Journal of Animal Environment
(E-ISSN 2717-1396, ISSN 2717-1388)

Original Research Paper

Agricultural Productivity and Technical Efficiency in Colombia: Evidence by Crop Type and Farm Size from the 2019 National Agricultural Survey

Running Title: *Agricultural Productivity and Technical Efficiency in Colombia*

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Abstract

Objective: This study examined the determinants of agricultural productivity and technical efficiency in Colombia, with particular attention to crop type and farm size. Methods: Data were drawn from more than 137,000 agricultural production units in the 2019 National Agricultural Survey, which covered 32 departments using a stratified probabilistic cluster design. Partial Factor Productivity of Land and Total Factor Productivity were calculated, and a Cobb–Douglas stochastic frontier model was estimated in Stata 16 to evaluate the effects of land, labor, machinery, inputs, producer characteristics, and institutional factors. Results: Land, labor, machinery, and inputs were positively and significantly associated with output, and the estimated technology exhibited increasing returns to scale. Technical efficiency varied with producer age, education, innovation, crop diversification, access to finance, and crop concentration. Productivity measures also showed substantial heterogeneity across crop types, especially among permanent crops. Conclusion: Agricultural productivity in Colombia depends on resource endowments as well as human-capital and institutional conditions. Policies that improve education, financing, innovation, and crop diversification, while supporting younger producers, could strengthen technical efficiency and sustainable rural development.

Keywords: agricultural productivity; technical efficiency; stochastic frontier analysis; farm size; crop type; Colombia

Abbreviations

Abbreviation	Full Form
ENA	Encuesta Nacional Agropecuaria (National Agricultural Survey)
UPA	Unidad de Producción Agropecuaria (Agricultural Production Unit)
PPFT	Partial Factor Productivity of Land
TFP	Total Factor Productivity
SFA	Stochastic Frontier Analysis
HHI	Herfindahl-Hirschman Index
TE	Technical Efficiency
SD	Standard Deviation
GE	Generalized Entropy Index
Min	Minimum value
Max	Maximum value
ORCID	Open Researcher and Contributor ID

Introduction

Agricultural sector has traditionally been a backbone of the Colombian economy, as it has played an essential role in the economic growth of the country, not only by creating job opportunities in the rural setting but also through food security (Pérez Gutiérrez et al., 2025). Moreover, almost half of the land in the country is in agriculture (Chaves Castro, 2017; Ramírez-Villegas et al., 2012). DANE data suggests that this economic

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Received: 25th May, 2026; Revised: 6th June, 2026; Accepted: 8th June, 2026; Available Online: 30rd July, 2026
(DOI): 10.70102/AEJ.2026.18.2s.18

activity contributed about 6% of GDP and 14.1% of productive activity of the working population in 2023. Nevertheless, the industry has significant problems of productivity and competitiveness in the international market, regardless of its significance.

Here, productivity and technical efficiency are critical in economic growth and development particularly among the emerging economies like Colombia. Authors such as Fuglie et al. have found that increases in productivity not only improve farmers' incomes but also contribute to reducing rural poverty, stabilizing food prices, and promoting environmental sustainability (Fuglie et al., 2020). For these reasons, understanding the factors that determine agricultural productivity is crucial for informing the design of effective policies that drive sectoral growth and, consequently, the country's economic development.

Research such as that by Perfetti et al. highlights the need to boost agricultural productivity through measures that include access to resources for technological development and the adoption of efficient production methods (Perfetti et al., 2019). Similarly, Leibovich et al. emphasize the role of farm size and market access (Leibovich et al., 2013), while Gómez and Higuera examine the relationship between productivity and institutional factors, such as access to credit and formalization of rural property (Gómez & Higuera, 2018). Although there is quite a rich literature base, the majority of studies are based on aggregated data or small sample size to represent the complexity of agricultural productivity in the country.

This paper aims to address this gap in the literature by examining the data presented in the 2019 National Agricultural Survey (ENA), which gives a more in-depth and recent perspective on the agriculture industry in Colombia (DANE, 2020). Thus, the objectives of the study are to define and examine the key factors of productivity and technical efficiency of agriculture in the country and focus on crop types and farm size (harvested areas). With 2019 ENA data, the research will pinpoint major issues that can be used to formulate policies that can enhance and uplift the agricultural sector.

This discussion is especially topical in the modern context, when the modernization of the rural sector is a priority of the Colombian society. This is encapsulated in the National Development Plan (DNP, 2022) of 2022–2026 that highlights the importance of supporting research and development (R&D) as a foundation of industrialization, modernization, and enhancing agricultural productivity (United Nations Network on Migration, 2022). It, therefore, emphasizes the need to develop, adapt and adopt technologies that satisfy the needs of producers. Additionally, given the climatic change issues (Ramírez-Villegas et al., 2012), it is crucial to learn the components that affect agricultural output to establish measures that can enhance the resilience of the sector.

The rest of the paper is organised in the following way: Section two discusses the theoretical framework and provides a review of the existing literature; section three discusses the data and methodology that is used; section four provides the analysis results; section five discusses the results in terms of existing literature and their implication to the agricultural policy; the last part section six and seven concludes the study and presents the main findings and recommendations.

Conceptual and Empirical Background

Concepts Associated with Agricultural Productivity

Productivity, as a fundamental variable for explaining economic growth, is not a recent concern. Early theorists such as Adam Smith (1776) and David Ricardo (1817) expressed concerns about the capacity of land to produce sufficient food to meet the demands of a developing society and a continuously growing population. Their works highlight the initial focus on the need to adopt technical improvements to increase the availability of agricultural goods and the productivity of land (Boianovsky, 2013).

In general terms, productivity refers to the efficiency with which resources are transformed into agricultural products (Fuglie et al., 2020). In other words, productivity is a ratio of output received with respect to the resources employed in the production process. The other way of interpreting this concept is that agricultural productivity is a measure of the amount of outputs produced through any given combination of inputs in other words how effectively farmers utilize productive factors e.g. land, labor, capital, inputs and services to yield goods (crops) and that is to produce more with less (Reza Anik et al., 2020).

Partial Factor Productivity (PFP) in its turn is a metric that calculates the output in relation to one of the factors of production and all the other factors remain the same (Murray, 2016). According to the economic literature, the most common PFP measures are land productivity and labor productivity. Land productivity is generally measured as yield per hectare (Sheng et al., 2019), whereas labor productivity is calculated as output per unit of labor and expressed in man-hours or man-days (Restuccia et al., 2008).

Although PFP measures are relatively easy to calculate, Syverson argues that such results do not necessarily capture the interactions that occur among different productive factors, which may lead to biased interpretations. For example, as noted by Syverson in 2011 yield per hectare (a form of PFP) could increase due to greater use of fertilizers or irrigation technology rather than an actual improvement in land-use efficiency (Syverson, 2011). Similarly, it is not always clear whether an increase in output per worker is attributable to higher mechanization or intrinsic labor productivity (Hamilton et al., 2021). For this reason, complementary measures of partial productivity are necessary.

Productivity growth reflects improvements in the efficiency of farmers' production, that is, changes in productivity over time supported by technical progress. According to the USDA, agricultural productivity growth depends not only on the ability to increase output but also on efficiency in reducing resource use while maintaining the same level of output (USDA, 2025). This growth measure is referred to as Total Factor Productivity (TFP). In the words of Fuglie, TFP is the ratio of total output to an aggregate index of all inputs (Perfetti et al., 2019), and is considered useful for measuring technological progress and efficiency changes over time (Fuglie et al., 2020).

Gollin et al. argue that measuring productivity, particularly in the agricultural sector, is not straightforward and faces several bottlenecks that must be considered in analyses and interpretations. These challenges include the heterogeneity of agricultural products, production seasonality, climate change, and differences in the quality of inputs and services used in the production process (Gollin et al., 2014).

Theoretical Review on the Determinants of Agricultural Productivity

Among the early contributors to agricultural economics are Theodore Schultz and Zvi Griliches, whose theories emerged during the 1950s and 1960s (Alston et al., 2010). Schultz in 1956 argued that declining productivity in traditional agriculture was due to the lack of modern technologies, implying that productivity growth requires the introduction of techniques capable of increasing both productivity and output within the production process (Schultz, 1956). Griliches in 1963, analysing agricultural productivity, posited that output depends more on the quality of inputs—including labor—and economies of scale than on technical change. In a similar vein, during the 1970s (Griliches, 1963), Hayami and Ruttan emphasized that the direction of technical change in agriculture is influenced by the relative prices of production factors, meaning that innovations tend to reduce the use of factors that are scarcer and therefore more costly (Hayami & Ruttan, 1971).

Recently, works by Acemoglu, and Adamopoulos and Restuccia, have contributed to the field of understanding the productivity dynamics (Acemoglu, 2002; Adamopoulos & Restuccia, 2014). Acemoglu writes on the issue of technological change not being neutral but this can be biased towards or directed to a particular factor of production, whereby specific innovations enhance the productivity of some factors more than others (Acemoglu, 2002). When applied to agriculture, it can be used to understand why some innovations can be of benefit to large producers more than to smallholders or vice versa. Any other way, agricultural innovations may be biased, such as towards capital-intensive use (commercial or mechanized farming) or toward labor-intensive use (smallholder or family farming).

Adamopoulos and Restuccia compare the agricultural productivity of rich and poor countries with the focus on the farm size distribution in each economy. Among their major findings are that agricultural productivity in poor countries is about 45 times less than that of the rich countries. The other important observation is that larger farms are more productive compared to smaller farms because of economies of scale and access to markets and technology (Adamopoulos & Restuccia, 2014).

During the late 1990s and the first 20 years of the 21st century, other views were put forward. To illustrate this, Scoones in 1998 underlines that productivity does not only refer to the economic meaning of output but also to sustainability and resiliency of rural livelihoods (Scoones, 1998). This is, the livelihoods of farmers are not just limited to agricultural activity. In line with this, further key ideas emerge, such as sustainable livelihoods (in harmony with nature), the various types of capital (natural, physical, financial, human and social), the environment under which producers work, life strategies, institutions, and other factors at play.

Empirical Research on Agricultural Productivity

This part explores different researches that have studied agricultural output based on various methods and approaches. The determinants of productivity in the industry, cross-country productivity differences, technology adoption, the effects of climate change, farm size, and efficiency are some of the issues that these works explore. The most important results are given below.

Mundlak et al. present findings in 30 countries based on panel data and a production function model with heterogeneous technology, revealing that human capital, research and development investment and infrastructure are the main determinants of productivity in the agricultural sector. One of the outstanding findings is that the country-specific policies based on the integration of local conditions and technological heterogeneity are necessary to enhance agricultural productivity. The paper also focuses on the need to make long term investments on education, research and rural infrastructure (Mundlak et al., 2012).

Gollin et al. use microeconomic household survey data on 151 countries to analyze the productivity gap between agricultural sectors and non-agricultural ones. The most interesting feature of this work is that it criticizes the statistics presented by the national agencies on productivity disparity between agriculture and other activities in developing countries, which have been used in making policies to make labor mobility out of the agricultural sector easy. The results suggest that the current gap is mainly brought about by variations in the quality of inputs especially human and physical capital (Gollin et al., 2014).

Foster and Rosenzweig summarise and analyse empirical studies on micro-level adoption of technology in developing countries in agriculture. Their study answers the question of why not all technologies which seem to be useful in terms of agricultural development are adopted rapidly and evenly in such situations. Some of the major findings point out to the obstacles to the adoption of technology, which depend on information access, education, and social networks (Foster & Rosenzweig, 2010).

In estimating the effects of climate change on key crops in sub-Saharan Africa by the middle of the 21 st century, Schlenker and Lobell consider 20 nations, by using predictions of 16 climate models of the 2046-2065 period. According to their findings, climate change will have adverse impacts on crops like maize, sorghum, millet, peanuts and cassava. Policy wise, the authors emphasize that there is a need to work out adaptation measures to agriculture, encourage crop diversification, and invest in urgent deployment of heat-resistant crops (Schlenker & Lobell, 2010).

Lastly, Adamopoulos and Restuccia examine the disparity in agricultural productivity between poor and rich countries with respect to the farm size distribution. The authors relate to the agricultural census data of several countries with some supplementary sources provided by FAO and others. Among the major discoveries is that the agricultural productivity gap between the rich and the poor countries can be attributed to differences in the distribution of farm size to the tune of 25% (Adamopoulos & Restuccia, 2014). Small-farm policies in the developing world can have an adverse effect on productivity because they induce producers to farm at a smaller scale than the optimal one, which will lower the aggregate productivity.

The Colombian Agricultural Sector Literature

Colombia has witnessed multiple studies on the subject of agriculture in the country taking various angles. Perfetti et al. provide an in-depth analysis of the agricultural sector, focusing on the development of agricultural production structure, productivity, and its determinants, indicating such factors as rural infrastructure, access to markets, education levels, and access to finance. Other agrarian policies, land distribution and tenure, innovation and technology, value chains, and sustainability are also taken into consideration in the study (Perfetti et al., 2019).

In terms of land tenure, the IGAC (2023) research reveals the level of land concentration in Colombia. Minifundios (0–3 ha) account for 68.8% of properties (2,385,084 plots) but only 4% of total land area (1,811,412 ha). The next category, small farms (3–10 ha), represents 17% of properties (619,547 plots) covering 7% of total area (3,499,820 ha). On the other end, big estates (latifundios, >200 ha) represent 0.8% of properties (29,525 plots) but 44% of the rural land (21,535,765 ha). According to IGAC (2023), the rural GINI coefficient of Colombia is 0.89, which indicates that the land ownership is extremely concentrated.

Compounding the issue of land distribution and tenure is the fragmentation of land, which has accelerated for plots smaller than one hectare (Paul & wa Gĩthĩnji, 2018). This problem is further exacerbated by climate change. Accordingly climate shocks lead to increased land fragmentation, resulting in more owners with smaller plots as a household-level response (Arteaga et al., 2025). Newly acquired plots tend to be managed by households or individuals with lower agricultural skills, reducing average skill levels following a climate shock. In the medium and long term, aggregate productivity may partially recover, but the deterioration in land allocation and sector composition—i.e., the presence of less productive new farmers—persists (Giller et al., 2021).

Based on the National Agricultural Survey and econometric methods, Gáfaro et al. analyse the relationship between land access, agricultural productivity, and rural poverty in Colombia. In addition to confirming the problem of land concentration, their study identifies an inverse relationship between property size and land productivity. According to the authors, determinants of productivity in Colombia include access to credit, technical assistance, producer education level, and infrastructure, including access to roads and markets (Gáfaro et al., 2012).

Junguito et al. present the history of agrarian policies in Colombia and assess their effectiveness in the development of the sector. Some of the variables investigated in the study comprise agrarian policies, productivity, international trade, agricultural credit, research and development, technological change and environmental sustainability. In their policy recommendations, they propose to enhance rural infrastructure, improve research and extension systems, producer associations, better market and value chain access, and innovation and adoption of technology (Junguito et al., 2014).

Ramírez-Villegas et al. evaluate the possible effects of climate change on Colombian agriculture in 2050 (Ramírez-Villegas et al., 2012). Global and regional climate models are employed by the authors to forecast temperature and precipitation changes, and crop models to assess the impact on agricultural productivity. According to the findings, agricultural production will more probably be impacted negatively without the intervention of adaptation and mitigation strategies and with large amounts of losses on the major crops and other effects related to the degradation of the soil and the decrease in the organic matter (Ramírez-Villegas et al., 2012).

Forero et al. assess and compare the efficiency of agricultural producers and challenge the fact that big farms are considered more efficient compared to small farms. Their results suggest that the majority of small producers are as efficient (or even more efficient) as large producers in terms of land productivity. To this end, they state that sectoral policy should be equipped along the lines of producer size and type and not biased towards large farms (Forero et al., 2013).

Lastly, Chaves compares the agricultural GDP cycles in Colombia during the period 1976-2013 and shows the nature of these cycles, length, and associations with the supply and demand variables. The research concludes that Total Factor Productivity (TFP) played a significant role in the growth of agricultural GDP in this period implying that there was a significant enhancement in the efficiency of production and adoption of technology in the field (Chaves Castro, 2017).

Materials and Methods

Data Source and Study Sample

In this work, the 2019 National Agricultural Survey (ENA) was applied, which was carried out by the National Administrative Department of Statistics (DANE) in Colombia. DANE says that the 2019 ENA serves all 32 departments of the country, in the primary agricultural areas of Colombia, with an effective coverage of 97.2 and serving only rural parts. The survey uses a stratified, probabilistic sampling design and cluster sampling design, which can be used to make representative estimates and inferences about the population (DANE, 2020).

The survey was carried out in two stages, which were related to the two semesters of 2019. During the first semester, DANE carried out an interview of 67,714 Agricultural Production Unit (UPA), of which 1,330 are Agricultural Exploitation Unit based on the list frame. During the second semester, 69,540 UPAs were interviewed out of which 1,330 are Agricultural Exploitation Units as per the list frame. The ENA contains extensive data about the agricultural production, inputs used, the nature of Agricultural Production Units (UPA), and socio-economic factors about the producers.

Data Preparation

Since the ENA uses probabilistic, stratified, and cluster sampling, data selection and cleaning were performed in the following way: First, the observations that have missing values in major variables have been eliminated. Second, the 1% and 99% winsorization method was used to identify and deal with outliers (Dixon, 1960). Third, measurement units were checked, and where necessary, conversions to standard or homogeneous units were done.

Productivity Measures

Partial Factor Productivity of Land (PPFT) is one of the most common variables of the literature that enables comparison between various types of crops (Sheng et al., 2019), which can be written as follows:

$$PPFT = \frac{\text{Production}}{\text{Cultivated Area}} \tag{1}$$

Technically, the previous formula is a calculation of yields; however, for the present case study, it will be used as a proxy variable for Partial Factor Productivity of Land (PPFT).

Another variable of interest is Total Factor Productivity (TFP), which provides a more comprehensive measure of productive efficiency by considering multiple inputs (Murray, 2016). This variable was calculated using the Stochastic Frontier Analysis (SFA) method. The set of independent variables included in the analysis is presented in Table 1.

Table 1. Measurement of Independent Variables

Type	Variable – Measurement	Theoretical Reference
UPA Characteristics	Farm size (hectares)	Adamopoulos and Restuccia (2014); Sheng et al. (2019)
	Crop diversification index (Herfindahl-Hirschman)	Murray, (2016)
	Irrigation use (dummy variable)	Foster and Rosenzweig (2010); Fuglie et al. (2020)
	Technology use (innovation) (dummy variable)	Foster and Rosenzweig (2010); Fuglie et al. (2020); Fuglie (2018)
Producer Characteristics	Farmer age (years)	Sheng et al. (2019); Fuglie et al. (2020); Gollin et al. (2014)
	Education level (years of schooling)	Foster and Rosenzweig (1995); Sheng et al. (2019)
	Gender (dummy variable)	Sheng et al. (2019)
Institutional Factors	Access to finance (dummy variable)	Fuglie et al. (2020)
	Technical assistance received (dummy variable)	Fuglie et al. (2020)

Source: *Own elaboration, based on literature review and theoretical framework.*

Stochastic Frontier Specification

On the other hand, the measures of productivity in question are, on the one hand, the Partial Factor Productivity (PFP), which was computed based on the 2019 data in the ENA. Based on the work of Murray in 2016 who have examined Total Factor Productivity (TFP) by employing parametric Stochastic Frontier Analysis (SFA) method to analyse panel data (Murray, 2016), this study takes the direction proposed by Aigner et al. to examine cross-sectional data by estimating a stochastic Cobb-Douglas production equation (Aigner et al., 1977). Following this, the given production function can be supposed to be the following:

$$Y_i = f(X_i; \beta) * \exp(v_i - u_i) \quad (2)$$

Where:

- YiY_iYi is the output of UPA iii.
- XiX_iXi are the production factors.
- νi\nu_iνi is the random error term, where νi∼N(0,σν2)\nu_i \sim N(0, \sigma_\nu^2)νi ∼N(0,σν2).
- μi\mu_iμi is the technical inefficiency term, where μi∼N+(μi,σμ2)\mu_i \sim N^+(\mu_i, \sigma_\mu^2)μi∼N+(μi,σμ2), with N+N^+N+ being a normal distribution truncated at zero.

By performing the corresponding transformations and substitutions, Equation 2 can be rewritten in the following form:

$$lnY_i = \beta_0 + \beta_1 \ln(Tierra_i) + \beta_2 \ln(Trabajo_i) + \gamma_1 Capital_i + \gamma_2 Insumos_i + v_i - u_i \quad (3)$$

Where:

- (\ln Y_i): Natural logarithm of the output of UPA (i).
- (\ln \text{Land}_i): Natural logarithm of the cultivated area.
- (\ln \text{Labor}_i): Natural logarithm of the number of workers.
- (\text{Capital}_i): Takes the value 1 if the unit uses capital; otherwise, 0.
- (\text{Inputs}_i): Takes the value 1 if the unit uses agricultural inputs; otherwise, 0.

The technical inefficiency term ((u_i)) is specified as follows:

$$u_i = \delta_0 + \delta_1 Z_1 + \delta_2 Z_2 + \cdots + \delta_m Z_{im} + w_i \quad (4)$$

Where:

- (Z_i): A vector of variables capturing technical inefficiency. This vector includes the following variables: producer age, producer education level, producer gender, irrigation use, technology use (innovation), access to finance, technical assistance received, and crop diversification index.
- (w_i): The error term.

The technical efficiency of each UPA is calculated as follows:

$$ET_i = exp(-\mu_i) \quad (5)$$

Finally, Total Factor Productivity (TFP) can be formulated as:

$$PTF_i = \frac{Y_i}{X_i; \beta} = exp(v_i - \mu_i) \quad (6)$$

Equation 6 is a calculation of crop yields, which we use as a proxy variable for TFP. This allows us to estimate the production function, identify technical inefficiency, calculate the technical efficiency of the UPAs, and derive the TFP measure.

The estimation of the stochastic frontier production was done with the maximum likelihood method in this study, which is a powerful statistical estimation method that enables simultaneous estimation of production parameters and the effects of technical inefficiency. Stata 16, a sophisticated econometric program, was used to conduct the analysis, which allowed accurately modelling the data of the cross-section, applying the Cobb-Douglas production function, and extracting the indicators of technical efficiency and total factor productivity. This approach will make sure that the effects of random noise and the effects of inefficiency are well captured so that we can have reliable and interpretable estimates of the determinants of agricultural productivity in the sampled UPAs.

Results

Descriptive Statistics

Figure 1 presents the distribution of total cultivated area by deciles. It can be observed that the cultivated area is concentrated toward the 10th decile. In other words, the variable "cultivated area" reflects the high concentration of agricultural land in Colombia.

Figure 1.
Distribution of average cultivated area by decile

Source: *Own elaboration.*

Descriptive Statistics

The Generalized Entropy (GE) indices also indicate a high level of concentration in cultivated area. Similarly, the Gini coefficient of 0.8378 reflects extremely high inequality.

Table 2.
Inequality Measures of Cultivated Area: Generalized Entropy (GE) Indices

GE(-1)	GE(0)	GE(1)	GE(2)	Gini
1.407,155	217,854	172,971	338,544	0,83786

Source: *Own elaboration.*

Table 2 also presents the main statistics for Partial Factor Productivity of Land (PPFT, crop yields). The PPFT for temporary crops shows a mean yield of 28.03 tons per UPA with a median of 0.24, ranging from 0 to 118,125 tons. The PPFT for permanent crops exhibits less variability, with a mean of 13.34 tons and a median of 0.16. For pastures, the mean is 13.95 tons per UPA with a median of 0.12, although the range is wide.

Table 3.
Land Yield Statistics by Crop Type – PPFT

Crop Type	Media	p50	SD	Max
Temporary crops	28.03	0.24	313.30	118.12500
Permanent crops	13.34	0.16	158.27	20.00000
Pastures	13.95	0.12	141.03	6.49773

Source: *Own elaboration. Note: PPFT measured in tons per UPA.*

Table 4 presents statistics for the main independent variables. Land (in hectares) has a mean of 32.0 ha per UPA, with a very wide range. The standard deviation exceeds the mean, suggesting the presence of both very large and very small farms.

Table 4.
Statistics of Key Non-Dummy Variables

Variable	Media	Desv. Est.	Min	Max
Land	32.0	295.7	0.0	16,05.00
HHI	0.9	0.2	0.3	1.0
Labor	5.0	43.2	-	2,32.90
Age	54.7	14.3	13.0	99.0

Source: *Own elaboration.*

The Herfindahl-Hirschman Index (HHI) shows high crop concentration with a mean of 0.9 and SD of 0.2. Labor indicates an average of 5 permanent workers per UPA, but with wide variation (SD = 43.2). The average age of producers is approximately 54.7 years, ranging from 13 to 99 years.

Econometric Results

Table 5.
Total Factor Productivity (TFP) by Crop Type

Tipo cultivo	Mean	p50	SD	Min	Max
Temporary crops	459.44	26.95	2.48505	0.00	124.98700
Permanent crops	281.54	21.77	1.17315	0.04	68.09540
Pastures	437.09	16.18	3.35694	0.08	60.48755
Total	438.21	25.63	2.40955	0.00	124.98700

Source: *Own elaboration.*

According to Table 5, TFP results indicate differences across crop types. Temporary crops have a higher mean TFP than permanent crops and pastures, but also exhibit the greatest variability.

Table 6.
Econometric Results for Output and Technical Efficiency

lnY	Coefficient	Std. err.	Z	P>z	[95% conf.	interval]
lnY	0.3761758	0.0008344	450.84	0.000	0.3745404	0.3778112
lnTierra	0.4092617	0.0025945	157.74	0.000	0.4041766	0.4143467
lnTrabajo	0.3690293	0.0032383	113.96	0.000	0.3626824	0.3753762
uso_maquinaria	0.3186258	0.0042009	75.85	0.000	0.3103922	0.3268594
uso_insumos	4.2000160	0.0052506	799.91	0.000	4.189725	4.210307
_cons						
lnsig2v	1.3962700	0.0011237	1.242.59	0.000	1.394067	1.398472
_cons						
lnsig2u	-0.026274	0.0010626	-24.73	0.000	-0.0283569	-0.0241917
edad	0.0002191	8.94E-06	24.5	0.000	0.0002015	0.0002366
edad2	0.078241	0.0115307	6.79	0.000	0.0556411	0.1008408
educ_2	-0.159644	0.014287	-11.17	0.000	-0.1876459	-0.1316418
educ_3	-0.351051	0.0425654	-8.25	0.000	-0.4344774	-0.267624
educ_4	-0.262499	0.0222119	-11.82	0.000	-0.3060336	-0.2189647
educ_5	-0.498573	0.0070421	-70.8	0.000	-0.5123756	-0.4847712
genero	-4.390.171	854.41180	-0.05	0.959	-1.718.518	1.630.715
riego	0.305693	0.0243274	12.57	0.000	0.2580121	0.3533738

lnY	Coefficient	Std. err.	Z	P>z	[95% conf.	interval]
innovacion	-0.270315	0.019041	-14.2	0.000	-0.3076345	-0.2329949
financiamiento	2.126.846	0.041032	51.83	0.000	2.046.425	2.207.267
HHI	-0.685881	0.0517539	-13,25	0.000	-0.7873171	-0.5844456
_cons						
sigma_v	2.01	0.0011293			2,007788	2,012215

Source: *Own elaboration*

According to Table 6, the results of the stochastic frontier model indicate that the production factors—land, labor, machinery, and inputs (considered individually)—have positive effects on UPA output and are statistically significant. Their elasticities suggest that a 1% increase in land increases output by approximately 0.38%, while a 1% increase in labor leads to a 0.41% rise in production. Similarly, a 1% increase in machinery use raises output by 0.37%, and a 1% increase in input use results in an approximate 0.32% increase in production.

Considering the sum of all coefficients, the total is 1.4731, indicating the presence of increasing returns to scale in Colombian agriculture, particularly for the crops included in the analysis (temporary, permanent, and pasture crops). Theoretically, this implies that operating at a larger scale is more efficient, as doubling all production factors (land, labor, machinery, inputs) results in more than double the output (147%).

Regarding technical inefficiency, the model results show that at the beginning of a producer's working life, the UPA is less efficient (positive age coefficient). However, as the producer's age increases beyond a certain point, UPA inefficiency decreases, reflecting that older producers gain experience and skills necessary for crop production. Eventually, the negative coefficient of age^2 indicates that inefficiency rises again after a certain age.

The crop concentration indicator, measured by HHI, shows that greater concentration in a single crop within the UPA reduces efficiency. Contrary to expectations, the innovation variable is positively correlated with technical inefficiency, meaning that higher innovation is associated with greater inefficiency in the production unit.

Education level is categorized as: no education, primary, secondary, technical/technological, and university (including postgraduate). Unexpectedly, primary education relative to no education increases UPA inefficiency. In contrast, secondary, technical/technological, and university levels significantly reduce technical inefficiency. In other words, incomplete primary education may be detrimental compared to no education, while secondary and higher education progressively enhance agricultural productivity.

Access to finance positively influences UPA technical efficiency, indicating that higher levels of financing allow production units to achieve greater efficiency. Gender also appears to favor technical efficiency; specifically, being female is associated with higher technical efficiency, suggesting that women are more technically efficient than men in Colombian agriculture. Finally, access to irrigation reduces technical inefficiency, although this variable is not statistically significant.

Discussion

The objective of this study was to identify and analyse the key determinants of agricultural productivity in Colombia, with particular attention to crop types and farm size. The determinants were identified and analysed using data from the National Agricultural Survey (ENA) during the second semester of 2019 through a stochastic Cobb-Douglas production function, similar to those used (Murray, 2016; Aigner et al., 1977).

Descriptive statistics of the variables indicate marked heterogeneity in yields and farm sizes in the agricultural sector, with concentration in certain crops and an uneven distribution of cultivated hectares. The observed high concentration aligns with the findings of and Gáfaro et al, who document the structural issues in land distribution in Colombia (Junguito et al., 2014).

Similarly, the wide ranges of variability observed in production, as well as in land and labor factors, may be related to the coexistence of large commercial farms alongside minifundios and microfundios. This duality reflects the coexistence of commercial and agroindustrial agriculture on one hand, and subsistence peasant agriculture on the other. This phenomenon contrasts with the PPFT statistics, which show high variability in productivity depending on crop type (permanent, temporary), with average productivity being higher in permanent crops.

Statistical results also indicate that the age of producers, with an average of 55 years, may reflect an aging population engaged in agricultural activities in Colombia's rural areas. Aging, beyond being a social issue, poses a threat to agricultural productivity and technical efficiency. Specifically, aging reduces the productive capacity of food and other agricultural products due to the higher proportion of exiting or declining producers, as captured by the age² variable in the model. This is compounded by low technology transfer, knowledge sharing, and low technological adoption, which are characteristics of the sector. Therefore, generational replacement programs that combine social and productivity-enhancing measures are necessary.

Total Factor Productivity (TFP) indicates that producers dedicated to temporary crops appear to achieve higher production levels than those focused on permanent crops. In other words, temporary crops generate a larger production volume per UPA relative to the inputs or factors used. Pastures and permanent crops show very similar mean TFP values (13.3 and 13.9 tons, respectively), suggesting possible similarities in the technologies used, derived from comparable production processes. Overall, the disparities in TFP suggest the coexistence of highly efficient farms alongside units with inefficient producers, reflecting the structure of the agricultural sector, consistent with the findings of Perfetti et al. (Perfetti et al., 2019).

Partial Factor Productivity of Land (PPFT) shows a wide range of variation, likely related to the high concentration of land in Colombia. This finding is consistent with Gáfaro et al., who demonstrate an inverse relationship between land concentration and productivity; that is, larger properties tend to be less productive (Junguito et al., 2014). In this context, the PPFT for temporary crops shows a mean of 28.03 tons per UPA with a median of 0.24, ranging from 0 to 118,125 tons. PPFT for permanent crops exhibits lower variability, with a mean of 13.34 tons and a median of 0.16. For pastures, the mean is 13.95 tons per UPA with a median of 0.12, but the range is broad.

The estimation of the production functions indicates that the coefficients of the factors of production, namely land, labor, and capital (machinery use) are positive and significant at the 1% level. The findings are in line with those of Mundlak et al. and Forero et al. (Mundlak et al., 2012; Forero et al., 2013) . In the same way, the inputs coefficient is positive and significant, which is in line with Gollin et al. findings, which highlight the significance of inputs and labor in boosting agricultural production (Gollin et al., 2014).

In regards to Technical Efficiency (TE), the education variable is also important, which is in line with studies like Gollin et al. that emphasize the importance of human capital as the important factor in boosting productivity in the agricultural sector (Gollin et al., 2014). These results also coincide with Foster and Rosenzweig; and Sheng et al. who associate producer schooling with increased productivity. The finding has implications in policy formulation, which suggests that education initiatives targeting rural producers might help to increase the use of technology and transfer of knowledge (Sheng et al., 2019; Foster & Rosenzweig, 2010).

The model reveals that initially during the working life of a producer, he or she has a negative contribution to the technical efficiency but as the years go by their skill is enhanced and hence their contribution is positive. This aligns with Sheng et al., Fuglie et al., and Gollin et al. (Fuglie et al., 2020; Sheng et al., 2019; Gollin et al., 2014). In the long run, age stops working and turns to have a negative effect. This has implications on the public policy since on average the age of the farmers in the 2019 ENA is about 55 years. This supports the descriptive statistics, implying that the agricultural sector has a hard time retaining or attracting young labor and as such, with aging, technical efficiency decreases and productivity is adversely affected.

Despite the fact that, in theory, increased crop concentration could prove to be helpful in production processes and enhancing the productivity, the results suggest the opposite: monoculture-based UPAs are less efficient. This can be connected to the long-term degradation of the soil, loss of nutrients, and biodiversity, implying that the diversification of crops is a possible solution in the optimization of agricultural production.

In the case of innovation, the coefficient of our model is not significant, as it appears to be counter-intuitive (Gáfaro et al., 2012).This implies two main points. From a policy perspective, program designers should adopt a more precise approach, ensuring technical assistance and extension services consider geographic, productive, social, and economic characteristics for each producer and UPA. Additionally, future studies should further explore the role of innovation in Colombian agricultural productivity.

Education remains significant and contributes to reducing technical inefficiency. Growth in human capital improves input use and decision-making processes within the UPA, consistent with Foster and Rosenzweig and Sheng et al, who show that producer education increases productivity and efficiency (Foster & Rosenzweig, 2010; Sheng et al., 2019). Similarly, access to finance contributes to higher technical efficiency and productivity, enabling producers to obtain greater volumes of higher-quality inputs and other production factors such as land and machinery (Fuglie et al., 2020).

Irrigation is associated with reduced technical inefficiency; however, the coefficient is not statistically significant. This partially aligns with Foster and Rosenzweig and Fuglie et al., who identify irrigation as key to achieving higher efficiency and productivity (Foster & Rosenzweig, 2010; Fuglie et al., 2020; Fuglie, 2018). Finally, technical assistance is not significant in this study, contrary to findings from Fuglie et al. (Fuglie et al., 2020), where assistance improves agricultural productivity.

One limitation of this research is that although the ENA 2019 provides data for most of the studied variables, many are binary (yes/no) variables. This limits analysis, as it provides no additional detail and cannot fully capture the behavior of variables included in the models.

Conclusion

This study used data on the second semester of 2019 on the National Agricultural Survey (ENA) to identify and analyse the key determinants of agricultural productivity in Colombia, both in terms of the type of crops and the area of land used. This analysis is meant to give inputs into the design of the public policies that are meant to boost the productivity in the sector. The findings suggest the high level of heterogeneity of Partial Factor Productivity of Land (PPFT) based on crop type with permanent crops being the most varied.

According to the outcomes of the stochastic frontier model, the above factors of production namely land, labor, capital (use of machinery) and inputs have a positive and significant impact on agricultural output. With the ceteris paribus assumption, the determined elasticities indicate that a 1 percent increase in each factor results in a 0.38 percent production increase in land, 0.41 percent in labor, 0.37 percent in machinery and 0.32 percent in inputs. These results underscore the significance of these four factors in increasing the levels of agricultural productivity.

On the technical efficiency, the findings reveal that the producer age and crop concentration in terms of the Herfindahl-Hirschman Index (HHI) have a negative impact on improvements in efficiency. To be specific, with the producer age, efficiency decreases or differs among the production units. Such results highlight the importance of policies to attract young workers to stay in rural communities and to encourage young non-agricultural workers to move into the industry. Equally, crop diversification policies should be incorporated in the policy design to ensure that these policies encourage technical efficiency and growth in productivity.

The education of producers is important in the development of human capital in production units. The findings reveal that the increase in education level is linked to the technical efficiency and productivity gains as more human capital enhances the adoption of productivity enhancing processes. Moreover, innovation adoption endorses greater rates of technical efficiency that is complemented by sufficient financing in the agricultural sector.

The findings of the econometric modeling have significant consequences on the formulation and execution of the government policies to enhance the productivity and technical efficiency in Colombian agriculture. The data indicate the necessity of variousiated policies, taking into consideration the type of crop, the specifics of production units and of producers, and the degree of land and crop concentration.

Lastly, the research paper is relevant in enhancing the comprehension of the factors that affect the productivity and technical efficiency in the Colombian agricultural sector. It also offers empirical data to facilitate the design and execution of policies that aid in the productivity of sectors.

Ethical Considerations

This study used anonymized secondary data from the 2019 National Agricultural Survey provided by the National Administrative Department of Statistics of Colombia. No direct human or animal participation was involved; therefore, additional ethical approval and participant consent were not required.

Funding

No funding was received for this study.

Conflict of Interest

The authors declare no competing interests.

Acknowledgments

The authors thank the National Administrative Department of Statistics (DANE) for providing access to the 2019 National Agricultural Survey dataset and acknowledge the colleagues and advisors who provided feedback during preparation of the manuscript.

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