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Abstract

This paper analyzes trends in agricultural total factor productivity in Bolivia between 2008 and 2015 and the factors driving these trends using national agricultural surveys. On balance, the findings suggest that agricultural total factor productivity increased by 1.8% annually between 2008–2015. Among productive inputs, land shows the largest marginal effect on the value of agricultural production. Regarding temperature shocks, the study finds that each additional harmful degree day during the growing season is associated, on average, with a 9.8% decrease in the value of agricultural output. With regards to policy drivers, no statistically significant effect of land titling within the last two years is detected on productivity. Public irrigation infrastructure has a positive effect on productivity, though its magnitude decreases with rising incidence of precipitation. These findings underscore the importance of continuing to invest public resources efficiently in infrastructure that can boost agricultural productivity and prioritize investments targeting regions with the lowest productivity growth rates and with the smallest share of land and workers.

JEL Codes: O13, O33, Q12, Q16

Key Words: Bolivia, Agriculture, total factor productivity (TFP), Latin America

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1. Introduction

In Latin America and the Caribbean (LAC), increasing agricultural productivity is necessary to feed its growing population, reduce pressure on natural resources, and improve the livelihoods of its rural population. Agriculture is a key sector in the region, accounting for 13% of global agricultural production value and 17% of agricultural exports (OECD/FAO, 2021). Moreover, agricultural productivity growth contributes two to four times more to poverty reduction than growth in other sectors (De Janvry & Sadoulet, 2010). However, the growth rate of agricultural productivity in LAC has slowed significantly in recent years. During the first decade of the century, Total Factor Productivity (TFP) in the agricultural sector grew at an annual rate of 2.2%. That rate, however, fell to 1.5% between 2010 and 2020 (Nin-Pratt et al., 2023). Stagnating productivity growth threatens the progress that has been made towards eliminating rural poverty and food insecurity. Looking toward the future, sustainable agricultural productivity growth must balance productivity improvements with the conservation of natural resources, enhanced ecosystem resilience, and reduced climate change impacts. To achieve this, public spending on agriculture plays a crucial role. In LAC, however, it represents about 5% of agricultural GDP, significantly lower than the average share achieved in other countries, including Canada and the U.S. (Conroy et al., 2024).

Bolivia exemplifies both the opportunities and challenges of sustainable agricultural productivity growth in the LAC region. Agriculture is a cornerstone of the country's economy, contributing an average of 12.28% to GDP over the past five years and employing 27% of the population in 2022 (World Bank, 2024). A large share of agricultural production is carried out by family farmers. Out of 871,927 Agricultural Production Units (UPAs), 80% are Family Production Units, involving nearly two million farmers of peasant, Indigenous, and intercultural origin (Ministerio de Desarrollo Rural y Tierras [MDRyT], 2021)

Bolivia's agricultural GDP has shown significant growth in recent decades. Between 2006 and 2019, the sector grew at an annual rate of 3.8%, outpacing the Latin American average of 2.6% (Alcaraz Rivero et al., 2021). This growth has largely been driven by the expansion of agricultural land and the increased use of inputs, while agriculture also played a crucial role in poverty reduction, with rural poverty rates falling from nearly 90% in the 1990s to 55% by 2017 (Diaz Ríos et al., 2019).

This sectoral growth has been supported by significant increases in agricultural production over the past sixty years. Using data from the United States Department of Agriculture (USDA), Salazar et al. (2024) find that the country registered an average annual growth rate of 3.6% of agricultural production, explained mainly by increases in TFP (average annual growth rate of 2.1%). To a lesser extent, during this same period, there was a positive trend in the use of inputs (average annual growth rate of 1.4%). The improved performance of productivity relative to input use is a dynamic that began in the decade of 1971-1980 and has continued since then.

Nevertheless, Bolivia continues to face challenges to increasing agricultural productivity. Despite the sector's expansion, the yields of key crops, soybean, quinoa, potato, and sugarcane, remained below the Latin American average between 2006 and 2018 (Alcaraz Rivero et al., 2021). Rising temperatures and increasing precipitation variability in recent decades have made climate one of the key factors influencing productivity in Bolivia. The country's geography, socioeconomic conditions, and limited institutional capacity to mitigate climate risks make it highly vulnerable to climate change, ranking 10th in the Global Climate Risk Index 2021 (Estado Plurinacional de Bolivia, 2021). The impacts of climate variability and extreme weather events are already evident; declines in agricultural GDP in 2010 and 2016 were driven by adverse weather conditions that severely affected soybean production (Alcaraz Rivero et al., 2021), and climate-related risks caused estimated losses of $6.4 billion between 1995 and 2017 (Diaz Ríos et al., 2019). These climatic challenges not only disrupt agricultural output but also heighten food insecurity and economic instability, particularly for rural populations that rely heavily on farming.

Therefore, improving productivity remains a central goal in the country's agricultural development plans. According to MDRyT (2017) several factors hinder productivity growth in Bolivia. These include limited innovation, restricted access to financial services, inadequate infrastructure, weak pest and disease prevention and control, ecosystem degradation, and biodiversity loss. Understanding which factors have contributed to the current rate of productivity growth is crucial for guiding future investments towards areas that can foster greater growth. In recent decades, public investments in the sector have focused on land titling, plant and animal health, food security, and, to a lesser extent, research and innovation. In addition, government programs have prioritized expanding irrigation and mechanization, along with direct support for producers and their organizations, particularly in poor and marginalized communities (Díaz Ríos et al., 2019).

To date, evidence on the dynamics and determinants of agricultural TFP growth in Bolivia is scarce, and has relied primarily on estimates within multi-country contexts and relying on aggregate production data at the national level. Such studies are limited in their capacity to identify and understand the underlying factors that may contribute to or hamper productivity growth within the country and at a subnational level, accounting for the significant geographic, climatic and sociocultural heterogeneities of Bolivia. Therefore, this study aims to fill a gap in the literature by estimating agricultural productivity growth and its components in Bolivia between 2008–2015 and exploring the role of specific policy drivers in shaping these trends. Using two rounds of nationally representative survey data and the most recent agricultural census at the farm level, we construct a municipal panel to estimate a stochastic production frontier. This allows us to decompose Bolivia's agricultural TFP growth into five components: scale efficiency (SE), technological progress (TP), technical efficiency (TE), weather effects (WE), and statistical noise (SN). Additionally, through a micro-econometric analysis with time and municipality fixed effects, we assess the impact of public investments in land titling and irrigation on productivity growth.

This study makes several notable contributions to advance researchers' and policymakers' understanding of agricultural productivity in Bolivia. First, it provides a robust econometric analysis of agricultural productivity growth in Bolivia by employing the stochastic frontier analysis (SFA) method. This approach allows for the measurement of TFP and its decomposition into various indices, identifying the key drivers of TFP change. Second, in contrast to previous productivity analyses in Bolivia that have used partial productivity measures (i.e. yields and labor productivity), this analysis assesses the effect of policy drivers and weather shocks on TFP, which best captures the interrelations between inputs and sources of growth (Giordano et al., 2023). Notably, our analysis also considers the effect of weather shocks on agricultural productivity, building on a growing body of literature that incorporates the agronomic concepts of degree days (DD) and harmful degree days (HDD) in econometric analysis in order to capture the non-linear effects of temperature on agricultural production (Aragon et al., 2019; Daga, 2020; Schlenker & Roberts, 2009). Additionally, we make use of a novel, municipal-level dataset created by integrating all available agricultural survey micro-data in Bolivia with satellite weather data and administrative data on land titling and irrigation. This allows for a more precise exploration of subnational agricultural dynamics that takes into account policy interventions, household characteristics, and weather conditions. Finally, in addition to assessing the impact of irrigation and land titling on TFP, this study also includes an analysis of the potential pathways through which irrigation and land titling may be influencing agricultural productivity in Bolivia.

This study finds that agricultural TFP in Bolivia grew at an average annual rate of 1.8% between 2008 and 2015, with growth largely driven by technological progress. However, technical efficiency declined slightly, and weather shocks, particularly harmful temperature extremes, negatively affected productivity. We find that public investment in irrigation infrastructure is associated with increased productivity, although its effectiveness is moderated by precipitation levels. In contrast, land titling efforts did not show a significant impact on productivity at the municipal level, potentially due to data aggregation. These results underscore the need for regionally targeted and weather-sensitive agricultural investments, alongside improved data systems to support evidence-based policymaking.

The remainder of the paper is organized as follows. In the next section, we outline the literature related to this study. In section 3, we provide some additional context for subnational heterogeneities within Bolivia as well as relevant history of public policy within the sector. Section 4 describes data sources and summary statistics. Section 5 details the methodology and empirical approach. Results are presented in section 6, section 7 discusses the results, and section 8 presents conclusions and policy recommendations.

2. Literature

2.1 Total Factor Productivity

Agricultural productivity and efficiency have been central topics in debates and agendas surrounding public policy, given the sector's fundamental role in economic growth. As the main source of food, income, and employment for rural populations, agriculture is key to economic development. Consequently, the measurement of agricultural productivity has been extensively studied, with its origins tracing back to classical economic growth theory (Solow, 1957; Diewert, 1980; Ball et al., 1997). This rich history has led to a substantial body of empirical evidence documenting the evolution of productivity across countries, highlighting its significance in shaping economic outcomes and policy decisions.

Various studies, using different methodologies, have analyzed the growth rates of agricultural productivity in Bolivia, often within global or regional multi-country contexts and relying on data from the Food and Agriculture Organization (FAO). Regarding TFP growth estimates, findings vary depending on the methodology used. Dias Avila and Evenson (2010) apply the accounting approach to estimate TFP growth for crop production, livestock production, and aggregate agricultural output across LAC countries between 1961 and 2001. They report an average regional growth rate of 1.85%, while Bolivia exhibits a slightly higher rate of 2.31%. Similarly, Ludeña (2010) uses the Malmquist Index to analyze TFP growth in the region between 1961 and 2007, estimating a TFP growth rate of 1.9% for Bolivia.

Other studies employing parametric and nonparametric approaches present less favorable results for Bolivia. Trindade and Fulginiti (2015) apply both the (parametric) stochastic frontier approach and the (nonparametric) Malmquist Index to analyze agricultural productivity in South America from 1969 to 2009. Their findings indicate a TFP growth rate of 0.7% using the parametric method, driven by efficiency change, and 2.22% using the nonparametric method, with Bolivia identified as the worst-performing country. Similarly, Nin-Pratt et al. (2015) combine the growth-accounting approach with Data Envelopment Analysis to assess agricultural performance in LAC from 1980 to 2012. They find negative efficiency growth for Bolivia but a high rate of technical change, leading to an average TFP growth rate of 1.6%.

Among the most recent studies, Neves et al. (2021) provide TFP growth estimates for South American countries over the period 1969–2016 using a stochastic frontier approach. Their findings indicate that average TFP change for South American countries is 1.5% per year, with Bolivia experiencing a growth rate of less than 1% per year. Similarly, Salazar, Ruesta, and Alvarez (2024) analyze historical trends in agricultural productivity in LAC from 1961 to 2021. Using a unique dataset compiled by USDA, combined with data from the FAO and ILO, they estimate TFP growth using a growth accounting approach, based on index number theory. To ensure robustness, they employ four comparative indices: Lowe, Färe-Primont, Hicks-Moorsteen, and the USDA index. For Bolivia, they estimate an average annual TFP growth rate of 1.41%, with average annual output and input growth rates of 3.56% and 2.12%, respectively.

Overall, the literature reveals variation in Bolivia's estimated TFP growth, largely influenced by differences in methodology. While some studies report moderate growth rates, others highlight Bolivia's lagging performance compared to its regional peers. Studies that focus solely on estimating TFP growth for Bolivia and do not use aggregate country-level data are limited. This significantly limits the ability of such studies to analyze the underlying factors that may contribute to or hamper productivity growth within the country. Díaz Ríos et al. (2019) conduct a SFA to identify the determinants of agricultural efficiency in each macro-region (Sub-Andean Region, Altiplano, Llanos, and Amazonian Region). They also perform a meta-frontier analysis to explore the differences in efficiency across regions, crops, and producer groups, all using data from the 2015 national agricultural survey (ENA; from Spanish *Encuesta Nacional Agropecuaria*). However, they do not estimate TFP growth.

The main limitations of the existing literature lie, first, in the lack of methodological consensus, which results in a wide range of findings, and second, the reliance on aggregate national-level data, which fails to capture the significant heterogeneity across regions and farms within the country (Bravo-Ureta et al., 2022). In contrast, this study stands out by using farm-level data aggregated to the municipality level, which allows for a better understanding of the subnational heterogeneity. We construct a balanced panel dataset at the municipal level and apply robust econometric methods to estimate TFP growth.

2.2 Weather Shocks as a Determinant of TFP

Another notable gap in the literature is the consideration of weather variables in the models used to derive TFP measures, thereby overlooking the direct contributions of weather to agricultural productivity. Agriculture is inherently weather-dependent, making it the sector most affected by weather variability and climate change. In Bolivia, the average surface temperature has increased by 1.2°C from 1890 to 2020 (Torrico Albino, 2021). Given its semi-arid climate and pronounced seasonality, the country also faces growing pressures related to water scarcity, which are becoming more acute as global temperatures rise. The worst drought of the past 25 years occurred in 2016/2017, affecting 125,000 families, 290,000 hectares of agricultural land, and 360,000 heads of livestock (Painter, 2020). Given the importance of temperature, rainfall, and weather shocks to agricultural production in the Bolivian context, this study incorporates weather variables – including measures of weather shocks – in its TFP analysis.

Economic theory generally establishes three possible sources of TFP growth; these are technological progress, technical efficiency, and scale effects (O'Donnell, 2018). However, O'Donnell (2018) identifies a fourth source of TFP growth: environmental change. According to O'Donnell, variables such as rainfall and temperature in agricultural contexts must be characterized as sources of environmental change when they are "physically involved in the production processes but never controlled by firm managers" (O'Donnell, 2018). In line with this theoretical framework and previous studies that have incorporated weather data in TFP decompositions (Lachaud et al., 2017), this study conceptualizes temperature and precipitation as determining characteristics of the production environment. As such, rather than considering weather variables as an input or a factor in the inefficiency term, our study isolates the effect of weather and weather shocks on productivity by including a WE index in our TFP decomposition. Conceptually, this establishes that temperature and precipitation affect TFP by determining the input-output combinations that are possible within a particular production environment.

In addition to establishing production frontiers that are contingent on environmental conditions, environmental variables can also affect TFP by confounding producers' optimization problems, particularly under conditions of uncertainty. O'Donnell (2018) argues that when environmental factors are predetermined, such as when they remain relatively constant over time or are established prior to the growing season, producers can adjust their input-output mix to effectively maximize output or revenue, or alternatively, to minimize inputs use and costs. In contrast, when conditions such as rainfall or temperature are uncertain ex-ante, producers' allocation decisions depend on subjective expectations regarding the most probable environmental outcomes as well as their individual degree of risk aversion (O'Donnell, 2018). Discrepancies between expected and realized environmental conditions increase the likelihood of selecting a suboptimal input-output mix, thereby reducing productivity relative to scenarios in which conditions are predetermined (O'Donnell, 2018). Theoretical considerations thus imply that greater environmental uncertainty, manifested through more frequent, severe, or unpredictable shocks, exacerbates the divergence between expected and actual conditions, raising the likelihood of suboptimal input–output choices and ultimately diminishing agricultural productivity.

In line with this theoretical framework, several studies have examined the relationship between weather shocks and agricultural outcomes in other countries (Burke & Emerick, 2016; Deschênes & Greenstone, 2011; Fisher et al., 2012; Wang et al., 2010), showing that high-temperature shocks reduce agricultural yields (Schlenker & Lobell, 2009; Chen et al., 2016; Feng et al., 2010). Within the literature examining the effect of weather shocks on productivity, a growing number of studies utilize the concepts of DD and HDD to define weather shocks; DDs are a measure of exposure to favorable temperatures that are positively associated with yields, whereas HDDs are a measure of exposure to extreme temperatures that are negatively associated with yields (Aragon et al., 2019; Daga, 2020; Schlenker & Roberts, 2009). Applying this strategy to the Bolivian context, Daga (2020) finds that temperature shocks, as measured by HDDs, were associated with a 15% reduction in yields, with even larger yield reductions – of about 35% – among farmers in the country's Highland region. Daga (2020) further finds that weather shocks do, indeed, affect farmers' input-output mix choices; in particular, exposure to extreme temperatures led to a significant increase in the allocation of household farm labor and a decrease in the use of hired farm labor in flood-prone municipalities.

2.3 Public Policy Determinants of TFP

The role of public policy interventions in the agricultural sector is essential for two principal reasons. First, markets, and particularly agricultural markets, do not always function efficiently. Issues such as imperfect markets and information asymmetries create inefficiencies that can hinder sectoral development. Due to these market failures, private investment alone may not be sufficient to drive agricultural growth, making public investment necessary. In particular, public investment is often necessary to improve the quality of and access to public goods that are non-rivalrous and non-excludable. In agriculture, such public goods including rural infrastructure, research and development services, animal and plant health services, agro-climatic and market information systems, among others (Cooper et al., 2009; Holcombe, 2000). In addition to resolving market failures that affect the availability of goods in agricultural markets, public investment can also play a role in ensuring optimal distribution of goods across market actors. Across the LAC region, the distribution of resources, such as land, infrastructure (including rural roads and irrigation), and government services has historically been uneven across society, and many of the poorest populations live in rural areas and depend on agriculture for their livelihoods. Public investment can help correct these imbalances in the distribution of resources in such a way that reduces productivity gaps and improves the performance of the agricultural sector as a whole (Mogues, et al., 2015).

This study examines the productivity effects of public investment in two key areas: irrigation infrastructure and land titling. The remainder of this section draws from existing literature in these policy areas to develop a theoretical framework for how these policy interventions can impact TFP by affecting the various components of the production frontier.

2.3.1 Irrigation

Empirical studies highlight a number of channels through which irrigation can positively impact agricultural productivity (Giordano et al. 2023). The expansion and improvement of irrigation infrastructure can lead to increases in agricultural TFP in several ways. First, increasing the availability of irrigation infrastructure can allow farmers to engage in multiple growing cycles by ensuring the continued availability of water throughout the year, even during months of low precipitation (Gebregziabher et al., 2012). Increasing the number of harvest cycles, in turn, directly increases total annual agricultural output. In this case, TFP increases would be primarily driven by technical change, or an outward shift in the production frontier (O'Donnell, 2018). Furthermore, by providing an alternative to precipitation, irrigation systems can reduce farmers' vulnerability to weather shocks, particularly those caused by droughts; this has a positive impact on production through direct and indirect effects. On the one hand, increasing resilience to droughts can increase annual output by reducing production losses, i.e. an increase in technical efficiency that moves a farmer closer to the production frontier (O'Donnell, 2018). On the other hand, strengthening drought resilience can indirectly increase production by reducing the risk associated with agricultural activities; risk reduction can in turn incentivize on-farm investment in high-value crops and new technologies, resulting in further increases in output and the value of production (Mehta, 2009; Moore, 2015). This secondary effect brought on by risk reduction could therefore produce a shift in the production frontier. Finally, irrigation can also increase agricultural output by enhancing the productivity of complementary inputs, which would also produce an expansion of the production frontier (Giordano et al. 2023).

Though the productivity effects of irrigation have been widely studied, empirical analyses in Bolivia's agricultural sector remain scarce. Salazar and Lopez (2018) evaluate the effects of a national irrigation program aimed at increasing agricultural income and productivity by expanding irrigated agriculture through public investment in the construction and rehabilitation of community irrigation systems. Their findings indicate an increase in production value, technological adoption, and market access. However, the authors find no statistically significant effects on yields. Consistent with Gebregziabher et al.'s (2012) study in Ethiopia, which found that irrigated farms had lower levels of technical efficiency compared to rain-fed farms due to the increased knowledge and capacity required to utilize irrigation systems efficiently, the authors suggest that the lack of productivity gains in Bolivia may be due to producers still being in the "learning-by-doing" phase of the technology adoption process (Salazar & Lopez, 2018).

2.3.2 Land Titling

With regards to land titling, economic theory and empirical evidence outlines a number of ways through which land titling can impact agricultural TFP. First, the lack of a land title restricts access to formal credit, limiting investments in agricultural inputs and technology among liquidity-constrained farmers (Zhang et al., 2019). Thus, obtaining a title may increase TFP via technological change, inducing an outward shift in the production frontier. Moreover, tenure security reduces the risk of expropriation, encouraging investment in agricultural improvements and, consequently, similarly increasing TFP through an expansion of the production frontier (Besley, 1995). Secondly, well-defined property rights improve the functioning of rural land markets. Facilitating the purchase, sale, and leasing of land can increase producers' technical efficiency by enabling the allocation of land to farmers that can utilize it more efficiently (Abdulai et al., 2011; Ali et al., 2011). Likewise, tenure security facilitates the negotiation of long-term contracts and allows landowners to select more productive workers outside their immediate family circle, which would produce an increase in TFP through increased technical efficiency (Deininger et al., 2008). Finally, land tenure security is associated with a reduction in land conflicts, thus increasing agricultural productivity through an increase in technical efficiency (Feder & Feeny, 1991).

Although economic theory and empirical evidence suggests the potential for land titling to increase TFP, empirical studies have also identified cases in which land titling can result in reductions in productivity. For instance, in rural communities that are located close to urban centers, land tenure security can induce a re-allocation of household labor away from the agricultural sector and towards higher-paying work in cities, resulting in reduced household agricultural output (Liu et al., 2023). Similarly, Rincon Barajas (2023) found that, in Colombia, farmers who obtained a land title experienced a negative productivity shock in the first 2.5 years, followed by an increase in productivity; the author also found that the existence of complementary programs, such as technical assistance, could offset the initial productivity shock.

In the context of Bolivia, literature suggests that the functioning of the first two impact mechanisms outlined above – easing of credit constraints and improved functioning of land markets – is limited by the existence of national legislation that prohibits legally defined smallholdings from being used as collateral (Murguia et al., 2018). Though designed to protect small farmers from asset seizure during times of economic shock, the restriction limits the potentially positive effect of titling on credit access and productive investments by smallholders. Furthermore, as Murguia et al. (2018) find, the non-seizability law distorts the functioning of land markets, producing heterogeneous welfare effects depending on the type of landholding: livestock ranchers received lower prices for their smallholdings as a result of the law, while agricultural producers received higher prices for their smallholdings. In terms of the efficiency effects associated with land titling, Schling et al. (2024) use a parametric approach to find that Bolivian farmers with land titles exhibit levels of technical efficiency that are 47.2% higher than of those without titles.

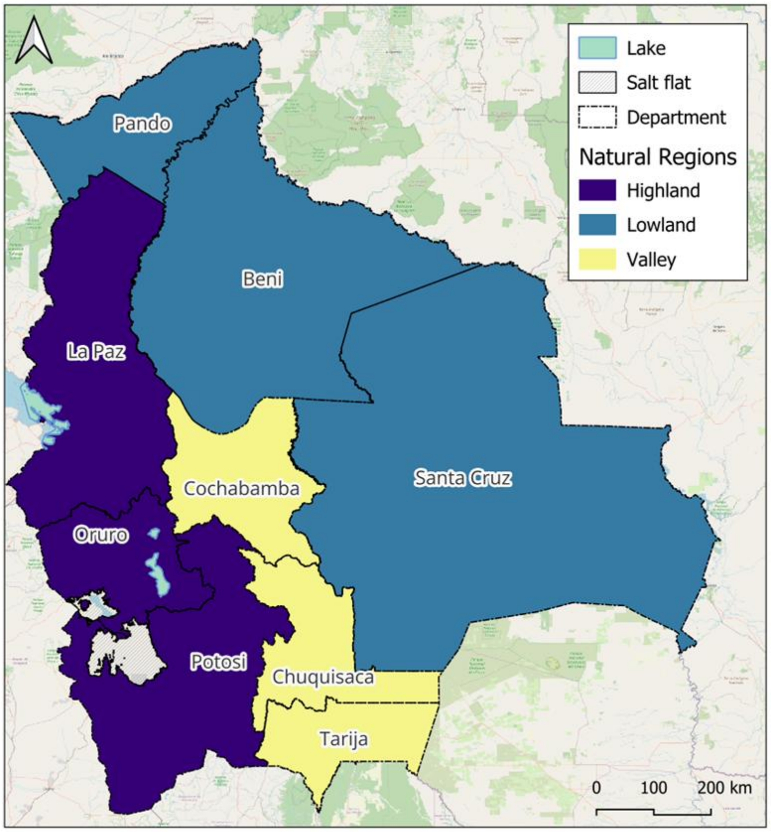
3. Bolivia: Subnational Heterogeneity and Policy Context

3.1 Subnational Heterogeneity

In order to properly situate the empirical analysis within the nuances of Bolivia's agricultural sector, this section provides an overview of Bolivia's administrative, geoclimatic, and productive characteristics. Bolivia is geopolitically subdivided into 9 departments, 112 provinces, 327 municipalities, and 405 Indigenous Originary Peasant Territories (TIOC; from Spanish *Territorio Indígena Originario Campesino*). Additionally, there are various types of territorial organizations with their own designations, such as communities, colonies, ranches, etc., which are collectively referred to as "Communities" by the INE.

Geographically, the country is divided into three natural regions: (i) *Altiplano or Highlands*, the Andean plateau region in the west, with an average elevation of 3,000 meters above sea level; (ii) *Llanos or Lowlands*, the tropical region in the northeast, with an average elevation of 600 meters above sea level; and (iii) *Yungas or Valleys*, located in the south-central portion of the territory between the Highlands and Lowlands, with an average elevation of 1,800 meters above sea level (Daga, 2020). These regions are represented in Figure 1.

Figure 1. Bolivian Natural Regions



In addition to their topographical variations, these regions are also distinct in terms of climatic characteristics. As shown in Figure 1, the Highlands, which comprises 28% of the national territory, is the country's driest region, characterized by low rainfall and low temperatures. Due to the precipitation and temperature characteristics in the Highlands, this region is prone to droughts, hail, and frost. The Lowlands, on the other hand, are home to the Amazon rainforest; they are characterized by high temperatures and high rainfall. In terms of climatic vulnerability, the Lowlands are most prone to flooding, particularly in the northernmost departments of Beni and Pando, where average rainfall is highest. Finally, the Valleys, which is nestled between the Lowland and Highland regions and represents just 13% of the national territory, experiences moderate rainfall and temperature. The most prominent climatic risks in this region are droughts in the central Valleys municipalities and hail in the southernmost municipalities.

Finally, agricultural practices and production vary across the three subregions. On average, productive units in the Lowlands have the largest landholdings in the country, experience the highest yields, and employ more hired farm labor than the other regions. In contrast, producers in the Highlands tend more towards small-scale, subsistence agriculture. On average, landholdings in the Highlands are the smallest in the country, the likelihood of employing hired farm labor is the lowest, and yields are the lowest of all regions. Similar to its geoclimatic indicators, the Valleys' agricultural characteristics land between the Highlands and Lowlands. The average size of agricultural landholdings, average yields, and use of hired labor are higher than those in the Highlands but lower than those in the Lowlands.

3.2 Policy Context

For more than two decades, agricultural and rural development has featured heavily on the Bolivian public policy agenda, leading to national-level agricultural interventions in areas like irrigation and land titling. In terms of irrigation, from 1996 to 2005, the government implemented the National Irrigation Program (PRONAR, per its Spanish acronym). This was followed by a two-phase successor program, launched in 2009, called the National Irrigation Program with a Watershed Approach (PRONAREC, per its Spanish acronym). These strategic initiatives by the Bolivian government, with financial and technical support by the Inter-American Development Bank, aimed at enhancing rural development through the sustainable use of water for agricultural and forestry production, with a focus on equity, social participation, and institutional strengthening (Salazar & Lopez, 2018). Of note, Bolivia's national irrigation programs followed a similar community-based, participatory framework. In particular, the programs primarily financed the construction and improvement of public irrigation infrastructure. This means that producers were required to make private, on-farm investments in channels, water pumps, and other complementary inputs in order to connect their plots to public irrigation infrastructure (Salazar & Lopez, 2018). Additionally, beginning with PRONAREC, producers were also required to take part in Water Use Associations (WUA) in order to access irrigation infrastructure; the purpose of the WUA was to promote community-based watershed management. The descriptive analysis of irrigation data in Section 4 sheds further detail on the significant changes that occurred in the country's irrigation infrastructure between 2013 and 2015.

In addition to implementing national irrigation programs, in 1996, Bolivia enacted the National Agrarian Reform Service Law, which formally tasked the newly created National Agrarian Reform Institute (INRA, per its Spanish acronym) with regularizing and titling the remaining rural land area in Bolivia. In 2002, the Inter-American Development Bank began supporting the Bolivian government with the implementation of the National Plan for Land Regularization and Titling. The establishment of this institution, combined with the implementation of the Third Agrarian Reform in 2006, marked a turning point by significantly accelerating the processes of land regularization, cadaster, titling, and registration in rural areas (Schling et al., 2024). This has resulted in significant progress: while in 2016, 30% of Bolivia's agricultural land was still awaiting regularization, titling, and registration (IDB, 2016), by 2024, 92% of rural land had been successfully titled (IDB, 2024). Drawing from our land titling dataset, Section 4 describes in greater detail the spatiotemporal dynamics of land titling efforts between 2008 and 2015.

4. Data

This section presents the various data sources used to analyze the evolution of agricultural productivity in Bolivia and its determinants, as well as the methodological decisions adopted. Specifically, Section 4.1 describes the agricultural data utilized; Section 4.2 explains the strategy for constructing the panel and its implementation; Section 4.3 details the variables included in the production function across the three survey rounds, including the treatment of missing values and descriptive statistics. Finally, Section 4.4 presents the data sources related to the policy drivers, describes the definition of each variable, justifies these definitions, and provides a geographic descriptive analysis of the variables.

4.1 Agricultural Data

The agricultural data used in this study come from two main sources: the National Agricultural Survey (ENA), conducted in 2008 and 2015, and the 2013 National Agricultural Census, both implemented by INE. These sources use Agricultural Production Units (UPA; from Spanish *Unidad Productiva Agropecuaria*) as the unit of observation, defined as "any land used, in whole or in part, for agricultural or livestock production, or both, managed by a producer (individually or with the help of others), regardless of the ownership regime or legal status" (Instituto Nacional de Estadística, 2013). Detailed information is measured at the UPA level on area, agricultural and livestock output, producer prices, infrastructure and equipment, labor, and other inputs used in the productive activities of each UPA during the agricultural cycle.

In the 2008 round of ENA, 8,022 UPAs were interviewed using a probabilistic, stratified, two-stage sampling design. In the first stage, the country was divided into departments (sub-universes), selecting 1,062 census segments nationwide[4] through simple random sampling. In the second stage, agricultural units were systematically identified and selected within each census segment during the fieldwork. The sampling frame was built using data from the National Population and Housing Census completed in 2001, agro-productive zones, and detailed cartographic maps, ensuring representative samples at the departmental level.

The 2015 round of ENA interviewed a total of 12,650 UPAs and used the 2013 National Agricultural Census as its sampling frame, employing an updated stratified, bi-stage, cluster sampling design with forced inclusion. In *Communities*, Primary Sampling Units were selected in the first stage, while UPAs were chosen in the second. In addition to the random selection of UPAs within each department, the sample forcibly included such farms which contributed most significantly to the production volume of the most relevant agricultural product in the department, the latter determined in terms of its contribution to the department's Gross Production Value according to the 2013 census data (INE, 2015). Given that these farms were not randomly selected nor likely to be representative of the underlying population of farmers in each department, we excluded these 1,215 UPAs (identified in the database by sample selection probability value of one) from the 2015 sample to mitigate the potential bias generated by this subsample. The smallest geographic unit for which the data are representative is the department.

Finally, the 2013 agricultural census covered all UPAs, both in rural areas and on the outskirts of urban centers, recording a total of 871,927 UPAs across the country.

4.2 Study Sample

4.2.1. Construction of Balanced Municipal-level Panel

In Bolivia, the lack of agricultural panel data limits the ability to track trends in farm productivity over time. Nonetheless, repeated cross-sectional surveys can be leveraged to construct a balanced panel dataset (Deaton, 1985), allowing for temporal analysis of the dynamics of agricultural activity in the country. This allows tracking changes in agricultural productivity across municipalities over time. Individual observations from these repeated surveys can be grouped into cohorts or groups based on shared characteristics that remain fixed over time. The resulting time series can then be analyzed using econometric methods typically applied to conventional panel data. This approach helps minimize common issues associated with cross-sectional data, such as attrition and non-response. It also enables the capture of certain unobserved characteristics through a fixed "cohort" effect, which could otherwise result in biased estimates (Verbeek, 2008). Therefore, this analysis combines information from the 2008 and 2015 ENA and the 2013 agricultural census to construct a balanced panel at the municipal level, which is used as our unit of analysis. Following the idea of Ishizawa et al. (2019), although the smallest geographic unit for which the survey data are representative is the department, opting for the municipal level allows for greater geographic disaggregation, better capturing unobservable time-invariant heterogeneity, such as the idiosyncratic characteristics of municipalities that affect agricultural

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[4] The sampling included the following number of segments per department: La Paz (266), Cochabamba (203), Potosí (173), Chuquisaca (108), Santa Cruz (134), Oruro (70), Tarija (49), Beni (42), and Pando (17).

productivity. Furthermore, this disaggregation increases the power of the estimates by incorporating greater variability in observed weather and productive conditions.

Although the national agricultural surveys and census are highly standardized, with most relevant questions consistently formulated and maintaining a comparable structure and timeframe, the census tends to address questions in a more general manner. In contrast, the surveys provide more detailed information, particularly regarding livestock production and input use. For instance, while the census typically captures whether an input was used, the surveys also report the quantities applied. Therefore, in order to combine the three sources into a single panel at the municipal level, it is necessary to harmonize the surveys by limiting the analysis to crop production and using dummy variables for input use.

The balanced municipal-level panel was constructed by averaging the variables of interest at the farm level for each round and aggregating them at the municipal level.[5] This aggregation process reduces the influence of idiosyncratic inefficiency at the unit level (Helfand & Rada, 2015), as producer-specific variations within a municipality tend to offset each other when the data are averaged. The final sample includes 231 municipalities observed across the three rounds. Note that due to changes in the country's administrative divisions with the creation or merging of new municipalities during the time period under analysis, eight municipalities were reassigned to their original 2008 divisions to maintain a constant unit of observation over time.[6] The average number of farms per municipality during the period is 897; however, 38% of municipalities have fewer than 10 farms, especially in the sample-based ENA. This could imply that cohort averages may not accurately represent the population means for these cohorts. Therefore, to assess whether the small number of observations in these municipalities affects the efficiency of the estimates, we conducted additional robustness checks restricting the sample to municipalities with more than 10 farms, finding similar results.

4.3 Construction of Key Variables

4.3.1. Agricultural cycle and variable construction

The agricultural cycle in Bolivia is divided into two periods: the winter season, which includes crops planted between March and June in the Valleys and Highlands, while in the Lowlands, planting extends until July; and the summer season, which includes crops planted from July in the Valleys and Highlands, and from August in the Lowlands of the east and the Amazon, through February. For this analysis, the production and area corresponding to the summer season have been considered. This choice is based on the fact that the 2008 ENA, unlike the census and the 2015 ENA, does not distinguish between the two seasons but collects information for the agricultural year from July to June. Therefore, it is assumed that much of the collected data refers to summer season crops.

Survey data are used to construct the variables that enter the production function for each round of panel data, defining output as the value of production in constant 2015 prices as reported by UPAs in the 2015 survey. These prices correspond to national averages, which are implicitly calculated from the information provided in the survey on the quantity sold of each crop and the income received from those sales. The inputs considered in the production function include land, family labor, expenditures on hired labor, use of capital, and inputs such as fertilizers and pesticides. Table 1 reports the definition of each variable, while Appendix B provides a detailed description of the processing of each variable.

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[5] The balanced panel averages the observations without applying survey weights.

[6] Alto Beni reassigned to Caranavi, Villa Charchas to Incahuasi, Chua Cocani to Achacachi, Escoma to Puerto Acosta, Cocapata to Morochata, Shinahota to Tiraque, Chuquihuta to Uncía, and Ckochas to Puna.

Table 1. Description of Production Function Variables

Variable	Description
Crop Production Value (US$)	Average value of permanent and temporary crop production per farm, at constant national 2015 prices (winsorized at the 95th percentile).
Land (Hectares)	Average area (in hectares) sown with permanent and temporary crops per farm during the agricultural cycle.
Family Labor Index	Average family labor used in agricultural activities per farm, expressed in adult male equivalents (children under 14 = 0.5, women = 0.8, men = 1).
Labor Expenses (US$)	Average labor expenses per farm in constant 2015 prices. Calculated by converting the number of workers into workdays (1 worker = 200 workdays) and multiplying by the average daily wage reported in the 2015 survey (winsorized at the 95th percentile).
Use of purchased inputs	Proportion of farms within each municipality reporting the use of purchased inputs (fertilizers, manure, or pesticides).
Use of capital	Proportion of farms within each municipality reporting the use of a tractor or animal traction for agricultural work.

Since the balanced panel is built at the municipal level based on averages of farm-level observations, each variable is defined as the municipal average of the corresponding farm-level measure. For example, the land input corresponds to the average number of hectares cultivated per farm in the municipality, hired labor is measured as the average farm-level expenditure on hired labor, and capital and input use are captured as the proportion of farms within the municipality that report using capital or applying inputs. To handle outliers, instead of eliminating them and thereby losing degrees of freedom (Riffenburgh, 2012), winsorization is applied to the top 5% of production value, area, and labor expenses.

4.3.2. Treatment of Missing Data

In the ENA rounds for 2008 and 2015, some municipalities report zero values for certain variables presented in Table D1. In particular, the variables related to expenditures on hired labor, input use, and capital use present missing values in both survey rounds. However, these zeros do not necessarily reflect a true absence of the corresponding productive components, but rather may be related to limitations in the sample size at the municipal level. Given that zeros in some variables may reflect statistical omissions due to the survey design rather than true zero values, a multiple imputation by chained equations procedure is implemented.[7]

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[7] *Multiple Imputation in Stata*. UCLA: Statistical Consulting Group. from https://stats.oarc.ucla.edu/stata/seminars/mi_in_stata_pt1_new/ (accessed April 19, 2025).

The multiple imputation approach 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.

4.3.3. Study Sample Descriptive Statistics

Table 2 presents the average values of the variables included in the production function after the imputation process. Values for each natural region can be found in Table A1 in Appendix A. The value of production experienced a decline between 2008 and 2013, followed by a recovery in 2015. Meanwhile, the average cultivated area showed a steady increase throughout the period, suggesting that agricultural activity expanded in terms of land use.

Capital use among farms remained relatively stable throughout the period, while the use of agricultural inputs increased significantly between 2008 and 2013 but then declined by approximately 22.5% in 2015, not returning to its initial level.[8] Labor expenses followed a similar trend, roughly doubling between 2008 and 2013 before declining somewhat in 2015. In contrast, family labor remained relatively stable throughout the period.

Table 2: Descriptive Statistics

Variables	2008	2013	2015
Crop Production Value (US$ 1,000)	3.15	2.50	3.22
	(8.98)	(6.74)	(5.65)
Land (Hectares)	2.44	2.55	2.93
	(3.61)	(4.04)	(4.51)
Family Labor Index	2.09	2.52	2.53
	(0.44)	(0.29)	(0.55)
Labor Expenses (US$ 1,000)	2.82	5.84	4.56
	(2.43)	(8.63)	(4.39)
Use of Agricultural Inputs (%)	0.46	0.80	0.62
	(0.27)	(0.24)	(0.31)
Use of Capital (%)	0.62	0.66	0.67
	(0.34)	(0.32)	(0.33)

Notes: Statistics are based on the final sample, consisting of a balanced panel of 231 municipalities per year, after missing values were imputed. Standard deviations in parentheses.

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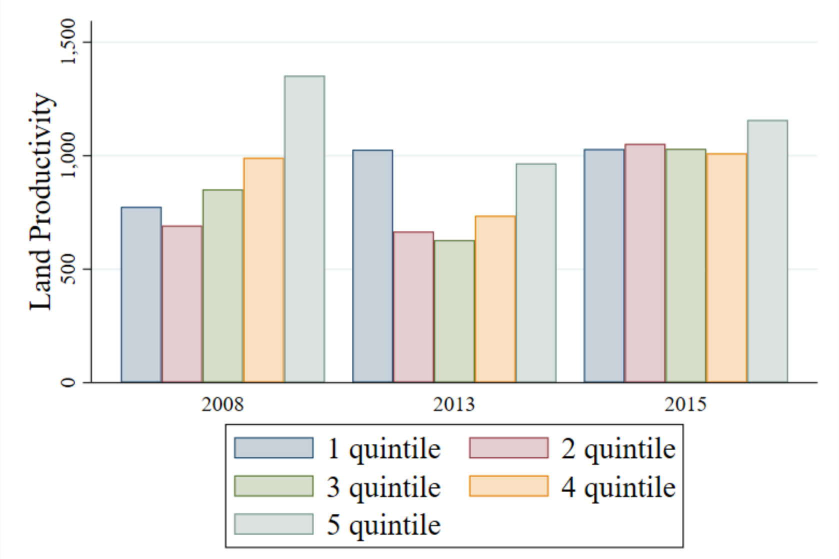
[8] The observed trend in agricultural input use is likely due to regulatory changes that occurred during the period of analysis; this is described in further detail in the discussion section.

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 to number of workers. As displayed in Figure 2, land productivity in Bolivia displays clear patterns by farm size and over time. In 2008, larger farms tended to have higher land productivity compared to smaller farms. By 2013, this pattern shifted, with smaller farms improving their productivity while medium and large farms saw declines. In 2015, productivity levels became more balanced across all farm sizes, although the largest farms continued to maintain an advantage. Overall, these trends suggest that while larger farms generally achieve higher productivity, smaller farms have closed the gap, leading to more evenly distributed productivity levels across farm sizes.

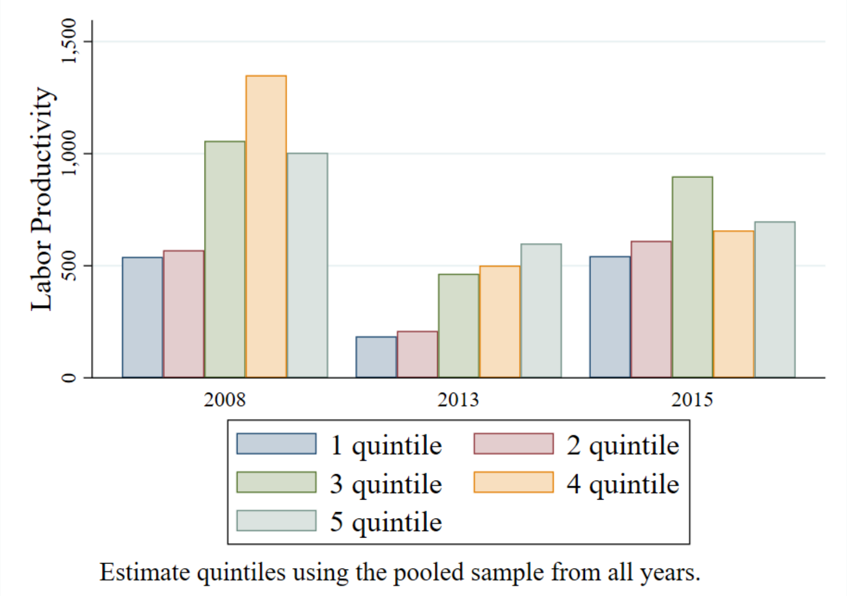
Figure 2*1*: Land productivity by land size distribution, 2008 - 2015



Estimate quintiles using the pooled sample from all years.

Labor productivity in Bolivia, as measured by output per number of family and hired workers, also shows distinct patterns across farms with different number of workers and over time. As Figure 3 shows, in 2008 farms with more workers achieved notably higher labor productivity compared to those with fewer workers. By 2013, the largest farms were still maintaining higher productivity, though average productivity levels had dropped significantly in comparison to 2008 across all quintiles. In 2015, labor productivity levels rebounded, especially among medium sized farms in terms of number of workers, and disparities were reduced between quintiles. These trends indicate that, consistent with patterns observed in land productivity, farms with more workers tend to be more productive, yet improvements among smaller farms have led to a more even distribution of labor productivity across quintiles.

Figure 32: Labor productivity by distribution, 2008 - 2015



Estimate quintiles using the pooled sample from all years.

4.4 Determinants of TFP

4.4.1. Weather shocks

Following the precedent in the literature, this study captures the non-linear effects of extreme temperature by measuring the effect of DDs and HDDs on agricultural productivity. Daily temperature data for these variables comes from NASA's MODIS Land Surface Temperature/Emissivity Daily (MOD11A1) data product, which provides daily Land Surface Temperature (LST) readings at a 1 km spatial resolution (Wan et al., 2021).[9] For the purpose of this study, satellite data on daytime LST readings from the MOD11A1 database is spatially aggregated to produce daily mean temperature values for each of Bolivia's municipalities during each of the survey round reference periods.

Daily precipitation data comes from the European Union's Copernicus dataset, "Essential climate variables for water sector applications derived from climate projections" (Copernicus Climate Change Service, 2018). This Copernicus dataset provides measures of daily precipitation rate based on a bias-adjustment methodology developed by the Swedish Meteorological and Hydrological Institute (SMHI). Precipitation data is provided in terms of precipitation flux (kg m^{-2} s^{-1}), which represents the mass of precipitation deposited (in kg) per unit of area (in meters) and time (in seconds) and is stored in a gridded dataset with a resolution of 0.5° x 0.5°. To aid in interpretation and match the unit of observation of this study, the gridded data was aggregated

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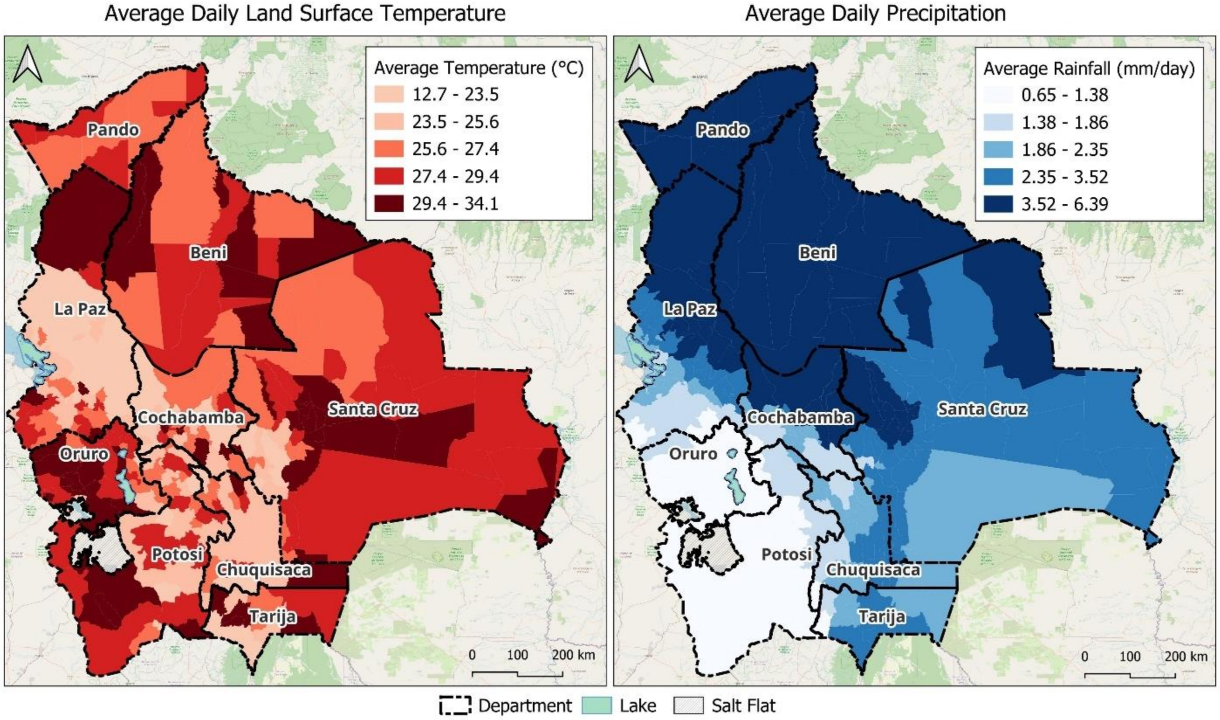
[9] It is important to note that the temperature data utilized in this study is based on land temperature, not air temperature. LST measures the temperature of earth's surface and is derived from imagery recorded by satellites like MODIS, whereas air temperature provides data about above-ground atmospheric temperature and is measured by weather stations (Ogawa & Tasumi, 2022). Though the two are highly correlated and the differences can be minimal, LST and air temperature are ultimately two distinct temperature measures that vary less or more depending on factors like vegetation, cloud cover, and seasonality (Ogawa & Tasumi, 2022; Lian et al., 2017). Readers should take these differences into account when making comparisons across studies that may use similar methodologies but differ in their choice of temperature data.

according to Bolivia’s municipal boundaries to generate spatial averages of daily precipitation and converted to millimeters per day.

Figure 4 shows the geographic distribution of the available weather data during the 2008, 2013, and 2015 growing seasons. The average municipal daily temperatures are displayed on the leftmost panel, while average municipal precipitation data is displayed on the rightmost panel. The graphic reveals significant regional heterogeneity in terms of temperature and precipitation. The Highlands region shows low rainfall and moderate temperature. The Lowlands region shows both high temperature and high rainfall. Finally, the Valleys region experienced relatively moderate rainfall and temperature. Histograms representing the distribution of daily mean temperature and precipitation across the 2008, 2013, and 2015 growing seasons can be found in Appendix E.

Figure 4: Average municipal daily temperature and precipitation during the 2008, 2013, and 2015 growing seasons



Note: *Average daily temperature reflects land surface temperature (LST) in each municipality. Average daily rainfall represents the average of cumulative daily rainfall in each of the three growing seasons.*
Source: *MODIS11 Dataset; Copernicus Essential Climate Variables.*

As evidence increasingly highlights the non-linear relationship between temperature and crop growth, more studies are employing the concepts of DD and HDD to assess the impact of temperature shocks on yields (Schlenker & Roberts 2009; Lobell, et al., 2013; Deryng et al., 2014). Drawing from agronomic literature, Schlenker and Roberts (2009) use fine-scale weather data to detect the dynamic relationship between temperature and yields. Specifically, their strategy uses a piecewise specification to capture the effect of DDs – an agronomic concept that measures crops' cumulative exposure to temperature within a favorable range – on corn, soybean, and cotton yields in the U.S. (Schlenker & Roberts, 2009). Since then, the application of DDs and the related concept of HDDs, which measures cumulative exposure to extreme temperatures, has become increasingly common. Research consistently shows that greater exposure to HDDs is associated with lower productivity (Amare & Balana et. al, 2023; Aragon et al., 2019; Daga, 2020).

For the purpose of this study, the definition of DD and HDD follows that of Aragon et al. (2019) and Daga (2020):

$$DD = \frac{1}{n}\sum_{d=1}^{n}(h_d - \tau_{\text{low}})\ \mathbf{1}(\tau_{\text{low}} \le h_d \le \tau_{\text{high}})$$

$$HDD = \frac{1}{n}\sum_{d=1}^{n}\left[(h_d - \tau_{\text{high}})\mathbf{1}(h_d > \tau_{\text{high}}) + |h_d - \tau_{\text{low}}|\mathbf{1}(h_d < \tau_{\text{low}})\right]$$

Where n is the number of days in the agricultural survey period with valid temperature data, h_d is the daily mean temperature, and τ_{high} represents an upper threshold of temperature, beyond which increased exposure is considered harmful to yields, and τ_{low} represents a lower threshold of temperature, below which increased exposure is considered harmful to yields. As such, DDs can be understood as a measure of the exposure to favorable temperature conditions during the growing season, whereas HDDs can be understood as a measure of a municipality's exposure to temperature extremes – both high and low – that are unfavorable for crop growth. In line with Aragon et al. (2019), the measures of DD and HDD adopted in this study represent the growing season averages.

A key consideration when applying the DD/HDD framework is how to define their upper and lower bounds. Some studies adopt the thresholds identified by Schlenker & Roberts (2009) – 8 °C for the lower bound and 29-32°C for the upper bound – and apply them to productivity analyses in other regions (Amare & Balana, 2023). Others, however, derive their own thresholds using context-specific data (Aragon et al., 2019; Daga, 2020). This variation reflects evidence that the temperature ranges favorable or unfavorable to crop growth depend on crop type, available technology, soil characteristics, and other contextual factors (Schlenker & Roberts, 2009; Aragon et al., 2019; Daga, 2020).

Following Aragon et al. (2019) and Daga (2020), this study utilizes context-specific thresholds to determine the temperature boundaries for DDs and HDDs. Specifically, we use the temperature thresholds identified in Daga (2020)'s study of weather shocks in Bolivia, which similarly utilized daytime LST data to construct its daily temperature variable, and yield data from the 2008 and 2015 ENA. At the national level, Daga's study (2020) identifies the lower-bound threshold for DDs as 5°C, and the upper-level threshold for DDs at 31°C. The upper-level threshold was identified by running 16 separate regressions of yields over temperature and precipitation and selecting the threshold that maximized the R^2. Rather than assuming a linear relationship between temperature and production, the strategy of defining upper and lower temperature thresholds allows for a nonlinear exploration between temperature and productivity.

4.4.2. Land Titling

Historic records on hectares titled annually between 1997 and 2024, as well as the total target area for titling in each municipality was provided by INRA and included municipal-level information for the country's 9 departments. The data is disaggregated by type of titled land (communal, medium-scale, small-scale, commercial, state-owned, etc.) and linked to agricultural information reported in the ENA and agricultural census. Such land categorized as state-owned ("*tierras fiscales*") is excluded from the analysis, as it refers to land titled in favor of the government for public use and in general is not intended for agricultural production.

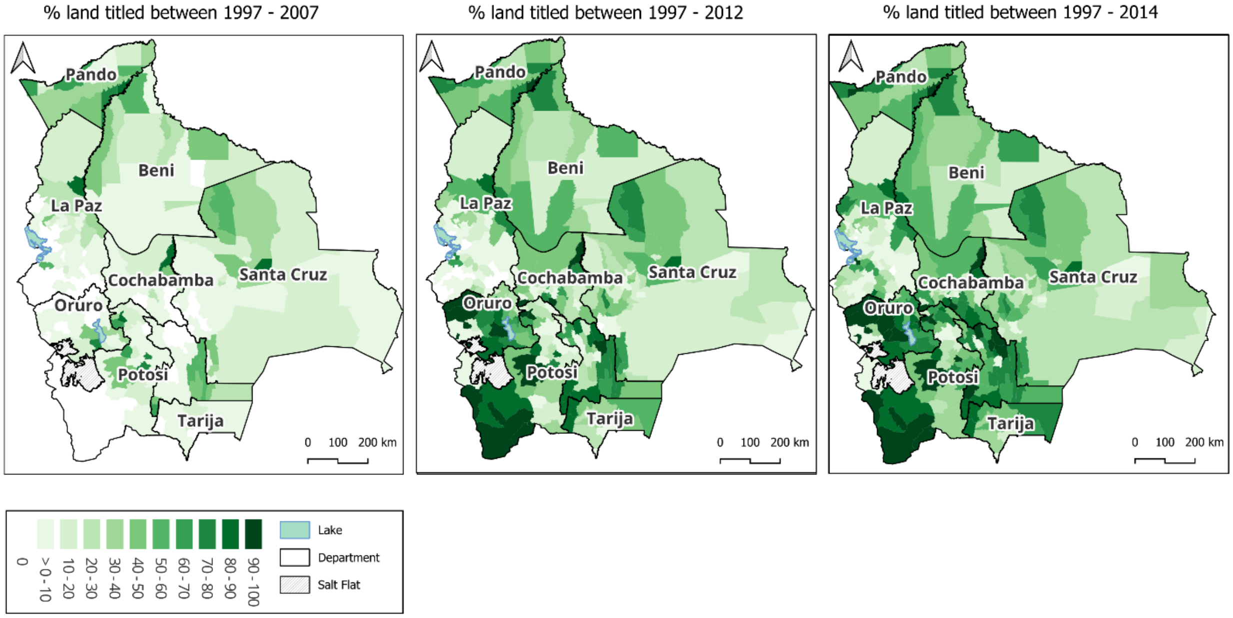
Previous studies have found that the productivity effects of land titling may vary over time. For instance, Rincon Barajas' (2023) study in Colombia finds that receiving a land title induced a negative shock on beneficiaries' agricultural productivity in the first 2.5 years after receiving a title, with productivity recovering by the fifth year. Similarly, Lawry et al.'s (2017) systematic review finds that the productivity effects of land titling may take time to become apparent. To capture the effect of progress in agricultural land titling on productivity, we construct two variables that reflect different temporal dimensions of the titling process. First, to measure potential short-term effects of tenure formalization, a variable is created to capture the number of hectares titled in the two years prior to each survey round, excluding the survey year itself. Because the titling process may incentivize investment, and more efficient labor allocation or input use in the short run, recent titling activity is likely to have a more direct and contemporaneous influence on agricultural outcomes. To account for differences in municipal scale, the titled area is normalized by the rural population in each municipality. For all survey years, we utilize municipal rural population data from the 2012 Bolivian Census, which, at the time of writing, is the most recent municipal-level measurement of rural population available for Bolivia and most closely matches the timeframe of this analysis.

To capture the long-term effect of land titling on productivity, a second variable is created to reflect the cumulative number of hectares titled from 1997 to the year immediately preceding each survey round. Specifically, we use the accumulated area titled from 1997 to 2007 for the 2008 survey, from 1997 to 2012 for the 2013 round, and from 1997 to 2014 for the 2016 round. While this measure is able to account for the historical extent of land regularization efforts in each municipality, its influence on current productivity may be more diluted, especially if titling occurred several years prior to the survey.

It is important to clarify that hectares titled during the same calendar year as the agricultural survey are not included in the cumulative measure for that round. This is due to the fact that each survey covers the agricultural cycle from July of the previous year to June of the survey year. While there is partial overlap between land titled from January to June and the reported agricultural production, there is no information available at monthly frequency to accurately link titling dates to production outcomes. To avoid attributing effects of land titling that are not captured by the survey, we exclude the entire survey year from the cumulative measure and incorporate it in the subsequent round. However, this approach may overlook early-year titling effects if land regularization carried out between January and June had an immediate influence on agricultural productivity. To assess the extent to which this omission matters, we estimate an alternative specification that includes the survey year in the cumulative titling measure.

Land regularization has shown significant progress over time. Figure 5 displays land titling progress across all municipalities. As shown, between 1997 and 2007, titling efforts were limited, with the most progress concentrated in the northeast region of the country and in the department of Santa Cruz. Focusing on the final sample, that is, the balanced panel covering 231 municipalities, an average of 9.8% of the target area was titled at the municipal level during this period. By 2012, however, the process had accelerated significantly nationwide, particularly in the departments of Potosí, Chuquisaca, and Oruro, and an average of 33% of the target area had been titled by then. By 2014, the average had increased to 45%. Although the pace of regularization slowed after 2014, titling continued. In Santa Cruz, progress was more limited in recent years because much of the work had already been completed in earlier stages, while in La Paz, advances remained modest overall. By 2024, the average share of titled land in the balanced sample had reached 74%, and 79 municipalities had surpassed 90% of their target area.

**Figure 5: Progress in municipal land titling (% of target area titled).
From left to right: cumulative 1997–2007, 1997–2012, and 1997–2014.**



Note: The maps above represent the cumulative titled area in each municipality (expressed as a percentage of the total area to be titled in each municipality). This progress indicator is used by INRA to measure the total area in each municipality that has received a land title relative to the total area that can be titled in each municipality.
Source: Administrative land titling data from INRA.

4.4.3. Irrigation

Detailed information on public irrigation investments carried out nationwide between 2011 and 2024 is provided by the Ministry of Environment and Water. These irrigation investments are implemented through 23 programs established under various institutional agreements, covering the departments[10] of Chuquisaca, Cochabamba, La Paz, Oruro, Potosí, Santa Cruz, and Tarija, with financing allocated in accordance with the demands received from municipal governments.

A total of 1,801 projects were recorded across 245 municipalities between 2011-2015, focusing on the construction, expansion, and improvement of irrigation and micro-irrigation systems. Available data includes location information at the province, municipality, locality, and community levels, as well as the implementation status of each project, start and completion dates, the number of beneficiary families, irrigated hectares, and investment amounts. It also provides details on the funding agency, executing entity, and other relevant project aspects.

The analysis focuses on the period from 2011 to 2015 and is restricted to the balanced panel in order to evaluate the impact of publicly financed irrigation on agricultural productivity. During this time, an average of 1,258 families per municipality benefited, amounting to a total of 266,758 beneficiaries, with an average irrigated area of 316 hectares per municipality.

The study then aims to assess the effects of public irrigation projects implemented between 2011 and 2015 on agricultural productivity. Given that the effectiveness of irrigation systems is highly dependent on local agro-climatic conditions, particularly precipitation patterns, the main

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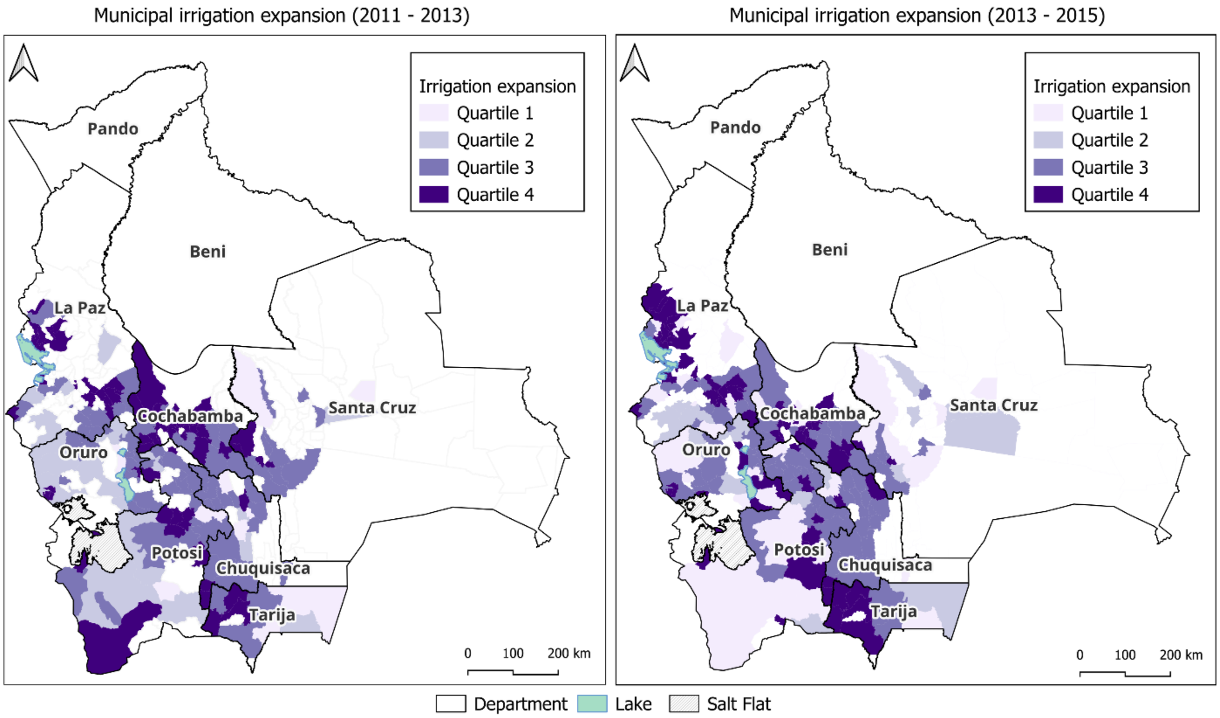
[10] Due to the agro-climatic conditions in the departments of Beni and Pando, these areas have not generated the same level of demand as other departments and, consequently, no projects have been recorded for them.

explanatory variable is constructed as the cumulative number of hectares irrigated under these programs, normalized by the total agricultural area in each municipality, as reported in the 2013 Agricultural Census. For the 2013 survey round, this measure aggregates hectares irrigated between 2011 and 2013; for the 2015 round, it covers the period 2011–2015. To account for the heterogeneous impact of irrigation depending on baseline climatic conditions, the determinant variable is interacted with the municipality-level average of daily precipitation, as well as with its squared term, to capture potential non-linearities in the relationship between rainfall and irrigation effectiveness.

Figure 6 illustrates the irrigated area between 2011 and 2013 (left panel) and the change in irrigated area between 2013 and 2015 (right panel). The departments of Beni and Pando, where irrigation projects are absent due to favorable agro-climatic conditions, exhibit the highest levels of precipitation. Similarly, in large parts of La Paz and Santa Cruz, where precipitation is also high, the number of implemented projects remains limited. In contrast, departments with lower precipitation levels, such as Oruro, Potosí, and Cochabamba, concentrate a greater share of these projects.

Figure 6: Spatial distribution of irrigated area (2011-2013) and change in irrigation coverage between 2013 and 2015



Note: The maps above represent the number of hectares irrigated via public investment in each municipality, for the periods of 2011-2013 (left) and 2013-2015 (right). Irrigated hectares are normalized by municipal agricultural surface area, as reported in the 2013 National Agricultural Census.

Sources: Administrative data from the Ministry of Environment and Water; 2013 National Agricultural Census.

Unlike the case of land titling, irrigation project data are available at the monthly level, which makes it possible to calculate the total number of hectares irrigated during the first six months of each year, matching the agricultural cycle covered by the survey. Thus, for the 2013 round, we consider the hectares irrigated between 2011 and the early months of 2013; for the 2015 round, we include the cumulative hectares irrigated from 2011 through the first six months of that year. Thus, the final sample is a balanced municipal panel for two years (2013 and 2015) covering 212 municipalities.

5. Empirical Approach

5.1 Stochastic Production Frontier

A stochastic production frontier (SPF) approach is employed to measure TFPG and to analyze its sources by decomposing TFPG into SE, TP, TE, WE and SN. Specifically, the Cobb-Douglas functional form is used to represent the production technology of the average farm within a municipality, ensuring compliance with the properties of index number theory necessary for the decomposition of TFPG (Lachaud et al., 2017).

An SPF model with a time-varying specification is used. Specifically, by modeling inefficiency using the true random effect model (TRE), time-varying inefficiency is separated from time-invariant unobserved heterogeneity specific to each unit (Greene, 2005a; Greene, 2005b), with the following stochastic frontier model is set:

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

Where y_{it} is the value of agricultural production for municipality i at time t; x_{kit} is a vector of k inputs (land, family labor, hired labor expenses, capital, fertilizers, and pesticides), and z_{jit} is a vector of j weather variables expressed in levels, including average daily precipitation, the square of average daily precipitation, DDs, and HDDs. D_t are year fixed effects; while R_{ri} refers to regional dummies (Lowlands, Valleys, and Highlands) to control for structural and geographical differences among the country's agroecological regions. The interaction terms $R_{ri} \times D_t$ allow for region-specific technical change over time.

The term α_i captures unobserved municipal heterogeneity. The error term consists of two components: u_{it} representing the technical inefficiency term, which follows a truncated-normal distribution and v_{it}, the idiosyncratic component, assumed to follow a standard normal distribution.

5.2 TFP Decomposition

Based on the coefficients estimated in equation (1), TFP is decomposed into the five previously mentioned components to explain changes in TFPG, which involves computing TFP indices. Specifically, the Total Factor Productivity Index (TFPI) compares the TFP of municipality i in period t with the TFP of municipality m in period s, defined as follows:

$$TFPI_{msit} = \frac{Q(q_{it}) \big/ X(x_{it})}{Q(q_{ms}) \big/ X(x_{ms})}$$

Here, $Q(.)$ and $X(.)$ are aggregator functions that combine outputs and inputs respectively into single composite measures. These functions are nonnegative, nondecreasing, and linearly homogeneous, satisfying axioms from index theory to (Njuki et al., 2019).

We compute a multiplicative index using elasticities from equation (1), which are scaled so they add up to one, following Njuki et al. (2018). These scaled elasticities act as weights that show how important each input is in production. TFPI is then defined as:

$$TFPI_{msit} = \frac{q_{it}}{q_{ms}} \times \left[\prod_{k=1}^{K} \left(\frac{x_{kms}}{x_{kit}} \right)^{\frac{\widehat{\beta_k}}{\sum_{k=1}^{K} \widehat{\beta_k}}} \right] \quad (2)$$

By substituting the antilogarithm of equation (1) into equation (2), the following decomposition of TFP change is obtained:

$$TFPI_{msit} = \left[e^{(\alpha_i - \alpha_m)}\right] \times \left[\prod_{k=1}^{K}\left(\frac{x_{kit}}{x_{kms}}\right)^{\beta_k - \frac{\widehat{\beta}_k}{\sum_{k=1}^{K}\widehat{\beta}_k}}\right] \times \left[\prod_{t=1}^{T-1}\frac{e^{(\delta_t D_t)}}{e^{(\delta_t D_s)}} \times \prod_{r=1}^{R-1}\frac{e^{(\gamma_r R_{ri})}}{e^{(\gamma_r R_{rm})}} \times \prod_{r=1}^{R-1}\prod_{t=1}^{T-1}\frac{e^{[\theta_{tr}((R_{ri}\times D_t)]}}{e^{[\theta_{tr}((R_{rm}\times D_s)]}}\right]$$

$$\times \left[e^{\sum_{j=1}^{J}\eta_j (z_{jit} - z_{jms})}\right] \times \left[\frac{\exp(-u_{it})}{\exp(-u_{ms})}\right] \times \left[\frac{\exp(v_{it})}{\exp(v_{ms})}\right] \qquad (3)$$

The first term of equation (3) captures municipality-level, time-invariant unobserved heterogeneity (UH). The second term measures the relative change in SE. The third term corresponds to the change in TP. The fourth term reflects changes in WE. The fifth term measures the relative change in TE, calculated according to Jondrow et al. (1982). The final term captures SN.

5.3 The effect of policy determinants on TFP

To estimate the impact that progress in land titling as well as the expansion of irrigated area had on agricultural TFP, we estimate the following production function:

$$\ln y_{it} = \rho\, T_{it} + \sum_{k=1}^{K}\beta_k\, ln x_{kit} + \sum_{j=1}^{J}\eta_j z_{jit} + \sum_{t=1}^{T-1}\delta_t D_t + \sum_{r=1}^{R-1}\gamma_r R_{ri} + \sum_{r=1}^{R-1}\sum_{t=1}^{T-1}\theta_{tr}\,(R_{ri}\times D_t) + \alpha_i + \lambda_t + \varepsilon_{\mathrm{it}} \quad (4)$$

The definition of the independent variable T_{it} varies depending on whether the analysis focuses on land titling or irrigation. When examining the effects of land titling, T_{it} captures the area titled in the two years prior to each survey round per rural inhabitant to reflect short-term impacts. Alternatively, it is defined as the cumulative titled area per capita to capture longer-term effects (see Section 4.4.2). For irrigation, T_{it} is defined as the cumulative number of irrigated hectares at the municipal level, capturing the medium-term impact of expanded water infrastructure on agricultural productivity (see Section 4.4.3).

All specifications include municipality fixed effects (α_i) to control for time-invariant unobserved heterogeneity across municipalities. Year fixed effects (λ_t) to account for common shocks over time. Additionally, we include region-by-year fixed effects ($R_{ri} \times D_t$) to flexibly control for time-varying regional trends and subnational policies that may influence productivity or the rollout of land titling and irrigation programs. This is particularly important in the Bolivian context, where the three main regions -Highlands, Valleys, and Lowlands- exhibit substantial differences in geography, climate, agricultural potential, economic structure, and social conditions. These structural disparities are likely to influence both the design and the implementation of public policies, potentially leading to heterogeneous impacts across regions.

6. Results

6.1. TFP Decomposition

Table 3 presents the coefficient estimates of the production frontier (Equation 1). All input variables show highly significant coefficients with the expected signs, except for the family labor index. Among the inputs, land exhibits the highest elasticity, indicating its dominant contribution to production.

Table 3: Stochastic Production Frontier Results, 2008 - 2015

Dependent Variable: Log Production Value	(1)
Log Land (Ha)	0.891*** (0.031)
Log Labor Expenses	0.125*** (0.025)
Log Family Labor Index	0.126 (0.098)
Log Input Use	0.094*** (0.035)
Log Capital Use	0.088*** (0.032)
Average Degree Days	-0.019 (0.015)
Average Harmful Degree Days	-0.098** (0.040)
Average Daily Precipitation in the Growing Season	0.120** (0.055)
Average of Squared Daily Precipitation	-0.000 (0.001)
Natural Region: Valley	-0.905*** (0.111)
Natural Region: Highland	-0.643*** (0.110)
Year: 2013	-0.667*** (0.074)
Year: 2015	-0.133* (0.069)
Valley*2013	0.634*** (0.091)
Valley*2015	0.477*** (0.096)
Highland*2013	0.437*** (0.089)
Highland*2015	0.190** (0.094)
Sigma u	11.982 (0.578)
Sigma v	0.250 (0.027)
Lambda	48.012 (0.597)
Observations	693
Municipalities	231

Notes: Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

In terms of environmental factors, this analysis finds that weather shocks are associated with statistically significant effects on agricultural productivity. In terms of temperature shocks, on average, each additional harmful degree day during the growing season is associated with a 9.8% decrease in the value of agricultural production, statistically significant at the 5% level. Regarding precipitation, a one-millimeter increase in mean daily precipitation during the growing season is associated with a 12% increase in the value of agricultural production, significant at the 5% level. This indicates that, on average, municipalities with higher precipitation have higher levels of agricultural productivity. We do not find a significant effect of an increase in the square of daily precipitation, our proxy variable for precipitation shocks.

The average TFPI and its components are reported in Table 4. The indices are constructed using the estimated elasticities and aggregated annually across all municipalities in the sample through the geometric mean. From these indices, we compute the annual growth rate of each component.

The annual output growth of 4.11% is predominantly driven by increased input usage, which explains approximately 55% of the growth, while productivity improvements account for about 44%. Notably, TFP exhibited a modest annual growth rate of 1.8% during the period from 2008 to 2015. These gains were largely driven by technological progress, which grew at an annual rate of 1.38%. Technical efficiency decreased during the study period, though at a negligible rate (-0.05%), while statistical noise, encompassing functional form misspecification and other unidentifiable error sources (O'Donnell, 2016), exhibits a slight decline over the study period at an annual rate of 0.01%. Nonetheless, it accounts for only a negligible fraction of the TFP dynamics. Weather conditions played a significant role in shaping productivity, reducing TFP growth by 0.27% per year on average. Finally, the positive sign of scale efficiency suggests that the rising scale of production during the study period has contributed to increased TFP growth.

Table 4. Annual Values and Growth Rates of Output, Inputs, TFP, and TFP Components (Index-Based)

Year	Output Index	Input Index	TFP Index	SE Index	TE Index	TP Index	WE Index	SN
2008	0.019	0.153	0.124	0.543	0.811	1.948	0.862	0.167
2013	0.017	0.170	0.101	0.563	0.855	1.465	0.862	0.167
2015	0.025	0.179	0.140	0.572	0.809	2.144	0.846	0.167
Growth Rate p.a. (%)	**4.112**	**2.275**	**1.796**	**0.732**	**-0.046**	**1.384**	**-0.266**	**-0.012**

As shown in Table 5, changes in productivity levels are heterogeneous across Bolivia’s natural regions. 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 improvements in scale efficiency, despite being the region with the largest decline in technical efficiency. The Highlands achieved moderate productivity growth of 1.18% per year, supported by steady technological progress and scale efficiency, despite limited improvements in technical efficiency.

In contrast, despite historically exhibiting the highest levels of productivity in the country, the Lowlands experienced an output contraction of 0.42% per year despite a 1.17% increase in input use, reflecting a sharp decline in TFP (-1.57%). This deterioration was driven mainly by a substantial loss in technological progress and adverse weather conditions, which outweighed the modest gains from technical efficiency and scale efficiency.

Table 5: Decomposition of the TFP by Natural Regions: Growth Rate p.a. (%) 2008 - 2015

Region	Output Index	Input Index	TFP Index	SE Index	TEC Index	TP Index	WE Index	SN
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

Across all regions, the scale efficiency index shows a positive contribution to TFPG, indicating that producers moved closer to the most productive scale of operation during the study period, while climatic conditions reduced productivity. The Lowlands were the most affected, with weather shocks contributing to a 0.62% annual decline in productivity, while the Valleys and Highlands experienced smaller negative impacts. These results highlight that, despite gains in technological progress and scale efficiency, weather variability remains a key constraint on agricultural productivity growth in Bolivia. Given that climate change is expected to increase the frequency and intensity of extreme weather events, these negative impacts are likely to intensify, posing an even greater challenge to sustained productivity gains in the coming decades.

To assess the robustness of our results, we estimate a stochastic production frontier (Table D2) and perform a TFP decomposition using an unbalanced panel, which comprises 269 households in 2008, 302 in 2013, and 264 in 2015 (Table D3). As an additional robustness check, Tables D and D5 present both the SPF results and the decomposition after excluding municipalities with fewer than 10 surveyed farms.

6.2. Policy Determinants

This section presents the estimated effects of municipal-level expansion of irrigated areas on agricultural productivity, as well as the impacts of progress in land titling, estimated from Equation 4. Table 6 reports the results for both effects. Section 6.2.1 provides a detailed discussion of the findings related to the impact of irrigation, while Section 6.2.2 focuses on the results concerning land titling.

6.2.1 Irrigation

The results presented in column (1) of Table 6 show that the effects of public investment aimed at expanding irrigation infrastructure depend on the municipality's rainfall level. The coefficient for the interaction term suggests that the positive effect of irrigation -measured as cumulative irrigated hectares normalized by 2013 cultivated area- on agricultural productivity declines with higher average daily precipitation. Specifically, for each additional millimeter of average daily rainfall during the growing season, the productivity gains from irrigation decline by approximately 9% for every 0.01 increase in the normalized irrigation ratio (i.e., one additional irrigated hectare per 100 hectares cultivated in 2013).

Table 6. Impact of irrigated area expansion and land titling on TFP

Dependent Variable: Log Production Value	(1)	(2)	(3)
Irrigated Hectares	6.593**		
	(2.737)		
Irrigated Hectares x Average daily precipitation	-8.929*		
	(4.747)		
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***
			(0.0007)
Log Land (Ha)	1.105***	0.984***	0.997***
	(0.084)	(0.065)	(0.063)
Log Labor Expenses	0.060	0.034	0.027
	(0.043)	(0.036)	(0.036)
Log Family Labor Index	0.104	0.117	0.117
	(0.216)	(0.155)	(0.153)
Log Input Use	0.002	0.033	0.029
	(0.070)	(0.041)	(0.041)
Log Capital Use	0.181***	0.099**	0.098**
	(0.064)	(0.043)	(0.042)
Average Degree Days	0.037	0.042	0.047*
	(0.036)	(0.027)	(0.027)
Average Harmful Degree Days	-0.137	-0.023	-0.021
	(0.138)	(0.112)	(0.113)
Average daily precipitation in the growing season	0.511***	0.210	0.181
	(0.175)	(0.129)	(0.125)
Average of squared daily precipitation	-0.009**	0.0001	0.0001
	(0.004)	(0.002)	(0.002)
Observations	424	693	693
Period	2013-2015	2008-2015	2008-2015
R-squared	0.959	0.929	0.929
Municipality FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes

Notes: "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

These results highlight that *weather* conditions are a key determinant in the effectiveness of water-efficient technologies such as irrigation systems. Allocating irrigation investments in contexts with abundant rainfall may be neither cost-effective nor necessary, and in some cases, even generate counterproductive outcomes. Over-irrigation can negatively affect crop health, lower yields, and lead to contamination of groundwater (Irmak, 2014). Moreover, studies have found that excessive water can create conditions that favor the spread of plant diseases (Brasier et al., 2022). In this context, the findings support the government's strategy of targeting irrigation projects to areas with lower rainfall, suggesting that these investments are being effectively allocated according to local water needs.

6.2.2 Land Titling

Column (2) of Table 6 presents the effect of recent land titling (within the two years prior to the survey year) on agricultural productivity. No statistically significant effect is observed. Alternative estimations were conducted by extending the time window (3-4 years), and the lack of effect persists in this specification. Additionally, a model was estimated to capture the long-term effects of land titling as measured by per capita cumulative titled hectares since 1997, which averaged 13.4 hectares per capita across the sample. The results are presented in Column (3) of Table 6, showing that the impact of per capita cumulative titled hectares is negative.[11] Specifically, an additional titled hectare per capita, with respect to the existing level of titling, is associated with a 0.3% decrease in average municipal TFP, suggesting a negligible impact on productivity. Therefore, our findings on the effect of land titling on productivity are inconclusive. This could be explained by several factors.

First, the potential productivity gains from land titling can be moderated by specific legal and institutional constraints where legal restrictions prevent smallholdings from being used as collateral, limiting access to credit and investment.[12] Additionally, distortions in land markets produce heterogeneous outcomes across types of land use, which may dilute the short-term productivity gains from titling. A second factor may arise from data limitations. Agricultural information is only available from 2008 onwards, and not on an annual basis, which prevents capturing potential productivity shocks between distant survey waves, for example, between 2008 and 2013, or may only capture limited progress, as in 2013–2015.

Moreover, the timing and geographic rollout of titling is important. As shown in Figure 5, early titling efforts were concentrated in departments with larger average farm sizes, such as Beni, Pando, and Santa Cruz, which had the highest per capita titled hectares by 2008. These areas likely experienced the largest productivity gains early on, which are not captured in the survey waves used for this analysis. The hectares titled in the two years prior to each survey may therefore be marginal, yielding little observable impact.

At the same time, recent titling efforts were concentrated mainly in the Highlands region. By 2007, 73% of rural land in municipalities in La Paz, 63% in Oruro, and 55% in Potosí had not yet been titled. These areas are characterized by smaller municipalities with more subsistence-oriented and less mechanized agriculture. In these areas, productivity gains may take longer to materialize, and early effects are likely smaller. Empirical evidence suggests that the impact of land titling follows a non-linear trajectory, operating through multiple complementary channels such as access to credit, improved land markets, tenure security, and investment incentives. The activation of these channels is typically slow, and in the absence of complementary policies, such

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[11] However, this long-term estimation is not the preferred specification. By using cumulative hectares, the variable captures impact over a long period, which reduces variability in the data. Many municipalities had already achieved substantial titling by 2013, so by 2015 the cumulative measure changes little or remains nearly constant. Moreover, as shown in Figure 5, several regions exhibit minimal progress in titling between survey rounds, particularly between 2013 and 2015, a period that covers only two years of activity. As a result, the cumulative variable may lack sufficient within-period variation to effectively capture meaningful changes in productivity at the municipal level.

[12] Bolivian national legislation limits legally defined smallholding's farm and ranch lands from being used as collateral, in order to prevent small landowners from selling out their land in response to temporary shocks and safeguarding smallholders' source of income, avoiding the seizure of their assets (Murguia et al., 2017).

as access to credit, technical assistance, or infrastructure, they may not be fully realized, further limiting observable short-term productivity gains.

The temporal mismatch between productivity and titling data, combined with the potential endogeneity inherent to the geographic rollout of titling efforts, helps explain the negative effect of cumulative titled hectares. Taken together, these factors suggest that the observed negative coefficient for cumulative titled hectares reflects the spatial and temporal pattern of title allocation and the constraints faced by less productive municipalities.

As previously discussed, hectares titled during the survey year are excluded when summing both the hectares titled in the two previous years and the cumulative hectares titled since 1997. To test whether this omission affects the results, Table D6 presents estimates that incorporate land titled during the survey year into the cumulative measure. The results remain consistent with our baseline findings.

To explore whether land titling operates through additional channels without necessarily generating immediate productivity gains, two alternative regressions were estimated. The effects of recently titled hectares (within two years prior to the survey) and cumulative titled hectares (from 1997 up to the year before the survey) were analyzed on: (i) the proportion of farms in the municipality with access to credit in the past three years (since 2013), and (ii) the proportion of farms that obtained their plot through purchase, according to the 2013 Agricultural Census. This is a cross-sectional analysis using the agricultural census as the data source, since ENA does not report this information. Consequently, municipality and year fixed effects cannot be controlled for, and these results should be interpreted as correlations rather than causal effects.

Results in Table D7 and D8 in the Appendix show no impact of recent titling on either mechanism, whereas cumulative titling exhibits a negative effect. These findings support the productivity results. In the short term, titling is not associated with a higher incidence of accessing credit or purchasing land, which is consistent with a lack of impact on TFP. In contrast, cumulative titling progress since 1997 is associated with a lower incidence of credit access and land purchase, which supports the observed negative long-term effect on productivity, reflecting that there may exist a correlation between the spatial and temporal rollout of titling and the productive characteristics of municipalities.

7 Discussion and policy recommendations

This study provides new evidence on agricultural productivity in Bolivia, addressing key knowledge gaps and offering insights for policymakers. The findings highlight the importance of using public resources effectively to boost productivity, strengthen food security, and improve rural welfare, while supporting agricultural investments that can drive long-term growth.

Given the modest average growth in agricultural TFP identified by this study, it is critical that Bolivia continue to prioritize and expand public investments aimed at boosting productivity. Productivity gains have been driven primarily by technological progress; however, these benefits have been unevenly distributed across regions. While the Highlands have seen only marginal technological advances, the Lowlands have experienced a decline, and most of the gains have accrued to the Valleys. This underscores the need for investments in research, development, and innovation (R+D+I) that foster technological development and adoption tailored to the specific socio-economic, agronomic and climatic conditions of each region. In the same way, municipalities with the lowest land and labor productivity would benefit from targeted support to help them continue catching up with the highest-performing quintiles.

The analysis also identifies a spike in agricultural input use in 2013, followed by a sharp decline in 2015. The observed trend is likely tied to regulatory changes that took place during the period of analysis. In particular, in 2015, Bolivia's agricultural sanitation agency (SENASAG, per its Spanish acronym) passed two administrative resolutions that banned the import, sale, distribution, and use of three pesticides commonly used in agricultural production: methamidophos, endosulfan, and monocrotophos (Banascope et al., 2018). Import data from the Bolivian Institute of Exterior Commerce (IBCE, per its Spanish acronym) shows these regulations had a marked effect on agrochemical markets.[13] After reaching an all-time high of 43,877 metric tons in 2013, pesticide imports declined to 16,287 metric tons in 2015 (IBCE, 2015).

Fertilizer imports also decreased, though to a lesser extent, from an all-time high of 99,108 metric tons in 2013 to 92,736 metric tons in 2015 (IBCE, 2017). Thus, the trend in self-reported agricultural input use summarized in Table 2 is consistent with the trends observed in the country's official import data. The observed decline in pesticide imports and self-reported pesticide use is to be expected as a direct result of the ban. However, the simultaneous reduction in fertilizer use, though perhaps unexpected, is likely explained through spill-over effects of the pesticide ban. At the level of importers, increased regulatory attention around agrochemical products may have incentivized Bolivian importers to diversify their portfolios towards less risky products, driving a reduction in fertilizer imports. At the level of producers, it is possible that producers under-reported their use of fertilizers and pesticides in 2015 to avoid being perceived as being noncompliant with the new regulation. This theory is consistent with previous studies that have identified under-reporting of pesticide use among farmers in Bolivia (Barrón Cuenca et al., 2024).[14]

We also find that climatic conditions emerge as a significant determinant of productivity. This highlights the need to incorporate climate adaptation strategies into Bolivia's agricultural development agenda. Policymakers should promote the use of 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 events. These measures are essential to safeguard productivity and ensure long-term sectoral sustainability.

Irrigation investments are found to have a statistically significant effect on productivity. However, access to irrigation remains limited and geographically uneven; in 2015 only 28% of farms used irrigation. Furthermore, this study finds that the positive effects of irrigation decline as municipal rainfall increases; this is consistent with previous literature that has identified that the positive effect of irrigation on yields is greater under dry conditions (Gajic et al., 2018). Although evidence on irrigation's effects in Bolivia is scarce, existing studies highlight the importance of coupling infrastructure with targeted technical assistance to support adoption, operation, and maintenance (Salazar & López, 2018). Additionally, the temporality of the effects must be considered as productivity gains may take several agricultural cycles to materialize, reinforcing the need for sustained investment and farmer support as well as long-term impact assessments to establish causal effects on productivity growth. Finally, special emphasis should be placed on promoting efficient use of water resources and protecting water sources.

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[13] During the period of analysis, Bolivia did not produce fertilizers or pesticides domestically and was entirely reliant on imports to meet local demand for these goods. As such, import data is an accurate reflection of the licit supply of these goods in Bolivian markets.

[14] The potential under-reporting of agrochemical use in the 2015 survey year introduces a risk of bias in our analysis, as these data form the basis for our TFP estimations. A review of other official sources, including FAOSTAT and the aforementioned IBCE, corroborates the general trends in agrochemical use observed in the survey data. In the absence of alternative official datasets that would allow us to explicitly adjust for possible under-reporting, we proceed with the survey data as the most reliable source currently available. Nevertheless, in interpreting the results, readers should note that, if agrochemical use was indeed under-reported, this would most likely induce attenuation bias in our SPF estimation. This would lead to an underestimation of the contribution of agrochemicals to productivity and a corresponding over-attribution of their effects to other inputs.

In the same way, the study finds mixed results of the effect of land titling on productivity, which may be related to the aggregate level of analysis or correlation between the spatial-temporal rollout of titling efforts and productive characteristics of municipalities. A study conducted in Bolivia by Schling et al. (2024) confirms that holding title has a positive impact on technical efficiency, as well as accessing credit, and increasing productive investments. Hence, while the evidence is mixed, public policy efforts should continue to improve land tenure security in order to improve farmers' access to credit, encourage long-term investment, and increase productive efficiency. Priorities should be put on titling efforts in municipalities with low regularization rates, ensuring institutional coordination, and providing support services (such as legal assistance and cadastral updates) to accelerate the process. Further research is needed to better understand the mechanisms through which land titling may affect tenure security and thus productivity, and to assess whether these effects are more detectable at more disaggregated levels of analysis. In the long term, the effects of land titling may depend on complementary policies that help sustain and amplify its benefits over time.

Finally, the analysis was limited by the unavailability of a panel data at the farm level, so productive heterogeneity across different types of farmers within a municipality could not be explored and yet may represent an important factor in determining the dynamics and drivers of productivity. With the aim of conducting longitudinal evaluations that more accurately represent Bolivian farmers and their productive systems, it is recommended that public investments be made into generating longitudinal agricultural statistics based on nationally representative farm household surveys. This investment would play a critical role in enabling an evidence-based decision-making process in policy making in the sector.

8 Conclusion

This study provides new empirical evidence on the evolution and determinants of agricultural productivity in Bolivia between 2008 and 2015. Using nationally representative agricultural surveys (2008 and 2015) and census data (2013), a balanced municipal-level panel is constructed. A stochastic production frontier model is applied to estimate TFP and decompose its growth components. The findings show that agricultural TFP grew at an average annual rate of 1.8%, primarily driven by technological progress. The positive sign of scale efficiency suggests that a rising scale of production also contributed to increased TFP growth. However, this growth was partially affected by declining technical efficiency and adverse weather shocks, particularly in the tropical Lowlands in the northeast of the country, which have historically enjoyed higher levels of productivity.

The analysis highlights strong heterogeneity of impacts across regions. The Valleys recorded the fastest TFP growth (5.58% annually), supported by gains in technology and scale, while the Highlands achieved modest growth (1.18%). In contrast, the Lowlands experienced a decline in TFP growth (-1.57%), largely due to adverse weather shocks and stagnation in technological progress. These results underscore the importance of tailoring policy interventions to regional conditions.

Furthermore, the study finds that temperature shocks significantly reduce agricultural output, while higher precipitation levels increase productivity. These results highlight the urgent need to integrate weather adaptation strategies into agricultural policy. In terms of public investment, this analysis shows that expanding irrigation infrastructure leads to productivity gains, although this impact is moderated by precipitation levels, emphasizing the importance of tailoring investments to local climatic conditions. In contrast, findings on the effect of land titling on productivity at the municipal level are inconclusive, which may be a result of aggregation or unobserved heterogeneity.

In addition to TFP, the analysis of productivity relative to farm size and number of workers provides important distributional dynamics. Larger farms generally maintain higher productivity, although smaller farms have improved over time, narrowing the gap and leading to more balanced productivity levels across farm sizes and labor groups. By 2015, disparities in both land and labor productivity had declined, suggesting a gradual convergence in performance between smaller and larger producers.

Based on these findings, several policy recommendations emerge. First, public investment in agricultural infrastructure, particularly irrigation, remains critical and should be prioritized in regions with lower rainfall and slower productivity growth. Second, investments in research, development, and innovation (R+D+I) are needed to foster technological advances and adoption tailored to the diverse socio-economic, agronomic, and weather conditions of each region. Third, expanding technical assistance and extension services is essential to ensure that land tenure security and infrastructure translate into tangible productivity gains. Finally, strengthening the agricultural statistical system through nationally representative longitudinal farm household surveys would enable more accurate monitoring and support evidence-based policy making. Overall, these findings underscore the importance of sustained, targeted public investment in productivity and weather resilience. These efforts are essential not only to boost productivity but also to promote inclusive rural development, food security, and long-term sustainability in Bolivia’s agricultural sector.

Future research should deepen the understanding of how regional heterogeneity, weather, and policy interventions interact to shape agricultural productivity in Bolivia. In particular, more disaggregated analyses at the farm level are needed to uncover distributional impacts across different farmer types and production systems, which were not fully captured in this study. Longitudinal data collection through nationally representative farm household panels would be needed to enable such analysis. Further work should also examine the long-term and complementary effects of land titling, irrigation, and other policy investments on productivity. These efforts would provide stronger causal evidence to guide policy design and ensure that productivity growth translates into inclusive and sustainable rural development.

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Appendix A: Detailed description of variables

Table A1: Descriptive Statistics by Natural Regions

	Lowlands			Valleys			Highlands		
Variables	**2008**	**2013**	**2015**	**2008**	**2013**	**2015**	**2008**	**2013**	**2015**
Crop Production Value (US$ 1,000)	9.01	7.00	7.67	1.11	1.17	1.95	0.92	0.60	1.30
	(15.92)	(11.87)	(9.22)	(1.01)	(1.14)	(2.08)	(1.01)	(0.36)	(1.29)
Land (Hectares)	5.17	6.03	6.36	1.52	1.56	2.01	1.37	1.06	1.41
	(5.97)	(6.54)	(7.48)	(0.87)	(0.86)	(1.36)	(1.19)	(0.74)	(1.12)
Family Labor Index	2.10	2.49	2.23	2.07	2.53	2.70	2.10	2.53	2.60
	(0.46)	(0.34)	(0.43)	(0.41)	(0.21)	(0.52)	(0.46)	(0.30)	(0.56)
Labor Expenses (US$1,000)	3.33	10.20	5.00	3.77	6.16	5.65	1.76	2.77	3.46
	(2.73)	(14.80)	(4.45)	(2.56)	(4.06)	(5.58)	(1.60)	(2.30)	(2.82)
Use of Agricultural Inputs (%)	0.39	0.58	0.44	0.59	0.92	0.67	0.40	0.85	0.70
	(0.27)	(0.28)	(0.33)	(0.25)	(0.11)	(0.23)	(0.24)	(0.19)	(0.31)
Use of Capital (%)	0.38	0.46	0.42	0.82	0.82	0.84	0.62	0.68	0.71
	(0.29)	(0.32)	(0.29)	(0.24)	(0.21)	(0.22)	(0.32)	(0.33)	(0.32)

Notes: Statistics are based on the final sample, consisting of a balanced panel of 231 municipalities per year, after missing values were imputed.

Table A1 presents descriptive statistics by natural regions, showing geographical structural contrasts in Bolivia's agricultural production. The Lowlands have the largest farms and the highest average production values, though both output and input use declined after 2013. Labor expenses peaked in 2013, consistent with the region’s greater reliance on hired labor, before falling again in 2015. The Valleys display rising production values over time, supported by high and increasing adoption of inputs and capital. In contrast, the Highlands have the smallest farms and lowest production values, though input use and labor expenses increased notably after 2008. Overall, these patterns underline the heterogeneity of Bolivian agriculture: scale and hired labor dominate in the Lowlands, input intensity in the Valleys, and small-scale and labor-intensive farming in the Highlands.

Appendix B. Variable Definitions and Processing

1. *Crop Production Value*

In each round of the surveys and the census, production from the summer growing season is considered, excluding forage crops, fibers, live plants, seeds, and forest plantations. Production is aggregated using implicit prices, calculated based on the 2015 survey, which reports both the quantity sold and the corresponding revenue, allowing for the derivation of unit prices. This procedure yields prices for 109 products, covering sugarcane, cereals, fruits, nuts, oilseeds, vegetables, pulses, roots and tubers, as well as crops used for stimulants, spices, and aromatic plants.

Once prices are assigned, the production value of each farm is calculated for every year. These values, originally expressed in Bolivianos, are converted into U.S. dollars using the 2015 exchange rate (6.86 Bs/USD)[15]. Finally, to mitigate the influence of outliers, production value variables are winsorized at the 95% level.

2. *Land*

Land is measured as the sum, in hectares, of all crops reported by each farm during the summer growing season. This measure corresponds to cultivated area, which may differ from the area actually harvested in the case of partial losses. To mitigate the influence of outliers, cultivated area was winsorized at the 95% level.

3. *Family Labor Index*

Household members engaged in agricultural activities on the farm during the growing season are taken into account. To incorporate family labor while accounting for differences in contribution by gender and age, conversion factors of 1 for men, 0.8 for women, and 0.6 for children aged 5 to 14 are applied, following Helfand and Rada (2015). In this way, family labor is expressed in terms of male adult equivalents.

4. *Labor Expenses*

This variable measures the number of hired workers engaged in agricultural activities during the growing season. In the survey data, both workers employed for less than six months and those employed for more than six months are included. By contrast, the census does not distinguish by length of employment; instead, it records paid and unpaid workers. To ensure consistency and avoid double counting with the family labor variable, only paid workers are considered in the census. Moreover, it is assumed that both temporary and permanent workers reported in the surveys most likely correspond to paid labor.

Once the total number of agricultural workers per farm is obtained, it is converted into workdays using a conversion factor of 200.[16] Finally, the number of workdays for each farm is multiplied by the average daily wage reported in the 2015 survey (USD 13), with the resulting values winsorized at the 95th percentile.

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[15] https://www.udape.gob.bo/portales_html/dossierweb2023/htms/CAP04/c040401.htm

[16] The conversion factor used follows the approach applied in the 2011 Paraguayan Agricultural Census. https://www.fao.org/fileadmin/templates/ess/ess_test_folder/World_Census_Agriculture/Country_info_2010/Reports/Reports_5/URY_SPA_REP_2011.pdf

5. Use of purchased inputs

A dummy variable equal to 1 if the farm reported using fertilizer, manure, or pesticides during the growing season. When aggregated at the municipal level by taking the average across farms, this variable is expressed as the proportion of farms within the municipality reporting the use of these inputs.

6. Use of capital

A dummy variable is set to 1 if the farm reported using tractors or animal traction for agricultural activities. When aggregated at the municipal level by averaging across farms, this variable represents the proportion of farms within the municipality that reported the use of these capital inputs.

Appendix C: Specification Tests

To evaluate whether the Stochastic Frontier Analysis (SFA) is an appropriate modeling approach, and to verify the validity of the chosen functional form and key assumptions about the production frontier parameters, a set of specification tests is carried out.

We conduct a series of log-likelihood ratio tests to support key methodological choices, with the results presented in Table B1. The first test compares the Cobb-Douglas (CD) and Translog (TL) functional forms. The null hypothesis, that all interaction and second-order terms are equal to zero, is rejected, indicating that the more flexible Translog specification provides a better statistical fit than the restrictive Cobb-Douglas form. However, to enable the decomposition of Total Factor Productivity (TFP), we adopt the Cobb-Douglas specification, as it satisfies the properties required by index number theory.

The second test evaluates whether a stochastic production frontier provides a better fit than an average production function estimated via OLS. The null hypothesis of no inefficiency is rejected, validating the use of a stochastic frontier approach.

Finally, the third test compares two assumptions about the distribution of inefficiency. The half-normal specification is rejected in favor of a truncated normal distribution, suggesting that the latter better captures the inefficiency structure in the data.

Table C1. Loglikelihood ratio tests for model selection

Null Hypothesis	**Test Statistic (λ)**	**Critical Value**	**Decision**	**Choice**
H_0: $\beta_{ij} = 0$	53.5	25.6	Reject H_0	Translog
H_0: $\gamma = \mu = \eta = 0$	139.6	7.04	Reject H_0	Stochastic frontier model
H_0: $\mu = 0$	9.9	2.7	Reject H_0	Truncated-normal

Appendix D: Additional specification results

Table D1. Imputed variables in survey data, 2008 and 2015

Variable	Obs. With information	Imputed obs.	Total
Labor Value (2008)	209	22	231
Labor Value (2015)	213	18	231
Prop. of fertilizer use (2008)	208	23	231
Prop. of fertilizer use (2015)	216	15	231
Prop. of capital use (2008)	194	37	231
Prop. of capital use (2015)	211	20	231

Table D2: Stochastic Production Frontier Results using Unbalanced Panel, 2008 - 2015

Dependent Variable: Log Production Value	(1)
Log Land (Ha)	0.879***
	(0.029)
Log Labor Expenses	0.131***
	(0.024)
Log Family Labor Index	0.147
	(0.090)
Log Input Use	0.111***
	(0.034)
Log Capital Use	0.062**
	(0.029)
Average Degree Days	-0.027**
	(0.013)
Average Harmful Degree Days	-0.114***
	(0.038)
Average daily precipitation in the growing season	0.088*
	(0.051)
Average of squared daily precipitation	0.001
	(0.001)
Natural Region: Valley	-0.928***
	(0.107)
Natural Region: Highland	-0.703***
	(0.104)
Year: 2013	-0.680***
	(0.074)
Year: 2015	-0.091
	(0.070)
Valley*2013	0.630***
	(0.092)
Valley*2015	0.435***
	(0.098)
Highland*2013	0.452***
	(0.087)
Highland*2015	0.143
	(0.093)
Sigma u	12.3
	(0.44)
Sigma v	0.28
	(0.022)
Lambda	43.839
	(0.452)
Observations	835
Municipalities	302

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table D3. Annual Values and Growth Rates of Output, Inputs, TFP, and TFP Components using Unbalanced Panel

Year	Output Index	Input Index	TFP Index	SE Index	TEC Index	TP Index	WE Index	SN
2008	0.017	0.150	0.114	0.534	0.787	1.975	0.849	0.162
2013	0.016	0.168	0.097	0.555	0.832	1.450	0.860	0.169
2015	0.027	0.185	0.144	0.573	0.792	2.159	0.851	0.173
Growth Rate p.a. (%)	**6.532**	**3.057**	**3.372**	**0.999**	**0.083**	**1.281**	**0.023**	**0.948**

Table D4: Stochastic Production Frontier Results using Unbalanced Panel 2008 - 2015, Excluding Municipalities with Fewer than 10 Surveyed Farms

Dependent Variable: Log Production Value	(1)
Log Land (Ha)	0.810***
	(0.040)
Log Labor Expenses	0.179***
	(0.030)
Log Family Labor Index	0.095
	(0.118)
Log Input Use	0.100***
	(0.037)
Log Capital Use	0.050
	(0.036)
Average Degree Days	-0.029*
	(0.017)
Average Harmful Degree Days	-0.032
	(0.050)
Average daily precipitation in the growing season	0.136*
	(0.071)
Average of squared daily precipitation	-0.001
	(0.001)
Natural Region: Valley	-0.993***
	(0.130)
Natural Region: Highland	-0.727***
	(0.134)
Year: 2013	-0.650***
	(0.084)
Year: 2015	-0.145*
	(0.078)
Valley*2013	0.552***
	(0.100)
Valley*2015	0.517***
	(0.105)
Highland*2013	0.242**
	(0.103)
Highland*2015	0.174
	(0.110)
Sigma u	9.467
	(0.145)
Sigma v	0.227
	(0.021)
Lambda	41.55
	(0.151)
Observations	441
Municipalities	147

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table D5. Annual Values and Growth Rates of Output, Inputs, TFP, and TFP Components, Excluding Municipalities with Fewer than 10 Surveyed Farms (Index-Based)

Year	Output Index	Input Index	TFP Index	SE Index	TEC Index	TP Index	WE Index	SN
2008	0.024	0.159	0.148	0.650	0.826	1.916	0.846	0.170
2013	0.020	0.181	0.111	0.670	0.851	1.339	0.861	0.170
2015	0.033	0.190	0.174	0.678	0.830	2.136	0.853	0.170
Growth Rate p.a. (%)	**4.987**	**2.571**	**2.356**	**0.596**	**0.068**	**1.565**	**0.124**	**-0.011**

Table D6. Impact of land titling on TFP in the short and long term, including hectares titled during the year of each survey

Dependent Variable: Log Production Value	(1)	(2)
Titled hectares per capita (last 2 yrs)	0.0003	
	(0.0027)	
Titled hectares per capita (1997- survey year)		-0.0024***
		(0.0007)
Log Land (Ha)	0.9828***	0.9961***
	(0.0650)	(0.0632)
Log Labor Expenses	0.0324	0.0272
	(0.0357)	(0.0359)
Log Family Labor Index	0.1179	0.1182
	(0.1548)	(0.1526)
Log Input Use	0.0317	0.0299
	(0.0410)	(0.0411)
Log Capital Use	0.0980**	0.0980**
	(0.0427)	(0.0426)
Average Degree Days	0.0422	0.0484*
	(0.0277)	(0.0268)
Average Harmful Degree Days	-0.0221	-0.0153
	(0.1134)	(0.1117)
Average daily precipitation in the growing season	0.2018	0.1796
	(0.1285)	(0.1252)
Average of squared daily precipitation	0.0001	0.0001
	(0.0022)	(0.0021)
Observations	693	693
R-squared	0.9291	0.9298
Municipality FE	Yes	Yes
Year FE	Yes	Yes
Region-Year FE	Yes	Yes

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table D7. Impact of land titling on access to credit in 2013

Dependent Variable: Credit access (prop.)	(1)	(2)
Titled hectares per capita (1997- survey year)	-0.0003*	
	(0.0002)	
Titled hectares per capita (last 2 yrs)		-0.0002
		(0.0005)
Average Degree Days	-0.0061**	-0.0068**
	(0.0030)	(0.0030)
Average Harmful Degree Days	-0.0004	-0.0047
	(0.0085)	(0.0083)
Average daily precipitation in the growing season	-0.0000	-0.0046
	(0.0089)	(0.0086)
Average of squared daily precipitation	0.0005**	0.0006**
	(0.0002)	(0.0002)
Natural region: Valley	-0.0614***	-0.0602***
	(0.0149)	(0.0150)
Natural region: Highland	-0.0827***	-0.0825***
	(0.0153)	(0.0154)
Observations	231	231
R-squared	0.2583	0.2466
Region FE	Yes	Yes

Note: "Credit access (prop.)" refers to the proportion of farms in the municipality with access to credit in the past three years (since 2013). "Titled hectares per capita (1997- survey year)" refers to the cumulative sum of titled hectares per capita from 1997 up to the year prior to the survey. "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.
Standard errors in parentheses p<0.01, ** p<0.05, * p<0.1

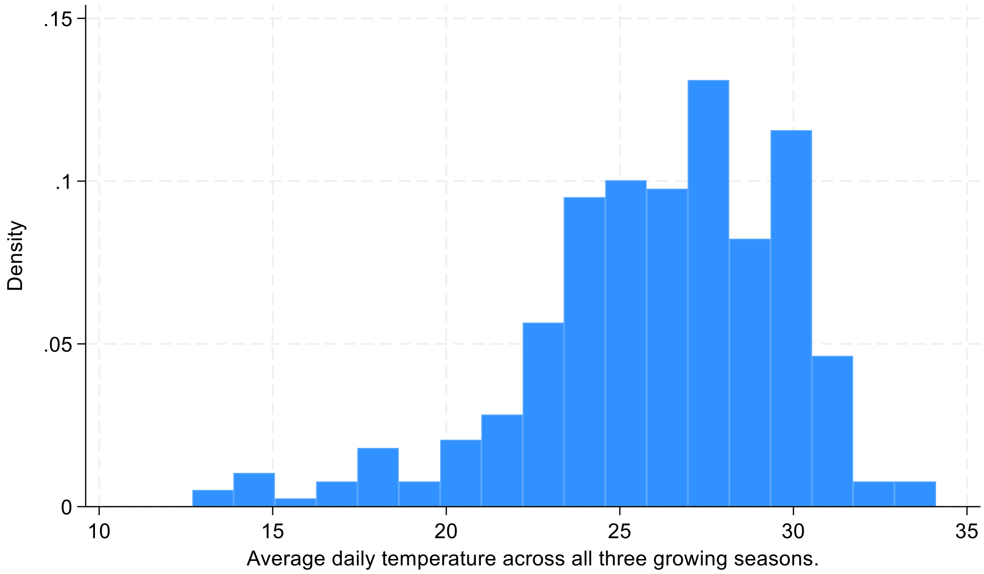
Table D8. Effect of land titling on farms obtaining land through purchase in 2013

Dependent Variable: Prop. farms purchased plot	(1)	(2)
Titled hectares per capita (1997- survey year)	-0.0017***	
	(0.0004)	
Titled hectares per capita (last 2 yrs)		-0.0019
		(0.0013)
Average Degree Days	-0.0165**	-0.0205***
	(0.0072)	(0.0074)
Average Harmful Degree Days	-0.0380*	-0.0617***
	(0.0205)	(0.0207)
Average daily precipitation in the growing season	-0.0532**	-0.0799***
	(0.0214)	(0.0215)
Average of squared daily precipitation	0.0029***	0.0034***
	(0.0006)	(0.0006)
Natural region: Valley	-0.0071	0.0003
	(0.0361)	(0.0376)
Natural region: Highland	-0.1292***	-0.1300***
	(0.0369)	(0.0385)
Observations	231	231
R-squared	0.3439	0.2856
Region FE	Yes	Yes

Notes: "Prop. farms purchased plot" refers to the proportion of farms in the municipality that obtained their plot through purchase. "Titled hectares per capita (1997- survey year)" refers to the cumulative sum of titled hectares per capita from 1997 up to the year prior to the survey. "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. Standard errors in parentheses. p<0.01, ** p<0.05, * p<0.1

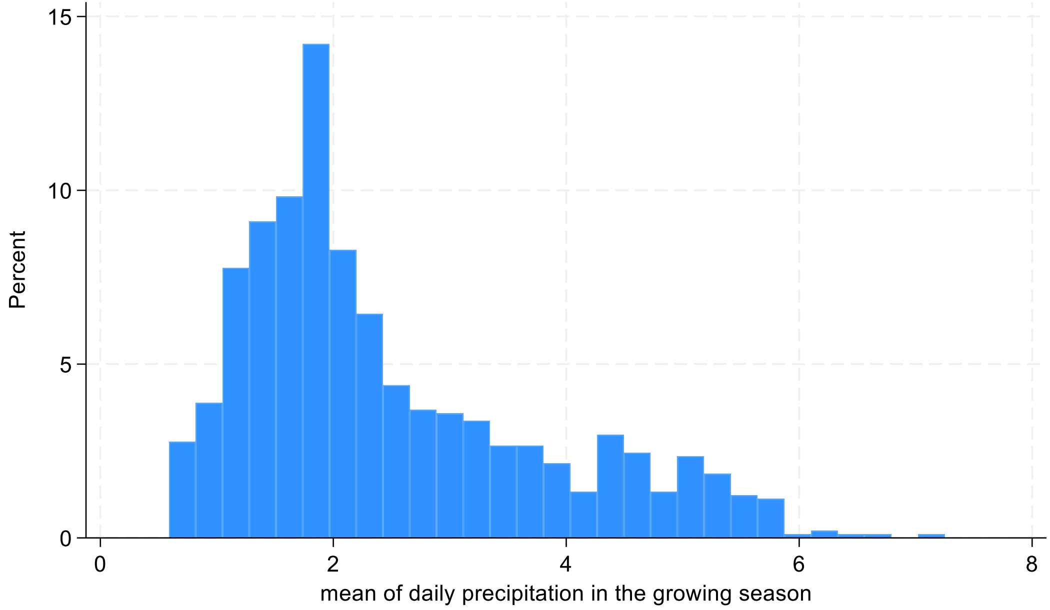
Appendix E. Histograms of daily growing season temperature and precipitation

Figure E1: Distribution of average daily temperatures across the 2008, 2013, and 2015 growing seasons



Note: Average daily temperature is expressed in degrees Celsius, and the growing season is defined as the survey reference period for each survey round.
Data source: MODIS Land Surface Temperature/Emissivity Daily (MOD11A1)

Figure E2: Distribution of mean daily precipitation across the 2008, 2013, and 2015 growing seasons



Note: Precipitation is expressed in mm/day, and the growing season is defined as the survey reference period for each survey round.
Data source: Copernicus Climate Change Service's Essential climate variables for water sector applications derived from climate projections