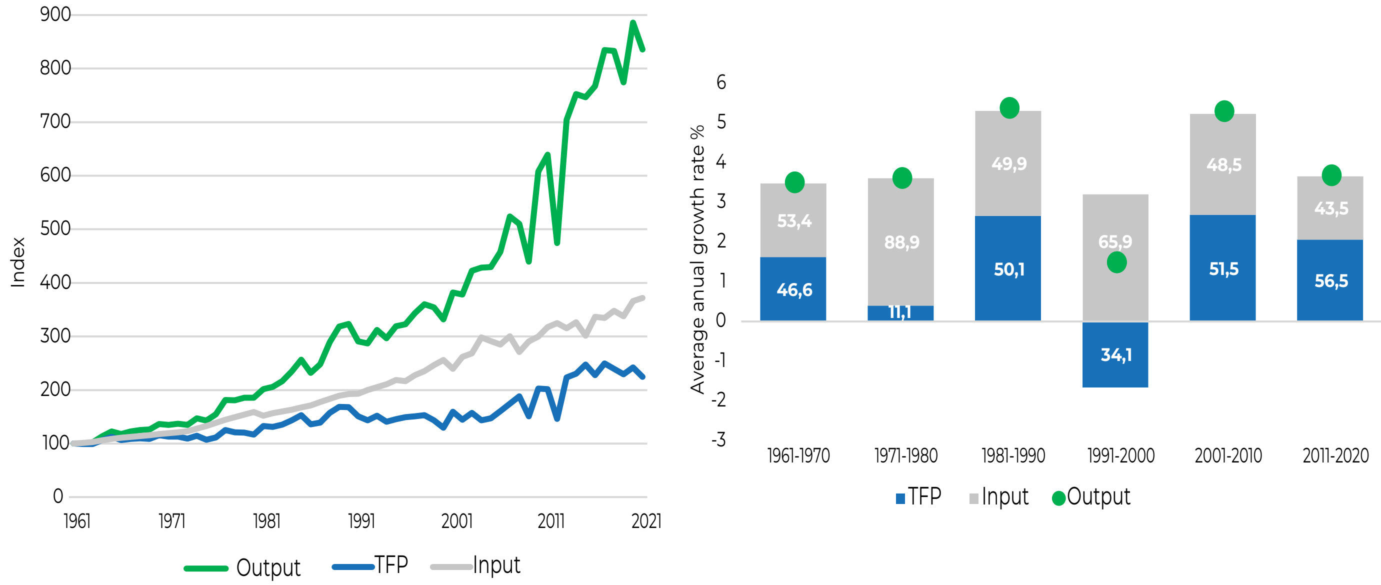
Figure 1. Evolution of agricultural production in Paraguay (1961–2022)



Source: Authors' calculations using FAOSTAT.
Note: Vertical lines represent the years of the agricultural censuses used in this study. Base prices 2014–2016=100.

A recent study published by the IDB (Salazar et al., 2025) highlights Paraguay's significant agricultural growth over the past 60 years (1961–2021). During this period, the country's agricultural output expanded more than eightfold, with an average annual growth rate of 3.6%. According to USDA-ERS data, this expansion was primarily driven by increased input use, which grew at an average annual rate of 2.2%. Total factor productivity (TFP) also contributed, although more moderately, averaging 1.4% per year, with periods of stagnation or even contraction in certain decades. Since 2000, however, agricultural growth in Paraguay has increasingly relied on productivity gains, which in several periods surpassed the effect of input use. This shift became more evident between 2011 and 2020, as agricultural output grew at an average annual rate of 3.7%, with 44% of this growth attributable to input use and 56% to improvements in TFP.

Figure 2. Total factor productivity estimations from the IDB (1961–2021)



Source: Salazar et al., (2025), based on USDA-ERS data.

To understand agricultural productivity in Paraguay, it is necessary to look at the policies implemented at different stages of the country's development. During the long period of de facto government from 1954 to 1989, policy sought to boost production for external markets (Nickson & Lambert, 2002). For example, soybean promotion programs launched in 1972 aimed to increase farmers' access to credit and help them modernize production (Wesz Junior, 2022). Immigration policies also played a role: migrants from Brazil and later from Argentina addressed Paraguay's low population density, as did the creation of agricultural colonies in the east of the country during the 1960s (Wesz Junior, 2022).

In the 1990s, a model based on the expansion of the agricultural frontier was consolidated, particularly for soybean farming, which displaced livestock production in the west of the country (Larsen, 2017). From 2000 on, the growing global demand for food and rising agricultural commodity prices intensified the internationalization of Paraguayan agriculture. This modernization process solidified toward the end of that decade (Cresta et al., 2019; López et al., 2017). Producers gained access to higher-quality inputs and private financing, while public policies were directed toward strengthening productive capital and innovation—mainly through the actions of the Ministry of Agriculture and Livestock, national universities, and the creation of the Paraguayan Institute of Agricultural Technology (IPTA) in 2009 (López et al., 2017).

This expansion led to an increase in deforestation. Although the country's forests had remained intact until recently, many have now been replaced by pastureland as ranchers from eastern Paraguay pushed the agricultural frontier westward, driving the conversion of the dry forests of western Paraguay (Baumann et al., 2017). Between 2001 and 2013, forest-to pasture conversion accounted for 62% of the new farmland in western Paraguay, although this pace slowed after 2007 (Graesser et al., 2015). At the same time, better road infrastructure has made the region more accessible, fostering economic activity and development (Henderson et al., 2021; Crespo et al., 2019).

The evolution of Paraguay's agricultural sector shows major production and productivity gains in recent decades. However, these gains have not been evenly distributed across regions or farm types, and significant disparities persist in resource use efficiency. Analyzing the evolution of productivity and efficiency is therefore critical to identifying the underlying drivers of growth to inform evidence-based policies to enhance the sector's competitiveness and sustainability.

Most existing studies focus on changes in Paraguay's agricultural productivity at the regional or national level, primarily using time-series data. Bharati and Fulginiti (2007) reported that agricultural TFP growth in South America increased from 1.96% in 1972–1981 to 2.33% in 1982–1991 and to 2.36% in 1992–2002. During the latter two periods, Paraguay was the only Southern Cone country to experience a significant decline in its TFP growth rate. Similarly, Dias Avila and Evenson (2010) found that Paraguay's TFP growth lagged behind that of Argentina, Brazil, Chile, and Uruguay until the beginning of the 21th century. Trindade and Fulginiti (2015) present a comparative analysis of agricultural productivity growth in South America between 1969 and 2009. They suggest that countries such as Chile, Brazil, and Argentina experienced greater technological change than Paraguay, likely due to faster adoption of new technologies, in line with the trends in developed countries.

There are few farm-level and activity-specific studies for Paraguay. Nin-Pratt (2018) examined the effects of agricultural growth and the role of smallholders and family farming. Using FAO data, he estimated annual TFP growth of 1.25% between 1989 and 2012. However, after a period of policy reforms between 1989 and 2002, the rate rose to 2.23%. Since 2000, the growth and improved performance of the country's agriculture sector are due to the rapid growth of soybean, corn, wheat, rice, and livestock production, driving gains in TFP, output per hectare, and output per worker. Bravo-Ureta and Evenson (1994) used stochastic efficiency decomposition to measure the efficiency of small-scale cotton and cassava producers. More recently, Lema and Gatti (2021) compared agricultural productivity in the Southern Cone countries between 1969 and 2016, finding that Brazil, Argentina, and Chile have the highest TFP growth rates, while those of Paraguay and Uruguay have been growing at 3% and 2% annually over the last 16 years, respectively. These rates are higher than those found by Nin-Pratt (2018), but should be interpreted with caution since rural household surveys are not necessarily representative of the average Paraguayan farm.

II. METHODOLOGY AND DATA

To present evidence on the determinants and evolution of productivity in Paraguay over the past 30 years, this chapter combines three main data sources: microdata from the 1991, 2008, and 2022 agricultural censuses, agricultural commodity price series, and historical climate data. The censuses provide farm-level demographic and production information. It is important to note that the number of farms analyzed decreased from 299,000 in 1991 to 209,000 in 2022. Agricultural commodity prices used to value farm-level production were obtained from the FAOSTAT database.

A price index with a base of 100 is used for 2014 to 2016 for the census years, and production values are expressed in constant value. Prices are available for the main agricultural commodities, primarily cereals and oilseeds. For livestock, total herds were converted to "cow equivalents" using standard measures of the relationship between forage supply and nutritional requirements of different cattle categories (Bavera, 2006). Climate data were obtained from the Climatic Research Unit, maintained primarily by the UK's Natural Environment Research Council (NERC) and the US Department of Energy (Harris et al., 2020). Specifically, the analysis used historical data on average monthly precipitation and temperature for 1901 to 2023. Since census data cannot be used to track the same producer over time, censuses are treated as pooled cross-sections for econometric estimation.[1]

The production frontier relates the logarithm of the total value of farm production per year to a vector of inputs. The stochastic frontiers for each census year are estimated following Aigner, Lovell, and Schmidt (1977) and Meeusen and Van Den Broeck (1977):

$$y_{im} = \alpha + X_i\beta + Z_i\gamma + M_m\delta + dm_i + v_{im} - u_{im}$$

where the dependent variable (y_{im}) is the log of the total value of production[2] for household i in municipality m; X is a vector of inputs in logarithms (labor, agricultural area, and machinery) and dummies for variable inputs (fertilizer and pesticide use); and Z is a vector of household dummy variables: technical assistance, credit access, membership of an association, location in the west of the country, foreign-born farmer, and large farm status (=1 if the farm is above size, 0 otherwise).

M is a climate vector including mean and deviation-from-long-term-mean rainfall and temperature variables at the municipal level; and d_{mi} is a dummy indicating missing observations due to log transformation. Lastly, v_{im} is the idiosyncratic error term, and u_{im} is the nonnegative error term representing inefficiency, which follows an exponential distribution.

Cobb-Douglas and Translog stochastic frontiers were estimated, and the latter specification selected for the baseline analysis due to its greater flexibility in representing the underlying production technology. This flexibility makes the translog form particularly suitable for heterogeneous agricultural systems, where input interactions such as between land, labor, and intermediate inputs may be nonlinear and context dependent.

The technical efficiency results are analyzed and grouped at the district (smaller political unit) and department (larger political unit) levels, as individual farms cannot be tracked and compared over time.

Variables were collapsed at the district level to approximate TFP growth.[3] Because this aggregation reduces the number of observations per regression, a Cobb Douglas functional form is employed for the district-level estimates. Beyond its parsimony, the Cobb Douglas provides economically interpretable parameters and remains robust in small-sample settings. Furthermore, empirical evidence suggests that, for aggregated agricultural data, the Cobb Douglas specification often produces efficiency rankings and marginal productivity estimates comparable to those obtained from more flexible functional forms (Bravo Ureta & Pinheiro, 1993; Bravo Ureta et al., 2007).

[1] Productivity comparisons over time should be interpreted cautiously, as pooled cross-sections may reflect changes in sample composition, producer entry or exit, and coverage changes rather than true productivity dynamics.
[2] Prices of agricultural and livestock products are expressed in 2014–2016 constant terms (2014–2016 = 100).
[3] All continuous variables were collapsed to their district-level averages by census year. For farm-level dummies, the aggregation yielded district-level percentage of farmer using specific inputs.

Table 1. Main variables of interest

Variable of interest	Description
Labor	Number of workers
Land[4]	Hectares of land
Capital[5]	Total machinery owned
Fertilizers	=1 if the farm uses fertilizers, 0 otherwise
Pesticides	=1 if the farm uses pesticides, 0 otherwise
Technical assistance	=1 if the farm receives technical assistance, 0 otherwise
Credit	=1 if the farm receives credit, 0 otherwise
Association	=1 if the farmer is a member of an association, 0 otherwise
Size	=1 if the farm is above median size (ha.), 0 otherwise
Foreigner	=1 if the farmer is foreign-born, 0 otherwise
Permanent crops	=1 if the farm grows permanent crops, 0 otherwise
West[6]	=1 if the farm is in Western Paraguay, 0 otherwise
Missing dummy	=1 if the farm does not use inputs, 0 otherwise
High temperature days	Number of days per year with temperature above historical mean at district level
Mean precipitation	Average annual precipitation (mm) at district level
Mean temperature	Average temperature at district level
Precipitation deviation	Deviation from historical mean precipitation (mm) at district level
Temperature deviation	Deviations from historical mean temperature at district level

[4] No adjustment is made for land quality. Given the ongoing modernization of agriculture, land quality is likely improving over time; therefore, technical efficiency estimates may be slightly overstated.
[5] Capital is measured as the linear sum of machinery available on the farm, including tractors, tillers, planters, sprayers, harvesters, plows, and vehicles.
[6] Aggregation at the district level may induce spatial correlation. To account for this, a dummy variable was included, equal to 1 for districts in Western Paraguay and 0 for those in Eastern Paraguay.

Accordingly, we aggregate the data at the district level and estimate stochastic production frontiers using a Cobb Douglas functional form, with land, labor, capital, and intermediate inputs as explanatory variables. To account for regional heterogeneity, departmental fixed effects and their corresponding time trends are included. The estimated coefficients on these fixed effects and trends are then used to infer average TFP growth rates across regions. Lastly, the technical change component was obtained as the difference between TFP and technical efficiency.

III. FINDINGS

Stochastic frontiers

A comparison of the stochastic frontiers estimated across census years reveals changes in the relative importance of production inputs in Paraguay (**Table 2**). These shifts in the marginal contribution of inputs to production value can be explained by structural changes in the agriculture sector. Over the 30 years covered by the censuses, Paraguay transitioned from peasant-based agriculture to a model increasingly dominated by agribusiness. In 1991, land and capital made similar contributions to production value—45% and 41%, respectively—while labor's contribution was negative (-12%). By 2008, land had become more significant (89%) compared to capital (12%), with labor contributing just 3%. In 2022, labor remained the least significant contributor to production value (11%), while land accounted for more than 60%, and capital for just over 39%.

Regarding the use of variable inputs, fertilizer use was associated with a 34% higher production value in 1991, a 33% lower value in 2008, and an 11% higher value in 2022. The effect of pesticide use was also varied: a -15% effect in 1991, +19% in 2008, and -58% in 2022 compared to farms that did not use pesticide.

Farmer characteristics also showed diverse patterns. On the one hand, foreign-born farmers exhibited, on average, from 24% to 32% higher production levels than local producers, suggesting a positive association between productivity and the inflow of new human capital, mainly from Brazil and Argentina, which may have accelerated technological change. These results might indicate positive effects of external migration into Paraguay. Farmers who received technical assistance or were members of associations showed, on average, lower production levels compared to other producers. This finding underscores the need to improve the quality and effectiveness of both public and private systems for information dissemination and knowledge transfer. In contrast, farmers with access to credit generally had production values that were 5% higher on average than those who did not.

Climate variables were observed to have heterogeneous effects across years. Measured at the district level, these variables capture annual shocks and their relative magnitude compared to long-term historical trends. The number of extreme temperature days (above each department's historical mean temperature) had, on average, a negative effect on production value.[7] Mean rainfall and mean temperature showed mixed effects across the census years, while deviations from historical averages were usually negative for both variables. One exception was observed in 2022, when deviations from the mean rainfall had a positive effect—likely due to its mitigating influence during an otherwise dry season.

[7] The historical mean temperature for Paraguay between 1901 and 2022 is 22.8 °C, with values ranging from 21.2 °C to 25.5°C across departments, based on the Climatic Research Unit.

Table 2. Translog stochastic frontier estimations

(continued on next page)

Variable	Coefficients		
	1991	2008	2022
Ln(labor)	-0.12***	0.03***	0.11***
	(0.01)	(0.01)	(0.01)
Ln(land)	0.45***	0.89***	0.63***
	(0.00)	(0.01)	(0.00)
Ln(capital)	0.41***	0.12***	0.39***
	(0.01)	(0.01)	(0.01)
Ln(labor)^2	0.05***	0.10***	0.08***
	(0.00)	(0.01)	(0.01)
Ln(labor)*Ln(land)	-0.00	-0.05***	-0.00
	(0.00)	(0.00)	(0.00)
Ln(labor)*Ln(capital)	0.03***	0.01	-0.12***
	(0.01)	(0.01)	(0.02)
Ln(land)^2	0.04***	0.04***	0.03***
	(0.00)	(0.00)	(0.00)
Ln(land)*Ln(capital)	-0.04***	-0.08***	-0.04***
	(0.00)	(0.00)	(0.00)
Ln(capital)^2	0.10***	0.13***	0.29***
	(0.00)	(0.01)	(0.02)
Fertilizer (=1 if used, 0 otherwise)	0.34***	-0.33***	0.12***
	(0.02)	(0.01)	(0.01)
Fertilizer*Ln(labor)	-0.03***	0.04***	-0.13***
	(0.01)	(0.01)	(0.02)
Fertilizer*Ln(land)	0.11***	-0.15***	0.20***
	(0.00)	(0.01)	(0.01)
Fertilizer*Ln(capital)	-0.05***	0.20***	-0.09***
	(0.01)	(0.01)	(0.02)
Pesticide (=1 if used, 0 otherwise)	-0.15***	0.19***	-0.58***
	(0.01)	(0.02)	(0.01)
Pesticide*Ln(labor)	0.12***	0.15***	0.02
	(0.01)	(0.01)	(0.02)
Pesticide*Ln(land)	0.14***	-0.17***	0.07***
	(0.00)	(0.00)	(0.01)
Pesticide*Ln(capital)	-0.06***	0.03***	-0.16***
	(0.01)	(0.01)	(0.02)
Fertilizer*Pesticide	-0.22***	0.01	0.08***
	(0.02)	(0.02)	(0.02)
Technical assistance (=1 if received, 0 otherwise)	0.12***	0.10***	-0.04***
	(0.01)	(0.01)	(0.01)

TABLE 2. TRANSLOG STOCHASTIC FRONTIER ESTIMATIONS (CONTINUED)

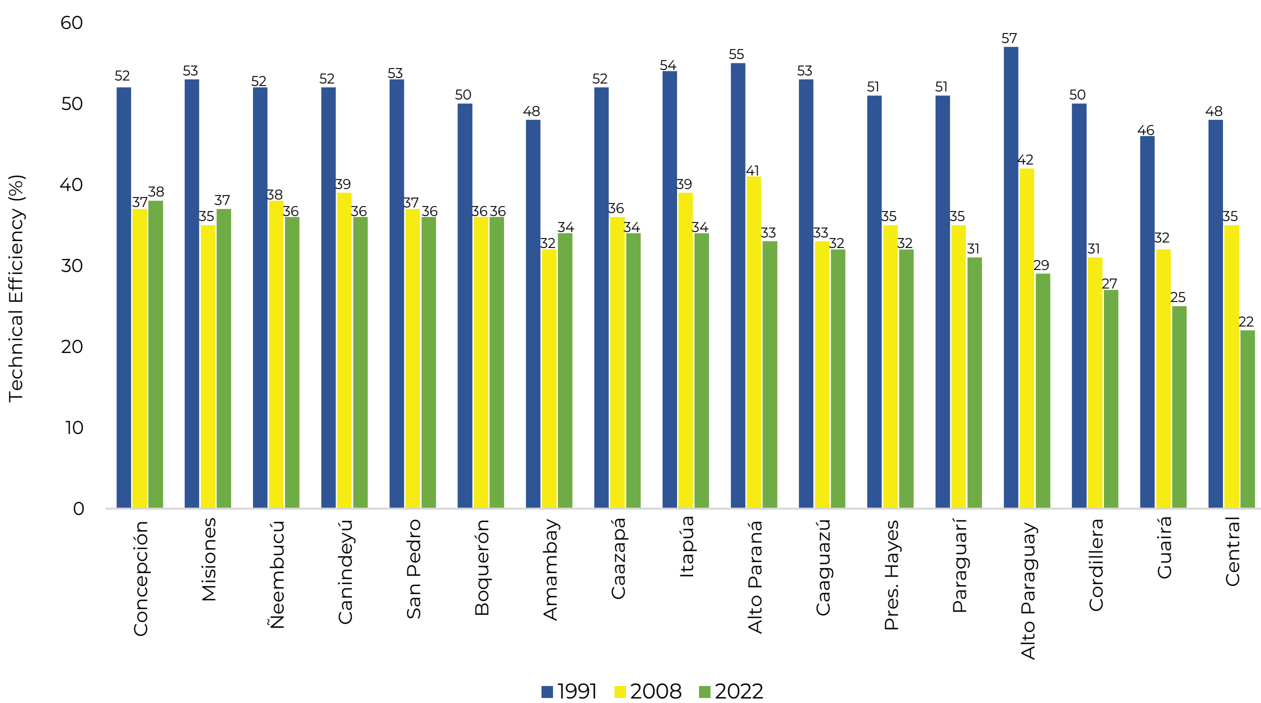
Variable	Coefficients		
	1991	2008	2022
Credit (=1 if received, 0 otherwise)	-0.08***	0.17***	0.04***
	(0.00)	(0.01)	(0.01)
Association (=1 if a member, 0 otherwise)	0.19***	0.40***	-0.04***
	(0.01)	(0.01)	(0.01)
Size (=1 if the farm is above median size, 0 otherwise)	0.17***	0.20***	0.09***
	(0.01)	(0.01)	(0.01)
Foreigner (=1 if the farmer is foreign-born, 0 otherwise)	0.24***	0.32***	0.29***
	(0.01)	(0.01)	(0.01)
Permanent crops (=1 if the farm grows permanent crops, 0	-0.06***	-0.25***	-0.35***
	(0.00)	(0.01)	(0.01)
West (=1 if the farm is in western Paraguay, 0 otherwise)	-2.71***	-1.74***	-1.15***
	(0.21)	(0.04)	(0.07)
Missing dummy (=1 if the farm does not use inputs, 0 otherwise)	-0.44***	-0.02***	-0.22***
	(0.01)	(0.01)	(0.01)
Ln(high temperature days)	-0.51***	-0.24***	-0.19***
	(0.03)	(0.04)	(0.06)
Ln(mean precipitation)	0.62***	-1.29***	-0.54***
	(0.06)	(0.07)	(0.07)
Ln(mean temperature)	9.21***	2.50***	0.73***
	(0.24)	(0.25)	(0.28)
Ln(precipitation deviation)	-0.05***	-0.09***	0.48***
	(0.00)	(0.01)	(0.06)
Ln(temperature deviation)	-0.03***	-0.07***	-0.00
	(0.00)	(0.00)	(0.01)
Department fixed effects	**Yes**	**Yes**	**Yes**
LRtest (σ_u=0)	Reject H_0	Reject H_0	Reject H_0
ln σ_v^2	-0.63***	-0.57***	-0.91***
	(0.01)	(0.01)	(0.01)
ln σ_u^2	-0.04***	1.40***	1.73***
	(0.01)	(0.01)	(0.01)
Observations	**309,908**	**292,274**	**212,488**

Note: Authors' calculations. Dependent variable is agricultural production. Data are expressed as deviations from the geometric mean by year to facilitate the interpretation of the main coefficients as input elasticities. The likelihood-ratio (LR) test evaluates the null hypothesis that the Cobb Douglas specification adequately represents the production technology against the alternative translog form. Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Technical efficiency by departments and districts

The results by department presented in **Figures 3** and **4** confirm that technical efficiency has declined in all regions compared to 1991. At the national level, it fell from 52% in 1991 to 32% in 2022. Furthermore, except for Concepción, Misiones, and Amambay, all departments also experienced a downward trend in technical efficiency from 2008 to 2022. This overall decline in efficiency over time, coupled with the low values estimated for 2022, might reflect a rapid outward shift of the production frontier driven by technological change that may have outpaced producers' ability to adapt their management practices. This highlights the substantial potential to boost output through improved managerial capacity, technical assistance, and knowledge dissemination, without requiring additional inputs or placing further pressure on natural resources.

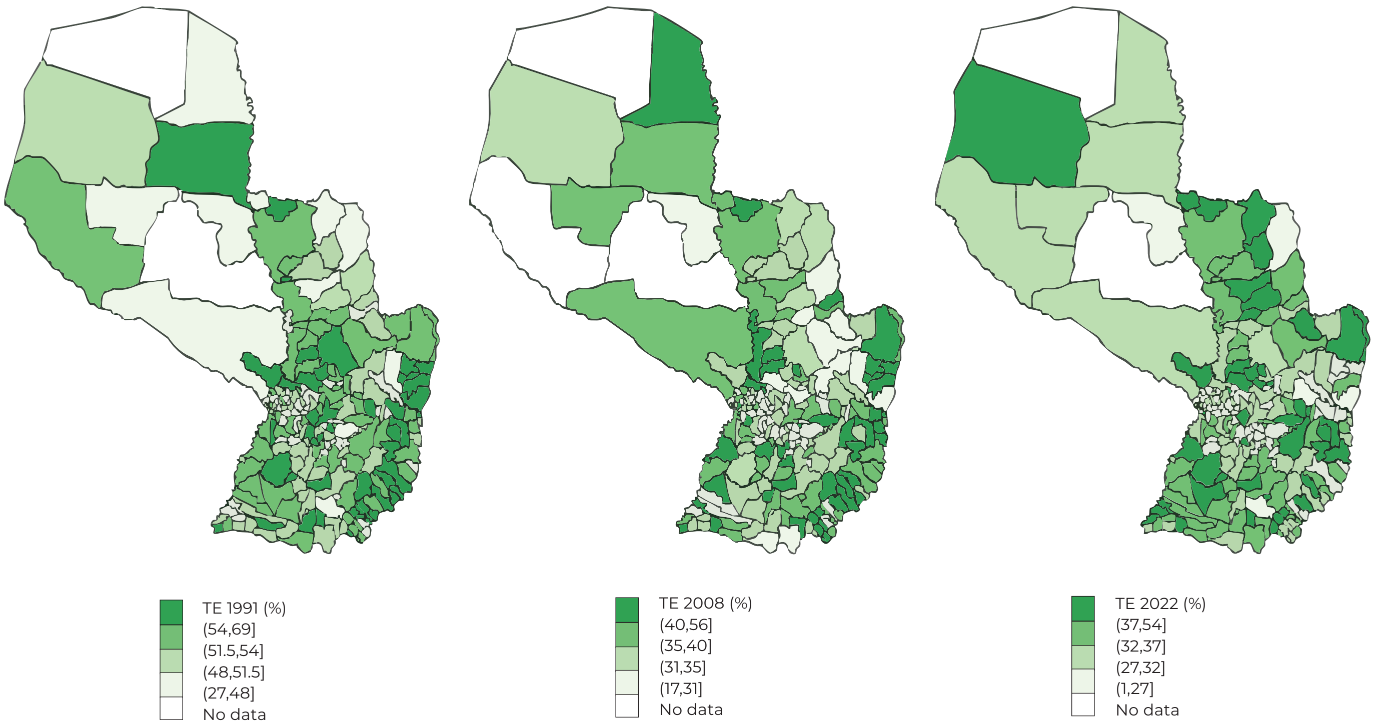
Figure 3. Mean technical efficiency by department and year



Note: Authors' calculations based on stochastic frontiers estimations using data from the National Agricultural Censuses. Technical efficiency values come from three separate cross-sectional estimates. Bars are sorted by department for 2022.

Figure 4 illustrates the heterogeneity in mean technical efficiency within departments over time. Disregarding the differences in department size with western Paraguay, the results show that technical efficiency in the east of the country shifted above the mean in most districts between 1991 and 2022. Specifically, technical efficiency in 80% of districts in Concepción, Canindeyú, Ñeembucú, San Pedro, and Misiones was above the mean in 2022. A second group of departments—Caazapá, Amambay, Boquerón, Itapúa, and Alto Paraná—has between 53% and 67% of districts above the mean. Lastly, fewer than 50% of districts in Central, Paraguarí, Presidente Hayes, Caaguazú, Guairá, Cordillera, and Alto Paraguay were above mean technical efficiency values in 2022.

Figure 4. Geographic distribution of technical efficiency by district and year (1991–2022)

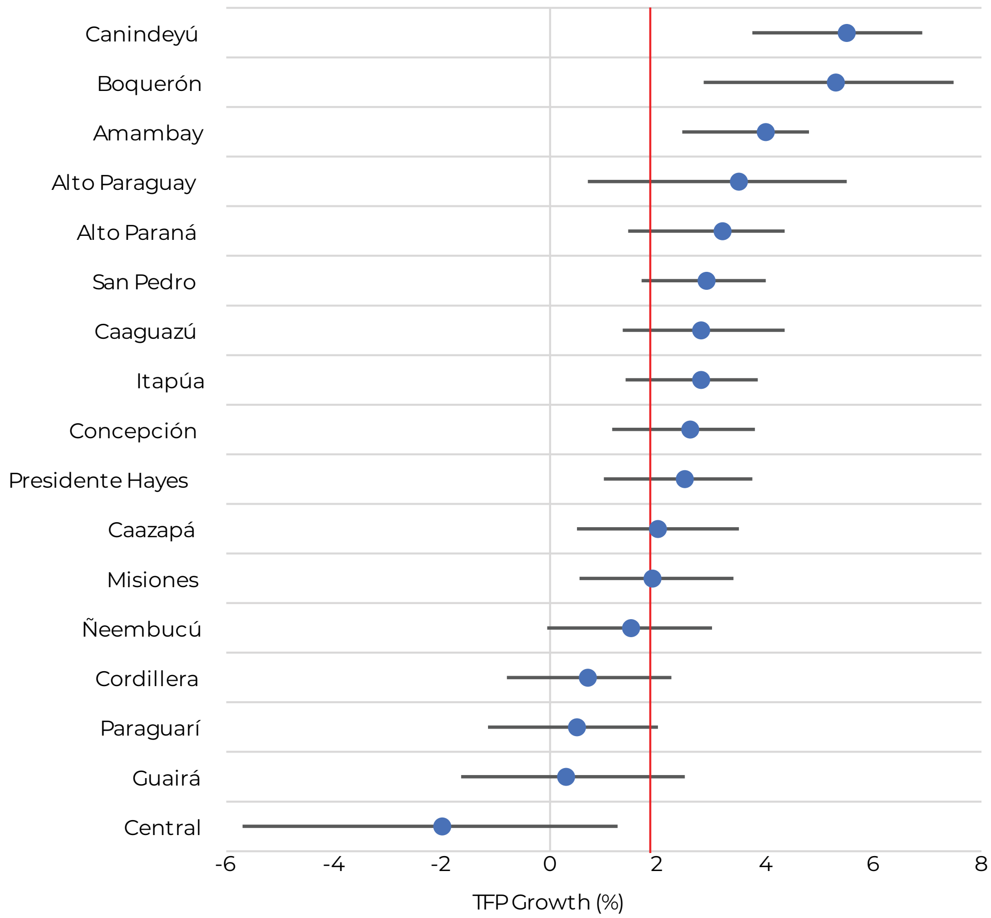


Note: Authors' calculations based on stochastic frontiers estimations using data from the National Agricultural Censuses.

Total factor productivity by department and district

The TFP estimates using production frontiers aggregated by district indicate that TFP increased at an average annual rate of 1.86% between 1991 and 2022 (**Figure 5**), aligning with estimates reported in previous studies (Lema and Gatti, 2021; Trindade and Fulginiti, 2015). Assuming constant returns to scale, this growth was primarily driven by technological change and structural transformations in the organization of production, rather than by improvements in efficiency (**Table 3**). Notably, TFP is growing above the national average in lagging departments (mostly in the west of the country), while more traditional areas closer to major urban centers are experiencing relative stagnation. Deviations from long-term mean precipitation and temperature are generally associated with positive growth rates, except for Ñeembucú, which experienced a 0.7% decrease. In contrast, short-term weather variations reveal negative rainfall growth rates across all departments, ranging from 0.5% to 1%. Mean temperature growth rates were generally close to 0.

FIGURE 5. AVERAGE TFP GROWTH RATE BY DEPARTMENT (1991–2022)



Note: Authors' calculations based on stochastic frontiers estimations using data from the National Agricultural Censuses. Growth rates are grouped by department and year. The red line represents the average TFP growth rate.

TABLE 3. ESTIMATED GROWTH RATES BY DEPARTMENT

(CONTINUED ON NEXT PAGE)

				% Climate		% Weather	
Department	% TFP	% Technical Efficiency	% Technical Change	% Rainfall Deviation	% Temperature Deviation	% Mean Rainfall	% Mean Temperature
Canindeyú	5.5%	-0.5%	6.0%	12.1%	-6.5%	-0.6%	0.1%
Boquerón	5.3%	-0.5%	5.7%	6.2%	1.9%	-0.9%	0.0%
Amambay	4.0%	-0.5%	4.4%	0.0%	6.9%	-0.5%	0.1%
Alto Paraguay	3.5%	-0.9%	4.4%	7.8%	4.3%	-1.0%	0.0%
Alto Paraná	3.2%	-0.7%	3.9%	6.3%	2.9%	-0.9%	0.0%
San Pedro	2.9%	-0.6%	3.5%	7.9%	3.1%	-0.7%	0.0%

Table 3. Estimated growth rates by department
(continued)

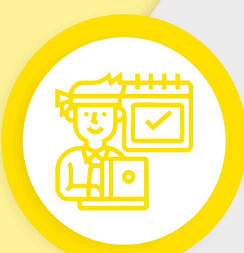
				% Climate		% Weather	
Department	% TFP	% Technical Efficiency	% Technical Change	% Rainfall Deviation	% Temperature Deviation	% Mean Rainfall	% Mean Temperature
Caaguazú	2.8%	-0.7%	3.5%	6.5%	2.1%	-0.9%	0.0%
Itapúa	2.8%	-0.7%	3.5%	7.2%	1.4%	-0.9%	0.0%
Concepción	2.6%	-0.5%	3.1%	0.0%	4.1%	-0.5%	0.0%
Presidente Hayes	2.5%	-0.6%	3.1%	7.1%	2.8%	-0.6%	0.0%
Caazapá	2.0%	-0.6%	2.6%	6.9%	2.2%	-0.9%	0.0%
Misiones	1.9%	-0.5%	2.5%	6.9%	2.0%	-0.8%	0.0%
Ñeembucú	1.5%	-0.5%	2.0%	7.6%	-0.7%	-0.8%	0.0%
Cordillera	0.7%	-0.7%	1.4%	6.1%	3.0%	-0.9%	0.0%
Paraguarí	0.5%	-0.6%	1.1%	6.5%	3.3%	-0.8%	0.0%
Guairá	0.3%	-0.7%	1.0%	5.8%	2.0%	-0.9%	0.0%
Central	-2.0%	-0.8%	-1.2%	8.3%	7.6%	-0.7%	-0.1%

Note: Authors' calculations based on stochastic frontiers estimations using data from the National Agricultural Censuses. Growth rates are grouped by department and year. The red line represents the average TFP growth rate.

IV. CONCLUSIONS AND POLICY RECOMMENDATIONS

This chapter provides empirical evidence on the evolution of agricultural productivity and technical efficiency in Paraguay from 1991 to 2022, using agricultural census microdata. The findings reveal a substantial improvement in the productivity of Paraguayan agriculture, driven primarily by technological change. During this period, the sector underwent major structural transformations, transitioning from predominantly smallholder-based farming to a more modern agricultural model. Based on these findings, the following policy recommendations are proposed:

I. Invest in technical efficiency to increase agricultural output



TFP grew at 1.86% per year between 1991 and 2022, driven predominantly by technological change and structural shifts toward enterprise-oriented production systems. However, the analysis reveals a significant decline in average technical efficiency—from 52% in 1991 to 32% in 2022—implying a substantial opportunity to increase output through improved management of existing technologies, rather than greater input use or land conversion. Prioritizing investments in knowledge dissemination, technical assistance, and extension services have the potential to improve agricultural performance without putting additional pressure on natural resources.

II. Enhance human capital by providing high-quality technical assistance and effective knowledge transfer mechanisms to improve the sector's performance

The results show that average technical efficiency has declined even as technology adoption has increased over the past 30 years. This suggests that future production gains must not rely solely on access to new technologies or greater input use, but rather on improving efficiency in the management of current technologies and resources. Training programs, field schools, and partnerships with universities and research institutes could be effective strategies to ensure producers can successfully adopt and manage new technologies.

III. Prioritize departments with low efficiency scores to enhance farmers' competitiveness

Strengthening rural extension services is especially critical to improve the adoption and management of available technologies and inputs in departments with the lowest technical efficiency scores, particularly in western Paraguay. Policies should seek to enhance the effectiveness of technical assistance and farm organizations, focusing not only on expanding coverage but also on increasing the quality and relevance of services provided to farmers in these areas.

IV. Strengthen resilience to climate shocks to boost agricultural productivity

Building resilient production systems is essential to reducing farmers' vulnerability to climate shocks. Evidence from this analysis indicates that climate-related disruptions may have significantly limited improvements to technical efficiency. To address this challenge, policies should promote the adoption of climate-smart technologies and practices and equip farmers with the tools and knowledge they need to effectively manage climate risks. This is more than a matter of adaptation; it is a strategic investment in raising TFP and ensuring sustainable agricultural growth.

In summary, Paraguay has a unique opportunity to unlock the full potential of its agricultural sector by boosting output growth and enhancing environmental sustainability. Achieving this will require targeted efforts to strengthen managerial capacities for the effective use of technologies and inputs while reducing regional productivity disparities. Equally important is the need to enhance institutional capacity and align policy incentives with productivity-driven strategies to ensure sustainable and inclusive agricultural development.

CHAPTER 10. **ARGENTINA**

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SUMMARY

Agriculture is an important component of Argentina's economy, accounting for nearly 60% of total export value and around 8% of GDP (INDEC, 2025). This chapter estimates agricultural total factor productivity (TFP) growth between 1961 and 2022 using FAOSTAT data and evaluates technical efficiency through a stochastic frontier model based on microdata from the 2018 Agricultural Census. The results show that agricultural TFP grew at an annual average of 1.78%, driven largely by crop production. The strongest growth period was the 1990s (3.29% per year), while the past decade has seen a marked slowdown. In 2018, average technical efficiency was estimated at around 50%, with significant disparities across farms and regions. These findings suggest that substantial productivity gains could be achieved by improving the management of existing technologies, rather than through additional input use or land expansion. Our findings underscore the importance of stable, market-oriented policies, better knowledge transfer, and targeted support for technology adoption.

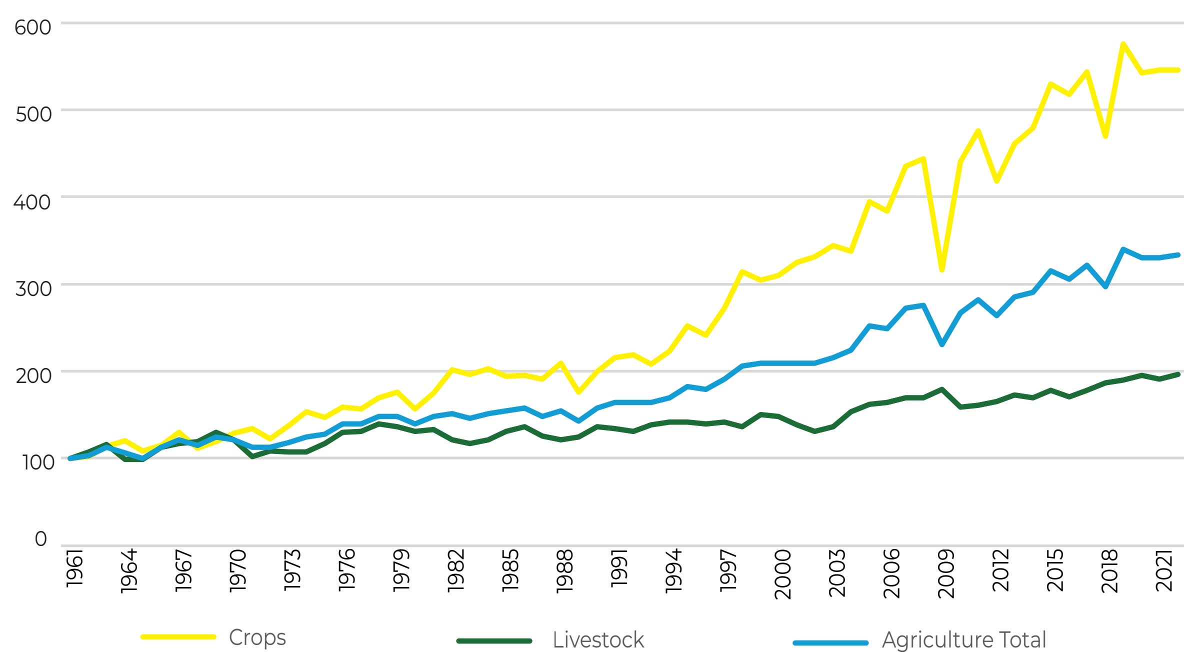
I. INTRODUCTION

Agriculture plays a central role in Argentina's economy. The primary agricultural sector contributes around 8% of total GDP, while agricultural and food products account for nearly 60% of total export value. When the agrifood processing industry is included—the set of activities that transform primary agricultural outputs into food, beverages, and other value-added goods, encompassing Argentina's 31 main agrifood chains—the sector's contribution to GDP increases to approximately 15% and generates about 10% of total employment (Lódola et al., 2019). Given its important role in output and trade agricultural performance is a key determinant of Argentina's macroeconomic stability and long-term growth prospects. Linkages with international markets could promote foreign direct investment to catalyze productivity improvements through technological progress and efficiency gains.

According to the OECD's *Agricultural Policy Monitoring and Evaluation Report 2024*, Argentina's agricultural sector has undergone considerable innovation, but policies providing negative support via export restrictions and taxes have often offset these advances. In the early 1990s, the elimination of the export taxes and trade restrictions that had prevailed throughout the previous three decades coincided with a marked expansion of grain production. Between 1990 and 2001, growth was driven by sustained capital accumulation, the accelerated adoption of new technologies, and the diffusion of improved practices. This period saw the widespread adoption of genetically modified crop varieties and soil and crop management practices like zero tillage and crop rotation.

Following the massive depreciation of the Argentine peso in 2002, most of the policy measures of the 1990s were progressively reversed. By late 2015, the agricultural sector was again subject to multiple taxes and regulations: (i) commodity producers faced export taxes of 20%– 35%, (ii) import taxes had been reinstated on capital goods, (iii) inflation averaged 20%–25% annually due to monetary policy, and (iv) the agricultural value chain was subject to increasing regulation, with export quotas on certain commodities and retail-level price ceilings (Lema et al., 2018). Despite these constraints, production of Argentina's main crops continued to expand, driven primarily by rising international commodity prices.

FIGURE 1. GROSS AGRICULTURAL PRODUCTION INDEX FOR ARGENTINA (1961–2022) (1961=100)

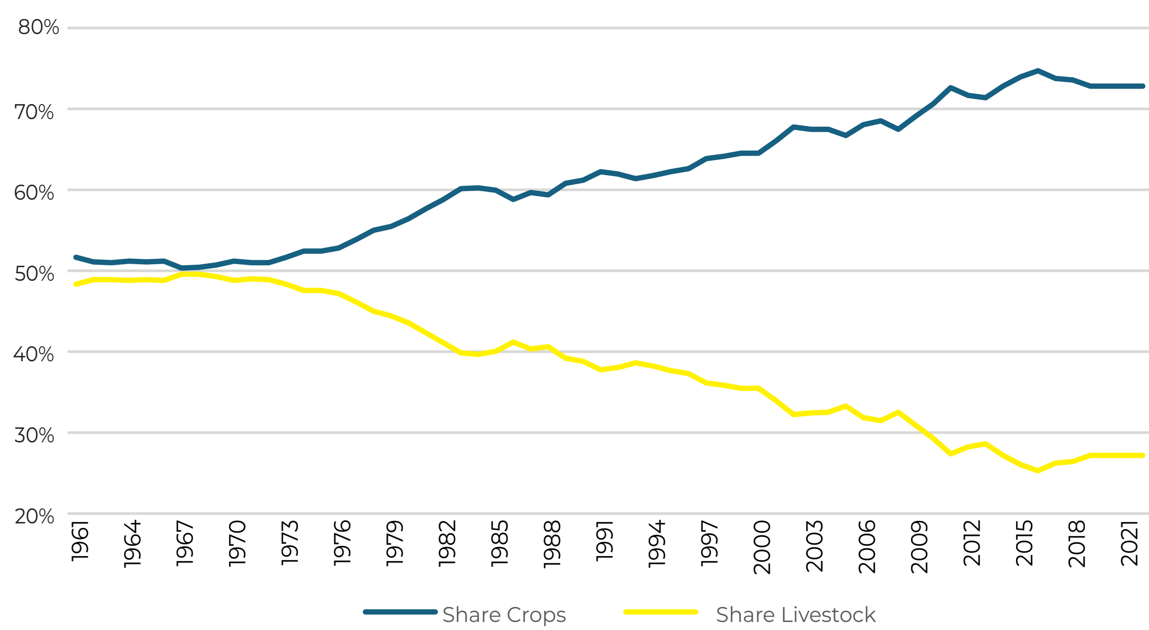


Source: Authors' calculations, based on FAOSTAT data 1961-2022

Figure 1 shows the evolution of Argentina's Gross Agricultural Production Index, as reported by FAO, from 1961 to 2022. Crop production grew at an estimated annual rate of 2.93%, compared to 0.95% for livestock and 2.02% for total agricultural production. These trends illustrate that crop production has expanded at a significantly faster pace than livestock production. Historically, Argentina's agricultural output was distributed relatively evenly between crops and livestock but crops now account for approximately 70% of the total value of agricultural production. This transformation is also reflected in production volumes: in 1990, the country's total grain output was about 40 million tons, while by 2024 it had risen to approximately 140 million tons—an increase of nearly 250%. In contrast, beef production over the same period has remained relatively stable at around 3 million tons per year.

Figure 2 further illustrates this transformation by showing the changes in the shares of crops and livestock in total agricultural value added. In the early 1960s, both contributed almost equally, but the share of crops has steadily increased since, while that of livestock has declined. Together, these figures highlight the long-term structural shift in Argentina's agriculture toward crop production.

FIGURE 2. CROPS AND LIVESTOCK AS A PERCENTAGE OF ARGENTINA'S AGRICULTURAL VALUE ADDED (1961–2022)



Source: Authors' calculations, based on FAOSTAT data 1961-2022

II. DATA AND METHODOLOGY

The objective of this chapter is to present updated estimates of agricultural total factor productivity (TFP) growth and efficiency levels in Argentina. Analyzing these factors is essential to identify opportunities for more effective resource use and strengthening competitiveness through targeted policies.

TFP growth rates from 1961 to 2022 were calculated using a Fare-Primont index number methodology (O'Donnell, 2010, 2012), with data on output and agricultural inputs obtained from the FAOSTAT database. The Färe–Primont index is particularly well suited for agricultural productivity studies when price information is often incomplete, distorted, or not comparable across regions and time. The Färe–Primont index overcomes this limitation by using only physical quantities. Additionally, unlike some other productivity indices (e.g., Tornqvist, Fisher), the Färe–Primont index satisfies transitivity and multiplicative consistency, enabling meaningful multi-period and multi-region comparisons.

Agricultural output is measured as an index representing gross agricultural production in constant dollars (prices for 2014–2016=100), while inputs include land, labor, machinery, fertilizers, nutrients, seeds, manure, pesticides, livestock, and animal feed.

The chapter also provides evidence on technical efficiency using a stochastic frontier model, drawing on microdata from the 2018 Agricultural Census (CNA 2018). The empirical analysis applies a cross-sectional stochastic frontier approach to detailed information on production, input use, and producer characteristics for soybean, wheat, maize, and sunflower farms in the provinces of Buenos Aires, Córdoba, Santa Fe, La Pampa, Entre Ríos, and San Luis. These provinces account for more than 70% of the country's grain and oilseed acreage and almost one-quarter of Argentina's total farmland—indeed, Santa Fe alone represents around 21% of the latter.However, although these provinces account for most of Argentina's agricultural output, they represent a smaller share of total producers because the analysis excludes the many small-scale farms in the northern and southern regions, which are numerous but operate relatively small areas of land. According to the 2018 Agricultural Census, approximately 90,000 agricultural establishments operate in the Pampas region (Buenos Aires, Córdoba, Entre Ríos, and Santa Fe provinces), representing about 36% of the 250,000 establishments recorded nationwide. Moreover, this region accounts for more than three-quarters of the national area devoted to the four commodities considered in this study—specifically, 90% and 82% of the wheat and corn area, and 88% and 73% of the soybean and sunflower area, respectively. In other words, while this chapter captures efficiency patterns in Argentina's core agricultural regions, which account for the bulk of national output, it focuses on a subset of agricultural establishments.

III. FINDINGS

AGRICULTURAL TFP, OUTPUT, AND INPUT TRENDS

The Färe-Primont TFP index used to estimate the TFP growth provides a transitive and quantity-based measure of total factor productivity. Unlike traditional price-based indices, it requires only physical quantities of inputs and outputs, making it particularly suitable for agricultural datasets where price information is limited (O'Donnell, 2011; 2012). **Table 1** presents the evolution of TFP, output, and input indices between 1961 and 2022 (base year 1961 = 100).[1]

On average, agricultural output grew by 2.6% per year, while TFP increased by 1.78%. Crop production and productivity experienced higher growth than livestock production. **Figure 3** shows that the evolution of output, input, and TFP followed different long-term trajectories, with variations in growth rates.

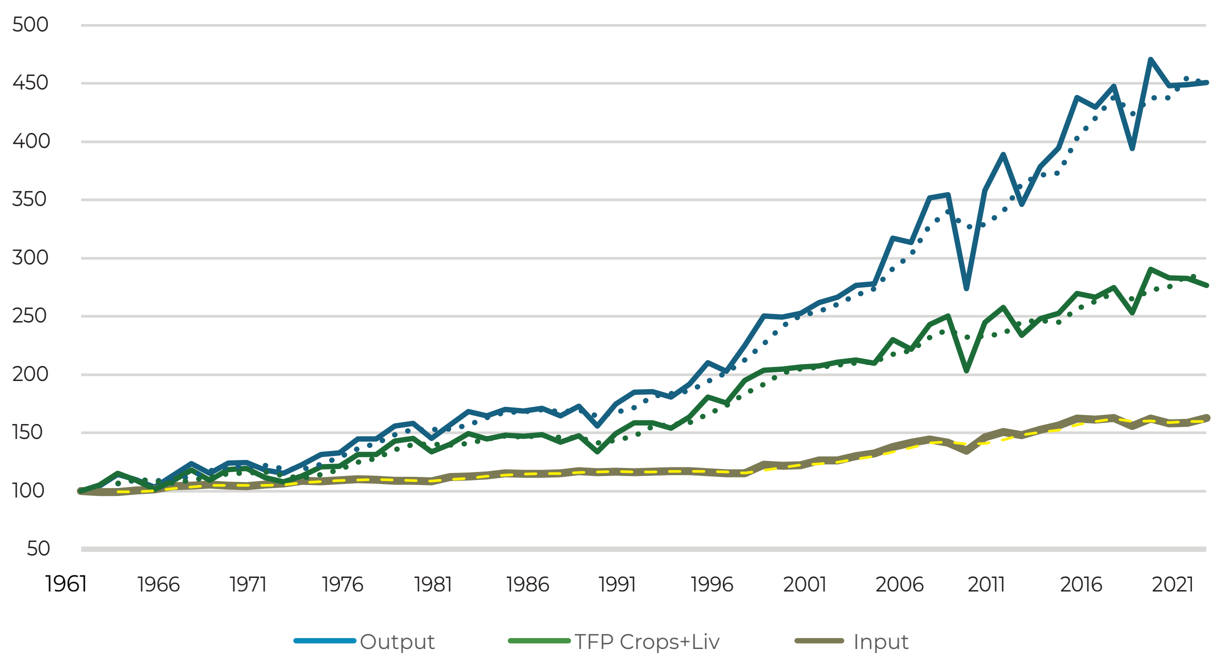
[1] O'Donnell DPIN program (version 3.0) was used to estimate the Färe-Primont indexes.

Table 1. Annual growth rates for TFP, output, and inputs (1961–2022)

Variable	Crops	Livestock	Agriculture (crops and livestock)
TFP	1.88%	0.88%	1.78%
Output	2.93%	0.95%	2.60%
Inputs	1.05%	0.07%	0.82%

Source: Authors', based on Färe-Primont index estimates using FAOSTAT data 1961-2022.

Figure 3. Output, inputs, and TFP indices for the agricultural sector (crops and livestock), Argentina (1961–2022)

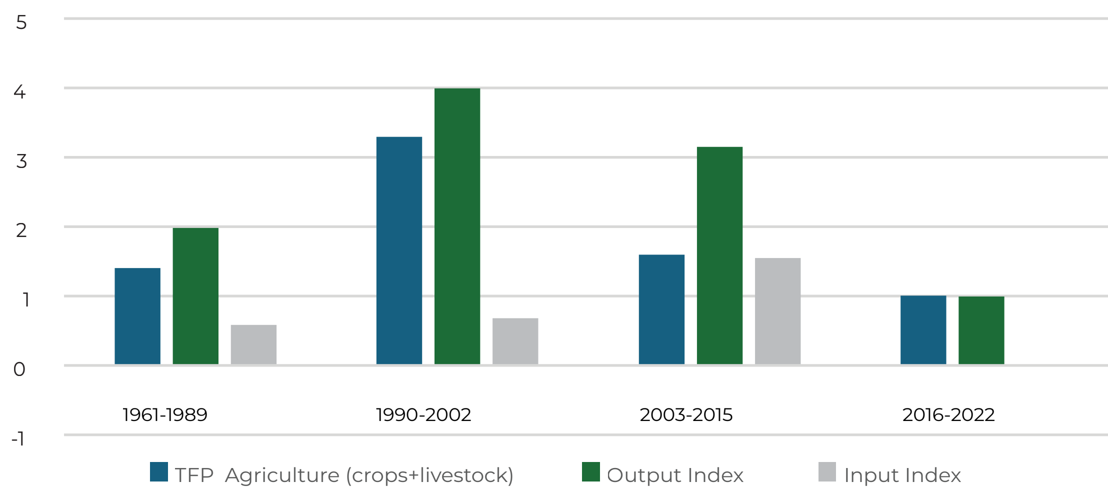


Source: Authors' calculations, based on Färe-Primont index estimates using FAOSTAT data 1961-2022.[2]

Figure 4 presents TFP growth for different periods that represent Argentina's major agricultural policy regimes, as suggested by the OECD (2019). This breakdown shows how policy shifts have shaped production and productivity performance over time. Defining subperiods according to these policy regimes provides a more meaningful interpretation of productivity trends than arbitrary decade-based divisions, as it links changes in total factor productivity directly to identifiable shifts in trade, fiscal, and regulatory policies affecting the sector.

[2]Dotted lines show the 3-year moving average, which is used to smooth short-term fluctuations and reduce the influence of random shocks, such as those caused by weather variability.

FIGURE 4. ANNUAL AGRICULTURAL TFP GROWTH, BY PERIOD (1961–2022)



Source: Authors' calculations, based on Färe-Primont index estimates using FAOSTAT data 1961-2022.

From 1961 to 1989, Argentina maintained a relatively closed economy characterized by price interventions, high import barriers, mandatory public stockholding, export taxes, and low levels of public investment in agricultural infrastructure and R&D (OECD, 2019). Annual output growth reached 1.98%, mainly driven by TFP growth (1.4%), rather than input use (0.58%), reflecting important production and productivity gains achieved with low factor use. Between 1990 and 2002, Argentina underwent substantial liberalization, a process that included dismantling public marketing institutions, lowering trade barriers, removing export taxation, and deregulating markets. Agricultural output grew at about 3.99% per year, primarily driven by TFP growth (3.29%) and a moderate increase in input use (0.68%).

In the early 2000s, particularly from 2003 to 2015, Argentina reinstated regulations such as export taxes and trade restrictions. Beginning in 2002, export taxes on agricultural exports, price controls, and market regulation policies were reintroduced in a context of high commodity prices. OECD data show that producer support (PSE) turned strongly negative, reflecting significant distortions caused by these regulations. Output growth slowed to 3.15% per year, TFP growth dropped to 1.6%, and input use accelerated to 1.55%.

Finally, 2016–2022 brought partial liberalization, followed by renewed intervention. This included initial efforts to reopen markets, the elimination of most export restrictions, and significant reductions in export taxes. OECD (2024) data confirms that negative support levels (PSE) declined from -42% of farm gross income in 2014 to approximately -9% by 2017. However, fiscal pressures and exchange rate crises prompted the restoration of higher export duties after 2018. Output during this period dropped to 1% annually, TFP growth fell to 1.0%, and input use declined slightly (–0.01%).

In summary, as shown in **Table 2**, productivity gains were strongest in the 1990s, when TFP growth exceeded 3% annually, while both output and input also expanded. In contrast, TFP growth slowed after 2002, coinciding with a greater reliance on inputs. The most recent period (2016–2022) is marked by a sharp deceleration in both output and productivity growth.

Table 2. Summary of Agricultural Growth and Productivity in Argentina (1961–2022)

Period	TFP Growth	Output Growth	Input Growth	Main Characteristics
1961–1989	1.4%	1.98%	0.58%	Slow but steady productivity gains; moderate output growth largely driven by input expansion.
1990–2002	3.29%	3.99%	0.68%	Strong productivity surge following economic liberalization and rapid technological adoption (biotech, no-till, fertilizers).
2003–2015	1.6%	3.15%	1.55%	Output growth mainly supported by input intensification; productivity slowed under trade restrictions and export taxes.
2016–2022	1.00%	0.99%	–0.01%	Stagnation in both output and productivity, driven by lower investment and macroeconomic instability.
1961–2022 (total)	1.78%	2.60%	0.82%	Long-term growth dominated by TFP improvements, especially in crop production.

Source: Authors' calculations, based on Färe-Primont index estimates using FAOSTAT data 1961-2022

A comparison of recent studies shows that estimates of agricultural Total Factor Productivity (TFP) growth for Argentina are broadly consistent across major international and national analyses, revealing long-term gains averaging between 1.5% and 2.0% per year. Differences among studies mainly reflect methodological choices, data coverage, and the inclusion of specific policy or technological turning points.

Using a stochastic frontier and Malmquist index, Trindade and Fulginiti (2015) estimate Argentina's TFP growth at 2.0–2.3% per year between 1969 and 2009. Nin-Pratt et al. (2015) estimate regional agricultural TFP growth in Latin America and the Caribbean at 1.6–1.8% per year between 1981 and 2012, with Argentina near the upper bound.

Long-run estimates by Dias Ávila and Evenson (2010), based on FAO data and growth accounting, show Argentine agricultural TFP growth of 1.83% between 1961 and 1980 and 2.35% between 1981 and 2001. Similarly, using a growth-accounting approach, Lema (2016) finds that TFP grew by 1.4% per year between 1961 and 1989, accelerated to 3.3% between 1990 and 2002, and then slowed to 1.6% between 2003 and 2015—a pattern closely mirrored by the current Färe–Primont index (1961–2022).

Overall, the Färe–Primont estimates confirm and refine the existing empirical consensus: Argentina's agricultural productivity peaked in the 1990s and slowed under renewed policy intervention after 2003. While the magnitude of TFP growth varies slightly across methodologies, all studies agree that Argentina's long-run agricultural performance has been driven primarily by technological progress and efficiency gains rather than input expansion, particularly in crop production.

TECHNICAL EFFICIENCY LEVELS 2018

Microdata from the 2018 National Agricultural Census (CNA 2018) were used to estimate technical efficiency scores. The data covers production, input use, and producer characteristics for soybean, wheat, maize, and sunflower plots in the provinces of Buenos Aires, Córdoba, Santa Fe, La Pampa, Entre Ríos, and San Luis, which comprise Argentina's Pampas region. Plot-level variation allows for a more detailed analysis of production practices that are often masked when data is averaged at the farm level. This provides a more precise estimation of technical efficiency by identifying within-farm variation in input use and output response.

The empirical model applies a cross-sectional stochastic frontier approach (Aigner, Lovell, and Schmidt, 1977) using a Cobb-Douglas functional form:

$$\ln Y_i = \beta_0 + \sum_{i=1}^{k} \beta_i \ln X_i + (v_i - u_i) \quad (2)$$

Where the dependent variable ($\ln Y_i$) is the logarithm of the value of production, calculated using production quantities from census data combined with international FOB (free on board) prices for each crop. The β_i are parameters to be estimated, while v_i is a symmetric error, which accounts for random variations in output, and u_i a non-negative random variable representing inefficiency in production relative to the stochastic frontier. The random error v_i is assumed to be independently and identically distributed as $N(0,\sigma_v^2)$, independent of the u_i, which are assumed to be a non-negative truncation of the $N(0,\sigma_u^2)$ distribution (i.e. half-normal distribution). The input vector (X_i) includes cultivated area, hired labor, and capital—represented by an index combining indicators of machinery, infrastructure, storage, and processing capacity. Binary variables are used to capture the use of chemical fertilizers, herbicides, pesticides, no-till farming, and precision agriculture, as well as membership of agricultural organizations or access to technical assistance. Additional control variables include seed use (certified or own), farm size (above or below the median), and the number of plots managed by each farmer. Province-level indicators are included, along with a binary variable identifying farms located in the southwest region of Buenos Aires—Argentina's primary wheat-producing area. The variables and definitions are presented in **Table 3**.

Table 3. Variables and definitions for stochastic frontier estimation

Variable	Definition
Ln(value of production)	Log of the value of production for the four main crops in current US$ (2018)
Ln(land)	Log of hectares devoted to wheat, corn, soybean, and sunflower
Ln(paid_labor)	Log of paid labor
Ln(capital)	Log of capital (infrastructure, primary production, machinery, grain storage, irrigation, grain processing machinery)
Fertilizer	= 1 if farmer uses fertilizer, 0 otherwise
Herbicides	= 1 if farmer uses herbicides, 0 otherwise
Pesticides	= 1 if farmer uses pesticides, 0 otherwise
Direct sow	= 1 if farmer uses no-till farming, 0 otherwise
Precision agriculture	= 1 if farmer uses precision agriculture, 0 otherwise
Own seed	= 1 if farmer uses their own seed, 0 otherwise
Associative	= 1 if farmer belongs to an association, 0 otherwise
Technical assistance	= 1 if farmer receives technical assistance, 0 otherwise
Land rent	= 1 if farmer rents land, 0 otherwise
Size	= 1 if area > median area, 0 otherwise
Ln(number of plots)	Log of number of plots in production
Main wheat areas	= 1 if the farm is located in southeast Buenos Aires province, 0 otherwise
i.prov	Province-level dummies

Source: Authors' elaboration

The estimated coefficients of the stochastic frontier estimation are reported in **Table 4**. In terms of inputs, the results show that land is the main determinant of output (98%), followed by labor (2%) and capital (0.6%). The use of chemical fertilizers and herbicides is associated with higher production values—29.7% and 6.5% more, respectively—compared to nonusers. Conversely, pesticide use is linked to a 10.7% negative differential in production value. No-till farming (13.5%) and precision agriculture (5%) both have a positive differnece on value of production. Use of own (stored) seeds has a negative differential of 27% compared with certified seed users. Membership of producer organizations has no statistically significant effect, whereas receiving technical assistance has a positive differential of 3.9% compared to those that did not receive it. These findings confirm the importance of prioritizing investments that facilitate access to new technologies, improved practices, and extension services. Neither land rental nor above-the-median farm size significantly affect production, suggesting that larger farms are not necessarily more productive. However, managing a greater number of plots is negatively correlated with production.

Results regarding pesticide use, own seed, and number of plots require special attention. Coefficients, while might sound counterintuitive, are likely affected by selection bias and simultaneity. First, farmers facing higher pest pressure are more likely to use pesticides which generates a negative correlation with the value of production, even if pesticides are beneficial for these farmers. Second, the use of own seed is associated with a lower production value. This effect is driven by soybean farmers, who often reuse part of their harvest as seed rather than purchasing new varieties each year. Third, the number of plots is negatively related to the value of production potentially due to land fragmentation and location bias. Since we do not have the geolocation of the farm, it is possible that fragmentation are heterogenous within farms. A second explanation is the fact that small fams may subdivide or rent parts of their land, increasing observed plot numbers as a result of low production.

Table 4. Coefficient estimates of the stochastic frontier

(continued on next page)

Dependent Variable: Ln (value of production)	
Variables	**Coefficients**
Ln(land)	0.988***
	(0.00322)
Ln(paid_labor)	0.0223***
	(0.00344)
Ln(capital)	0.00657**
	(0.00323)
Fertilizer (=1 if used, 0 otherwise)	0.260***
	(0.00514)

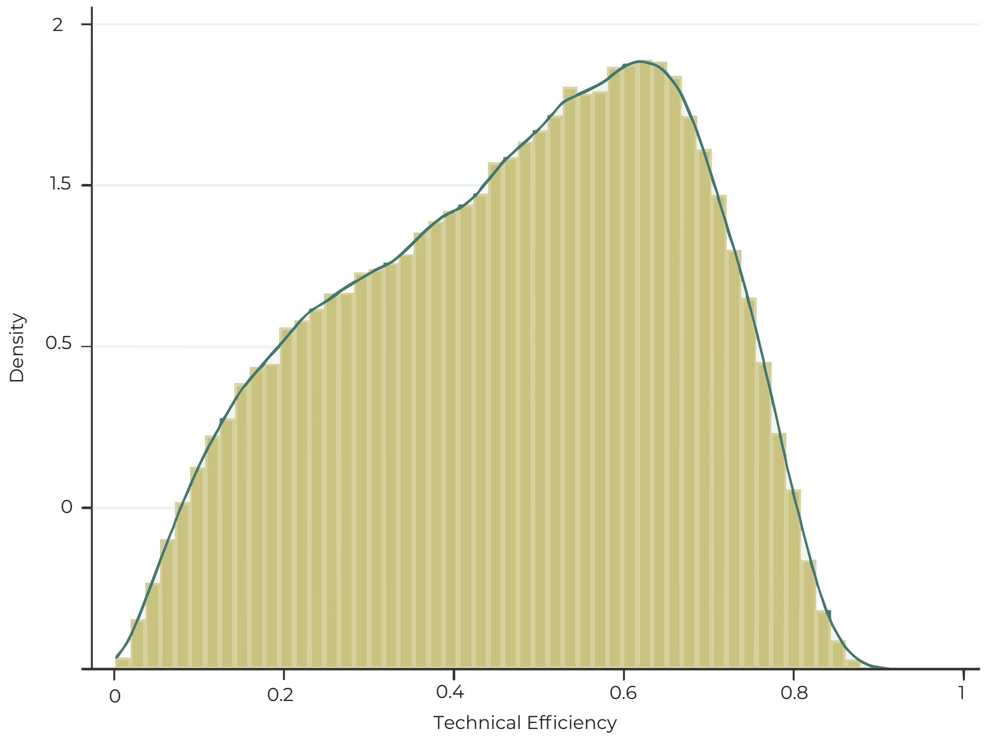
Table 4. Coefficient estimates of the stochastic frontier (continued)

Dependent Variable: Ln (value of production)	
Variables	**Coefficients**
Herbicides (=1 if used, 0 otherwise)	0.0627***
	(0.0119)
Pesticides (=1 if used, 0 otherwise)	-0.113***
	(0.00440)
No-till (=1 if used, 0 otherwise)	0.127***
	(0.00944)
Precision agriculture (=1 if used, 0 otherwise)	0.0496***
	(0.00497)
Own seed (=1 if used, 0 otherwise)	-0.327***
	(0.00438)
Associative (=1 if true, 0 otherwise)	0.00228
	(0.00432)
Technical assistance (=1 if received, 0 otherwise)	0.0387***
	(0.00541)
Land rent (=1 if true, 0 otherwise)	0.00458
	(0.00444)
Size (=1 if area > median area, 0 otherwise)	-0.0103
	(0.00669)
Ln(number of plots)	-0.997***
	(0.00295)
Main wheat areas (=1 if true, 0 otherwise)	-0.155***
	(0.00792)
Missing dummy correction	**Yes**
Province dummies	**Yes**
lnsigma2v	-1.185***
	(0.0116)
lnsigma2u	0.400***
	(0.00899)
Observations	**182,535**

Notes: The estimation method used is a cross section stochastic frontier. Province dummies approximate fixed effects. Robust standard error in parentheses. ***p<0.01, **p<0.05, *p<0.1.
Source: Authors' calculations based on CNA (2018).

The stochastic frontier estimates are used to calculate technical efficiency scores at the plot level. The distribution of scores across plots is concentrated in the intermediate ranges: most values fall between 0.3 and 0.8, with a mode around 0.6 (**Figure 5**). Very low efficiency scores (below 0.2) and scores near the frontier (above 0.8) are rare, indicating that most producers operate at moderate efficiency levels.

Figure 5. Technical Efficiency Histogram



Source: Authors' calculations, based on cross-sectional estimates from the CNA 2018.

When technical efficiency is disaggregated by plot size (**Table 5**), a quintile analysis shows a slight decline in average efficiency as plot size increases—from 0.487 in the smallest quintile to 0.454 in the largest. At the same time, variability rises with scale: the standard deviation increases from 0.174 to 0.216, and the range of minimum and maximum values also widens, suggesting that larger plots encompass both highly efficient and very inefficient producers (greater heterogeneity). Overall, these results point to substantial room for efficiency improvements across all farm sizes, with small and medium farms tending to exhibit marginally higher average efficiency while larger farms show greater dispersion in performance outcomes.

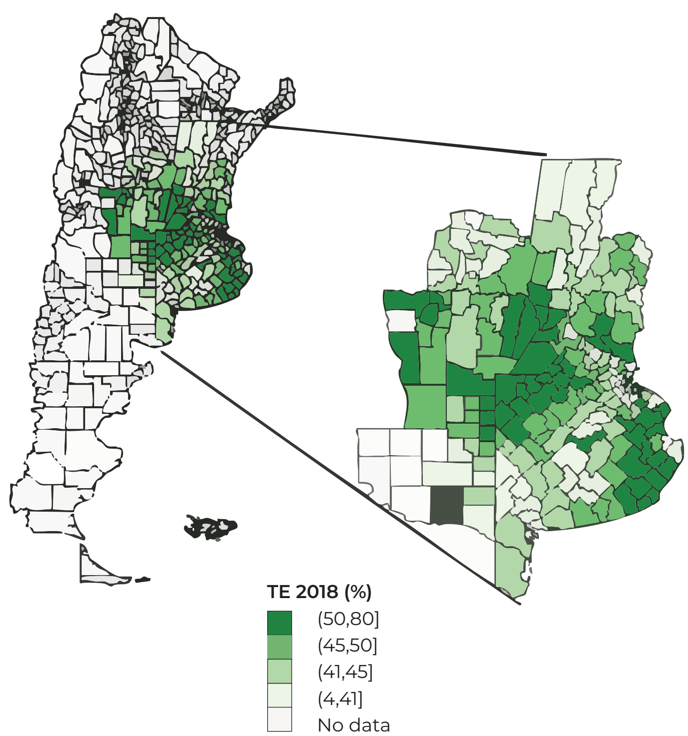
Table 5. Technical efficiency by plot size

Quintiles	N	Mean	SD	Min.	Max.
1	36310	0.487	0.174	0.012	0.851
2	36279	0.474	0.189	0.007	0.859
3	36533	0.47	0.195	0.006	0.876
4	36949	0.463	0.204	0.002	0.895
5	36464	0.454	0.216	0.002	0.914

Source: Authors' calculations based on cross-sectional estimates from CNA 2018.

Figure 5 shows the geographic distribution of technical efficiency by municipality (*partido* or department) across Argentina's central agricultural provinces. The average national technical efficiency is estimated at 49%, with farm-level scores ranging from as low as 0.1% to as high as 92%. Efficiency levels are generally higher in the core agricultural areas of the Pampas, particularly in central and northern Buenos Aires, southern Santa Fe, and eastern Córdoba, where average values frequently exceed 0.50. By contrast, municipalities located in more peripheral areas, including parts of western Córdoba, La Pampa, and marginal zones of Entre Ríos, tend to exhibit lower efficiency, often below 0.45. There is no recent evidence on technical efficiency estimations for agricultural farms in Argentina. Although not directly comparable, we contrast our results with studies from Brazil and Paraguay, where technical efficiency levels are also relatively low. For instance, de Freitas et al. (2021) used data from the Brazilian Agricultural Census and found that farmers' technical efficiency (TE) averaged approximately 30–32%, with small differences between those who received technical assistance and those who did not. In Paraguay, Lema and Gatti (2025) showed that TE decreased from 52% to 32% between 1991 and 2022. Both cases illustrate the coexistence of heterogeneous production technologies, suggesting that low efficiency may persist due to delayed adaptation in managerial capacity.

Figure 5. Geographic distribution of technical efficiency by municipality



Source: Authors' calculations, based on cross-sectional estimates from the CNA 2018.

When comparing efficiency levels aggregated by province (**Table 6**), the results reveal relatively small differences in average performance and some variation in dispersion. Mean technical efficiency ranges from 0.448 in Entre Ríos to 0.483 in San Luis. The core producing areas of Buenos Aires, Córdoba, and Santa Fe are clustered around 0.47. Across provinces, minimum technical efficiency values are close to zero, while maximum values fall between 0.85 and 0.91. Overall, the distribution by province confirms the broader finding that average technical efficiency remains moderate, with substantial heterogeneity both within and across provinces.

Table 6. Average technical efficiency by province

Province	Plots	Mean	SD	Min.	Max.
Buenos Aires	61291	0.471	0.194	0.002	0.890
Córdoba	44486	0.473	0.191	0.003	0.899
Entre Ríos	14430	0.448	0.222	0.006	0.914
La Pampa	3380	0.481	0.178	0.008	0.857
San Luis	1009	0.483	0.177	0.030	0.863
Santa Fe	57939	0.469	0.197	0.005	0.889

Source: Authors' calculations, based on cross-sectional estimates from the CNA 2018.

IV. CONCLUSIONS AND POLICY RECOMMENDATIONS

Between 1961 and 2022, Argentina's agricultural sector experienced significant growth in both output and productivity, though with distinct patterns across crops and livestock. On average, agricultural output increased by 2.6% annually, while TFP grew at 1.78%. The main driver of growth was the crop sector, where output and TFP rose by 2.93% and 1.88% annually, respectively, compared to livestock, which grew at less than 1% in both dimensions. Input use rose only modestly, at 0.82% per year, suggesting that efficiency gains and technological change, rather than factor accumulation, accounted for much of the observed increase in production. The following recommendations are drawn from this analysis.

I. Improve productive efficiency to increase agricultural output without raising input use

The efficiency analysis reveals considerable room for improvement, primarily through better use of existing technologies and resources. The estimated average technical efficiency is approximately 50%, indicating that producers are currently operating at only half of their potential. This underscores the opportunity to boost yields by optimizing current practices rather than increasing input quantities. Importantly, as the analysis did not find significant variation in technical efficiency across plot sizes, potential productivity gains could be achieved across different scales of production, reinforcing the potential for broad-based impact through better resource utilization.

II. Invest in agricultural research, extension services, managerial capacity, and knowledge transfer to boost productivity and increase agricultural output

The findings on TFP and technical efficiency suggest that Argentinian agriculture has substantial potential for growth through improved efficiency and faster adoption of innovations. To unlock this potential, policies should focus on strengthening R&D, expanding extension services, and enhancing mechanisms for knowledge transfer to producers. The analysis confirms that promoting the adoption of innovative technologies such as certified seeds, precision agriculture, and direct sowing, could contribute significantly to agricultural performance.

III. Gather disaggregated data to inform the design of targeted policies that address variability in efficiency levels across farms

The coexistence of highly efficient and inefficient farmers within the same geographic areas suggests that uniform policy approaches are inappropriate. Improving overall productivity requires differentiated strategies and tailored interventions that address the specific constraints faced by less efficient producers.

IV. Invest in information systems and open data to support evidence-based agricultural policies

Strengthening agricultural information systems and ensuring the public availability of reliable data are essential for designing and implementing effective policies. To improve policy design and targeting, investments should prioritize improvements to the availability and accessibility of detailed information on outputs, inputs, prices, access to technologies, adoption of practices, and socioeconomic characteristics. Regular agricultural censuses and regionally representative surveys are indispensable tools for generating this evidence. Such efforts enable deeper analysis and allow estimations of the causal impacts of specific policies on agricultural productivity over time.

CHAPTER 11. **URUGUAY**

Authors: Federico García, José María Gil, Daniel Lema, Juan Hernán Cabas Monje, Mahdieh Khezrinejadgharaei, Bouali Guesmi, Carmine Paolo De Salvo

SUMMARY

Uruguay's agribusiness sector is a central pillar of the national economy. Agricultural production in the country benefits from favorable natural conditions, but its performance increasingly depends on productivity improvements. In this context, sustainable intensification has emerged as the guiding principle of contemporary agricultural development in Uruguay, aiming to address concerns regarding environmental impacts while fostering economic growth. Total factor productivity (TFP) is thus an appropriate indicator to assess the sector's performance over time. Using national data on production and inputs, this chapter constructs a TFP index to analyze productivity trends and evaluate the role of agricultural research and knowledge generation in shaping agricultural performance. Our results indicate that agricultural productivity grew at an average annual rate of 1.53% between 1980 and 2022. Furthermore, the empirical evidence suggests that public investment in agricultural R&D has a significant positive influence on agricultural productivity in Uruguay. These findings underscore the importance of sustained, long-term public support for agricultural research, as continued investment is essential to preserve and enhance its contribution to national development and societal welfare.

I. INTRODUCTION

Uruguay is an agro-exporting country whose main production sectors include livestock, agriculture, pulpwood, rice, and dairy. The competitiveness of these sectors is crucial for gaining and maintaining access to international markets. This strong export orientation, together with a favorable environment for foreign agribusiness investment, could drive productivity improvements through innovation, technological progress, and deeper integration across value chains. By 2023, agriculture accounted for 5.8% of Uruguay's GDP, a share that rises to 21% when food and fiber processing industries are included. The sector generated US$6.6 billion in exports, equivalent to 72% of the country's total exports (DIEA-MGAP, 2024). This figure excludes the value added from pulp mills located in free trade zones. Beef is Uruguay's leading export product, followed by grains and forestry products. Employment in rural and mining activities accounted for 8% of total employment, most of which was in agriculture. When agro-industrial processing is included, this share increases to approximately 12%.

The agricultural sector in Uruguay has evolved dynamically across subsectors. From the 1990s, forestry expanded rapidly, culminating in the establishment of three pulp mills that attracted record investment flows for the country. Grain production was boosted by the introduction of soybeans and a technological package combining no-till practices with herbicide-resistant GMO varieties. In the beef sector, a structural transformation in the fattening stage has reduced the average slaughter age and increased meat output. Collectively, these subsectors drove significant productivity gains until the mid-2010s, after which growth began to stabilize. Given that Uruguay's agricultural frontier is geographically constrained, the expansion of forestry and crops has occurred at the expense of pastureland, resulting in a reduction in cattle grazing areas. Likewise, beef production has progressively replaced sheep farming, leading to a sustained decline in ovine stocks.

Total factor productivity (TFP) growth is a key indicator of agricultural competitiveness. Several studies have examined the trajectory of Uruguay's agricultural TFP. Trindade and Fulginiti (2015) reported average annual growth of 1.3% between 1969 and 2009, while Ludeña (2010) found growth of less than 1% annually. Nin-Pratt et al. (2015), applying a deterministic approach for Latin America and the Caribbean (LAC), estimated average annual growth of 1.5% between 1981 and 2012. Coelli and Prasada Rao (2005) applied the Malmquist index across 93 countries and found no significant growth in Uruguay's TFP between 1980 and 2000. Lachaud et al. (2017) estimated Uruguay's TFP growth at 1.22% for 1961–2012 when controlling for unobserved heterogeneity, and 1.03% when accounting for climate effects. Other studies of the sector include Sotelsek-Salem and Laborda-Castillo (2019) and Nin-Pratt et al. (2019).

In Mercosur countries, agricultural productivity grew at an average annual rate of 2.1% between 1961and 2021 (Salazar et al., 2024), influenced by institutional drivers such as public investment in agricultural R&D and favorable trade environments (Bharati and Fulginiti, 2007). Farm-level studies in Uruguay have shown that innovation efforts have a positive impact on agricultural productivity, influenced by factors such as farm size and cooperation (Aboal et al., 2019).

Over the past 10 to 15 years, research impact assessments (RIA) have gained prominence, providing public research organizations with valuable insights into the effectiveness of their R&D activities. The literature has consistently provided estimates of the "social rate of return" on research, underscoring the high value of public investment in agricultural R&D (Alston et al., 2000; Andersen, 2019). While a substantial body of evidence exists for developed countries, empirical studies remain relatively scarce in developing economies, particularly in LAC. In Uruguay, Bervejillo et al. (2012) estimated annual rates of return to public agricultural research of between 23% and 27%.

This study contributes to updating TFP estimates for the agricultural primary sector and time trends following Bervejillo et al. (2012).

It expands the limited body of literature examining the role of agricultural R&D at the institutional governance level in LAC. By employing long-term time-series data on productivity and public R&D spending, the analysis reduces model bias and yields more robust estimates.

II. METHODOLOGY AND DATA

This study addresses two central questions.

I. **How has Uruguay's agricultural TFP evolved?** To answer this question, we updated the estimations of Bervejillo et al. (2012), which covered 1961–2010, focusing our analysis on 1980–2022.

II. **To what extent can productivity growth be attributed to public-sector R&D efforts?** To estimate TFP, we employed an index ratio of outputs to inputs for 1980–2022. Fisher indices were constructed using 21 input factors and 39 agricultural products, allowing us to capture compositional changes in both aggregates over time and to mitigate common problems associated with index number construction (Bervejillo et al., 2012).

After estimating TFP, we conducted a regression analysis to quantify the role of R&D activities in driving agricultural TFP, using the following specification:

$$\ln TFP_t = \alpha_0 + \alpha_1 \ln K_{INIAt} + \alpha_2 \ln K_{NOINIAt} + \alpha_3 \ln SE_t + \alpha_4 C_t + \varepsilon_t$$

Our explanatory variables capture R&D undertaken by the National Agricultural Research Institute (INIA) (K_{INIAt}) and by public universities and an extension agency ($K_{NOINIAt}$). The model also controls for weather (C_t), and spillovers (SE_t).

The public stock of agricultural knowledge was constructed using data on INIA's total R&D expenditures from 1961 to 2022. Given that the effects of R&D are not immediate, a 25-year lag structure is applied to value the accumulated stock of public research over time(Alston et al., 2010). The model assumes that R&D initially generates only limited impacts, followed by a period of stronger influence, and then a gradual decline.

III. FINDINGS

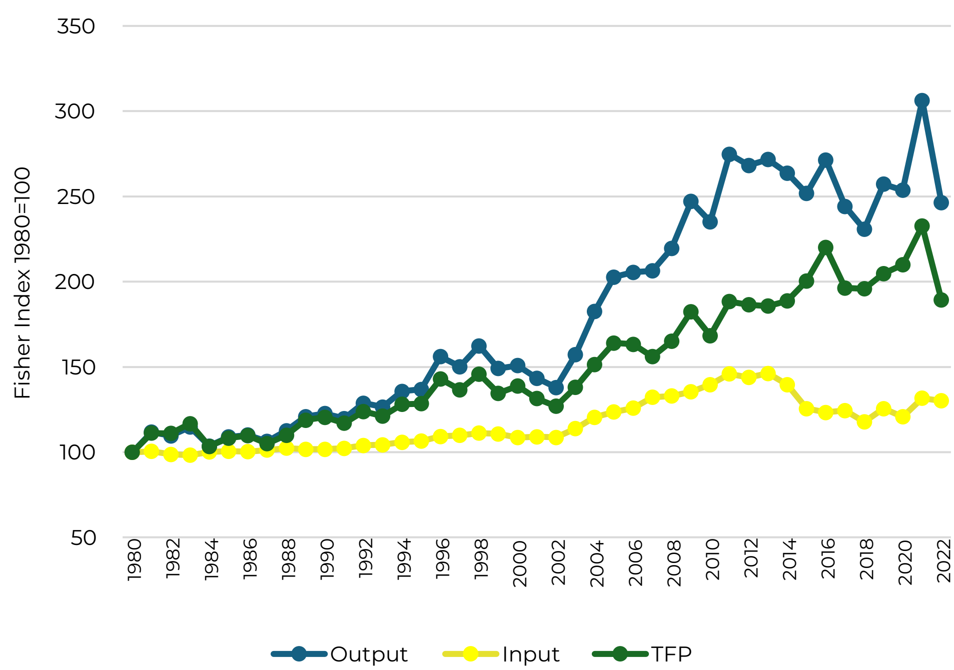
TOTAL FACTOR PRODUCTIVITY

The evolution of TFP, output, and input indices is presented in **Figure 1**. Between 1980 and 2022, productivity grew at an average annual rate of 1.52%, reflecting a moderate-to-low rate of expansion. Several sub periods can be distinguished. From 1980 to 1988, TFP grew at an annual rate of 1.2% before accelerating to an average of 3% between 1988 and 1998, largely driven by transformations in the beef cattle sector and the expansion of forestry. Productivity fell by -1.48% annually in 1998–2002, attributable primarily to the economic recession and the outbreak of foot-and-mouth disease. From 2002 to 2016, TFP growth rebounded to 3.4% per year, coinciding with the expansion of soybean cultivation. TFP growth turned negative in the final years of the series, averaging -0.8% between 2016 and 2022, a period marked by exceptional events including the COVID-19 pandemic in 2020, economic recovery in 2021, and a severe drought in 2022.

Crop expansion in Uruguay is constrained by soil suitability and the public policy requirement of crop rotations to prevent erosion, placing structural limits on soybean cultivation (Molfino, 2013; Alvarez and Ernst, 2024). When international prices declined in 2012–2013, marginal areas with higher transportation costs and poorer soils were withdrawn from grain production. Between the

2013/14 and the 2020/21 seasons, soybean area contracted by 30% (DIEA-MGAP, 2019; DIEA-MGAP, 2024). This area reduction is mostly explained by price reductions, that made some marginal areas less favorable to cropping. Wheat, the main winter crop, experienced similar sustained reductions in planted area from the 2011/12 season through the early 2020s (DIEA-MGAP, 2019 and 2024). Between 2017 and 2020, the expansion of planted forests also slowed (DGF-MGAP, 2025). By contrast, beef production remained relatively stable during this period (Aguirre, 2022), while milk production peaked in 2013/14, declined, and only returned to previous levels in 2019/20.

Figure 1. Agricultural output, inputs, and TFP in Uruguay (1980–2022)



Livestock outpaced agriculture in terms of TFP growth. Over the last 12 years of the study period, crop TFP declined, partially offset by a reduction in the input index between 2013 and 2016 (**Table 1**). This negative trend for crops was driven primarily by reductions in extensive crop production, particularly soybeans and, to a lesser extent, wheat. Meanwhile, the decline in the input index was insufficient to prevent an overall decrease in crop TFP between 2010 and 2022. This contraction was largely explained by falling international prices, which tightened profit margins and displaced crops from marginal lands. Recurrent droughts further reduced yields, especially in summer crops such as maize and soybeans, the latter of which remains Uruguay's largest crop, with more than one million hectares under cultivation.

By contrast, livestock TFP recorded annual growth of 2.08% during 2010–2022 and averaged 1.6% per year over the entire 1980–2022 period. Interestingly, input use in livestock has declined since 2011, reflecting the reallocation of land toward crops and forestry. Livestock is a key sub-sector of agricultural production in the country, being it the most important in terms of total land use and number of farmers employed. For that reason, TFP calculations are calculated separately for crops and livestock.

Table 1. Annual growth in output, inputs, and TFP for agriculture, crops, and livestock in Uruguay (%)

Period	Overall			Crops			Livestock		
	Output	Input	TFP	Output	Input	TFP	Output	Input	TFP
1980–1990	2.04	0.18	1.87	3.20	0.88	2.32	1.47	-0.10	1.57
1990–2000	2.06	0.65	1.41	2.78	1.48	1.30	1.59	0.16	1.42
2000–2010	4.44	2.52	1.93	8.91	5.83	3.09	0.75	-0.50	1.25
2010–2022	0.39	-0.59	0.98	-1.16	-0.81	-0.35	1.71	-0.36	2.08
1980–2022	**2.15**	**0.63**	**1.52**	**3.21**	**1.72**	**1.50**	**1.40**	**-0.21**	**1.60**

The last 12 years of analysis, in which Uruguayan crops experienced negative growth, can be divided in two sub-periods, before and after 2014, as planted area and agricultural production peaked in that year. The reduction in crop prices experienced after 2014 explains the reduction in planted area and total output.

Public research investments significantly contributed to agricultural productivity. A key pathway for increasing TFP is the adoption of new technologies, which is what prompted our analysis of the contribution of R&D to productivity growth. We looked at two main sources of public R&D: the National Institute for Agricultural Research (INIA) and, jointly, the University of the Republic (UDELAR) and the Agricultural Extension Institute (IPA). Additional control variables included international spillovers, infrastructure, and weather effects. The results show that a 1% increase in the agricultural knowledge stock is associated with a 0.14% to 0.30% increase in TFP, depending on the model specification (Table 2).

Table 2. Results of alternative models analyzing the impact of R&D on TFP

Parameters	Models			
Range[1]	1	2	3	4
Adjusted R^2	0.946	0.945	0.943	0.941
Lag distribution characteristics				
δ	0.50	0.70	0.50	0.60
λ	0.75	0.60	0.65	0.50
Maximum lag (years)[2]	4,00	5,00	2,00	2,00
Elasticity (INIA stock of knowledge)	0.300***	0.266**	0.180*	0.140*
Elasticity (non-INIA stock of knowledge)	0.015	0.003	0.147	0.193*
Spillover effect	0.003	0.007	0.007	0.008
Weather variable (C)[3]	-0.020	-0.013	-0.023	-0.027

Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

[1] Models are classified according to the sum of squared errors (SSE).
[2] The maximum lag indicates the number of years required for research investments made in the initial year to reach their maximum impact.
[3] We tested other weather controls, including the square of precipitation and temperature variables, but the results proved robust to these alternatives.

The models presented in **Table 2** differed in their assumptions regarding the distribution of research investment impacts (δ and λ) on production and the length of the maximum lag (the time between investment and maximum research impact). All specifications incorporated a proxy for the knowledge stock generated by other institutions, international spillover effects from machinery imports (capturing the role of imported technologies), and precipitation as a weather control variable.

The only control variable to yield a statistically significant effect was non-INIA knowledge stocks in model 4. Additional weather-related variables were also tested, but none improved model fit. The results further suggest that when the time to reach the peak impact of research investment is assumed to be shorter, the estimated contribution of INIA diminishes, while that of other institutions grows. This pattern indicates that the transmission of research impacts takes longer in the case of INIA than for other sources. The calculated internal rate of return of agricultural research investments ranges between 18 to 25%, a value that is lower, but aligned, with the results found by Bervejillo et al. (2012).

IV. CONCLUSIONS AND POLICY RECOMMENDATIONS

The results presented in this chapter indicate that agricultural productivity in Uruguay increased between 1980 and 2022. However, the pace of growth slowed markedly in the most recent years, with the TFP index showing declining growth rates and, in some cases, outright losses (notably for crops between 2010 and 2022). Over the full study period, nearly 50% of total production growth can be attributed to productivity gains. Based on the results, the following recommendations are proposed:

I. Support agricultural R&D

The findings confirm that R&D activities have a significant positive impact on agricultural productivity. Estimates suggest that investments in scientific knowledge and research capacity enhance productivity gains. These results underscore the importance of sustained, long-term public investment in agricultural R&D to preserve and expand its contribution to societal welfare. An expansion of resources allocated for INIA, public universities, and other key research and innovation institutions could potentially reinforce Uruguay's capacity to generate and disseminate agricultural innovations.

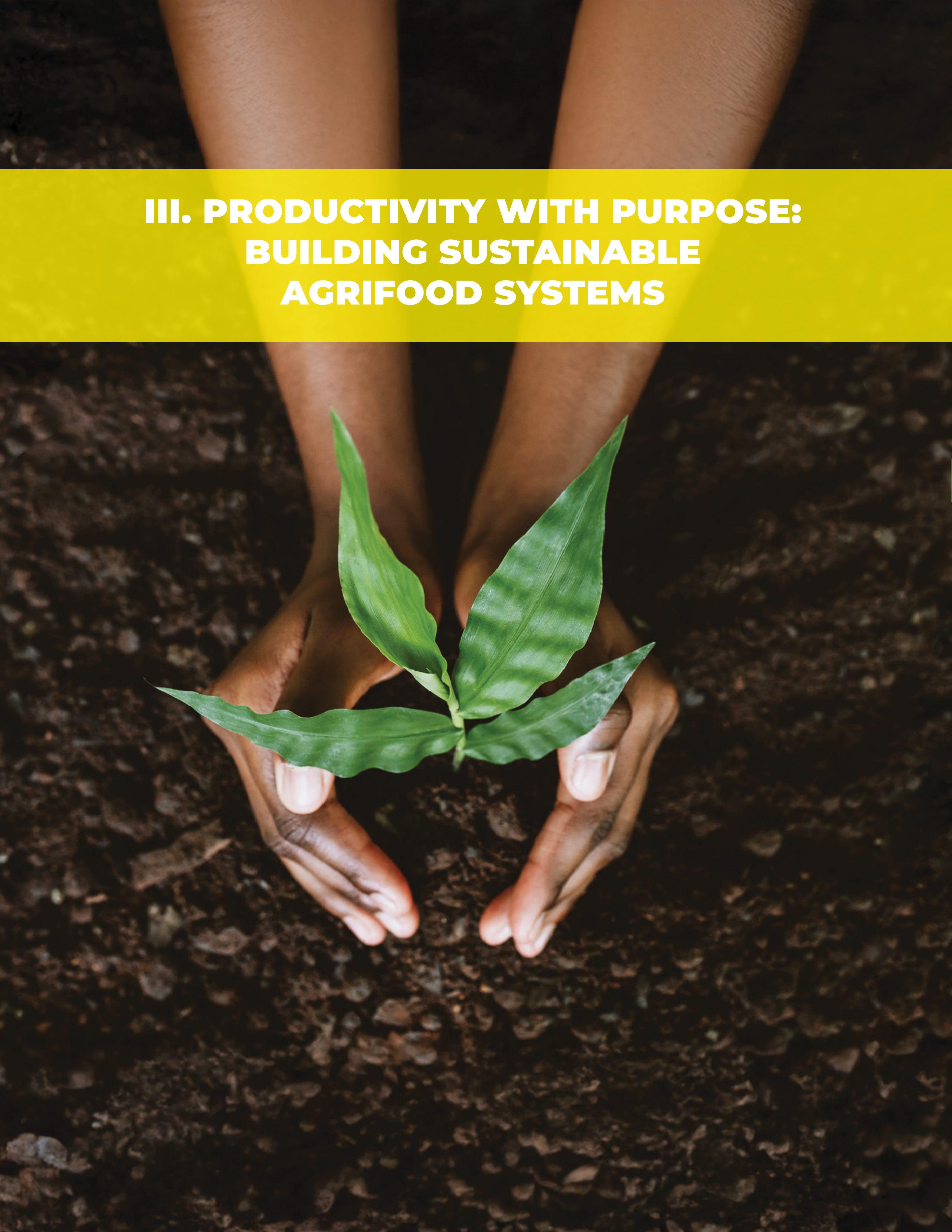
II. Stabilize cropping cycles and strengthen market access

Extensive crops in Uruguay have shown cyclical behavior, alternating between periods of high TFP growth and phases of stagnation or decline due to market or climate conditions. Even when the TFP response to weather shocks is not statistically significant, we observe that crops TFP is affected by output variability due to droughts and rainy seasons. Policies should therefore aim to mitigate the impact of climate variability on output, such as by incentivizing the adoption of supplemental irrigation and supporting research on agronomic practices that enhance drought resilience. At the same time, the recent slowdown in TFP growth has coincided with a period of lower international prices, highlighting the sector's vulnerability to global market fluctuations. Improving and diversifying market access through trade agreements or subsector-specific competitiveness policies would help sustain growth in Uruguay's export-oriented agricultural economy.

III. Strengthen agricultural information systems through periodic microdata collection

The lack of publicly available, department-level agricultural data prevented this chapter from providing more than an overview of agricultural performance at the national level. While informative, aggregate conclusions might not always be sufficient for designing targeted policies that respond to the needs of specific regions or areas. Strengthening the availability and accessibility of microeconomic data could provide a stronger evidence base for designing and implementing context-specific policies based on rigorous analysis.

III. PRODUCTIVITY WITH PURPOSE: BUILDING SUSTAINABLE AGRIFOOD SYSTEMS



CHAPTER 12.

REASSESSING AGRICULTURAL GROWTH: INTRODUCING A SUSTAINABLE PRODUCTIVITY INDEX FOR LATIN AMERICA AND THE CARIBBEAN

AUTHOR: ALEJANDRO NIN-PRATT

SUMMARY

This chapter introduces a sustainable productivity index (SPI) to evaluate agricultural growth in Latin America and the Caribbean (LAC) between 1995 and 2021, integrating economic output with environmental costs. While LAC doubled its agricultural output and led global productivity gains during this period, this progress came with significant environmental degradation, including a 50% rise in pollution and pressures on natural resources, such as water stress, soil erosion, and deforestation. The SPI adjusts conventional total factor productivity (TFP) by penalizing undesirable outputs like greenhouse gas emissions and nutrient runoff, offering a more accurate picture of sustainable growth. Findings reveal that while productivity increased by 60%, sustainability-adjusted productivity rose by only 13%, with sharp disparities across subregions. The Southern Cone achieved the highest output and productivity growth but also incurred the steepest environmental costs. Central America and the Andean region recorded moderate gains with varying environmental impacts, while the Caribbean fell behind. The study underscores that agricultural modernization in LAC has often been capital-intensive and export-driven, marginalizing smallholders and degrading ecosystems. The results call for a policy shift toward integrated, context-sensitive strategies that balance productivity with environmental stewardship. Technological innovations—such as precision fertilization and biological alternatives—combined with policy incentives like payments for ecosystem services and environmental taxes, institutional reforms to strengthen interministerial coordination, and public investment in dual-purpose R+D+i systems, are essential to support sustainable and resilient agricultural systems across the region.

I. INTRODUCTION

Agriculture has long played a pivotal role in the socioeconomic fabric of Latin America and the Caribbean (LAC), underpinning livelihoods, ensuring food security, generating employment, and contributing substantially to national and regional GDP and export revenues. However, agricultural production has often carried steep environmental costs. The region is home to some of the world's most biodiverse ecosystems, now increasingly threatened by deforestation, soil degradation, and climate variability.

Sustainable agricultural production—defined here as the capacity to increase output while preserving ecological integrity and enhancing long-term resilience—has thus become a central policy and research challenge in LAC. The traditional focus on productivity metrics such as TFP, measured as total output per unit of aggregated input, fails to fully account for environmental externalities and long-term sustainability. Although LAC experienced the fastest TFP growth among developing regions over the past 25 years, much of this growth was uneven and often decoupled from environmental performance. This disconnect between productivity and sustainability creates a pressing need for integrated metrics that balance the two.

Several scholars have highlighted the limitations of existing productivity assessments. While technological advances and efficiency gains have driven regional productivity improvements, concerns remain over resource depletion, ecological impacts, and disparities in operational and environmental efficiency across LAC countries. These studies suggest that measuring productivity without incorporating environmental dimensions paints an incomplete picture and may encourage long-term unsustainable practices.

In response, this chapter develops a sustainable productivity index (SPI) for agriculture in LAC and analyzes the trends and dynamics over time. This composite index seeks to integrate production performance and environmental stewardship into a unified metric. The goal is to provide policymakers, researchers, and stakeholders with a robust, multidimensional tool to evaluate and guide sustainable agricultural strategies. By aligning productivity with sustainability goals, the SPI seeks to foster agricultural systems that are both high performing and resilient, capable of supporting the region's development while safeguarding its natural capital. This type of instrument is crucial for identifying trade-offs between productivity and environmental performance, prioritizing investments in sustainable technologies, and informing long-term policy design.

II. METHODOLOGY AND DATA

To assess the environmental sustainability of agricultural growth in LAC between 1995 and 2021, this study applies an SPI for agriculture, proposed by O'Donnell (2022) and tailored to the region. The analysis addresses five core research questions:

I. How have agricultural production and productivity evolved in LAC

II. What are the environmental impacts of this growth

III. Are subregions within LAC following different sustainability paths?

IV. What are the key drivers of productivity and environmental change?

V. What policy implications arise from the current trends in TFP and the SPI?

The study draws on harmonized data from FAO (2024), USDA-ERS (2024), and national sources for 24 countries in LAC. It incorporates 14 desirable agricultural outputs, 10 inputs, and 6 undesirable outputs:

Table 1: Agricultural outputs, inputs, and undesirable outputs considered in the analysis

Indicator	Variables Included
Desirable outputs	Cereals, roots and tubers, pulses, oil crops, vegetables, fruits, sugar crops, cash crops, fiber crops, beef, dairy, sheep and goats, pigs, poultry
Undesirable outputs	Labor, capital, energy, fertilizer, pesticide, feed, water, cropland, pasture, irrigated area
Inputs	Greenhouse gas (GHG) emissions, pesticide risk, soil erosion, deforestation, water stress, nutrient budget

Source: Authors' calculations.

THE SPI COMBINES THREE INDICES:

1. **Desirable output index** *(GI)*: Agricultural production of crops and livestock.
2. **Undesirable output index** *(BI)*: Negative environmental impacts.
3. **Input index** *(XI)*: Use of agricultural inputs.

$$SPI = (GI^{1-\alpha} X\ BI^{-\alpha}) / XI$$

SPI functions like a TFP index but penalizes countries for generating undesirable outputs that deplete natural capital and damage the environment. The SPI thus reflects relative sustainable growth, increasing with higher agricultural desirable outputs and decreasing with higher input use and environmental harm. A parameter α (ranging from 0 to 1) is introduced to balance the weight assigned to undesirable outputs. If $\alpha=0$, undesirable outputs are ignored and SPI equals TFP; if $\alpha=1$, the focus is solely on measuring undesirable outputs relative to inputs.

Aggregation uses fixed output and input market prices as weights[1]. Because undesirable outputs lack market prices, shadow prices are estimated from the value of agricultural output forgone per unit reduction in those outputs[2]. This approach provides a comprehensive measure of sustainable productivity across countries and over time.

III. FINDINGS

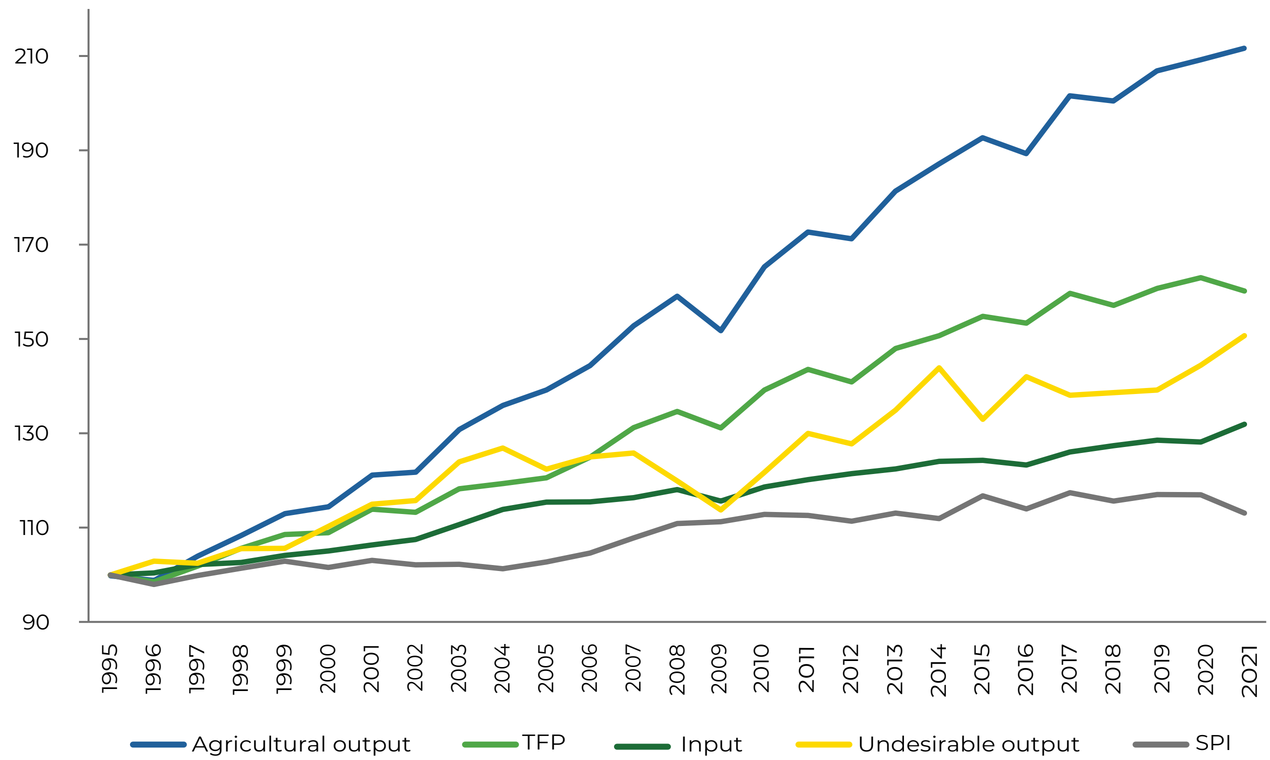
The transformation of agriculture

Between 1995 and 2021, LAC underwent a profound agricultural transformation marked by robust gains in output and productivity. Total output volume more than doubled, driven by structural shifts toward export-oriented, high-value commodities.

These changes culminated in a 60% increase in TFP. Input use grew by 31% and undesirable outputs—pollution, emissions, and environmental stressors—rose by 50%. When environmental costs are included, productivity growth is reduced to 13%, reflecting the negative environmental impact of agricultural expansion in LAC.

[1] Total desirable and undesirable outputs and total input were calculated using a Young multiplicative index, which applies output and input shares as weights. For example, the Young input index for country *j* in period t for two inputs, land *(A)* and labor *(L)* is: $\frac{(A_{j,t}^{SA} \times L_{j,t}^{SL})}{(A_{i,t_0}^{SA} \times L_{i,t_0}^{SL})}$ where SA and SL are the shares of land and labor, and i and t_o denote the reference country and year, respectively. This means that $XI_{j,t}$ measures the input of country j in year t relative to the input of country i in period t_o.
[2] For instance, reducing agricultural GHG emissions by one ton of CO_2eq in LAC results in an average production loss of $12, implying a shadow price of $12 per ton of CO_2eq.

Figure 1. Trends in agricultural total factor productivity (TFP), the sustainable productivity index (SPI), inputs, and desirable/undesirable outputs in Latin America and the Caribbean, 1995–2021



Source: Authors' calculations using FAO (2024).

The two phases of agricultural growth in LAC

The first phase (1995–2011) coincided with the global commodity price boom. LAC leveraged this period for rapid annual output expansion (3%) and modest input increases (1.1%). However, agriculture had a negative environmental impact in the region: annual growth of undesirable outputs (1.4%) reduced annual TFP growth from 2.2% to an SPI growth of just 0.8%. The second phase (2012–2021) followed the commodity price downturn. Export prices fell by 0.8% annually, slowing annual agricultural output growth to 2.1% and halving TFP growth to 1.3%. Despite the slowdown in the growth of desirable agricultural output and TFP, undesirable output growth remained stable, while SPI stagnated at 0.3%. This suggests a constraint on the ability of environmental outcomes to adjust alongside declining productivity growth (see Table 2).

The Drivers of Growth

The drivers of LAC's agricultural expansion reflect greater specialization and input intensification, as well as stronger integration into international markets. Specifically, the use of pesticides, fertilizers, and feed surged, while mechanization and feed intensification displaced labor and pasture, marking a transition toward capital-intensive systems. Oil crops (soybean and palm oil), poultry, and pigs led output growth, accounting for 75% of the total. These productivity gains came with mounting environmental impacts. Nutrient pollution, primarily from fertilizer use and manure management, was the fastest-growing undesirable output, followed by GHG emissions and deforestation. Nutrient imbalance leading to water pollution accounted for nearly 60% of the value of agricultural environmental damage, while GHG emissions contributed 17%[3].

Diverging regional outcomes, converging models

Agricultural transformation in LAC has followed a broadly shared path of export-led modernization, but the results have been mixed across LAC subregions. Some achieved substantial productivity gains, but development and sustainability outcomes have diverged widely. Most benefits have been concentrated in capital-intensive areas, whereas other regions have experienced stagnation or rising environmental costs. These costs—particularly nutrient imbalances, deforestation, and GHG emissions—threaten the long-term viability of agricultural activities.

Tables 2 and 3 highlight the heterogeneity of agricultural transformation across LAC subregions, revealing sharp contrasts in growth trajectories, environmental impacts, and input use strategies. The Southern Cone stands out for maintaining the highest productivity and SPI gains, albeit at the expense of significant environmental trade-offs. Central America and the Andean region experienced a more fragile progress, increasingly constrained by ecological pressures. Meanwhile, the Caribbean lagged across all performance dimensions, reflecting persistent structural and environmental vulnerabilities.

Table 2. Annual average growth rates of outputs, inputs, TFP, and SPI in LAC and subregions (1995–2021 and subperiods)

Period	Indicator	Andean	Caribbean	Central America	Southern Cone	LAC
1995–2011	Desirable outputs	2.8	0.2	2.3	3.8	3.3
	Undesirable outputs	1.6	0.6	-0.7	2.0	1.4
	Inputs	1.8	0.8	0.6	1.1	1.1
	TFP	1.0	-0.6	1.7	2.6	2.2
	SPI	-0.3	-0.8	1.2	0.9	0.8
2012–2021	Desirable outputs	1.8	1.0	2.0	2.2	2.1
	Undesirable outputs	0.1	2.4	3.0	1.1	1.4
	Inputs	1.2	0.0	0.8	0.7	0.8
	TFP	0.6	1.0	1.1	1.6	1.3
	SPI	0.0	0.0	-0.4	0.6	0.3
1995–2021	Desirable outputs	2.4	0.5	2.2	3.2	2.8
	Undesirable outputs	1.0	1.3	0.7	1.6	1.4
	Inputs	1.5	0.5	0.7	0.9	1.0
	TFP	0.8	0.0	1.5	2.2	1.9
	SPI	-0.2	-0.5	0.6	0.8	0.6

Source: Authors' calculations using FAO (2024).

[3] Authors' calculations using FAO (2024).

Table 3. Comparative matrix of environmental burdens, key inputs, and dominant production systems resulting from agricultural growth in LAC and across subregions (1995–2021)

Subregion	Main environmental burden	Key input trends	Dominant crops/livestock
Andean	Water stress, nutrient imbalance, deforestation	Irrigation expansion, high feed/pesticide use, rising labor costs	Oil crops, poultry, pigmeat, fruits
Caribbean	GHGs, nutrient imbalance, pesticide risk	Capital concentrated, declining labor/water use, stagnation	Roots, fruits, vegetables, poultry
Central America	GHGs, nutrient imbalance, water stress	Moderate input growth, irrigation, early mechanization	Vegetables, poultry, milk, maize
Southern Cone	Nutrient imbalance, GHGs, deforestation	High pesticide/fertilizer use, mechanization, feed intensification	Soybeans, maize, poultry, beef
LAC	Nutrient pollution from pesticide, fertilizer & manure management, followed by GHG and deforestation	Surge in the use of pesticides, fertilizers, mechanization, and feed	Soybeans, poultry, pigs

Source: Authors' calculations.

The analysis now turns to agricultural productivity and sustainability dynamics across the four subregions of Latin America and the Caribbean—Southern Cone, Andean Region, Central America, and the Caribbean. For each subregion, trends in desirable and undesirable outputs, TFP, and the SPI are presented. This framework highlights both the drivers of productivity growth and the environmental trade-offs involved, providing a comprehensive picture of how different parts of the region balance agricultural expansion with long-term sustainability.

A. Southern Cone: Regional powerhouse with high environmental costs

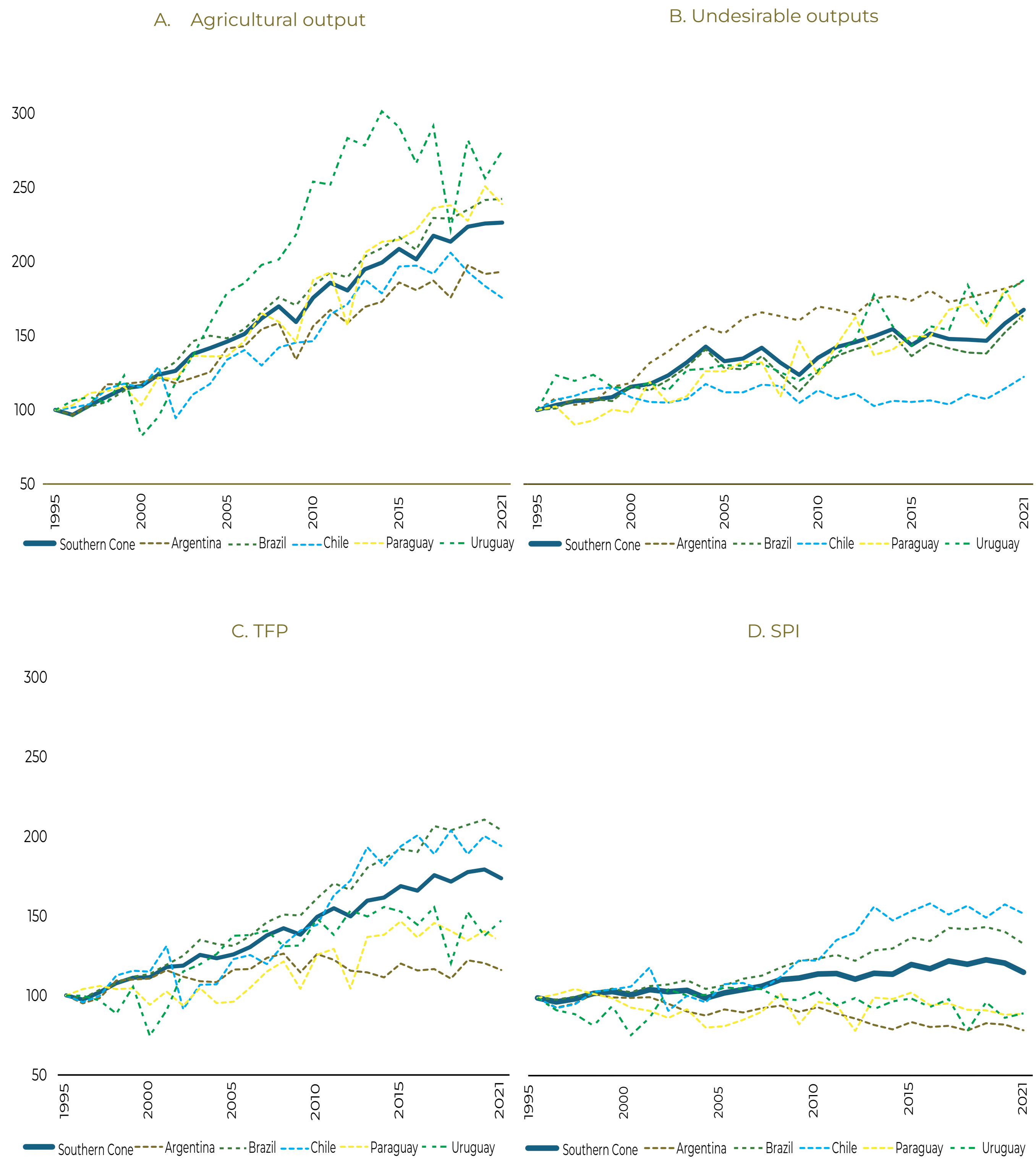
The Southern Cone emerged as the region's productivity leader, recording the highest growth in desirable outputs and TFP, driven by intensive use of pesticides, fertilizers, and concentrated feed. However, this success carried steep environmental costs, primarily due to nutrient imbalances, GHG emissions, and deforestation. Desirable output grew at an average annual rate of 3.2% over the full period, with faster growth between 1995–2011 (3.8%), before slowing to 2.2% in 2012–2021. TFP growth was the highest in LAC, averaging 2.6% annually before 2011 and 1.6% after, averaging 2.2% overall.

SPI growth was consistently positive—0.9% before 2011 and 0.6% after, for an average of 0.8%—making the Southern Cone the only subregion to sustain SPI gains in both periods. However, the subregion also saw the most rapid growth of undesirable output (1.6% annually), highlighting the environmental trade-offs associated with intensive agricultural expansion. Southern Cone, Brazil and Chile led the subregion in both SPI and TFP growth.

When comparing conventional TFP with its sustainability-adjusted counterpart, Uruguay registered the largest productivity loss, followed by Brazil, Paraguay, and Argentina, while Chile experienced the smallest reduction. Chile thus stands out as the country that combined strong growth with relatively limited losses once environmental costs are considered.

By contrast, Argentina not only recorded the slowest TFP growth and a negative SPI, but also started from already low productivity levels, which further weakened its sustainable performance (Figure 2).

Figure 2. Southern Cone: trends in desirable and undesirable outputs, total inputs, total factor productivity (TFP), and the sustainable productivity index (SPI) by country and regional average (1995–2021)



Source: Authors' calculations using FAO (2024).

B. Central America: Moderate gains, rising environmental pressures

Central America recorded moderate gains in both output and productivity while containing environmental burdens at the beginning of the period.

However, a sharp rise in undesirable output in recent years points to intensifying sustainability challenges, particularly linked to GHG emissions from deforestation, livestock, and crop residue burning.

Desirable agricultural output grew by 2.2% annually, declining slightly from 2.3% in 1995–2011 to 2.0% in 2012–2021. TFP growth averaged 1.5%, second only to the Southern Cone, but slowed from 1.7% in the first period to 1.1% in the second. Central America recorded moderate gains in both output and productivity while containing environmental burdens at the beginning of the period. However, a sharp rise in undesirable output in recent years points to intensifying sustainability challenges, particularly linked to GHG emissions from deforestation, livestock, and crop residue burning.

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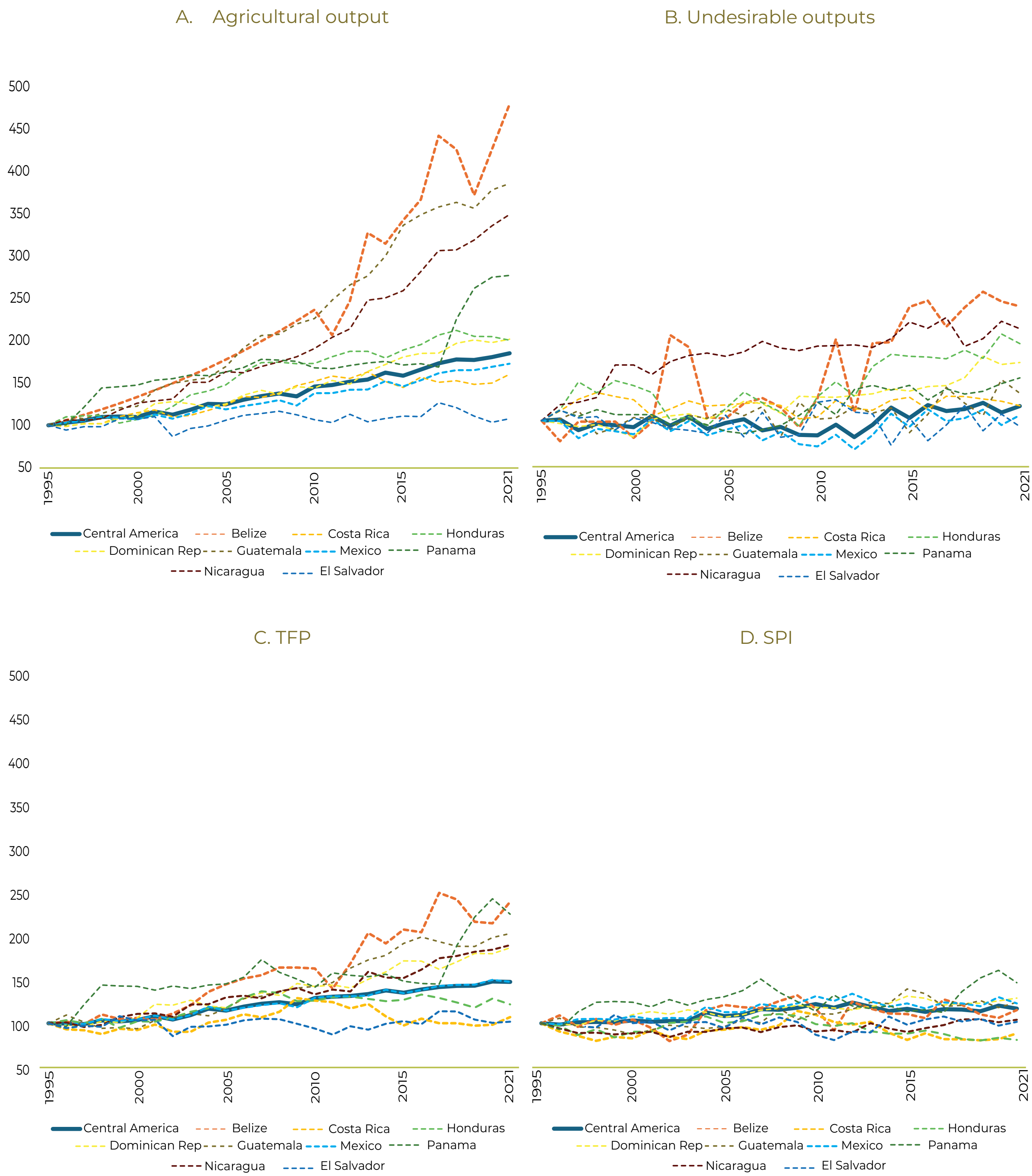
Figure 3. Central America: trends in desirable and undesirable outputs, total inputs, TFP, and the sustainable productivity index (SPI), by country and regional average (1995–2021)



Source: Authors' calculations using FAO (2024).

C. Andean region: Modest gains and growing sustainability risks

The Andean region showed moderate output growth, but SPI gains remained weak due to mounting water stress, deforestation, and soil degradation—signs of increasing pressure on fragile ecosystems. According to FAO (2021), human-induced deterioration of land, soil and water resources reduces production potential, limits access to nutritious food and undermines the biodiversity and environmental services that sustain resilient livelihoods. These pressures are reflected in the region's productivity dynamics, where output and efficiency gains have slowed in recent years. Desirable output grew at 2.4% per year, slowing from 2.8% in 1995–2011 to 1.8% in 2012–2021. TFP growth averaged 0.8%, declining from 1.0% to 0.6% across the two periods. SPI growth was negative for the entire period at −0.2%, despite a marked drop in undesirable output growth, which fell from 1.6% to just 0.1% after 2011, indicating some improvement in environmental management. As a result, SPI improved only marginally, from −0.3% before 2011 to 0% after, revealing limited sustainability progress. Peru led the subregion in TFP and desirable output growth, but this performance was offset by high input and undesirable output growth, which translated into low SPI gains. Nevertheless, Peru continues to register the highest productivity levels in the Andean region. Most other countries in the subregion followed a similar pattern, albeit with slower productivity growth. Bolivia, in particular, experienced poor TFP performance despite strong output growth, which was largely input-driven (Figure 4)[4].

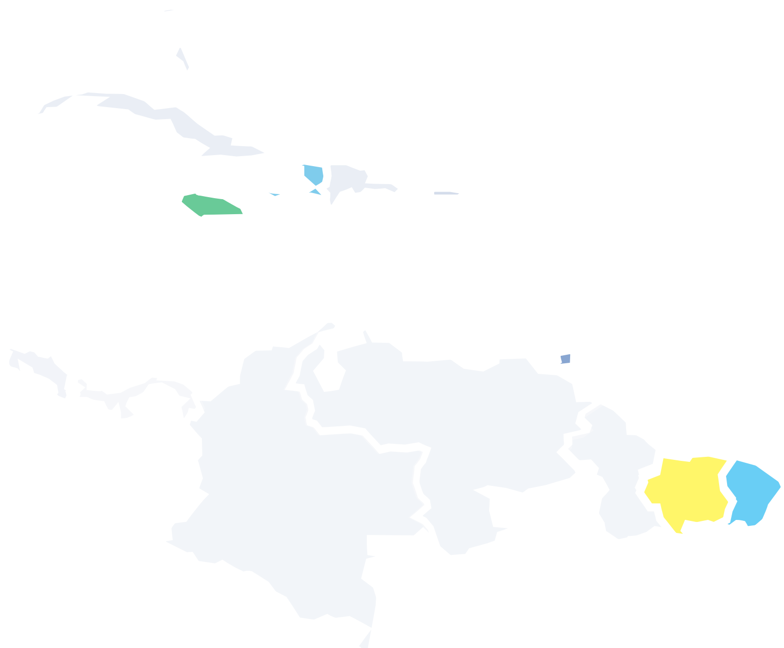
[4]Index results should be interpreted with caution, as data limitations are more pronounced for some countries than for others.

Figure 4. Andean region: Trends in desirable and undesirable outputs, total inputs, total factor productivity (TFP), and the sustainable productivity index (SPI), by country and regional average (1995–2021)

Source: Authors' calculations using FAO (2024).

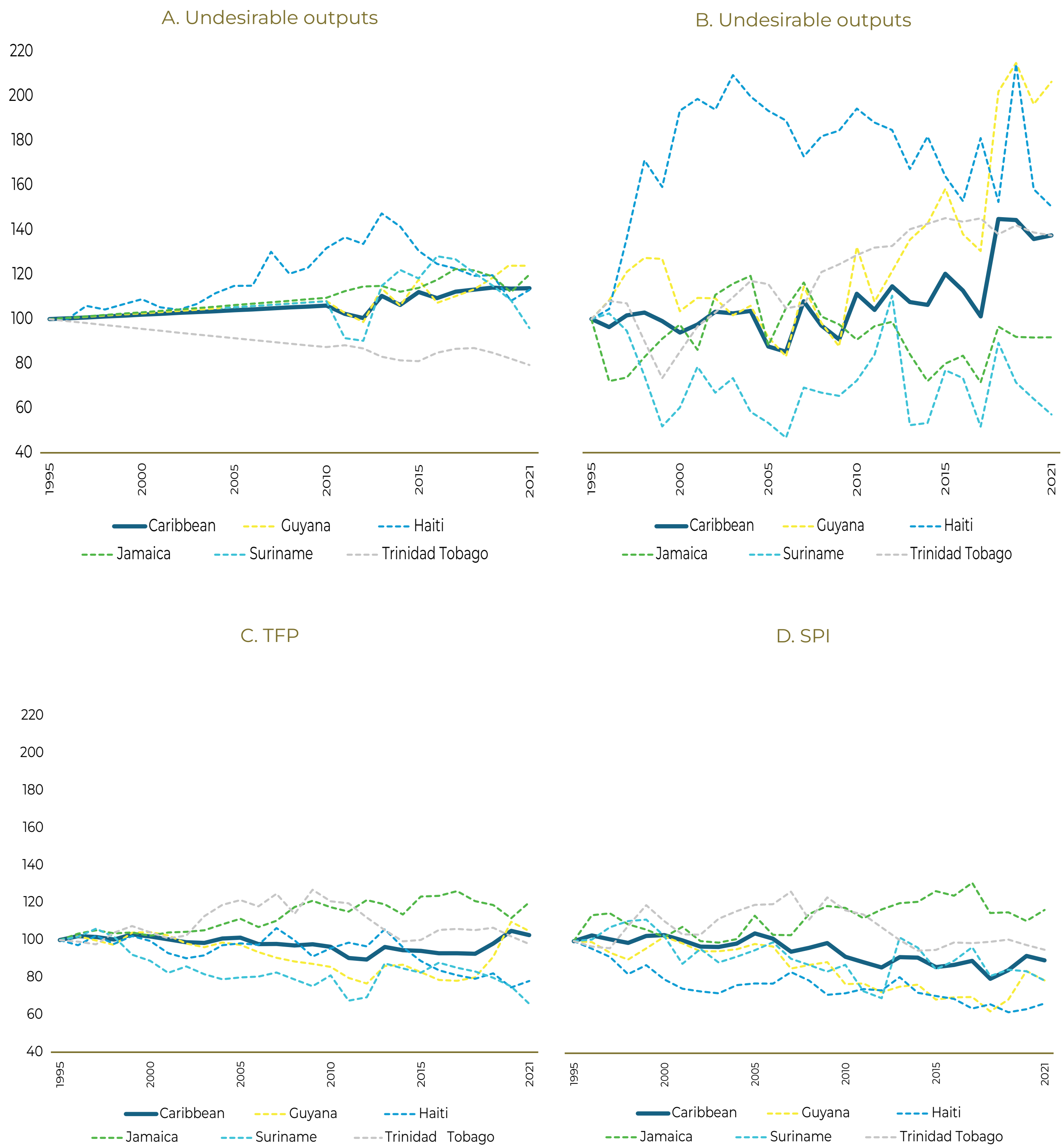
D. Caribbean: Stagnation and vulnerability

The Caribbean experienced stagnation across all fronts, presenting minimal output growth, weak TFP growth, and increasing environmental degradation. These outcomes reflect the region's retreat from agriculture and its vulnerability to ecological stressors, such as soil degradation that undermines productive capacity (FAO, 2021), and to economic pressures, particularly the high dependence on food imports that increases exposure to external shocks (ECLAC, 2022).



Desirable output grew by just 0.5% annually, with particularly low growth (0.2%) in 1995–2011, rising modestly to 1.0% thereafter. TFP growth averaged 0% over the entire period, recovering from −0.6% in the first phase to 1.0% in the last decade. Undesirable output increased substantially after 2011 (2.4%), despite the subregion's very modest desirable output growth. SPI remained at or below zero throughout (−0.8% before 2011, 0% afterward), pointing to a persistent failure to align productivity gains with sustainability outcomes. Within this overall poor performance, Jamaica stands out for recording the highest SPI and TFP growth, driven by modest output gains, no input growth, and a sharp reduction in undesirable outputs (Figure 5).

FIGURE 5. CARIBBEAN: TRENDS IN DESIRABLE AND UNDESIRABLE OUTPUTS, TOTAL INPUTS, TOTAL FACTOR PRODUCTIVITY (TFP), AND THE SUSTAINABLE PRODUCTIVITY INDEX (SPI), BY COUNTRY AND REGIONAL AVERAGE (1995–2021)



Source: Authors' calculations using FAO (2024).

IV. CONCLUSIONS AND POLICY RECOMMENDATIONS

This chapter provides a comprehensive analysis of agricultural growth in LAC from 1995 to 2021 by employing an SPI approach that integrates outputs, inputs, and undesirable outputs representing the negative environmental effects of agricultural production. It constitutes one of the first efforts to construct a comprehensive indicator of sustainable productivity for the region, directly linking agricultural growth to environmental impact.

The findings reveal a region that has successfully transformed its agricultural sector, achieving notable increases in output, productivity, and exports. However, when performance is adjusted for environmental sustainability, the gains appear far more limited. This imbalance underscores a structural challenge: productivity improvements have often been achieved at the expense of ecological health, exacerbating pressures such as GHG emissions, nutrient runoff, water scarcity, and deforestation. Because ecological health underpins long-term agricultural performance, these trends signal significant risks to sustaining output growth in the near future. Although conditions vary across subregions and countries, this analysis points to several policy recommendations that could be broadly applied across the region:

I. Internalize environmental costs through sustainability-adjusted metrics

LAC countries should adopt sustainability-adjusted performance indicators, such as the SPI and shadow pricing of undesirable outputs, to capture the trade-offs inherent in agricultural growth more accurately. These metrics should inform public investment, subsidy allocation, and performance monitoring across agricultural programs.

II. Promote efficient and regulated input use

Given that nutrient imbalance accounted for nearly 60% of the total value of environmental damage in LAC, improving fertilizer use efficiency is paramount. Policies should encourage integrated nutrient management, precision fertilization, and greater reliance on biological alternatives. Regulatory approaches such as nutrient application caps or zoning-based restrictions may be required in high-risk areas.

III. Expand the use of market-based economic instruments

Market-based mechanisms—such as payments for ecosystem services, environmental taxes, and tradable permits—should be assessed to align producer incentives with sustainable outcomes. Grounded in the "polluter pays" principle and widely adopted in OECD countries, these tools have proven effective in promoting conservation within agricultural landscapes.

IV. Strengthen institutional capacity and policy coherence

Weak interministerial coordination and limited regulatory enforcement constrain environmental progress in LAC. National strategies should promote cross-sectoral integration between agriculture, environment, and finance ministries, with decentralized agencies equipped to enforce land-use regulations, monitor emissions, and provide technical support.

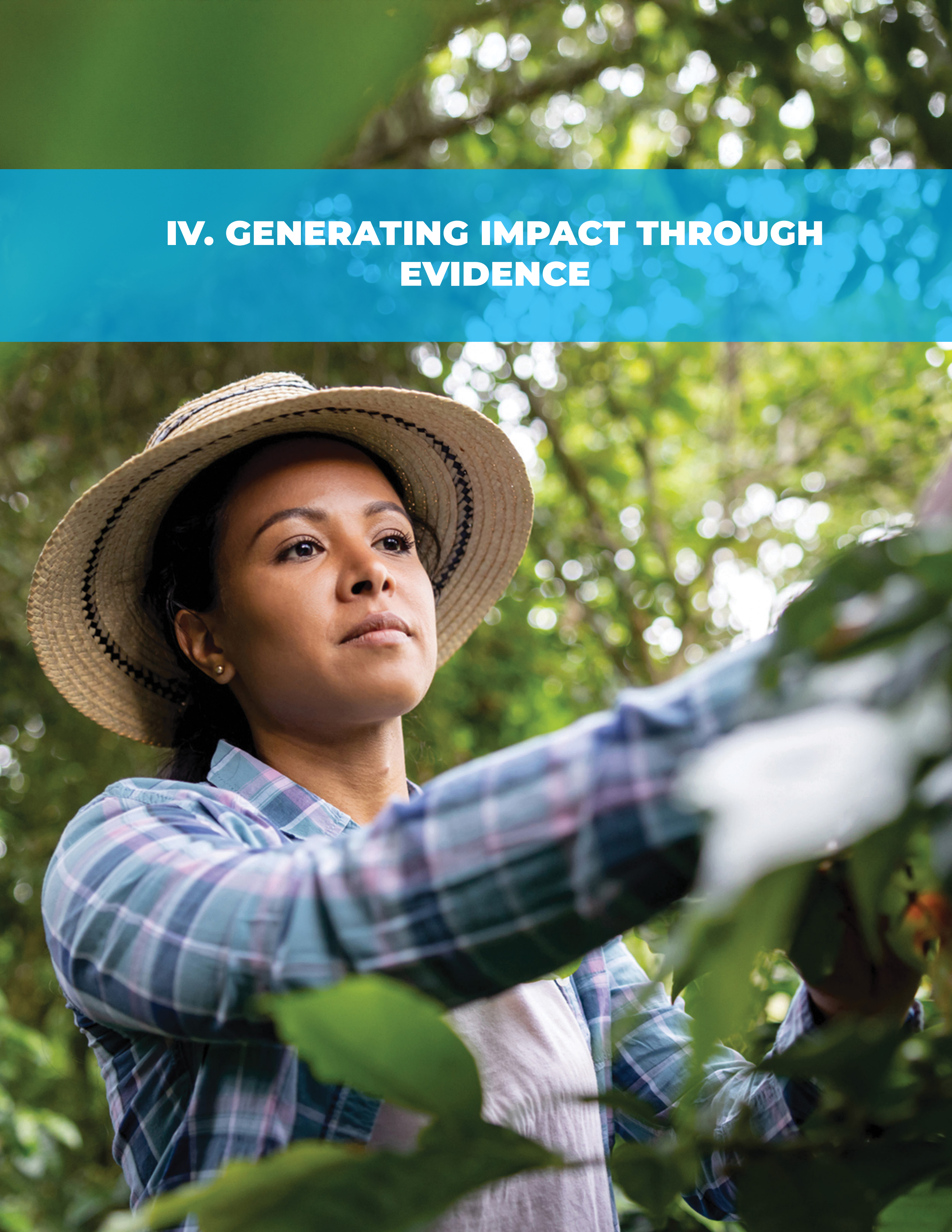
V. Design dual-purpose research, development, and innovation (R+D+i) systems

Agricultural growth will benefit from agricultural R+D+i systems designed to pursue both agricultural productivity and environmental sustainability goals. Developing and disseminating technologies, practices, or inputs that improve yields, efficiency, or output quality while improving environmental performance is fundamental for the long-term sustainability of the sector.

VI. Assessing the environmental impacts of agricultural interventions

Evaluations of agricultural interventions must account for both productivity and environmental outcomes. While assessing economic and productive effects remains fundamental, equal priority should be given to measuring environmental indicators. To achieve this, cost-effective mechanisms must be identified to ensure consistent measurement and monitoring of environmental outcomes.

IV. GENERATING IMPACT THROUGH EVIDENCE



CHAPTER 13.

ADVANCING AGRICULTURAL DEVELOPMENT THROUGH EVIDENCE: A DECADE OF IDB IMPACT EVALUATIONS IN THE REGION

AUTHORS: MAJA SCHLING, LINA SALAZAR, RENÉE PÉREZ MASSARD, DANIEL BARBOSA, DASUN LEE

SUMMARY

This chapter examines evidence from 26 impact evaluations of IDB-supported agricultural development programs published between 2014 and 2025. We summarize evidence across the multiple intervention categories: input and technology transfers (11 studies), rural infrastructure (5 studies), land regularization and administration (4 studies), animal and plant health (2 studies), and extension services and capacity-building (4 studies). The following findings emerge from the evidence base: (1) measuring heterogeneity across productive units and value chains is key to understanding program effectiveness; (2) productivity effects are dynamic over time, and medium- and long-term evaluations are critical for accurately measuring productivity impacts; (3) agricultural programs can be effective in achieving welfare impacts even in the absence of expected changes in productivity or income; (4) agricultural programs can improve women's empowerment and household food security, but relevant evaluations are still relatively scarce; (5) designing agricultural programs and evaluations for measuring spillover effects can provide important insights into development effectiveness; and (6) the complementarity of survey data and remote sensing data can be a powerful strategy for overcoming the challenges posed by field data collection. We conclude with a series of actionable recommendations to strengthen program design and evaluation based on these findings.

I. INTRODUCTION

Over the last 15 years, the IDB has intensified efforts to strengthen evidence on the development effectiveness of its projects. This decision has led to a growing number of impact evaluations of the causal effects of interventions across sectors, generating a growing body of rigorous empirical evidence. The agricultural sector is no exception: a steady increase in evidence-based analyses is now informing more effective policies and programs. This chapter aims to provide an overview of the body of knowledge generated between 2014 and 2025 and to summarize the main findings derived from this empirical evidence base. It aims to provide policymakers with actionable insights regarding interventions that strengthen food security, rural welfare, and resilience to climate change, while improving agricultural productivity.

In order to promote evidence-based interventions, the IDB complements its operational portfolio with robust knowledge generation efforts. The present chapter provides a narrative review of quantitative evaluations of IDB projects, many of which were authored by IDB specialists. Some of the evaluations considered in this chapter are published through the IDB's knowledge portal, making them subject to the bank's own rigorous peer review process, which often begins at the program planning stage. Others are published in academic, peer-reviewed journals, which are subject to their own peer-review processes. Given the nature of the evidence base and the review method undertaken, readers should note that the present chapter does not draw universal conclusions about the effectiveness of different intervention types. Rather, the chapter intends to identify cross-cutting findings about the IDB's interventions, from an evaluation perspective, highlighting the lessons learned from evidence-based policy making in the sector.

The analysis draws from 26 impact evaluations of IDB-supported projects published since 2015. The impact evaluations analyzed are counterfactual assessments that compare treatment and control groups to measure the causal impacts of agricultural projects through experimental or quasi-experimental methods. The body of evidence encompasses a diverse range of interventions, including input and technology transfers, infrastructure development, land regularization and administration, animal and plant health, and extension services and capacity-building.

In sum, several key lessons emerge from the evidence from these 26 impact evaluations:

I. Measuring impact heterogeneity across productive units and value chains is key to understanding the dynamics of causal effects on both productive and socioeconomic outcomes.
II. Productivity impacts are dynamic, and their effects may emerge over different time frames. Implementing medium- and long-term evaluations may therefore be critical to accurately measure productivity impacts.
III. Agricultural programs can be effective in achieving welfare impacts even in the absence of expected changes in productivity or income.
IV. Agricultural programs can serve as strategic mechanisms to improve women's empowerment. However, the evidence is still scarce, despite documented links to food security.
V. Designing agricultural programs to measure spillover effects can provide critical insights into development effectiveness.
VI. Complementing survey data with remote sensing data can be a powerful strategy to overcome the challenge-posed by field data collection.

The remainder of this chapter is structured as follows. Section 2 summarizes the analytical framework, including an overview of the IDB's role in implementing and evaluating agricultural interventions. Section 3 presents a literature review describing key characteristics of each of the 26 studies considered in this chapter. Section 4 highlights and describes the lessons learned from ten years of IDB impact evaluations. Finally, Section 5 summarizes actionable guidance for policymakers and development practitioners seeking to advance food security and sustainable growth in the region.

II. ANALYTICAL FRAMEWORK

The IDB has been a key partner in the design and implementation of agricultural interventions to enhance farmers' productivity, output, and incomes in Latin America and the Caribbean (LAC). Between 2010 and 2025, the IDB financed 105 agricultural and rural development projects for a total of US$7,203 million in approved loan amounts. Between 2014 and 2025, the IDB also published 26 analytical papers that evaluated IDB-financed agricultural operations addressing a broad spectrum of challenges and opportunities. This analysis groups the interventions studied across these 26 publications into the following intervention categories:

I. INPUT AND TECHNOLOGY TRANSFERS: Interventions that provide producers with inputs or technologies, typically accompanied by technical assistance. Transfers may occur either through (i) the direct distribution of inputs; (ii) vouchers that can be used to purchase inputs from pre-approved vendors; or (iii) credit/loans that can be used to make input purchases or capital investments.

II. RURAL INFRASTRUCTURE: Interventions that construct, rehabilitate, improve, or expand rural infrastructure (i.e., irrigation or roads).

III. LAND REGULARIZATION AND ADMINISTRATION: Interventions that aim to increase access to land titling, characterize agricultural land use, redistribute land assets, or otherwise strengthen land administration systems.

IV. ANIMAL AND PLANT HEALTH: Interventions that strengthen the provision of sanitary and phytosanitary services across agricultural value chain actors (i.e., pest eradication programs, animal vaccination campaigns, etc.)

V. EXTENSION SERVICES AND CAPACITY-BUILDING: Interventions that aim to overcome information and capacity barriers through the provision of information and training regarding the technical or business aspects of agricultural production.

This chapter summarizes the IDB's experience in supporting agricultural productivity in LAC, identifying patterns across intervention types and assessing the enabling conditions that contribute to sectoral growth. Reviewing the evidence from past IDB-financed projects is particularly important for drawing lessons, ensuring accountability, and guiding future investments in the region.

III. Review of IDB impact evaluations (2014–2025)

This section provides a narrative literature review of the 26 impact evaluations of IDB interventions published between 2014 and 2025. For each intervention category, we describe the available studies and key findings. **Table 1** provides an overview of the number of relevant studies in each intervention category, as well as the countries in which the evaluations took place.

A detailed table outlining each study's intervention category, methodology, and key findings is included in annex 1.

Table 1. Summary of intervention categories and countries studied

Intervention category	Number of studies[1]	Countries studied
Input and technology transfers	11	Argentina (3), Bolivia (2), Dominican Republic (2), Guatemala, Haiti, Nicaragua (2)
Rural infrastructure	5	Argentina (2), Bolivia, Ecuador (2)
Land regularization and administration	4	Bolivia, Ecuador (2), Peru
Animal and plant health	2	Peru (2)
Extension services and capacity-building	4	Haiti, Uruguay, Peru, Costa Rica

Source: Authors' own elaboration.

III.i. Input and technology transfers

The most frequently studied intervention category was input and technology transfers, which are analyzed across 11 studies. Of these, two studies evaluated programs where farmers were provided with inputs directly (Salazar et al., 2018a; Mullally et al., 2019); eight evaluated transfer programs that were executed via vouchers to support technology adoption (Aramburu et al., 2019; Salazar et al., 2015; Salazar et al., 2018b; Schling and Pazos, 2022b; Salazar et al., 2021; Maffioli et al., 2018; Salazar et al. 2025; González Flores and Le Pommellec, 2017), and one study evaluated a transfer program that established a revolving credit fund that could be used for variable input purchases or capital investments (Schling et al., 2025a).

In terms of direct provision of inputs, a difference-in-differences approach with propensity score matching in Nicaragua showed that livestock technologies increased agricultural output by 60%, tripled income from livestock sales, and improved women's participation (Salazar et al., 2018a). In Guatemala, a program that provided farmers with local chicken varieties in exchange for completing a poultry extension program had no significant effects on productivity indicators but showed a considerable positive impact on girls' anthropometric indicators. The impact evaluation, which used a randomized phase-in design, found the program reduced stunting and severe stunting among girls by 23.5 percentage points (p.p.) and 14 p.p., respectively (Mullally et al., 2019).

Eight of the studies of programs that promote technology adoption examined non-reimbursable voucher-based input and technology transfers. In Nicaragua, an agroecology program provided subsidized technological packages and technical assistance across multiple value chains, with the aim of improving productive outcomes and promoting environmental resilience by establishing agroecological production systems (González Flores and Le Pommellec, 2017). In addition to increasing farmers' production values by US$195 per hectare, it also led to increases in tree coverage, use of rainwater harvesters, and the adoption of sustainable productive practices (González Flores and Le Pommellec, 2017). In Bolivia, the Direct Support for the Creation of Rural Agrifood Initiatives (CRIAR) program distributed vouchers covering 90% of the cost of technologies chosen by producers, leading to increases in productivity, household income, and food security, as estimated using an instrumental variable approach (Salazar et al., 2015). A subsequent evaluation of the second phase of CRIAR found that the program had both direct and spill-

[1] Maffioli et al. (2018) evaluate the complementary effects of two intervention types (rural infrastructure and input and technology transfers), which results in a total count of 24 studies in this table.

over effects, with direct and indirect beneficiaries experiencing increases in household income, value of production, and technology adoption (Salazar et al., 2025).

Although studies in Bolivia and Nicaragua documented success across social, productive, and environmental outcomes, the results were mixed in other contexts. In the Dominican Republic, a two-stage randomized experiment found that voucher-based technology transfers had limited effects on productivity (Aramburu et al., 2019). However, the authors observed that irrigation technologies encouraged a shift in crop portfolios from temporary to permanent crops. They also found evidence to suggest that productivity effects may increase over time (Aramburu et al., 2019). In Haiti, a program offering smart subsidie[2] for crop inputs and agroforestry technical packages yielded mixed results depending on the value chain. Specifically, input vouchers for rice, horticulture, and peanuts did not produce positive effects on productivity or production value. However, vouchers for agroforestry technical packages increased profits and production value by 63% and 38%, respectively (Salazar et al., 2018b).

Two studies of voucher programs combined survey data with normalized difference vegetation index (c) analysis over several years, finding that voucher programs had dynamic effects over time. In Argentina, the evaluation of the Rural Development and Family Agriculture (PRODAF) program combined survey data with satellite-based NDVI analysis. The authors found that PRODAF increased technology adoption by 21 p.p. and credit access by 47 p.p. However, production impacts varied by value chain: positive, statistically significant productivity effects were only detected in the citrus value chain, with the largest effects materializing two to three years after exposure to the program (Schling and Pazos, 2022b).

Similarly, in the Dominican Republic, a voucher program demonstrated dynamic effects on productivity resulting from the adoption of irrigation technologies. Increased vegetation indices were observed as of the third year after treatment, and differences between the treatment and control groups dissipated over time, possibly due to spillover effects (Salazar et al., 2021).

In Argentina, input vouchers for viticulturists increased production and productivity by 9.4% and 7.7%, respectively. However, when the voucher program was combined with the construction of public irrigation canals, production and productivity rose by 16.6% and 16%, respectively (Maffioli et al., 2018). Notably, farmers exposed to both interventions achieved larger yield increases than the sum of each intervention separately.

Finally, one evaluation examined the effect of input transfers via the establishment of a revolving loan fund for smallholder dairy producers in Argentina (Schling et al., 2025a). The revolving loan fund was administered by smallholder dairy associations and provided two different lines of credit: short-term loans that could be used for the purchase of variable inputs (such as pasture fertilizers and hired labor), and longer-term loans that could be used for capital investments (such as farm infrastructure and equipment). Short-term credit used for variable inputs had no measurable effect on production. In contrast, credit used for capital investments increased output by 17.2% the year after the credit was received. Furthermore, larger loans were associated with more sustained productivity impacts: farmers who received investment loans above the median experienced production increases three years after the credit was received (Schling et al., 2025a).

[2] Smart subsidies are a type of agricultural intervention designed to address two common barriers faced by producers: liquidity constraints and limited technical knowledge. Broadly speaking, they combine a conditional financial transfer tied to the purchase of certain agricultural inputs or equipment with technical assistance to support the adoption of a new technology by the beneficiary farmer.

III.ii. Rural infrastructure

The rural infrastructure category included one evaluation of a rural road improvement program (Corral and Zane, 2021) and four studies of irrigation infrastructure programs (Maffioli et al., 2018; Corral and Zane, 2020; Salazar and López, 2017; Schling et al., 2025b).

In Ecuador, the Chimborazo Rural Investment Project was evaluated using household survey data with a difference-in-differences and propensity score matching approach (Corral and Zane, 2021). Improvements to 38.9 km of road significantly reduced travel time and costs, leading to higher secondary school enrollment rates at ages 13 and 18 and improved health outcomes. However, there were no significant impacts on crop production, household income, or food security.

Four evaluations examined the effect of irrigation infrastructure programs. Two of these combined rehabilitation and expansion of infrastructure networks with the creation and strengthening of water-use associations. One such program in Ecuador, which focused on Indigenous highland communities, increased overall crop yields by about 33% and reduced food insecurity[3] (Corral & Zane, 2020). However, the authors also found a simultaneous decrease in crop sales, suggesting food insecurity decreased via an increase in household consumption of crops (Corral and Zane, 2020). In contrast, an evaluation of Bolivia's national irrigation program found no statistically significant impact on yields at the time of the assessment. Nonetheless, the authors found positive, statistically significant effects on agricultural production value, household income, use of certified seeds, and market access (Salazar and López, 2017). They attribute the lack of statistically significant effects on yields to the learning curve associated with transitioning from rainfed to irrigated agriculture, concluding that producers are likely still in the learning-by-doing stage of technology adoption (Salazar and López, 2017).

In Argentina, two studies evaluated the effect of an irrigation program in the wine-producing region of San Juan. One study conducted by Maffioli et al. (2018) found that irrigation expansion alone increased viniculture production and productivity by 4.2% and 4.6%, respectively. However, when irrigation was combined with input vouchers, production and productivity increased significantly more—by 16.6% and 16%, respectively. Schling et al. (2025b) used a combination of survey and remote sensing data to evaluate a subsequent phase of the same program, which focused on the restoration of irrigation channels in the wine-producing area of San Juan province. In line with the previous evaluation, this long-term impact study revealed increases in grape production of between 31.4% and 53% and increases in grape yields of between 0.93% and 1%, with productivity effects (as measured by NDVI) becoming stronger over time (Schling et al., 2025b). The authors also found that the program increased the area of land under effective irrigation and reduced the probability of farmers reporting irrigation-related losses (Schling et al., 2025b).

III.iii. Land regularization and administration

Four studies examined the impact of land regularization and administration programs in the Andean region (Schling et al., 2024; Corral et al., 2024; Schling et al., 2023; Schling and Pazos, 2022a).

[3] Food insecurity was measured through a survey module based on the Food and Agriculture Organization's (FAO) Food Insecurity Experience Scale Survey Module, in which the person responsible for preparing meals in the household is asked a series of questions regarding their family's exposure to food insecurity episodes, such as having to skip meals.

In a study of land tenure security in Bolivia, Ecuador, and Peru, evidence from propensity score matching and a bias-corrected stochastic production frontier analysis shows that smallholders with formal land titles are, on average, 38.6% more technically efficient than those without them (Schling et al., 2024). Although the magnitude of the efficiency effects varies by country, two main pathways emerge: improved access to credit and increased productive investment. Together, these findings highlight the importance of comprehensive land regularization in enhancing agricultural productivity (Schling et al., 2024). In Ecuador, Corral et al. (2024) used a doubly robust design (difference-in-differences with inverse probability weighting). They found that cadastral mapping through the SigTierras program did not improve perceptions of tenure security, reduce land conflicts, or increase input use. However, it significantly raised agricultural wages and household income for beneficiary landowners.

Two evaluations focus on the link between land tenure, women's empowerment, and household welfare. In Ecuador, Schling et al. (2023) found that although SigTierras did not affect aggregate indicators of women's empowerment, female beneficiaries gained greater access to credit and engaged more in off-farm income-generating activities. Additionally, households receiving jointly titled cadastral maps also reported higher food security and shifted production toward more marketable and nutritious products (Schling et al., 2023). Similarly, Schling and Pazos (2022a) analyzed the effects of self-declared informal land ownership on women's empowerment and household welfare in Peru. Using an instrumental variable approach, the authors found that women's self-reported land ownership increased crop diversity, reduced time spent on farm work, and improved household food security by 20 p.p. (Schling and Pazos, 2022a).

III.iv. Animal and plant health

Two studies evaluated animal and plant health interventions. Salazar et al. (2017) evaluated a fruit fly eradication program in Peru's coastal regions using a geographical discontinuity design, finding significant improvements in fruit crop productivity and sales, as well as increases in farmers' knowledge of pests and adoption of best practices. A follow-up study by Salazar et al. (2023) combined a regression discontinuity with vegetation indices to examine the long-term impact of the fruit fly eradication program over 10 years. The study found that productivity gains increased over time, with estimated impacts on yields ranging from 12% to 49% (Salazar et al., 2023). However, the authors also find, through quantile regression, that benefits were larger for more productive farmers, suggesting the need for complementary support to ensure equitable outcomes across different producer segments (Salazar et al., 2023).

III.v. Extension services and capacity-building

Four studies examined the effect of extension services and capacity-building interventions. In Uruguay, Mullally and Maffioli (2014) analyzed the Uruguayan Livestock Program, finding that it raised calf production by 11.36–15.3 calves and net calf sales by 4.35 on average. While these results demonstrate positive impacts, the modest effect sizes suggested room for improvement in the design and delivery of extension programs (Mullally and Maffioli, 2014). In Haiti, Arráiz et al. (2015) assessed an extension program that created and trained producer business groups in various aspects of the production and commercialization of mangoes, one of Haiti's main agricultural exports. A primary aim of this capacity-building program was to increase incomes for small farmers by facilitating their access to mango export markets. To accomplish this, the project's capacity-building program promoted the adoption of Francique mango trees (an export variety) and connected smallholder producers to exporters via PBGs. In addition, they trained PBGs in practices that would improve the quality and quantity of their mango yields while aligning their production practices with export standards. Using matching methods combined with a difference-in-differences approach, the study found that the project led to increased planting of young Francique mango trees and greater adoption of best production practices within 16 months. However, impacts on yields and sales had not materialized at the time of the evaluation, which the authors attribute to the short evaluation period (Arráiz et al., 2015). Beyond these cases, two IDB evaluations have documented complementary effects through trade and investment channels. Carballo, Rodríguez, and Volpe (2018) found that digital platforms such as ConnectAmericas boosted export performance—particularly among agrifood firms. Likewise, Carballo, Graziano, Schaur, and Volpe (forthcoming, IDB Working Paper) show that the digitalization of trade procedures in Costa Rica's VUCE[4] system, supported by the IDB, increased agricultural exports, especially among small firms and non-central regions. These findings highlight how trade facilitation and digitalization can enhance agricultural productivity by reducing transaction costs, improving quality standards, and fostering technological diffusion.

IV. FINDINGS

Our review of 26 impact evaluations of IDB-supported agricultural development programs in LAC published between 2014 and 2025 yielded six key insights, which are discussed below.

IV.i. Impact heterogeneity across productive units and value chains

Measuring variations in impact across productive units and value chains is key to understanding the dynamics of causal effects on both productive and socioeconomic outcomes. For any given intervention, the distribution of program impacts often showed significant variation across households, value chains, and productivity scales. For instance, Guatemala's livestock program produced no detectable effects on household-level food consumption indicators, but led to significant decreases in stunting among girls (Mullally et al., 2019). In Peru, quantile analysis revealed that the most productive farmers experienced the largest productivity gains from a fruit fly eradication program (Salazar et al., 2017). Smart subsidy programs like PRODAF in Argentina, PTTA in Haiti, and PATCA II in the Dominican Republic showed significant variability in their productivity and income effects depending on the value chain (Salazar et al., 2018b; Schling and Pazos, 2022b; Aramburu, et al., 2019). In Bolivia, the distance of farmers from voucher distribution events was strongly linked to program uptake (Salazar et al., 2015). Similarly, in a revolving credit fund program in Argentina, the size of loans and whether they were used for variable inputs or capital investment affected the statistical significance and timeframe of production impacts (Schling et al., 2025a). Loans used for input purchases had no effect on production volumes, whereas loans used for capital investments yielded positive impacts. Moreover, larger investment loans led to more sustained impacts over time (Schling et al., 2025a). Overall, the heterogeneity of program effects across households and productive units suggests that program outcomes are highly dependent on household composition and dynamics, making one-size-fits-all approaches potentially less effective.

[4] *Ventanilla Única de Comercio Exterior.*

IV.ii Time horizons and the need for long-term evaluations

Productivity impacts are dynamic and may require different timeframes to materialize, so implementing medium- and long-term evaluations is critical to measure productivity impacts accurately. The effect of programs on agricultural productivity was found to vary over time, both in short- and long-term assessments. For example, the evaluation of a technology adoption program in the Dominican Republic found that some irrigation technologies initially had a negative impact on income, but each additional month of exposure was associated with a 14% income increase (Aramburu et al., 2019). Longer-term evaluations of voucher programs in Argentina and the Dominican Republic found that productivity effects only became visible two to three years after exposure (Schling and Pazos, 2022b; Salazar et al., 2021). Similarly, long-term analyses of the fruit fly eradication program in Peru and an irrigation improvement program in Argentina showed that impacts became stronger over time (Salazar et al., 2023; Schling et al., 2025b). Notably, long-term evaluations also indicate that productivity effects can be nonlinear, with multiple studies showing positive effects that dissipate over time (Schling and Pazos, 2022b; Salazar et al., 2021; Schling et al., 2025a). However, the fading of significant impacts in the long term does not necessarily indicate declining effectiveness. For instance, in the Dominican Republic, Salazar et al. (2021) find evidence to suggest that spillover effects may be driving the loss of significant differences between treatment and control groups.

Some studies note that the timing of endline surveys may make impacts on productivity less visible. For instance, Haiti's extension program for mango producers found no significant change in production or sales within 16 months, despite increased adoption of best practices. The authors noted that the endline data collection was likely too early for changes in yields and sales to become apparent (Arráiz et al., 2015). Similarly, the evaluation of Bolivia's national irrigation program notes that the lack of statistically significant impacts on yields may be due to farmers being in the learning-by-doing stage of the technology adoption curve (Salazar and López et al., 2017). Taken as a whole, these findings suggest that interventions may require a longer time horizon to show full impacts, particularly for interventions that imply learning significant curves (Salazar and López et al., 2017) or encourage shifts in crop portfolios (Aramburu et al., 2019; Arráiz et al., 2015).

IV.iii Welfare effects beyond productivity and income

Agricultural programs can generate welfare gains even in the absence of expected increases in productivity or income. Theories of change in agricultural development often describe intervention mechanisms through which increased yields lead to higher incomes (via sales), which in turn improve welfare indicators such as food security (via higher incomes and better food supply from agricultural production). However, the studies analyzed reveal a more complex, dynamic relationship between social, economic, and productive indicators. For instance, some programs produced no visible increases in yields or agricultural incomes, but nonetheless led to significant, positive effects on welfare indicators like health outcomes (Corral and Zane, 2021) and girls' anthropometric indicators (Mullally et al., 2019). Bolivia's national irrigation program was associated with a statistically significant increase in food security and agricultural incomes despite not increasing yields (Salazar et al., 2015). In Ecuador, an irrigation infrastructure program in Indigenous communities decreased food insecurity and increased yields, but had no detectable impact on income and even led to a significant weight on customary land tenure arrangements. As such, the authors hypothesize that the community sensibilization meetings conducted through the SigTierras program, which were used to disseminate official cadastral maps, may have reinforced landowners' sense of tenure security, enabling them to devote more time to off-farm economic activities to supplement their income (Corral et al., 2024). Together, these findings suggest the presence of multiple pathways through which agricultural interventions can improve social and economic outcomes. In particular, they reveal that agricultural programs can be effective in improving welfare indicators without necessarily increasing productivity or incomes. Similarly, increases in yields do not necessarily translate into the expected social or economic outcomes. Local market factors, intrahousehold dynamics, and other contextual factors significantly influence the impact mechanisms of agricultural program interventions.

IV.iv Women's empowerment

Agricultural programs may serve as strategic mechanisms to improve women's empowerment. However, the evidence on this is still scarce, despite documented links to food security. Only three evaluations explicitly examined the effect of agricultural programs on women's empowerment indicators (Salazar et al., 2018a; Schling et al., 2023; Schling and Pazos, 2022a). However, the studies that adopted a gender analysis consistently found links between women's empowerment and household nutrition. In Ecuador and Peru, women's tenure security had positive effects on food security and crop diversity (Schling et al., 2023; Schling and Pazos, 2022a). Similarly, households participating in a technology transfer program in Nicaragua were less likely to experience women's disempowerment, while food security also increased (Salazar et al., 2018a).

These findings align with the broader body of evidence showing that women's participation in household decision-making is closely tied to improved nutritional outcomes. This suggests that women's empowerment is an important but underleveraged pathway to achieving food security and reducing rural inequalities.

IV.v Spillover effects

The presence of spillover effects can strengthen the effectiveness of agricultural programs. Only three evaluations explicitly examined program effects on indirect beneficiaries, all within the input and technology transfer category (Aramburu et al., 2019; Salazar et al., 2021; Salazar et al., 2025). The findings are mixed, highlighting the need for future evaluations that test for spillovers and explore the conditions under which they occur. For example, in Bolivia, a technology adoption program generated positive indirect effects: nonparticipating producers in treated communities showed higher agricultural production values, household incomes, and technology adoption rates compared to the pure control group (Salazar et al., 2025).

In contrast, evidence from the Dominican Republic suggests that spillovers may change over time. While an initial evaluation of a technology transfer program found limited evidence of spillovers in the short-term (Aramburu et al., 2019), a follow-up evaluation of the same program found evidence to suggest that the program may have produced long-term spillover effects, potentially reducing the observable differences between treatment and control groups (Salazar et al., 2021). The effects of spillovers on indirect beneficiaries suggest that capturing only direct impacts may underestimate the true impact and cost-effectiveness of investments.

IV.vi Remote sensing data as a complement to survey data

Remote sensing data has emerged as a powerful tool to overcome the challenges posed by field data collection. The IDB has advanced impact evaluations that integrate survey and satellite data to measure the effects of agricultural programs. This approach has proven versatile across countries and intervention types, particularly for tracking outcomes over longer time horizons. For example, researchers paired household survey data with satellite-based vegetation indices to assess the effects of input and technology transfers in Argentina and the Dominican Republic (Schling and Pazos, 2022b; Salazar et al., 2021), irrigation expansion in Argentina (Schling et al., 2025), and fruit fly eradication in Peru (Salazar et al., 2023). In these cases, researchers combined satellite data such as NDVI with survey data to generate nuanced insights into how productivity effects unfold in the short, medium, and long term. This growing body of evidence suggests that remote sensing data can be a powerful complement to survey data. In addition to providing evaluators with another tool to verify the robustness of survey-based data, it also helps bridge the practical and financial barriers often posed by field data collection.

IV. CONCLUSIONS AND POLICY RECOMMENDATIONS

In response to these findings, several key recommendations emerge for the design and evaluation of agricultural programs, which are listed below:

I. Interventions should avoid one-size-fits-all approaches, and evaluations should measure heterogeneous and distributional effects

Given the variability of program impacts across households, productive units, and value chains, interventions should be carefully tailored to account for local heterogeneities. To fully assess the multidimensional impacts of these programs in rural contexts in addition to productive improvements, it is advisable that project and evaluation design consider complementary impacts on household welfare, including food security, health, and empowerment. Wherever possible, evaluations should incorporate heterogeneity analysis and examine distributional and heterogeneous effects (by geography, age, ethnicity, gender, scale of production, etc.). This requires collecting representative data that permits the disaggregation of effects.

II. Integrate a long-term perspective into program design, monitoring, and evaluation

Programs should ensure that evaluation timelines are aligned with crop cycles and the time horizons required for impacts to materialize. Multiple follow-up rounds (short-, medium-, and long-term) should be built into programs. Short- and medium-term evaluations should include intermediate indicators in addition to measures such as agricultural productivity and income. Adding these will provide program implementers with the opportunity to test theories of change and, where necessary, adapt interventions based on preliminary findings. Long-term evaluations should include follow-up surveys and/or satellite data several years after the intervention to accurately capture all possible benefits and develop fuller understandings of the long-term sustainability of agricultural programs

III. Measure program impacts on indirect beneficiaries to capture the true scope and cost-effectiveness of investments and identify externalities

Failure to assess these effects may underestimate a program's true impact. Although relatively few studies have been designed to measure spillover effects, the evidence in this area suggests that these do occur and may evolve over time. Agricultural programs and evaluations should be designed to measure spillover effects, which can be achieved through various strategies, including staggered roll-out designs, two-stage randomization, and clustered randomization with buffer zones. Because spillover measurement is highly sensitive to implementation timelines and geographic factors, evaluators should work closely with implementers at all stages of design and delivery to select the most appropriate evaluation strategy and execute it successfully. Measuring program impacts on indirect beneficiaries would enable stakeholders to better understand the true scope, cost-effectiveness, and externalities associated with investments.

IV. Combine satellite-based data with survey data to enhance the quality, scope, and depth of impact evaluations

Studies incorporated satellite data alongside survey data to measure productivity effects across multiple countries and intervention categories. The use of satellite data was particularly common among long-term evaluations, enabling researchers to identify nuanced productivity dynamics that evolve over time. While survey data provides rich insights into household-level dynamics and should remain central to impact evaluations, integrating remote sensing data allows evaluators to observe productivity and land-use outcomes at scale, over time, and in areas where field data collection is costly or logistically challenging.

CHAPTER 14.

UNCOVERING EVIDENCE GAPS IN AGRICULTURAL PRODUCTIVITY RESEARCH: A SYSTEMATIC MAPPING

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SUMMARY

This chapter presents findings from a systematic mapping of agricultural productivity interventions across Latin America and the Caribbean (LAC) to uncover critical evidence gaps that obstruct effective policy design. This initiative draws on methods applied in LAC through Avanzar2030: Innovating for Sustainable Agrifood Systems, led by the International Food Policy Research Institute (IFPRI), the Inter-American Institute for Cooperation on Agriculture (IICA), and the Juno Evidence Alliance with support from other international organizations. The ongoing Avanzar2030 initiative aims to identify evidence-backed policies for sustainable food systems transformation in LAC using evidence synthesis methods.

By identifying key knowledge gaps, the analysis provides a foundation for shaping future research and guiding policy decisions to better support sustainable productivity growth in the region. The initial search identified 8,193 potentially relevant studies from academic databases based on title and abstract information. From these, a representative sample of 805 studies was examined at full text by a team of trained experts, as well as a representative sample of studies from grey literature, resulting in 82 studies that met all inclusion criteria. This random sample of 82 studies served as the primary evidence base that was assessed to identify knowledge gaps.

This systematic mapping exercise revealed the following insights: (i) the literature shows pronounced geographic disparities, with countries in Central America and the Caribbean notably underrepresented; (ii) the evidence is concentrated on cash crops and export-oriented products, while staple crops and diversified farming systems are relatively unexplored; (iii) evidence gaps persist

around both emerging intervention types and longstanding mechanisms that have been widely implemented in LAC for decades; (iv) methodologically, rigorous impact evaluations that apply counterfactual analysis are scarce; (v) the absence of heterogeneity analyses and studies examining the differential impacts of interventions on diverse groups (women farmers, Indigenous producers, and afro-descendant farmers) was one of the most pronounced gaps in the literature base; and (vi) although growing attention has been given to climate-related dimensions of agricultural interventions, a more systematic and in-depth approach is needed to assess long-term sustainability and resilience outcomes.

I. INTRODUCTION

Why do we need a systematic map of agricultural productivity interventions in Latin America and the Caribbean?

From an economic, social, and environmental perspective, ensuring sustainable agricultural productivity growth is key to advancing LAC's development goals. In this context, it is crucial to identify effective interventions to equip stakeholders with the tools to design and implement evidence-based policies. This chapter systematically maps the literature on agricultural productivity interventions implemented in LAC and published in the last decade. It builds on methods developed under the Avanzar2030 initiative, led by IFPRI, IICA, and the Juno Evidence Alliance, with support from international organizations such as the Inter-American Development Bank (IDB), the Food and Agriculture Organization of the United Nations (FAO), CGIAR, and the World Bank. Avanzar2030 is an evidence-based initiative seeking to identify promising innovations in agrifood systems (IFPRI, 2023).

Although systematic reviews have been applied across diverse fields and thematic areas, geographic regions, their use in agricultural development policy remains limited. Only in recent years have researchers begun to apply systematic reviews and other evidence synthesis methods to address the sector's most pressing policy questions. For instance, a scoping review conducted by the CERES2030 initiative examined the relationship between agricultural policy incentives, adoption, and outcomes. The authors found that, regardless of incentive structure, the long-term adoption of sustainable practices was strongly linked to farmers' perceptions of economic and/or environmental benefits (Piñeiro et al., 2020). The methodological rigor of systematic reviews and evidence synthesis approaches, along with their capacity to analyze large bodies of literature, makes them a powerful tool for advancing evidence-based policy. Despite this, their application within LAC remains limited.

A systematic review carried out by the US Department of Agriculture (USDA) examined the effect of farmer cooperatives on agricultural outcomes (Islam et al., 2015). The authors report that cooperative membership was associated with a positive, statistically significant effect on yields in most studies. However, only 3 of the 21 included studies were from LAC, and only one LAC study considered productivity outcomes (Islam et al., 2015). Another systematic review by the USDA examined the effect of rural roads on various agricultural outcomes, with inconclusive results about the effect of rural roads on agricultural productivity (Ludwig et al., 2016).

Although LAC countries were slightly better represented in this review (accounting for 26% of the 15 studies), only four LAC countries were represented in the dataset, and none of the LAC-based studies measured productivity outcomes (Ludwig et al., 2016). Similarly, a World Bank meta-analysis focusing on agricultural input subsidies found that, on average, input subsidy programs increased yields by about 20% (Nguyen et al., 2023). However, despite the study's global scope, none of the 12 included studies came from LAC (Nguyen et al., 2023).

In addition to this uneven representation of LAC countries in existing productivity-focused reviews, most systematic maps of agricultural interventions focus on a single intervention type, agricultural sector, or agricultural product. For instance, Holle et al. (2025) developed a systematic map of agroecosystem management and biodiversity linkages that included studies from several LAC countries but focused on a single intervention type and one crop: agroecosystem management and coffee. Similarly, Miller et al. (2019) reviewed the effect of agroforestry interventions on agricultural productivity across low- and middle-income countries worldwide. Overall, the scope of studies with similar methodologies is generally limited to a single intervention category, and LAC countries are only partially represented. The most comparable initiative in LAC is the Avanzar2030 initiative, which focuses specifically on LAC countries. Avanzar2030 applied evidence synthesis and systematic mapping to identify knowledge gaps in the following areas: interventions that support sustainable agrifood systems, the adoption of technologies and practices that promote sustainability in the bovine sector, and scaling climate action (IFPRI, 2023). The systematic map presented in this chapter complements Avanzar2030's efforts to systematically map the evidence landscape in LAC by providing a deep-dive on the topic of agricultural productivity.

Part of a small but growing body of literature, the systematic map described in this paper analyzes studies on agricultural productivity in LAC region, comparing literature across a variety of intervention types, quantitative methodologies, agricultural systems (crops, livestock, forestry, and mixed systems), and population groups. As a result, it is the first study in the region to identify research gaps across intervention types, as opposed to exploring tendencies within a single intervention category. In addition, by considering multiple agricultural systems and products—namely, livestock, crops, forestry, and mixed systems—our analysis is the first to highlight gaps within and across agricultural systems, as well as across LAC countries.

At a time when agricultural productivity growth in LAC shows signs of slowing, this comprehensive map offers the region's stakeholders critical insights into the distribution of evidence across countries, agricultural systems, and intervention types. By synthesizing large volumes of literature on a specific topic using strict inclusion criteria, systematic maps provide concise snapshots of the areas where evidence is abundant and where it is scarce. This map therefore equips policymakers, researchers, multilateral institutions, and other decision-makers in LAC with the information they need to allocate research and development resources more effectively, enabling them to pinpoint and address critical knowledge gaps.

This systematic map addresses the following research questions:

I. What are the most studied types of agricultural productivity interventions?

II. Which countries have the strongest evidence base, and which require further research efforts?

III. What are the current knowledge gaps regarding agricultural productivity interventions in LAC?

Theory of change: Agricultural productivity interventions in LAC

This chapter analyzes a range of policy and program interventions implemented to increase agricultural productivity, which are organized into clusters.[1] **Figure 1** illustrates the theory of change model for this map, including these clusters.

The model centers on our topic of study: increasing agricultural productivity growth in LAC. It identifies several barriers that hinder LAC countries from increasing agricultural productivity. Some are cross-cutting issues—such as climate change, poverty, and inequality—that intensify the impact of more specific barriers, such as weak institutions, lack of regulatory frameworks, and the increased prevalence of pests and diseases.

Next, several types of interventions (i.e. intervention clusters) are identified for each of these barriers to productivity growth. As **Figure 1** shows, each intervention cluster addresses a particular set of barriers and may also address across-cutting barriers. For example, the financial services cluster encompasses interventions that seek to address the lack of access to agricultural credit and insurance in rural areas.

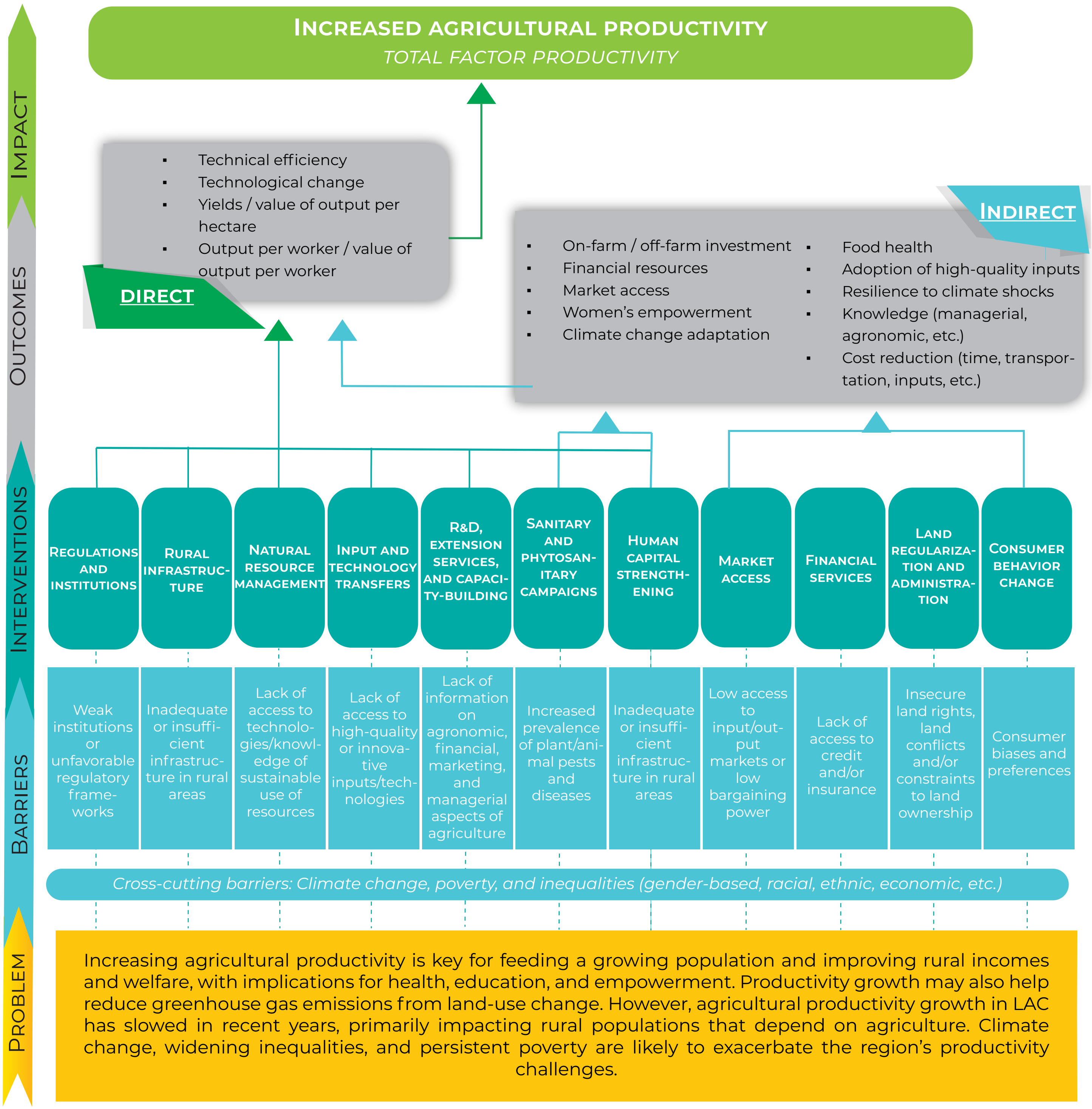
Finally, the model illustrates how interventions can then increase agricultural productivity, either through direct or indirect channels. For example, natural resource management interventions like integrated water management can directly increase productivity by improving yields through increased water availability. Other intervention categories may also produce productivity gains through indirect pathways. For example, certain ***regulations and institutions*** interventions (such as government-wide institutional strengthening, government transparency initiatives, and tax reforms) can incentivize foreign direct investment, resulting in technology transfers and knowledge spillovers that promote productivity gains.

Interventions that impact productivity indirectly—such as trade agreements and foreign direct investment—can produce signficant structural shifts that shape productivity dynamics markedly, especially over longer time horizons. Taking the example of foreign direct investment, a study examining 123 countries between 1995 and 2019 finds a positive relationship between renewable energy consumption, foreign direct investment, financial inclusion, and agricultural productivity (Wang et al, 2023). Regarding trade, Farrokhi and Pellegrina (2023) find that, on average, between 1980 and 2015, reductions in trade costs of agricultural inputs were associated with an 8.5% increase in agricultural productivity through technology adoption and international crop specialization. The authors find that agricultural trade cost reductions had signficant but heterogenous impacts on global productivity trends; while narrowing the productivity gap between middle- and high-income countries, they widened the gap between low- and middle-income countries (Farrokhi & Pellegrina, 2023). Overall, these type of studies demonstrate the importance of considering interventions, such as trade and investment, that affect agricultural productivity through spillovers and indirect channels, as their long-term effects can be far-reaching.

Our analysis draws on the intervention typology developed in our theory of change as a framework for comparing the evidence across intervention clusters.

[1] A detailed list of definitions, examples, and impact mechanisms for all intervention clusters is available in the Appendix of the published review protocol (Salazar et al., 2024). The intervention cluster typology was created at the protocol stage in order to develop a uniform theory of change that encompassed the review's comprehensive definition of agricultural productivity interventions. It was maintained throughout the subsequent review phases to standardize data collection and analysis, enabling systematic comparisons across a variety of intervention categories.

Figure 1. Theory of change for agricultural productivity interventions in LAC



Source: Diagram originally prepared and published by the authors in the review protocol (Salazar et al., 2024).

II. METHODOLOGY AND DATA

What is a systematic map?

Systematic maps analyze all relevant literature on a given topic—in this case, agricultural productivity interventions in LAC—using a rigorous process that complies with international standards (CEE, 2022). This approach provides policymakers and researchers with a broad picture of the available evidence, highlighting both widely studied topics and aspects where rigorous assessments are lacking, such as specific countries, interventions, and methods.

What type of studies were included in this map?

The first phase of a systematic map consists in establishing the inclusion criteria. Studies qualified for inclusion if they:

I. Measured the productivity of agricultural systems (specifically crops, livestock, forestry, or mixed systems);
II. Analyzed a country or subregion in LAC;
III. Were published between 2014 and 2024;
IV. Applied a quantitative methodology (i.e., stochastic production frontier estimation, experimental methods, quasi-experimental methods, simulations, or other econometric or statistical methods);
V. Examined public policy or program interventions in the agricultural sector; and
VI. Assessed agricultural productivity outcomes (e.g., total factor productivity, yields, labor productivity, or technical efficiency).

How was the relevant literature identified?

The first step in the search was to design a keyword search string to capture all potentially relevant articles. This search was subsequently refined through a series of screening steps, progressively narrowing the evidence base to include only those articles that fully met the established inclusion criteria. This was achieved through a combination of manual and artificial intelligence-assisted screening of studies, using a custom large language model (LLM) developed for this study. Specifically, manual screening was used in several rounds to assure the reliability of the LLM's screening decisions. After the initial keyword search, a total of 43,000 potentially relevant studies were identified. However, after refining the search through manual revisions of abstracts and titles, a total of 8,193 relevant studies were identified as candidates for full-text analysis.

Lastly, the full-text analysis focused on a representative sample of 10% of the evidence. The protocol applied to identify all relevant literature was published prior to the full review (Salazar et al. 2024). The process is summarized below, while the number of studies at each stage of the review process is shown in **Figure 2**.

I. Keyword search in bibliographic databases

Searches were conducted across seven academic databases using a comprehensive list of keywords in English, Spanish, and Portuguese.[2] This step yielded 43,624 potentially relevant academic articles. Gray literature was also gathered through key-

[2] The full search strings in all three languages are available in the study's published protocol (Salazar et al., 2024). In total, the string comprises more than 300 distinct terms across four categories: agricultural system terms, outcome terms, geographical terms, and method terms. Agricultural system terms include keywords such as "crops," "livestock," and "smallholder," reflecting our agricultural system inclusion criteria. Outcome terms, such as "productivity" and "yield," capture the outcomes of interest. Geographical terms, including "Mexico," "Andean region," and "Latin America," identify studies conducted in the LAC region.

word searches in the institutional repositories of the IDB, the World Bank and IMF, FAO, Economic Commission for Latin America and the Caribbean (ECLAC), IICA, the International Fund for Agricultural Development (IFAD), CGIAR, the Organization for Economic Co-operation and Development (OECD), USDA-ERS, and the Latin American and Caribbean Economic Association (LACEA).[3]

ii. Manual and AI-assisted screening of titles and abstracts

From the initial pool of 43,824 articles, a sample of 2,675 titles and abstracts (4%) was screened by a team of 7 experts who were trained in the application of the review's inclusion and exclusion criteria. The inclusion decisions were used to train a machine learning model, which screened the remaining titles and abstracts. The final model achieved a recall rate of .986, precision of .846, and an F1 score of .911.[4] Once trained, the model identified 8,193 potentially relevant records that advanced to the next stage of the review process.

iii. Full-text screening

A random sample of 10% of these 8,193 records (equivalent to 805 studies) was reviewed manually at full-text level to verify compliance with all inclusion criteria. In parallel, a 10% subsample of gray literature studies with relevant abstracts (equivalent to 20 studies) was also screened at full text. These two processes yielded a sample of 82 relevant studies, spanning academic and gray literature.

iv. Data extraction and Synthesis

After training to ensure consistent application of the structured data extraction form, the research team extracted data from the representative sample of 82 studies. This data was then synthesized into a systematic map identifying major trends and gaps in the literature base.

v. Supplementary AI-assisted full-text screening and data extraction

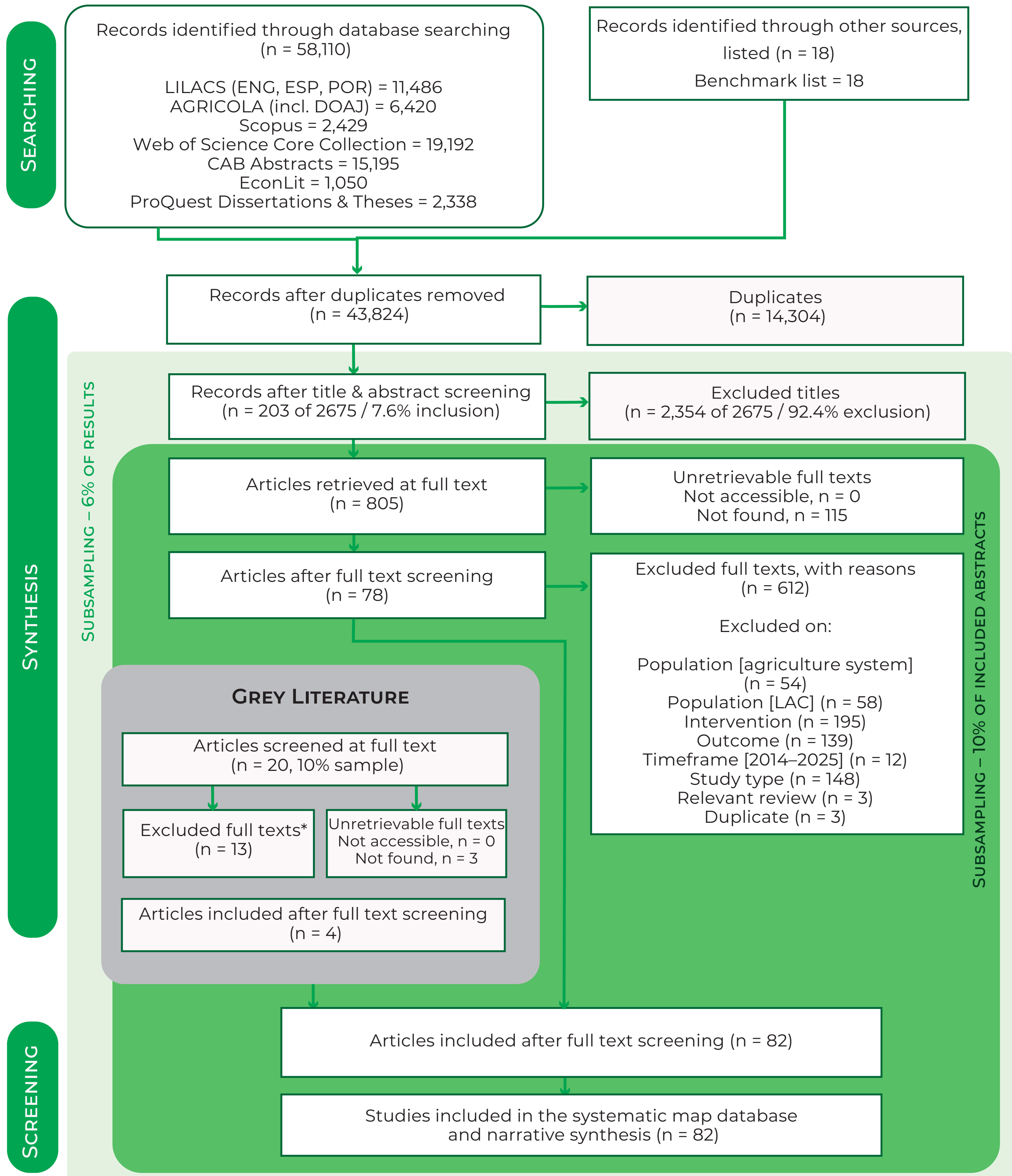
In addition to the primary full-text screening and data extraction results based on the representative sample of 10% of relevant texts, the study also incorporated a machine learning-assisted screening and data extraction component. To understand the trends present in the remaining 90% of potentially relevant studies that were not manually screened, the research team developed and trained an artificial intelligence model using the results of the manual screening and data extraction. This model was then applied to a set of 1,836 retrievable studies (from our initial pool of 8,193 potentially relevant studies) to extract data on the categories where its performance was reliable. The results of this AI-assisted data extraction are included as a supplement to our primary, manual data extraction findings.

Finally, method terms such as "econometric" and "farm-level data" indicate the use of quantitative analysis. In order to be captured by the search, articles had to mention at least one keyword from each of the four categories in the title and/or abstract. The search string was developed and validated using a set of benchmark papers that the research team identified as representative of studies meeting the inclusion criteria.

[3]For gray literature sources, we utilized institutional repositories' built-in year filters (and, when available, geography filters) to identify all LAC-based publications published after 2014. We then downloaded the publicly available metadata for these publications and applied the same keyword search string used in the academic databases to identify entries that mentioned the search terms in the title and/or abstract. All relevant codes and data collected during the gray literature search is available upon request and will be published in the annex of the forthcoming working paper.

[4] Recall refers to the model's ability to find all relevant items; in the case of this model, a recall rate of .986 means the model identified 98.6% of the relevant studies. Precision measures how many of the items flagged as relevant were actually relevant; in this case, a precision of .846 means that 84.6% of the articles included by the model were actually relevant. Finally, the F1 score represents the harmonic mean, which combines both the recall and precision. In this case, an F1 score of .911 shows that the model achieved a strong balance between recall and precision, finding almost all relevant studies (high recall) while minimizing the proportion of false inclusions. Recall and precision rates were calculated by manually reviewing samples of the model's inclusion/exclusion decisions.

FIGURE 2. ROSES FLOW DIAGRAM SHOWING THE NUMBER OF RECORDS AT EACH STAGE OF THE REVIEW PROCESS



Note: *For the purpose of brevity, grey literature exclusion reasons are not listed in the diagram. However, all excluded grey literature articles were excluded with reasons. The full list of excluded articles with exclusion reasons can be found in the forthcoming working paper.
Source: Authors' own elaboration.

III. FINDINGS

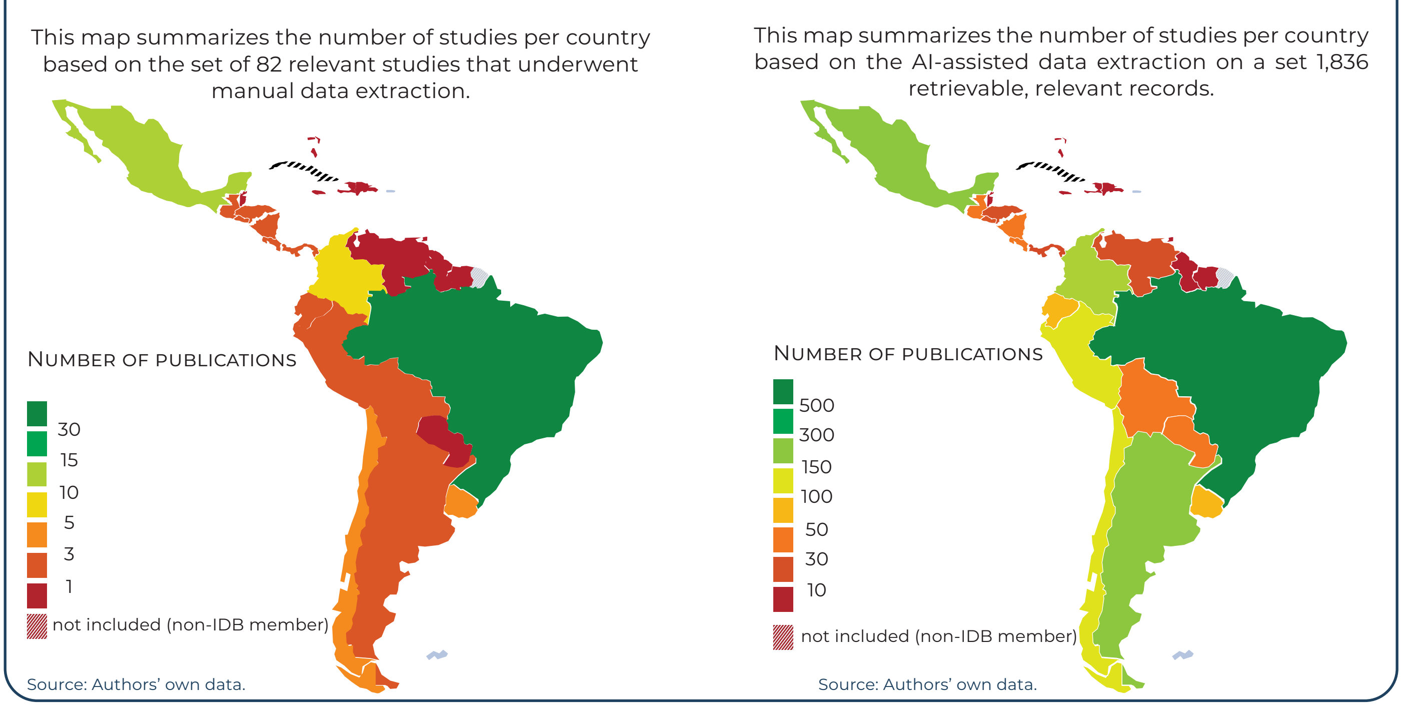
This section summarizes the main findings of the manual data extraction from the evidence base of 82 studies.

1. There are significant geographic disparities in the literature base

The results reveal significant geographic disparities in the number of studies by country. The left panel of **Figure 3a** shows the number of studies by country based on our random sample of 82 studies that was analyzed using manual data extraction. Brazil was by far the most studied country (n=36), followed by Mexico (n=14) and Colombia (n=6). In contrast, no studies were conducted in Caribbean countries,[5] and five countries were represented by only a single study, further underscoring the uneven distribution of evidence across the region.[6] These results are generally consistent with the geographic distribution of the 1,836 additional studies reviewed using AI-assisted full-text analysis (**Figure 3a**, right panel).

Figure 3b provides a side-by-side graphical comparison of the results of the manual data extraction results and the AI-assisted data extraction results. As figures 3a and 3b show, both methods identified a concentration of evidence in Brazil and Mexico, while the least-studied countries are predominantly located in the Caribbean and, to a lesser extent, Central America. Unsurprisingly, the countries with the largest number of studies were those for which censuses or agricultural surveys were available. Primary sources were, in fact, the most frequently used data source in the evidence base. This geographic imbalance poses challenges for evidence-based policymaking because the effectiveness of interventions is highly dependent on local conditions such as agronomic environments, ecologies, social dynamics, markets, and institutions. These context-specific factors must be carefully considered to ensure policies are appropriate.

Figure 3a. Number of publications by country: manual data extraction (left) and AI-assisted data extraction (right)



Source: Authors' own data.

Source: Authors' own data.

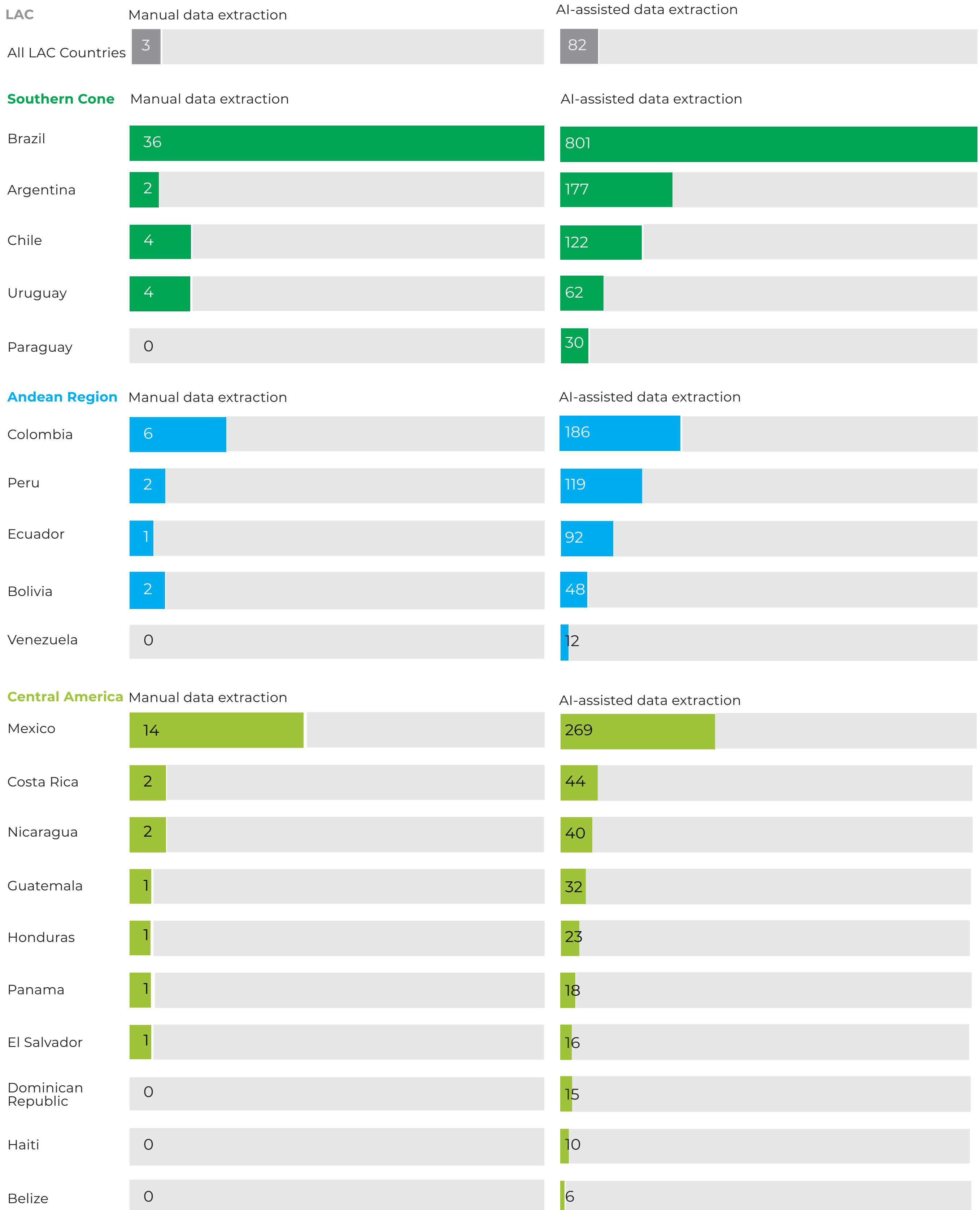
[5] In Central America, no studies were found for Belize, the Dominican Republic, or Haiti. In the Andean Region, no studies were found for Venezuela. In the Southern Cone, no studies were found for Paraguay. It should be noted that no relevant studies were found for these countries in our sample evidence base (that is, the 10% subsample).

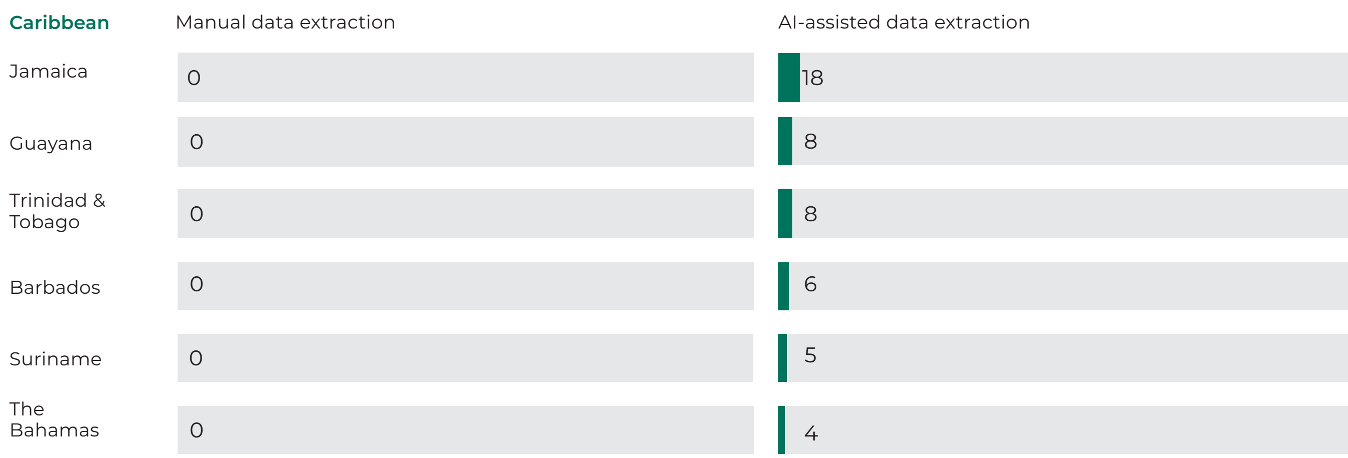
[6] The countries with only one relevant study were Ecuador, El Salvador, Guatemala, Honduras, and Panama.

Figure 3b. Number of publications by country: manual data extraction (left) and AI-assisted data extraction (right)

(continued on next page)

Bars on the left show the number of studies per country from the total of 82 in the random sample that underwent manual data extraction.





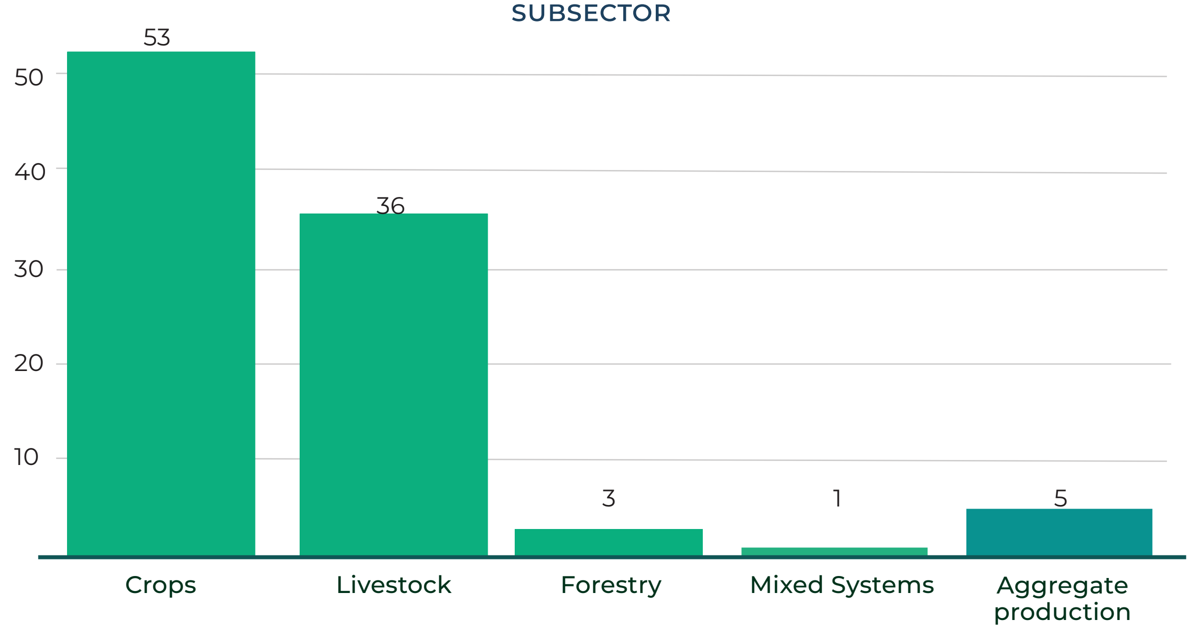
Notes: Some studies analyze multiple countries. As a result, the sum of the individual country counts is greater than the number of studies in the dataset.

Source: Authors' own data.

2. Evidence is clustered in primary crops and livestock, with a focus on cash crops and export products

Figure 4 shows the distribution of evidence across agricultural subsectors. The most studied subsectors were agricultural crops (n=53) and livestock (n=36). Few studies examine forestry (n=3) or mixed systems, such as agroforestry and silvopastoral production (n=1). The concentration of evidence on crops and livestock suggests that productivity interventions in forestry and mixed systems are widely understudied.

Figure 4. Studies by agricultural subsector



Notes: Some studies analyze more than one subsector. The figure is based on a representative sample of studies analyzed through manual data extraction. The listed values are therefore not reflective of the absolute number of studies in the literature base, but rather the relative distribution of studies in the overall literature base.

Source: Authors' own data.

A more detailed analysis of the crop and livestock studies reveals that evidence focused primarily on export products and cash crops, such as: cattle (n=19), meat (n=14), cereals (n=12), and fruit (n=12).

In contrast, crop and livestock products that play an important role in food security and traditional economies were among the least-studied categories. Specifically, among the crop categories with the fewest studies were nutritionally significant products, such as pulses (e.g. beans, chickpeas, and other legumes) (n=1), roots and tubers (e.g. potatoes, cassava, and sweet potatoes) (n=3), and vegetables (n=4). In terms of livestock, no studies examined chicken, llamas, alpacas, or their subproducts (e.g. eggs, wool) (n=0), despite their critical role in local diets and traditional economic activities.

3. Evidence gaps persist not only for emerging intervention types, such as environmental and social certifications, but also for longstanding policy approaches that have been widely implemented across LAC for decades, including price support mechanisms and trade agreements

Figure 5 shows the distribution of studies across specific intervention types (outer ring) and intervention clusters (inner ring). To aggregate specific interventions, a total of 11 intervention categories or clusters were identified. The cluster containing the largest number of studies is ***natural resource management*** (n=56), followed by ***extension services, technical assistance, and agricultural R&D*** (n=35).

The clusters with the fewest studies included ***associativity*** (n=3), ***input support / subsidies*** (n=3), ***human capital strengthening*** (n=5), and ***land regularization and administration*** (n=7).

The outer ring of the figure shows the number of studies associated with each intervention type. The least-studied interventions include more recent and innovative approaches such as ***environmental and social certifications*** (n=1), ***payments for ecosystem services*** (n=1), ***public purchases of agricultural products*** (n=1), ***smart subsidies*** (n=2), and ***agricultural insurance*** (n=3).

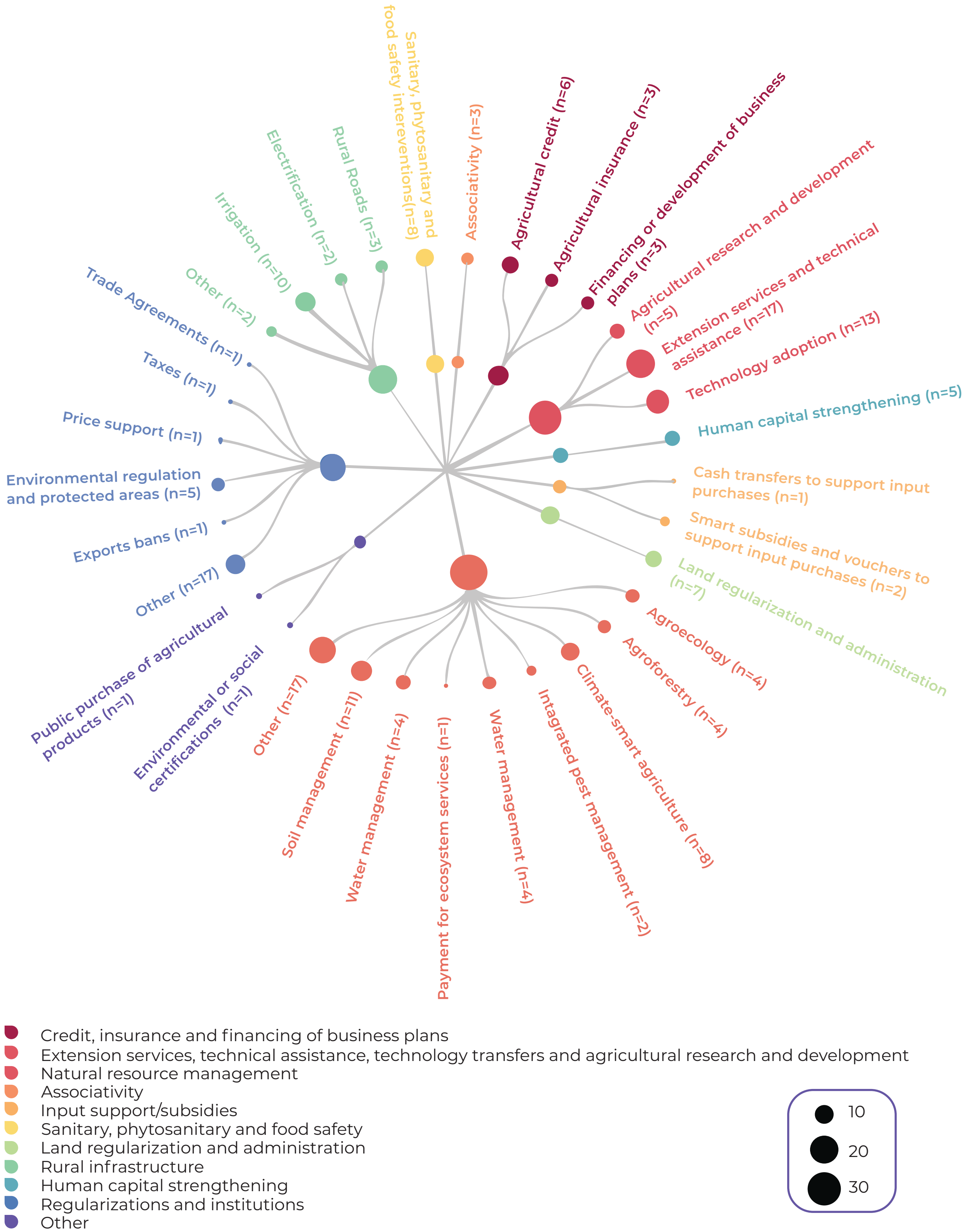
Notably, gaps were also evident in relation to interventions that have been cornerstones of LAC's agricultural policy toolkit for decades, such as ***trade agreements*** (n=1), ***price support*** (n=1), and ***cash transfers*** (n=1), along with ***associativity*** (n=3), as mentioned above.

Some variation in intervention types was observed across LAC subregions. Across LAC subregions, natural resource management was the most studied intervention type.

However, extension services, technical assistance, and technology adoption were the most frequently studied categories in the Southern Cone.

In Central America, regulations and institutions were more prominent, while in the Andean region, rural infrastructure was the second-most studied intervention type (**Table 1**).

Figure 5. Number of publications analyzing each intervention type, grouped into categories



Notes: Bubble size reflects the number of publications. Some studies analyze more than one intervention type. The figure is based on a representative sample of studies analyzed through manual data extraction. The listed values are therefore not reflective of the absolute number of studies in the literature base, but rather the relative distribution of studies in the overall literature base.
Source: Authors' own data.

Table 1. Number of publications analyzing each intervention cluster, by subregion

	Andean Region	Caribbean	Central America	Southern Cone
Agricultural research and development			2	3
Associacivity				3
Environmental or social certifications				1
Extension services and technical assistance	1		3	13
Financial services	1		2	5
Financing or development of business plans				3
Food safety				1
General human capital strengthening	2		1	2
Input support/subsidies			2	1
Land regularization and administration	2		3	2
Natural resource management	4		7	22
Public purchases of agricultural products				1
Regulations and institutions	3		7	7
Rural infrastructure	4		5	7
Sanitary and phytosanitary			4	3
Technology adoption	1		2	10
Total	18		38	84

Number of Publications: 1-5, 6-10, 11-15, 16-20, 21-25

Notes: Some studies analyze more than one intervention type and/or subregion. The figure is based on a representative sample of studies analyzed through manual data extraction. The listed values are therefore not reflective of the absolute number of studies in the literature base, but rather the relative distribution of studies in the overall literature base.

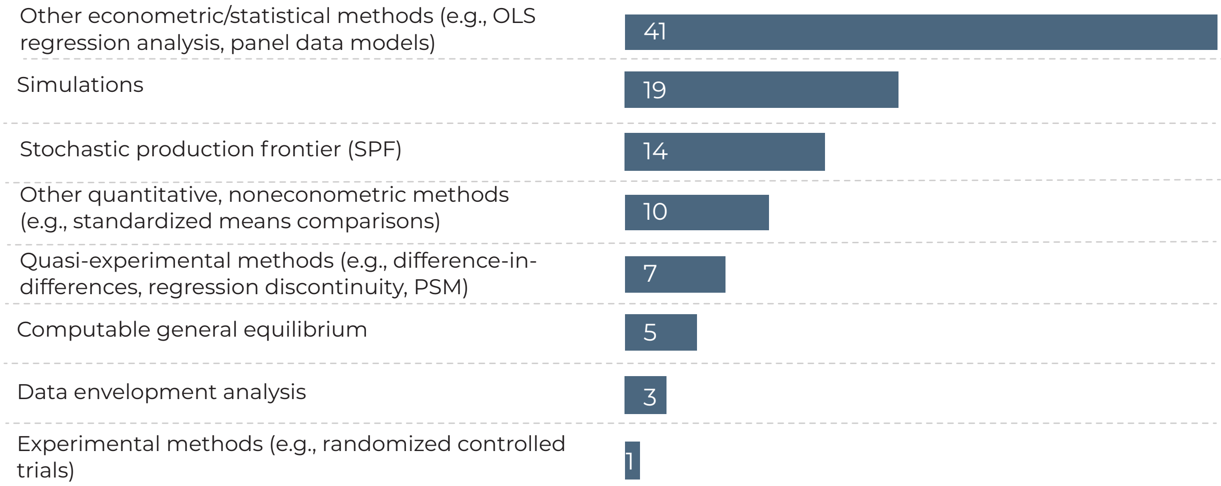
Source: Authors' own data.

4. Rigorous impact evaluations are uncommon

While this review did not conduct a critical evaluation of each study's validity, the overview of methodologies used provides some insight into the quality of the evidence base. Figure 6 shows the number of publications by methodology. Experiments or randomized controlled trials (RCTs—the gold standard in impact evaluations—were the least-used methodology (n=1). Quasi-experimental methods relying on counterfactual analysis to measure the causality of interventions were more common but still scarce (n=7). On the contrary, methodologies (such as simple statistical analysis, linear regressions and panel data) were the most widely applied (n=41).

Table 2 shows the distribution of studies by methodology and intervention type, highlighting knowledge gaps at the intersection of intervention clusters and methodological approaches. Notably, stochastic production frontier (SPF) analysis was used across more intervention clusters (14 out of 16) than any other methodology. While SPF models are a rigorous methodology that yields crucial insights into the drivers of productivity growth and technical efficiency, these can only establish causality when paired with quasi-experimental or experimental methods, which were used to study relatively few clusters (5 and 2, respectively).

Figure 6. Number of publications by methodology



Notes: Some studies use more than one methodology. The figure is based on a representative sample of studies analyzed through manual data extraction. The listed values are therefore not reflective of the absolute number of studies in the literature base, but rather the relative distribution of studies in the overall literature base.

Source: Authors' own data.

Table 2. Number of publications by intervention category and methodology

	Stochastic production frontier	Quasi-experimental	Experimental	Data envelopment analysis	Computable general equilibrium	Simulations	Other econometric/ statistical	Other quantitative/non-econometric
Agricultural research and development				1	1	2	4	1
Associativity	2						1	1
Environmental or social certifications	1						1	
Extension services and technical assistance	7		1	1	1	4	8	4
Financial services	3	2					5	1
Financing or development of business plans	2					1		1
Food safety	1							
General human capital strengthening	1						4	1
Input support/subsidies	1						2	
Land regularization and administration	3					1	3	
Natural resource management	4	2	1	2	3	11	13	7
Public purchases of agricultural products		1						
Regulations and institutions	1	1			1	3	10	1
Rural infrastructure	3	1			2	4	7	
Sanitary and phytosanitary	2					2	4	2
Technology adoption	3			1	1	4	9	2
Total	34	7	2	5	9	32	71	21

Number of Publications: 1-2 | 3-5 | 6-7 | 8-10 | 11-13

Notes: Some studies analyze more than one intervention category and/or use more than one methodology. The figure is based on a representative sample of studies analyzed through manual data extraction. The listed values are therefore not reflective of the absolute number of studies in the literature base, but rather the relative distribution of studies in the overall literature base.

Source: Authors' own data.

5. Limited evidence on heterogeneous effects across diverse populations constrains the design of targeted, evidence-based policies for vulnerable groups

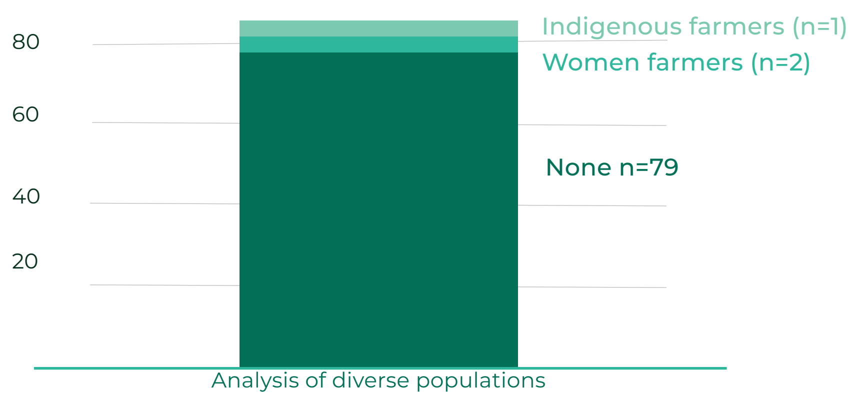
Our analysis also categorized studies that assessed the effects of interventions on diverse populations. A study was classified as focusing on diverse populations if (i) the intervention itself specifically targeted groups such as women or Indigenous communities or (ii) the study explicitly examined heterogeneous effects on these groups. As **Figure 7** shows, the vast majority of studies did not meet either criterion (n=79). Two studies analyzed effects on women producers (n=2), one study analyzed effects on indigenous producers (n=1). Additionally, no studies looked at young farmers or afro-descendant producers (n=0). This lack of evidence hinders the design of inclusive agricultural policies that address the needs of the diverse populations that play a fundamental role in sustaining food systems across LAC, who still face persistent gaps in access to inputs, technologies, and public services.

6. Interventions have been increasingly analyzed through a climate lens

Although a slight majority of studies (n=43) did not incorporate climate considerations, a substantial share did (n=39). Of these, 21 examined climate change adaptation interventions, 18 examined climate change mitigation interventions, 10 evaluated the effects of climate change on agricultural productivity (e.g., rising temperatures), and 8 projected the expected or future impacts of climate change on agricultural productivity. Additionally, 9 studies estimated the effect of agriculture on climate (e.g., through deforestation, emissions, etc.).

These results suggest that there is growing interest in generating empirical evidence on the link between agriculture and climate change. However, there is room for more studies that assess the effectiveness of interventions while simultaneously considering the impacts of climate change on agricultural productivity (for example, through the increasing severity and frequency of droughts, unpredictable rainfall patterns, and biodiversity loss).

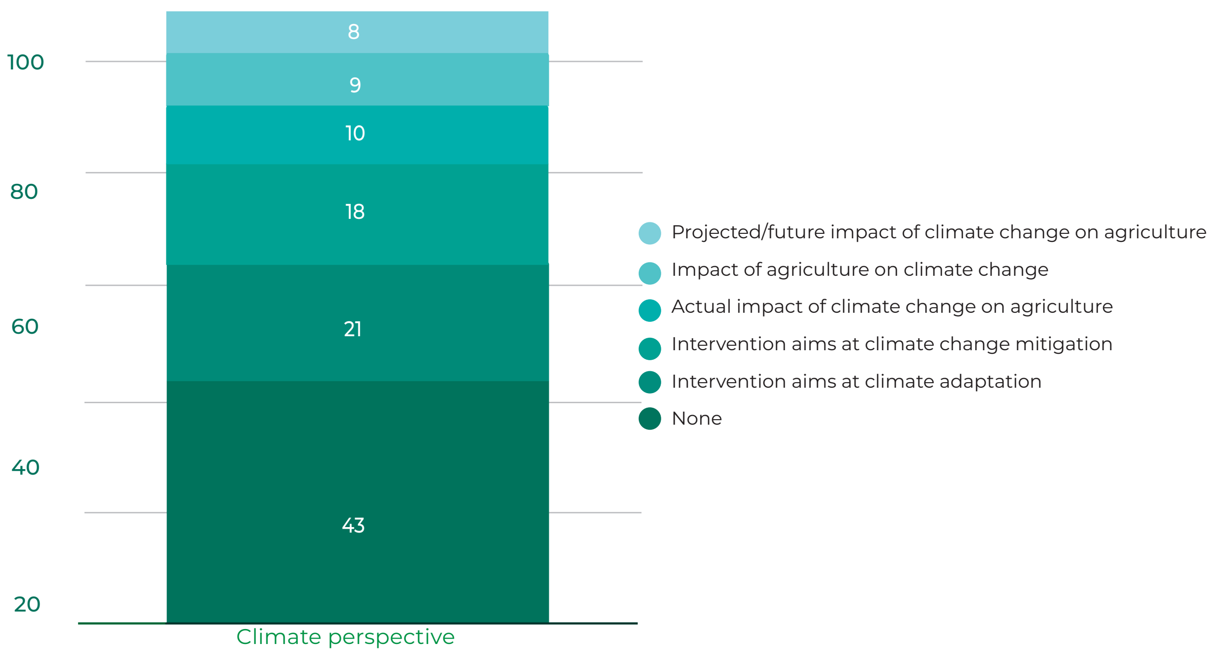
Figure 7. Number of publications focusing on diverse populations



Notes: The figure is based on a representative sample of studies analyzed through manual data extraction. The listed values are therefore not reflective of the absolute number of studies in the literature base, but rather the relative distribution of studies in the overall literature base.

Source: Authors' own data.

Figure 8. Number of publications by climate perspective



Notes: Some studies analyze more than one climate perspective. The figure is based on a representative sample of studies analyzed through manual data extraction. The listed values are therefore not reflective of the absolute number of studies in the literature base, but rather the relative distribution of studies in the overall literature base.

Source: Authors' own data.

IV. CONCLUSIONS AND POLICY RECOMMENDATIONS

I. Promote rigorous impact evaluations that analyze the effects of agricultural interventions on productivity outcomes, especially in understudied countries and intervention types

When designing agricultural productivity interventions, particularly in understudied countries in the Caribbean, Andean region, and Central America, policymakers and other stakeholders should collaborate with universities and research centers to develop impact evaluations at the early stages of intervention planning. Incorporating an evaluation perspective early on helps ensure that interventions are implemented under the conditions needed to conduct rigorous counterfactual analysis. Priority should also be given to assessing interventions for which little evidence exists, including associativity efforts, certification schemes, trade agreements, public purchases of agricultural products, price support, and cash transfers.

II. Foster conditions to expand the empirical evidence base beyond export crops, with priority given to food staples

Assessing the effects of interventions on export crop productivity should remain central to agricultural development agendas; however, productivity-enhancing interventions should also be analyzed in relation to crops and livestock products that have high nutritional value, are central to local diets, and feature in traditional economic activities. This includes pulses, roots, tubers, chickens, and camelids (llamas and alpacas). For this purpose, it is key to implement strategies for periodic data collection that includes all crops and livestock products, such as national agricultural censuses and representative agricultural surveys.

III. Address persistent evidence gaps on how interventions impact women producers, Indigenous farmers, and other diverse groups in order to design more inclusive and equitable policies

Groups like women producers and Indigenous farmers remain understudied in the existing evidence base. This lack of analysis could result in ineffective interventions that widen gender and ethnic gaps, thereby reinforcing existing inequalities in access to resources, services, and productivity gains. To close the gaps among vulnerable populations, policymakers should develop interventions that target these groups and assess their impact to ensure effectiveness. In addition, disaggregated data collection by gender and ethnicity needs to be mainstreamed to capture the differentiated effects of interventions on marginalized and underrepresented populations.

IV. Develop and evaluate productivity-enhancing interventions for mixed production systems such as agroforestry and silvopastoral systems

Despite their well-documented contributions to the environmental sustainability of production, mixed systems were the least-studied agricultural subsector. To encourage their adoption and ensure they can provide sustainable livelihoods for rural communities, policymakers should design, implement, and evaluate more interventions aimed at increasing the productivity of agroforestry and silvopastoral systems.

V. Integrate climate considerations into agricultural productivity interventions and evaluations

Assessments of agricultural productivity interventions should explicitly include a climate perspective. This includes measuring the effects of adaptation and mitigation efforts on agricultural productivity and capturing the effects of climate-related factors (such as rainfall and temperature patterns) through impact evaluations. Embedding climate analysis in policy design will enhance the relevance, effectiveness, and resilience of agricultural development strategies. This approach also requires improving the collection and integration of data on climate-related variables and extreme weather events alongside productivity data.

VI. Strengthen data systems for evidence-based agricultural policy

Reliable, disaggregated, and timely data are essential for designing, monitoring, and evaluating agricultural interventions. Investments should be directed toward improving data systems that capture key variables such as gender, ethnicity, farm size, and geographic location. This should include not only agricultural censuses and survey data but also satellite and remote sensing systems for agricultural productivity analysis, which can complement microeconomic data and reduce costs. More comprehensive and integrated information systems would incentivize a broader range of research to guide the implementation of evidence-based agricultural policies that enhance productivity while promoting inclusivity, resilience, and sustainability.

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Section II. Agricultural Productivity in Focus: Evidence from Country Studies

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Section III. Productivity with Purpose: Building Sustainable Agrifood Systems

Chapter 12. Reassessing Agricultural Growth: Introducing a Sustainable Productivity Index for Latin America and the Caribbean

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Section IV. Generating Impact through Evidence

Chapter 13. Advancing Agricultural Development through Evidence: A Decade of IDB Impact Evaluations in the Region

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Chapter 14. Uncovering Evidence Gaps in Agricultural Productivity Research: A Systematic Mapping

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Chapter 13: IDB Impact Evaluations-Annex 1. Summary of publications' characteristics and key findings

Publication	Category	Country	Methodology	Program name and description	Key findings	Publication title	Additionally published in a peer review Journal
Salazar et al. (2018a)	Input and technology transfers—direct transfer	Nicaragua	DiD + PSM	Agrifood Support Program (APAGRO): Producers received different combinations of cows, pigs, sheep, and chickens, and technical assistance on livestock management and commercialization.	**Productivity:** Agricultural output: 60% increase; income from livestock sales: more than 200% increase. **Others:** Household consumption: 60% increase; probability of women's disempowerment: 15% decreased; probability of gender imbalance: 18% decrease; protein intake: 12% increase; food consumption: 11% increase.	Agrifood Support Program (APAGRO).	
Mullally et al. (2019)	Input and technology transfers—direct transfer	Guatemala	RCT (phase-in design)	Recovery of the Natural Capital of the Dry Corridor Region Program: Provision of naked-neck chicken varieties in exchange for completing a poultry extension program.	**Productivity:** No significant effects on egg production or egg sales. **Others:** No detectable effect on household food consumption indicators; significant positive impacts on girls' anthropometric indicators—reduced stunting by 23.5 p.p. and severe stunting by 14 p.p.	All they're cracked up to be?: The impact of chicken transfers in Guatemala.	
Aramburu et al. (2019)	Input and technology transfers—voucher	Dominican Republic	RCT (two-stage random assignment)	PATCA II: Non-reimbursable vouchers to finance a portion (33%–59%) of an agricultural technology chosen by the farmer, including technical assistance. Technologies evaluated: (i) improved pasture technologies and (ii) modern irrigation technologies.	**Productivity/production:** Improved pastures increased agricultural income by 627% over time (only 10% significance); one additional month of exposure associated with 14% increase in income; irrigation had initial negative effects on agricultural income. **Others:** increased technology adoption (by 62%–68%); irrigation associated with a shift in crop portfolios (temporary to permanent crops); limited spillover effects.	Direct and spillover effects of agricultural technology adoption programs: Experimental evidence from the Dominican Republic (PATCA II).	

Publication	Category	Country	Methodology	Program name and description	Key findings	Publication title	Additionally published in a peer review Journal
Salazar et al. (2015)	Input and technology transfers—voucher	Bolivia	IV model using distance to voucher distribution events	CRIAR: Non-reimbursable vouchers covering 90% of the cost of producer-chosen technologies and technical assistance.	**Productivity:** Annual value of production per hectare: 92% increase; net annual agricultural household income: 36% increase. **Others:** Probability of a household being food secure: 32% increase; distance from events strongly reduces likelihood of participation.	Food security and productivity: impacts of technology adoption in small subsistence farmers in Bolivia.	Salazar, Lina, Julián Aramburu, Mario González-Flores, and Paul Winters. "Sowing for food security: A case study of smallholder farmers in Bolivia." **Food Policy** 65 (2016): 32-52.
Salazar et al. (2018b)	Input and technology transfers—voucher	Haiti	Multiple evaluations; RCTs and PSMs	PTTA: Smart subsidies to give farmers vouchers for various inputs (seeds, seedlings, fertilizer, labor tasks) and technological packages for agroforestry.	**Productivity:** Agroforestry technical package subsidies increased the total value of crop production by 38% and profits by 63%; smart vouchers for rice, horticulture, and peanut production had no significant difference on productivity variables or a significant negative impact, which the authors attribute to factors such as climate shocks, implementation challenges, and information gaps that influenced investment decisions. **Others:** No significant difference in food security.	Technology Transfer to Small Farmers Program (PTTA) in Haiti: Implementation, evaluation, and lessons learned.	
González Flores and Le Pommellec (2019)	Input and technology transfers—voucher	Nicaragua	DiD + PSM	PAGRICC: Vouchers to subsidize technological packages and technical assistance to establish agroecology systems.	**Productivity:** Value of production per hectare: increased by US$195 ha. **Others:** Tree coverage increased (22 plants and 3 hectares); number of plants managed with ecoforestry practices increased (1,045 plants); rainwater harvesters increased (from 34% to 44%); volume of water collected increased (204 m^3); number of productive practices adopted increased.	Evaluación de impacto del componente 1 del programa ambiental de gestión de riesgos de desastres y cambio climático (PAGRICC)	

Publication	Category	Country	Methodology	Program name and description	Key findings	Publication title	Additionally published in a peer review Journal
Schling and Pazos (2022b)	Input and technology transfers—voucher	Argentina	IPW and NDVI	PRODAF: Smart subsidies and technical assistance for the adoption of sustainable technologies (PRODAF).	**Productivity:** Positive and statistically significant impacts on yields only for the citrus value chain, with largest effects at 2–3 years; effects on other value chains not statistically significant in most estimations. **Others:** Technology adoption: 21 p.p. increase; credit access: 47 p.p. increase; labor costs for dairy producers: decrease.	The impact of smart subsidies on agricultural production: Innovative evidence from Argentina using survey and remote sensing data	
Salazar et al. (2021)	Input and technology transfers— Voucher	Dominican Republic	DiD + event study methodology; NDVI + OSAVI	PATCA II: Voucher to purchase modern irrigation technology.	**Productivity:** Dynamic effects on productivity, with increased vegetation indices beginning in year 3 (NDVI and OSAVI used as proxies for productivity); differences between treatment and control dissipate in later years, possibly due to spillovers. **Others:** Evidence suggests spillover effects into neighboring communities.	Using satellite images to measure crop productivity: long-term impact assessment of a randomized technology adoption program in the Dominican Republic.	
Schling et al. (2025b)	Input and technology transfers—credit	Argentina	Synthetic DiD	Revolving loan fund for smallholder dairy farmer associations. The fund provides short-term credit lines to cover input purchases (feed, veterinary products, etc.) and long-term credit lines for capital investments (equipment, infrastructure, etc.).	**Productivity:** Effects not reported; credits for variable inputs showed no significant effect on dairy production; credits used for capital investment increased production by 17.2% the year after the credit was received; larger investment loans had positive production impacts for 3 years after the credit was received (between 11%–17.4%). **Others:** N/A	Evaluación de fondos rotatorios de crédito: Evidencia de la cadena lechera argentina.	

Publication	Category	Country	Methodology	Program name and description	Key findings	Publication title	Additionally published in a peer review Journal
Salazar, et al. (2025)	Input and technology transfers—voucher	Bolivia	Two-phase RCT with randomization at the geographic and community levels with spillover measurement	CRIAR II: Nonreimbursable financial support to cover the cost of an agricultural technology chosen by the producer, and technical assistance.	Increased value of production for direct beneficiaries (US$946) and indirect beneficiaries (US$466). Increased household income for direct beneficiaries (US$1,691) and indirect beneficiaries (US$528); increased likelihood of technology adoption for direct beneficiaries (+64 p.p.) and indirect beneficiaries (+14 p.p.); increased crop diversification among direct beneficiaries.	CRIAR II: Creation of Agrifood Initiatives (Phase II).	
Corral and Zane (2021)	Rural infrastructure—rural roads	Ecuador	DiD and PSM	Chimborazo Rural Investment Project: Rural road improvement.	**Productivity:** No statistically significant effect on agricultural productivity, income, or investments. **Others:** Reduced travel time and costs; improved health outcomes; increased secondary education enrollment at crucial transition ages (13 and 18).	Chimborazo Rural Investment Project: Rural roads component impact evaluation.	
Maffioli, Gibbons, and Rossi (2018)	Rural infrastructure—irrigation Input and technology transfer—voucher	Argentina	DiD (long term: 12 years)	PROSAP: Construction of irrigation canals PROVIAR: Distribution of vouchers for viticulturists to purchase winemaking inputs such as hail-resistant nets, wood, and wire. PROVIAR and PROSAP.	PROVIAR: production: 9.4% increase; productivity: 7.7% increase. PROSAP: production: 4.2% increase; productivity: 4.6% increase. PROVIAR+PROSAP: total production: 16.6% increase; productivity: 16% increase. Others: N/A.	Programa de Apoyo a Pequeños Productores Vitivinícolas en Argentina (PROVIAR) y Programa de Servicios Agrícolas Provinciales (PROSAP).	

Publication	Category	Country	Methodology	Program name and description	Key findings	Publication title	Additionally published in a peer review Journal
Corral and Zane (2020)	Rural infrastructure—irrigation	Ecuador	DiD	Chimborazo Rural Investment Project: Rehabilitation of irrigation systems in Indigenous highland communities; creation of water-use associations; technical assistance focused on water management.	**Productivity:** Overall crop yields: approximately 33% increase; agricultural income effects were positive but not statistically significant. **Others** Share of irrigated plots: 10 p.p.; decreased crop sales (suggesting increased self-consumption); reduced food insecurity.	Chimborazo Rural Investment Project: irrigation component impact evaluation.	
Salazar and López (2017)	Rural infrastructure—irrigation	Bolivia	PSM	PRONAREC: Public irrigation infrastructure for use by water-use associations; technical assistance.	**Productivity:** No statistically significant effect on yields; agricultural production value: 60%–70% increase; total household income: 35%–45% increase. **Others:** Spending on irrigation equipment: 100%–160% increase; use of certified seeds: 80%–90% increase; market access: 20%–30% improvement.	PRONAREC Bolivia: National Irrigation Program with a Watershed Approach.	
Schling et al. (2025a)	Rural infrastructure—irrigation	Argentina	Synthetic DiD, PSM, and IPW on NDVI (long-term impact evaluation)	PROSAP III: Rehabilitation of irrigation channels (public infrastructure) in Argentina's wine-producing San Juan province.	**Productivity:** Positive impact on production volume of grapes: 31.4%–53.2% increase; yields: 0.93%–1% increase, with impacts becoming stronger over time- **Others:** Reduced probability of farmers reporting irrigation-related losses; increased area under effective irrigation.	Infraestructura de riego y productividad de los viñedos: evidencia mediante teledetección y diferencias en diferencias sintéticas en Argentina (PROSAP III).	

Publication	Category	Country	Methodology	Program name and description	Key findings	Publication title	Additionally published in a peer review Journal
Schling et al. (2024)	Land regularization and administration	Bolivia, Ecuador, Peru	PSM and SPF analysis	Three national-level land tenure security programs that provided formal land titling for smallholder farmers. Bolivia: Land Management Program for Sustainable Rural Development Ecuador: SigTierras Program (in Ecuador) Peru: PTRT	**Productivity:** Technical efficiency levels of farmers with legal titles were 38.6% higher than those without titles (effects varied based on country). **Others:** Increased access to credit; increased productive investments.	Land regularization and technical efficiency: an empirical study in Andean countries.	Schling, Maja, Magaly Saenz Somarriba, Juan de Dios Mattos, Rodrigo Chang Huaita. "Land regularization and technical efficiency in agricultural production: An empirical study in Andean countries." **Rural Studies** 121 (2026): 103912
Corral et al. (2024)	Land regularization and administration	Ecuador	Double robust estimation (DiD and IPW)	SigTierras: Cadastral mapping to improve land tenure security in Ecuador.	**Productivity:** No statistically significant effects on crop or livestock income. **Others:** Increase in total household income; increase in agricultural wages; no effect on tenure security perception; no effect on land conflicts; no effect on input use.	Effects of land administration: evaluation of Ecuador's Rural Land Administration Program (SigTierras).	
Schling et al. (2023)	Land regularization and administration	Ecuador	Double robust estimation (DiD and IPW)	SigTierras: Cadastral mapping under rural land administration program in Ecuador (including joint titling).	**Productivity:** N/A **Others:** Jointly titled cadastral maps led to increased food security and shifts in production portfolios toward higher-value/higher-nutrition value chains; increased women's off-farm wages and time spent on nonagricultural activities; increased investment in women's business.	The effects of tenure security on women's empowerment and food security: evidence from a land regularization program in Ecuador.	Schling, Maja, Nicolás Pazos, Leonardo Corral, and Marisol Inurritegui. "The effects of increasing tenure security on women's empowerment and food security: Evidence from Ecuador." **Land Use Policy** 158 (2025): 107695.
Schling and Pazos (2022a)	Land regularization and administration	Peru	Instrumental variable	PTRT: Effective (self-declared) land ownership by women.	**Productivity:** N/A **Others:** Women's informal land ownership increased crop diversity, reduced time in farm work, and improved household food security by 20 p.p.	Effective land ownership, female empowerment, and food security: evidence from Peru.	Schling, Maja, and Nicolás Pazos. "Effective land ownership, female empowerment, and food security: Evidence from Peru." **World Development** 181 (2024): 106680.

Publication	Category	Country	Methodology	Program name and description	Key findings	Publication title	Additionally published in a peer review Journal
Salazar et al. (2017)	Animal and plant health	Peru	Geographical regression discontinuity	Fruit Fly Eradication Program: Multipronged program that includes technical assistance on pest eradication, installation of fruit fly traps, application of fruit fly pesticides, release of male sterile flies to prevent reproduction, and implementation of quarantine centers.	**Productivity:** Increased fruit crop productivity and sales. **Others:** Improved farmers' knowledge of posts and adoption of prevention practices.	Estimating the impacts of a fruit fly eradication program in Peru: A geographical regression discontinuity approach.	Salazar, Lina, Julian Aramburu, Marcos Agurto, Alessandro Maffioli, and Jossie Fahsbender. "Sweeping the flies away: evidence from a fruit fly eradication program." **European Review of Agricultural Economics** 47, no. 5 (2020): 1920-1962.
Salazar et al. (2023)	Animal and plant health	Peru	Regression discontinuity and NDVI over 10 years, quantile regression	Fruit Fly Eradication Program: Multipronged program that includes technical assistance on pest eradication, installation of fruit fly traps, application of fruit fly pesticides, release of male sterile flies to prevent reproduction, and implementation of quarantine centers.	**Productivity:** 12%–49% increase with productivity gains increasing over time. **Others:** Most productive farmers experienced largest productivity increases.	Estimating the long-term effects of a fruit fly eradication program using satellite imagery.	
Mullally and Maffioli (2014)	Extension services and capacity-building—extension	Uruguay	IPW (long term—8 years)	ULP: Extension program to improve cattle management practices.	**Productivity:** Increased calf production (11.36 and 15.3 calves) and net sales (4.35 calves). **Others:** Net calf sales increased by 4.35 on average; IRR analysis suggests modest effects.	The impact of agricultural extension for improved management practices: An evaluation of the Uruguayan Livestock Program.	Mullally, Conner, and Alessandro Maffioli. "Extension and matching grants for improved management: An evaluation of the Uruguayan livestock program." **American Journal of Agricultural Economics** 98, no. 1 (2016): 333-350.
Arráiz et al. (2015)	Extension services and capacity-building—associativity	Haiti	DiD + PSM	Haiti Hope Project: creation of producer business groups for mango production, training in mango production and commercialization, promotion of Francique mango variety (export variety).	**Productivity:** No significant change in production or sales. **Others:** Increased number of Francique trees (export variety) planted; increased adoption of several improved practices (e.g., fencing plot, pruning trees); decreased use of intermediaries; increased participation in producer business groups; authors note short timeframe.	Planting the seeds: The impact of training on mango producers in Haiti.	

Publication	Category	Country	Methodology	Program name and description	Key findings	Publication title	Additionally published in a peer review Journal
Carballo et al. (2018)	Extension services and capacity-building —associativity	Peru	DiD	ConnectAmericas: online B2B platform that has been explicitly established to foster cross-country trade.	**Productivity:** The use of the platform resulted in additional exports. **Others:** Increased visibility of firms to foreign buyers and holds even if they do not actively look for business opportunities in the platform.	Online Business Platforms and International Trade	Carballo, J., Chatruc, M. R., Santa, C. S., & Martincus, C. V. (2022). Online business platforms and international trade. **Journal of International Economics,** *137*, 103599.
Carballo et al. (forthcoming)	Extension services and capacity-building —associativity	Costa Rica	Staggered DiD	Digitalization of trade documents (ESW)*: online application and issuance of trade-related permits and certificates through a single website.	**Productivity:** Digitalization increased exports at the implementation level along both the firm intensive and extensive margins. **Others:** Firms using the digitalized procedures exported more and at a higher frequency than non-treated firms. More pronounced effect for smaller firms located in non-central regions and in destinations that also have operative ESWs.	Trade Policy Meets Digital Technologies: How Digitalization of Trade Procedures Affects Firms' Exports	

Notes: RCT = randomized controlled trial; DiD = difference-in-differences; PSM = propensity score matching; IV = instrumental variables; IPW = inverse probability weighting; NDVI = normalized difference vegetation index; OSAVI = optimized soil-adjusted vegetation index; SPF = stochastic production frontier; B2B = business to business; *ESW = electronic single window. Unless otherwise specified, key findings are statistically significant at the 5% level.

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