Improving Agricultural Efficiency in Zimbabwe: A Labor Productivity Analysis

Tsepeso Setoboli, Nothando Tshuma, Emmanuel Sibanda

Department of Banking and Economic Sciences,

National University of Science and Technology, Zimbabwe

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ABSTRACT

Developed countries have witnessed agricultural production growth alongside increased global pesticide and fertilizer use. However, Sub-Saharan African nations, including Zimbabwe, face stagnant agricultural productivity, resulting in consistently low output. Over the 2008 to 2018 decade, Zimbabwe's agricultural sector experienced a decline in its contribution to total output from 19.02% to 5.07%. To realize Zimbabwe's vision, it is crucial for agriculture to grow and enhance productivity. This study explores how agricultural efficiency can be improved by analyzing the determinants of agricultural labor productivity. Time series data spanning from 1991 to 2018 was analyzed using the Dynamic Linear model. Findings reveal a concerning trend: agricultural labor productivity is declining. The determinants of labor productivity in agriculture include economic development, national expenditure, rainfall, fertilizer use, cropping land area, raw material imports, and reinvestment in capital. To enhance agricultural efficiency, the study recommends several efforts. First, allocate more cropping land area to farmers, allowing for increased cultivation and promote the adoption of climate smart agricultural practices such as optimal water resource utilization to the farmers who already have a significant portion of productive land in their hands. Second, consider opening borders to facilitate the importation of essential agricultural raw materials. Third, ensure consistent access to fertilizer through government schemes. Lastly, support income-generating projects that promote overall economic development. Additionally, further studies should explore and differentiate the factors influencing agricultural labor productivity among both smallholder and large-scale commercial farmers.

Keywords: Agriculture, Efficiency, Labor Productivity, Dynamic Linear Model, Determinants

INTRODUCTION

Numerous challenges exist in today's society including the rising global population, climate change, accelerated urbanization, and increasing scarcity of water, land, and forest resources giving rise to questions about the food and agricultural systems being able to meet needs, and the capability to achieve the production increases required (Vos & Bellù, 2019). This is a growing crisis as there are several internal and external factors threatening food and nutrition security, especially in the developing world (Hebsale Mallappa & Babu, 2021). Based on the slower rate, between 2009 and 2050, it is expected that the population will grow by 2.3 billion people (FAO, 2009). This translates to nearly a 10 billion world population (Vos & Bellù, 2019). The population growth accompanied with rising incomes, increased demand for a high quality and more varied diets that require more production inputs, and changing diets in growing economies will put pressure on the food system (Serraj & Pingali, 2018). Consequently, this will lead to an expected food demand increase of about 59% to 98% by 2050 (Elferink & Schierhorn, 2016).

The agricultural sector occupies a very important position in the global food system as it is the major source of food for the world population (Khudoynazarovich, 2021). Given the escalating demand for food, farmers are under pressure to boost crop production. This objective can be accomplished by either expanding cultivated land or improving productivity (Elferink & Schierhorn, 2016). Increasing productivity is the more sustainable choice. Agricultural productivity is a measure of efficiency, given as the ratio of outputs to inputs of a production system (Card, 2006; Doss, 2018; Krugman, 1994). High productivity implies that a production system has relatively lower costs since high production can be achieved with lower input use. As such, growth in agricultural productivity is an essential condition for rural poverty reduction, industrialization, and promotion of inclusive growth prospects (Wickramasinghe et al., 2017).

In the last decades, agricultural production grew alongside global pesticide and fertilizer use in developed and a few developing countries like China (Knudsen et al., 2006). Sub-Saharan African (SSA) countries have been experiencing a stagnant agricultural productivity growth ranging from -0.05 to 0.05, which has resulted in low agricultural production and a small global share of agricultural exports (Mwangi et al., 2020). One of the barriers to agricultural growth in SSA is poor performance by labor (Rufai et al., 2018).

Zimbabwe's contribution of agriculture to national output has also declined from 19.02% in 2008 to 5.07% in 2018 (O'Neill, 2021). Agricultural value added has fallen precipitously since 2000 when it reached its peak (IMF, 2020). Soon after Zimbabwe gained independence during 1980 to 1995 period, a 1.3% annual growth in agricultural land productivity was experienced where land productivity grew from US$34 to US$41 per hectare (Weiner et al., 1985; Wiebe et al., 2001). However, in the same period, agricultural labor productivity declined from US$294 to US$266 per worker equating to an average of 0.7% decrease per annum (Wiebe et al., 2001). This decline raises concerns about the effectiveness of existing strategies and policies aimed at enhancing productivity.

According to Maiyaki (2010), the trend of having agriculture as the backbone of Zimbabwe's economy was reversed in recent years because of challenges including political instabilities in the country. The smallholder farming sector which is an important part of the agricultural system of Zimbabwe faces several challenges such as poor soil fertility, poor infrastructure, poor rainfall and droughts, low investment, poor access to irrigation facilities, lack of farm labor and draft power, poverty, and periodic food insecurity, all of which have led to low production and productivity in the agricultural sector (FAO, 2021a). Rural infrastructure such as energy and transport are important for agricultural productivity to be achieved (Llanto, 2012). According to Kessides (1996), infrastructure impacts economic development through its effects on agricultural productivity in terms of transportation and irrigation facilities. This aids to ease of market access and water availability which are important for the success of agriculture.

The entire agricultural value chain has been experiencing severe challenges including lack of funding and affordable inputs which are worsened by climate change impacts such as occasional floods and prolonged droughts (FAO Zimbabwe, 2016). The sector is vulnerable to periodic droughts as smallholder farmers who produce about 70% of the staples access less than 5% of Zimbabwe's irrigation facilities (FAO, 2021a). Other challenges faced include poorly functioning markets, and farmers' limited access to knowledge, best practices, and credit facilities (FAO, 2021b).

Since 2015, the government of Zimbabwe started placing further emphasis on agriculture's importance through the Command Agriculture program (IMF, 2020). More so, the government has continued to intensify efforts to improve agricultural productivity in the country as it is a top priority sector in achieving its vision (World Bank, 2019). However, interventions in Zimbabwe's agricultural sector have primarily focused on income support and subsidies rather than long-term financing for sustainable growth. This emphasis on short-term measures may not address the underlying issues affecting agricultural productivity in the long run. Consequently, low productivity is the greatest challenge in Zimbabwe's agricultural sector (ZimStat and World Bank, 2019). To realize its goals, Zimbabwe's agriculture has to grow and improve productivity (IMF, 2020). Challenges such as policy uncertainty, foreign exchange shortages, land rights issues, environmental shocks, and macroeconomic instability have hindered private investment in the agricultural sector in Zimbabwe. These market distortions and uncertainties can impede efforts to improve agricultural efficiency. According to Headey et al. (2010), knowing about agricultural productivity together with its determinants is important. However, no studies on determinants of agricultural labor productivity were identified in Zimbabwe. Therefore, this paper addresses this gap in the empirical literature by identifying the determinants of agricultural labor productivity in Zimbabwe to achieve agricultural efficiency.

LITERATURE REVIEW

Agricultural Labor Productivity

Productivity is a measure of efficiency that focuses on the usage of inputs in the production of a given level of produce in an economy (Krugman, 1994). According to Burja (2012), it is a synthetic expression of how efficiently the factors of production are being utilized and it is important because it highlights the competitiveness of economic systems. Usually, productivity is defined as a ratio of outputs produced to inputs used in production (Card, 2006; Doss, 2018; Krugman, 1994).

According to Bureš and Stropková (2014), labor productivity refers to the amount of goods produced per unit of labor, although this differs across industry sectors. As an example, according to construction managers and project managers, it refers to the ratio between work hours earned and work hours used. Labor productivity is important because it has a huge effect on production costs and processes (Auzina-Emsina, 2014).

For a long time, economists have been largely interested in the measurement of agricultural productivity (Nin et al., 2003). As such, there are several methods of measuring agricultural productivity amongst which the choice depends largely on the availability of data and purpose (Schreyer & Pilat, 2001). Within the literature, two main classifications of agricultural productivity measures arise where one is about single and multi-factor productivity, and the other is about the ratio of gross output to inputs and the value-added concept which is mainly relevant at the industry level (Schreyer & Pilat, 2001). In other terms, the first classification refers to total factor productivity (TFP) as well as partial factor productivity (PFP) measures of which the components of the second classification can fall in either in the case of agriculture.

TFP is more informative as it measures agricultural output produced from a set of combined inputs including capital, labor, land, and material resources used indicating the overall rate of change in technology and efficiency (USDA, 2021). PFP measures lack in that they relate output to a single input such as land or labor (Murray, 2016). However, because of data limitations, economists have been forced to use PFP measures which are highly imperfect as they usually overestimate productivity in developing countries and underestimate it in developed countries (Nin et al., 2003). Although PFP measures suffer from limitations, they are very useful and informative (Headey et al., 2010).

Within value-added-based measures, double counting which could cause over and underestimation does not arise making these measures more suitable (Schreyer & Pilat, 2001). Most often, value-added-based labor productivity is computed such that its data is usually available (Schreyer & Pilat, 2001). Therefore, in this study, labor productivity is employed as an indicator of agricultural productivity and is measured as agriculture value added per worker.

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Theory of Production

The theory of production examines the physical relationships between inputs and outputs, physical in the sense that relationships are in terms of variables in which inputs and outputs are measured, for example, hectares of land, number of workers, and barrels of oil (Wilkinson, 2005). Production functions are usually used to present such relationships. According to (Romeo, 2020) the Cobb-Douglas production function which uses labor and capital as inputs is probably the most used in economic production theory;

$$y = A\left(L^{\alpha} K^{\beta}\right) \qquad (1)$$

$$y = A.f(L) \qquad (2)$$

where; y is total production, A is factor productivity, L is labor, K is capital, and α and β are labor and capital output elasticities respectively. Although there are numerous inputs in the production system, usually a two-input (1) case is assumed (ceteris paribus) for simplicity, of which, in the short run, capital is assumed to be constant (2).

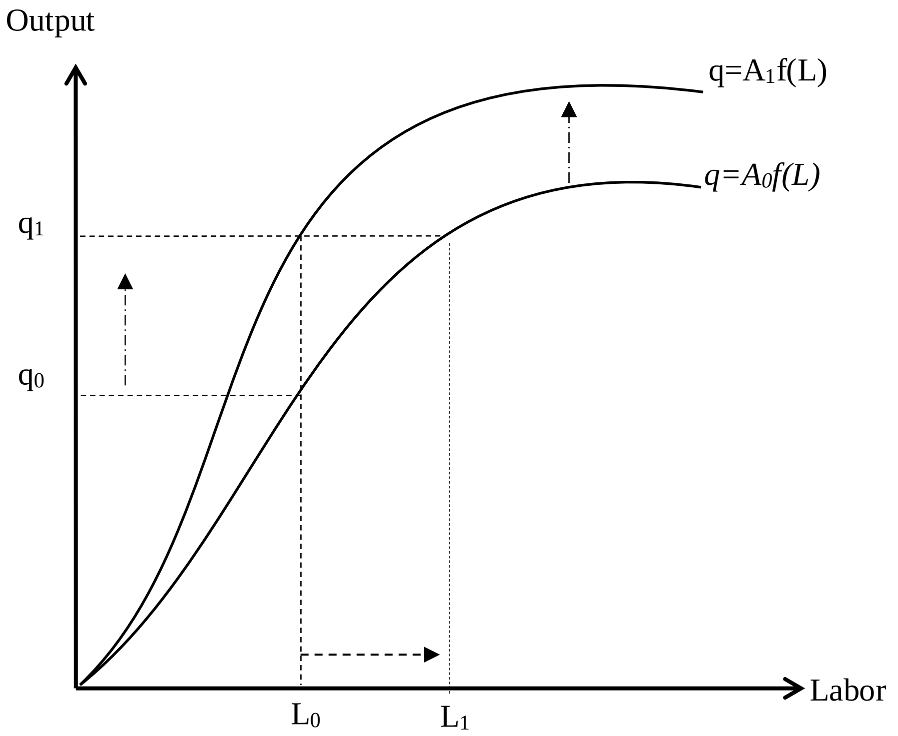

Fig. 1 Graphical Presentation of the Production Function Adapted from Solow (1957)

Fig. 1 presents a production function showing the relationship between output and labor. Changes in the level of production would be achieved either through a movement along the production function or a shift of the production function (Krugman, 1994). Movements along the production function take place when the change in output is caused by a change in the level of inputs such as increasing labor from L_0 to L_1 resultingin an increase in output from q_0 to q_1. A shift in the production function, on the other hand, indicates changes in productivity, and in this case, output either increases or decreases at the same level of input usage (Krugman, 1994). As shown in fig. 1, output increases from q_0 to q_1 at the same level of labor, L_0 indicating an improvement in labor efficiency. Factor productivity, the main focus of

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the study, increases from A_0 to A_1 highlighting the increase in labor productivity. Nicholson & Snyder (2008) notes that such changes in productivity represent technical progress. According to the production theory, technical or productivity improvement arises from better methods of economic organization as well as the use of more productive and improved inputs (Nicholson & Snyder, 2008). In this study, therefore the factors that lead to these improvements were determined.

Empirical Literature

Knowing about agricultural productivity together with its determinants is important (Headey et al., 2010). Various studies have been conducted across the globe on the determinants of agricultural productivity but most of these were done at the household level (Anyanwu, 2013; Deininger et al., 2014; Ekbom, 1998; Owuor, 2019; Sheng et al., 2015; Urgessa, 2015), and only a few at aggregate level (Dayal, 1984; Imahe & Alabi, 2005; Muraya, 2017). In addition, there is not much work that has been done on the determinants of agricultural productivity in Zimbabwe.

Recent studies on the determinants of agricultural productivity include Muraya (2017), Owuor (2019), Urgessa (2015), and Coppola et al. (2018). In these studies, several determinants were observed including fertilizer use (Urgessa, 2015), annual rainfall (Muraya, 2017), pesticide use (Urgessa, 2015), drought (Urgessa, 2015), labor (Urgessa, 2015; Muraya, 2017), the share of the adult population with secondary education (Coppola et al., 2018), government expenditure (Muraya, 2017), the growth rate of firms (Coppola et al., 2018), inflation (Muraya, 2017), road infrastructure (Coppola et al., 2018), exchange rates (Muraya, 2017), off-farm income (Owuor, 2019), quality of resources and market orientation (Coppola et al., 2018), the value of crop per unit of land (Owuor, 2019), and quality agricultural products (Coppola et al., 2018). Some of these determinants were also observed in Adams & Bumb (1979), Ajao (2012), Anyanwu (2013), Ortega & Lederman (2004), and Reimers & Klasen (2013).

Anyanwu (2013) showed that the determinants of agricultural productivity in Nigeria include farm size, farming experience, non-farm income, number of crops planted, level of education, labor effort, spending on planting material, market distance, and capital input. More so, Headey et al. (2010) illustrated that the determinants include public expenditure on agriculture, policy and institutional variables, agricultural policy reforms on pricing, and geographic factors. Another list of determinants includes human capital, development flow to agriculture, level of urbanization, agricultural imports, and economic development according to the findings of Liu et al. (2020). In addition, Burja (2012) showed that the labor force affects agricultural productivity.

In the first decade of the 2000 era, the determinants observed by Ortega & Lederman (2004) and Imahe & Alabi (2005) studies included electricity generating capacity per capita, roads, credit availability, loans to agriculture, fertilizer use, average rainfall, food imports value, spending on agricultural capital and arable land per capita. Some of these determinants such as credit, fertilizer use, and farm size were identified in the early studies namely Adams & Bumb (1979), Dayal (1984), and Ekbom (1998) respectively.

There were a few studies that were done before the year 2000 including Adams & Bumb (1979), Dayal (1984), and Ekbom (1998) all of which were done in developing parts of the world. Adams & Bumb (1979) identified the determinants of land productivity in India as natural conditions (rainfall and factor supplies), policies, and inputs. As for Dayal (1984), the determinants observed included fertilizer use, irrigation, urban industrial development, agricultural wages, and population density. Ekbom (1998) on the other hand found that labor availability, production costs, farm size, and distance to key resources are the determinants of agricultural productivity in Kenya. Similar studies done after the year 2000 showed different determinants as a result of differences in variables used in model specification and the indicator of agricultural productivity used for example labor productivity (Dayal, 1984), land productivity (Adams & Bumb, 1979; Dayal, 1984), aggregate productivity (Dayal, 1984; Block, 1994; Imahe & Alabi, 2005), and total factor productivity (TFP) (Ortega & Lederman, 2004; Liu et al. 2020).

From the studies reviewed, it can be identified that the measurement of agricultural productivity varies across studies. Some of the studies including Coppola et al. (2018), Dayal (1984), Benin (2016), Urgessa (2015), and Imahe & Alabi (2005) used a combination of several variables to measure agricultural productivity most of which include land, labour and aggregate productivity. The advantage of doing so is that one of the variables will likely give the accurate measure of agricultural productivity, although the presence of inaccurate variables will be misleading.

Other studies attempted to calculate the TFP which supposedly captures all the inputs and/or factors of production used in the production process as well as the outputs obtained which are used in calculating the output input ratio, and these include, Liu et al. (2020), Benin (2016), Headey et al. (2010), Ajao (2012), and Ortega & Lederman (2004). The idea of measuring agricultural productivity as TFP might be good however, the challenge comes in trying to meet the data requirements of the measure especially when using secondary data and/or dealing with traditional agricultural systems where record keeping is poor. As a way of dealing with missing data, other studies including Owuor (2019) use PFP with less data requirements as it focuses on few inputs.

More so, the remaining group of studies measures agricultural productivity using individual PFP measures which include either land productivity (Adams and Bumb, 1979), or labor productivity (Burja, 2012). According to Nicholson & Snyder (2008), labor productivity is often used to indicate average productivity such that when there are productivity increases in an industry, this is commonly taken to imply an increase in output per unit of labor. Labor is a unique input as it often changes either in terms of units or hours when a firm makes efforts to increase the level of production even through increasing other inputs. For example, when a farmer increases the level of fertilizer or introduces a new pesticide in order to improve production, more labor will be required to perform these tasks unless there is an increase in the productivity of labor. This implies that labor is responsive to changes in other inputs. Therefore, in this study labor productivity is used as a measure of agricultural productivity.

Evidence from the studies reviewed reveals that there is no clear agreed list of determinants of agricultural productivity within the literature as these differ across studies. In addition, little is known about the determinants of agricultural productivity in Zimbabwe. Therefore, this paper examines the determinants of agricultural labor productivity in Zimbabwe.

METHODOLOGY

Data Collection and Sources

The study uses annual secondary time series data comprised of variables dating from the year 1991 to 2018 due to data availability among the key variables. Data was obtained from a combination of online statistical databases including FAOSTAT, Knoema, World Development Indicators (WDI), and the Climate Change Knowledge Portal (CCKP) of the World Bank Group. Table I shows the data that was used for this, indicators for each variable and the sources where the data was obtained.

Analysis

Table I. Variables and Sources of Data

Variable		Description/Indicator	Source
$pdty_t$	Agricultural labor productivity	Agriculture, forestry, and fishing, value added per worker (constant 2015 US$)	WDI

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$gdpcap_t$	Economic development	GDP per capita (2015 US$ prices)	FAOSTAT
fdi_t	FDI	Total FDI inflows (Million US$)	FAOSTAT
gne_t	National expenditure	Gross national expenditure (current US$)	WDI
$rain_t$	Annual rainfall	Annual mean rainfall (mm)	CCKP
$cland_t$	Cropping land area	Cropping land area (1000 ha)	FAOSTAT
$fert_t$	Fertilizer usage	Consumption of fertilizer (kg per hectare of arable land)	Knoema
$agimport_t$	Agriculture raw material imports	Agricultural raw material imports (Million US$)	Knoema
$capit_t$	Reinvestment in capital deflator	Gross fixed capital deflator value (US$, 2015 prices)	FAOSTAT

To analyze the data, the Dynamic Linear Model (DLM) was used as it is very flexible in time series analysis (Petris, 2010). According to Nobre et al. (2001), DLMs are very useful models for forecasting, and they possess advantages including being easy to apply on different time series and the fact that they do not require a new cycle of identification and modeling when new data become available. In addition, they can also handle data with varying accuracies, missing values, non-stationary properties, and non-uniform sampling (Laine, 2020). The data was analyzed using a DLM with 8 independent variables and agricultural labor productivity as the dependent variable. This model was selected based on the smallest Akaike Information Criterion (AIC) backward elimination method (stepwise regression) after analyzing a model with several explanatory variables suggested by literature depending on the availability of sufficient data in the sources used. The following model was assumed;

$$pdty_t = \gamma_0 + \gamma_1 gdpcap_t + \gamma_2 fdi_t + \gamma_3 gne_t + \gamma_4 rain_t + \gamma_5 cland_t + \gamma_6 fert_t + \gamma_7 impo_t + \gamma_8 capit_t + \varepsilon_t$$

where, $pdty_t$ is agricultural labor productivity, γ_0 is the intercept, ε_t is the random error term, γ_i's are the coefficients and the independent variables are as indicated in table I. For the ease of interpretation, logarithms were introduced to the model, as such, the following model was estimated;

$$\begin{aligned} Lpdty_t = \delta_0 + \delta_1 Lgdpcap_t + \delta_2 Lfdi_t + \delta_3 Lgne_t + \delta_4 Lrain_t + \delta_5 Lcland_t + \delta_6 Lfert_t + \delta_7 Limpo_t \\ + \delta_8 Lcapit_t + \omega_t \end{aligned}$$

where, $Lpdty_t$ is the logarithm of agricultural labor productivity, δ_0 is the intercept, ω_t is the random error term, δ_i's are the coefficients, and the independent variables are presented as logarithms.

RESULTS AND DISCUSSION

Descriptive Statistics

Table II presents the descriptive statistics of each variable including the mean, minimum, maximum, initial, and latest values. As shown, over the period of 1991 to 2018, agricultural labor productivity (agriculture, forestry, and fishing, value added per worker) had a mean of US$596, a minimum of US$268, and a maximum of US$1046, of which in 2018 it had declined to US$478.00 from US$784.00 in 1991. Economic development (GDP per capita) increased from US$973 to US$1529 and had a mean of US$1023. Similarly, FDI, national expenditure, population size, labor force, and annual rainfall increased over the period.

The import of raw materials for the agriculture sector, agricultural labor productivity, fertilizer usage, and domestic credit reduced during the same period. GDP per capita ranged between US$597 and US$1529, while FDI ranged between US$3.1 million and US$118.2 million. Fertilizer usage declined from 55.7kg/ha in 1991 to 38.4kg/ha in 2018 and ranged between 18.3kg/ha to 55.7kg/ha. Similarly, agricultural raw material imports were US$56.8 million in 1991 and had a lowest of US$9.3 million. Furthermore, the deflator for capital formation indicated a rise in reinvestment in capital over the period.

Table II. Descriptive Statistics

Variable	Mean	Minimum	Maximum	Initial	Latest
Agricultural labor productivity (US$)	596	268	1046	784	478
Economic development (US$/capita)	1023	597	1529	973	1529
FDI (mil. US$)	63.9	3.1	118.2	40.2	103.5
National expenditure (thous. US$)	12.1	5.59	34.9	7.38	34.9
Annual rainfall (mm)	635	430	876	524	607
Cropping land area (1000 ha)	3810	3050	4350	3050	4100
Fertilizer usage (kg/ha)	36.6	18.3	55.7	55.7	38.4
Agriculture raw material imports (mil. US$)	36.7	9.3	132.2	56.8	32.2
Reinvestment in capital deflator (US$)	184.13	2.80	744.64	2.80	744.64

Productivity of Labor in Agriculture

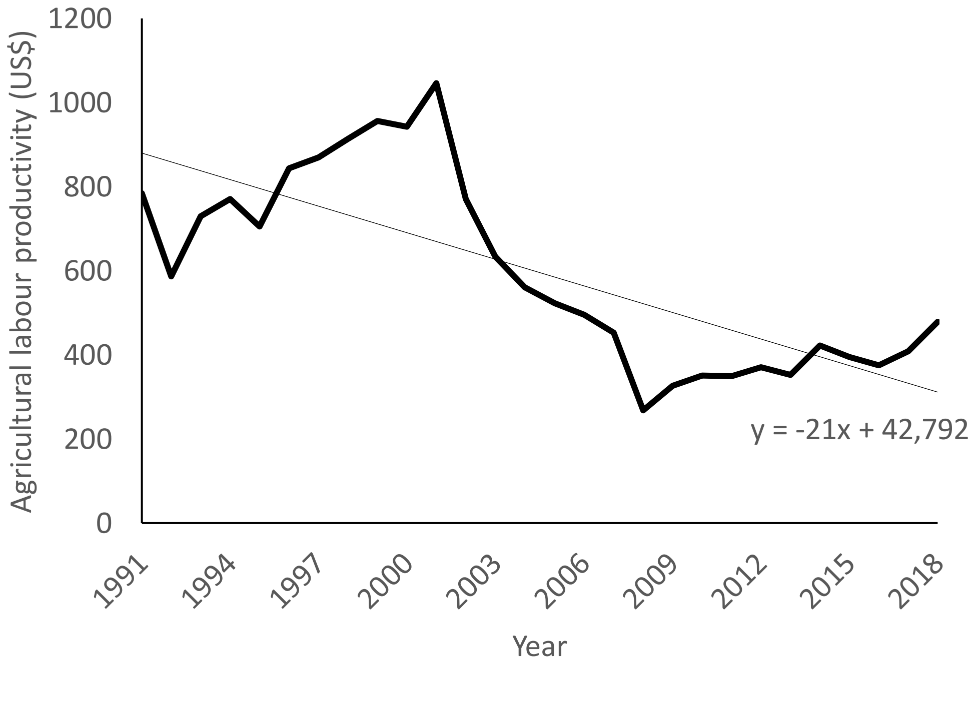

Fig. 2 Labour Productivity Tend in Zimbabwe's Agriculture

Fig. 2 shows that agricultural labor productivity fluctuated throughout the period from 1991 to 2018 in Zimbabwe although the fluctuations varied in terms of size. Before 2002, agricultural labor productivity was increasing slowly. In 2002, the highest level of agricultural labor productivity was reached. However, after 2002 there was a continuous decline in the level of agricultural labor productivity until 2008 when the minimum was reached. Over the 2008 to 2018 decade, there was a slight increase although it was associated with some years of slight decrease. The trendline for agricultural labor productivity shows that there was an overall decline of about US$21 per year over the 1991 to 2018 period in Zimbabwe.

A decreasing agricultural labor productivity implies that the agricultural production system is experiencing a

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downward shift in the production function. As explained before, such a shift would result in lower production per unit of labor such that more labor would be required to achieve a higher level of production. This implies that the rate of increase in output would be slower than the rate of increase in labor (Fuglie et al., 2021). As a result, the cost of production would increase and in turn, lead to higher commodity prices. More so, high costs of production would lead to lower agricultural production. Agricultural productivity is very crucial for the development of the agricultural sector (Kumar et al., 2008). A declining agricultural labor productivity would therefore be detrimental to this sectoral development.

The results differ from the findings of Block (1994), Ortega & Lederman (2004), Benin (2016), Fulginiti et al. (2004), Ajao (2012), and Burja (2012), while they agree with the findings of Liu et al. (2020). Benin (2016) study showed that African agricultural productivity was increasing during the 1961 to 2012 period. Likewise, Block (1994) observed that there was a notable recovery in African countries' agricultural productivity in the 1980s although its sustainability was in question. Therefore, the findings of this study validate this questioning by Block (1994) in the Zimbabwean case proving that the recovery was not sustainable. According to the findings of Fulginiti et al. (2004), although agricultural productivity was increasing in SSA, it was reduced during periods of war and political conflicts. Ortega & Lederman (2004) showed that internationally there was an increase in agricultural productivity during the 1961 to 2000 period.

According to FAO (2021a), causes of low agricultural productivity in Zimbabwe include poverty, periodic food insecurity, poor soil fertility, poor infrastructure, low rainfall and droughts, poor access to irrigation, lack of labor and draft power, and low investment. Stellmacher & Kelboro (2019) highlight poor adoption of technology amongst family farmers as the major cause of low agricultural productivity. Environmental factors such as increasing frequency of droughts, deterioration of land resources as well as declining soil fertility also reduce agricultural productivity (Malley et al., 2009). In addition, Phillip et al. (2009) state that low agricultural productivity is associated with low public expenditure on agricultural research. It is therefore not surprising that agricultural productivity is reducing in Zimbabwe since most of these challenges are experienced in its agricultural system. To improve efficiency, Zimbabwe therefore needs to address these challenges.

Determinants of Labor Productivity in Agriculture

According to Laine (2020), our model did not require stationarity as the DLM can handle non-stationary processes. As indicated in table III, the Augmented Dickey-Fuller test showed that the agricultural labor productivity variable was not stationary both as an actual value and as a logarithm transformation since the p-values were greater than 0.05. However, since the DLM has the advantage of being able to handle non-stationary data, the data was analyzed.

The model had a p-value less than 0.01 and an adjusted R^2 value of 0.734. The p-value indicates that the model is statistically significant at a 5% level of significance. The goodness of fit measure, adjusted R^2 value indicates that the changes in the explanatory variables explain 73.4% of the variations in the dependent variable therefore, the model assumed is a good fit.

Table III. Stationarity Test

Variable	ADF Statistic	Lag order	p-value	Stationarity
pdtyt	-2.1088	3	0.531	Non-Stationary
$Lpdty_t$	-1.6677	3	0.700	Non-stationary

Table IV shows the results of the DLM indicating that seven independent variables were statistically significant at a 5% level of significance. These include economic development, national expenditure, annual rainfall, cropping land area, fertilizer usage, import of raw materials for agriculture, and reinvestment in

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capital. This implies that there is statistical evidence that the coefficient estimates of these variables in the model are not equal to zero, therefore, the study concludes that these variables affect agricultural labor productivity. FDI is not significant at the 5% level hence we do not have sufficient statistical evidence that its coefficient is not equal to zero. Therefore, the study concludes that FDI does not affect agricultural labor productivity as per the results of this model.

Table IV. Dynamic Linear Model Results

Independent Variable	Estimate	Standard Error	t value	Pr(>|t|)
Intercept	-16.99	8.88	-1.91	0.071
$Lgdpcap_t$	2.03	0.61	3.31	0.004*
$Lfdi_t$	-0.11	0.08	-1.35	0.193
$Lgne_t$	-1.09	0.32	-3.40	0.003*
$Lrain_t$	-0.66	0.28	-2.38	0.028*
$Lcland_t$	2.65	1.02	2.60	0.018*
$Lfert_t$	0.56	0.21	2.63	0.017*
$Limpo_t$	0.24	0.10	2.47	0.023*
$Lcapit_t$	-0.14	0.05	-2.73	0.013*
Adjusted R^2 = 0.839, p-value = 0.00, Significance code: 0.05 = '*'				

The DLM results indicate a positive coefficient of 2.03 for the economic development variable GDP per capita meaning that increases in economic development result in an increase in agricultural labor productivity. Increasing GDP per capita by 1% results in an increase in agricultural labor productivity by 2.03% *ceteris paribus*. Therefore, to increase the declining agricultural productivity in Zimbabwe, there is a need to improve economic development (GDP per capita). These findings differ from the findings of Liu et al. (2020) where it was observed that economic development has a negative effect on agricultural productivity. Economic development refers to the wealth of a country and can be narrowed down to the availability of resources and opportunities to the people living within the country (Straza, 2019). Wealth and resources can be used to boost agriculture by investing in machinery, irrigation infrastructure, and improved inputs which would then increase agricultural productivity as indicated by the results. Zimbabwe has been experiencing low productivity because low economic development has negative impacts on effects on access to infrastructure, technology and inputs which then lower agricultural productivity (Qing-hua, 2011).

Annual rainfall has a negative coefficient of -0.66 meaning that receiving high rainfall in Zimbabwe reduces agricultural labor productivity. Holding other factors constant, a 1% increase in annual rainfall would lead to a 0.66% decrease in agricultural labor productivity. This differs from the findings of Muraya (2017) and Urgessa (2015) where rainfall had a positive effect on agricultural productivity. Rainfall is one of the major inputs in Zimbabwean agriculture as the availability of water from rain is a necessity for agricultural production to succeed. The management of agricultural water systems is a key part of successful agriculture and it has the potential to improve agricultural productivity (Molden et al., 2011). Studies such as Imahe and Alabi (2005), and Adams and Bumb (1979) also suggest that rainfall is a key variable affecting agricultural productivity. However, during the rains, workers have limited time to work on the farm since they cannot work when it is raining, as such their effectivity is reduced leading to an overall labor productivity reduction. There are also incidences of water logging and the spread of diseases which affects production. Similarly, a good weather forecast such as high rainfall can lower wages (Rosenzweig and Udry, 2014) leading farmers to get more labor which is likely less productive. More so, Subash et al. (2011) highlight that due to increased greenhouse gases from global warming, extreme rainfall occurrences are a threat to agriculture. To improve efficiency, there is a need to improve farm conditions to prevent the negative effects of high rainfall.

On the other hand, increasing the cropping land area would result in an increase in agricultural labor productivity as indicated by a positive coefficient of 2.65. This implies that if the cropping land area is increased by a percentage holding other factors constant, agricultural labor productivity in Zimbabwe would increase by 2.65%. Therefore, to improve efficiency there is a need to increase the cropping land area. Yan et al. (2009) observed a similar result in China where agricultural productivity slightly increased as a result of increasing cropping land. Similarly, Rahman and Anik (2020) suggested that in the face of climate change, land is a key factor in achieving increased agricultural production. However, the results are different from Sheng et al. (2019) study which revealed that increasing the area in terms of farm size leads to misallocation of resources in larger farms as less efficient labor-intensive technologies are used. Ensuring that technologies used in the farm are efficient is important to achieve higher labor productivity even in larger cropping areas. Access to more land can create the need for farmers to invest in technologies to enable them to manage tasks in the area. By so doing, labor productivity can improve. Farmers with less manageable land would not see the need to invest in technology since labor requirements are low and it is likely that there is more than necessary labor which then reduces productivity.

Likewise, the results show a positive coefficient of 0.56 for fertilizer usage highlighting that there is a positive effect from fertilizer usage to agricultural labor productivity in Zimbabwe. The coefficient implies that an increase of 0.56% in agricultural labor productivity if fertilizer usage is increased by 1% holding other factors constant. A positive effect of fertilizer usage on agricultural productivity was also observed by Endale (2011) in Ethiopia. According to Teklu and Hailemariam (2009), limited fertilizer application impedes agricultural productivity in less developed countries when soil fertility is depleted. Low access to fertilizer in Zimbabwe is a notable challenge which has resulted in depletion of soil nutrients and stagnant yields most particularly for maize the staple crop (Pasley et al., 2019). Therefore, increasing fertilizer usage is important as it reduces the impacts of soil fertility depletion in Zimbabwe ensuring high productivity.

Import of agricultural raw materials has a positive effect on agricultural labor productivity as shown in table IV by a positive coefficient. The results imply that if other factors are held constant, increasing agricultural raw material imports by 1% would result in a 0.24% increase in agricultural labor productivity in Zimbabwe. Importation of raw materials in the agricultural sector gives farmers access to cheaper inputs. According to Hidayah et al. (2022), the cost of raw materials has a huge effect on production. To improve efficiency in agriculture there is therefore need to support the import of these raw materials. However, Rufai et al. (2018) observed that there is a negative relation between input usage and agricultural labor productivity.

National expenditure has a negative coefficient of -1.09 implying that increasing the national expenditure by 1% would lead to a 1.09% decrease in agricultural labor productivity *ceteris paribus*. Furthermore, the reinvestment in capital variable had a negative coefficient of -0.14 in the model implying that agricultural labor productivity reduces by 0.14% for every percentage increase in reinvestment in capital holding other factors constant. Therefore, reducing national expenditure and reinvestment in capital would be required to increase agricultural efficiency in Zimbabwe.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

The study aimed to identify and analyze the determinants of agricultural labor productivity in Zimbabwe to achieve agricultural efficiency. According to the results of the research study, it can be concluded that agricultural labor productivity is declining in Zimbabwe. This raises concerns about the current interventions aimed at improving agricultural efficiency in Zimbabwe. The determinants of agricultural productivity include economic development, national expenditure, reinvestment in capital, rainfall, fertilizer use, cropping land area, and agricultural raw material imports. Economic development, cropping land area, fertilizer usage, and imports of agricultural raw materials have a positive effect on agricultural labor productivity while national expenditure, reinvestment in capital, and rainfall have a negative effect.

Recommendations

It is therefore recommended that the government of Zimbabwe should consider continuing with its efforts of increasing agricultural productivity in the country as it is declining. Recommended efforts include allocating more cropping land area to farmers, opening up borders for the importation of agricultural raw materials, providing fertilizer through government input schemes, and supporting income-generating projects that promote economic development. In addition, measures such as use of greenhouses and construction of farm waterways are important in preventing detrimental effects of heavy rainfall. Reducing national expenditure and reinvestment in capital could lead to an increase in productivity in agriculture.

Enhancing the efficiency of resettled farmers is crucial, given that a significant portion of highly fertile land is under their stewardship. Efforts to boost efficiency are imperative in combating grain shortages and food insecurity within the nation (Musemwa et al., 2013). Promoting the adoption of climate-smart agricultural practices among rural farmers can mitigate the impact of climate change on crop yields (Mpala and Simatele, 2024). Measures such as optimizing water usage, utilizing early maturing seeds, implementing soil and water conservation techniques, managing nutrients effectively, and integrating cost-efficient labor practices can bolster resilience to climate change. Embracing conservation agriculture methods like intercropping and water conservation can enhance agricultural output by minimizing soil disruption and curbing water wastage. These approaches aid in addressing labor shortages and enhancing soil fertility amidst recurrent droughts (Ermyas, 2023).

Supporting initiatives like enhancing livestock production systems can boost food output for local consumption and ensure a stable supply of animal feed, particularly during dry spells. Collaborating with governmental bodies and partners to promote the adoption of proven technologies can elevate livestock productivity and fortify resilience against climate change impacts. By prioritizing these strategies, Zimbabwe can make strides in enhancing agricultural efficiency, elevating productivity levels, and bolstering resilience against the array of challenges confronting its farming community. Investment in infrastructure, particularly in improving access to markets, is crucial for enhancing agricultural productivity in Zimbabwe. In conclusion, tackling the challenges faced by Zimbabwe's agricultural sector and implementing the proposed measures can significantly enhance the efficiency and productivity of agriculture in the country.

Further Study

The study recommends further studies that can differentiate factors affecting agricultural labor productivity amongst smallholder and large-scale commercial farmers to establish sector-specific recommendations for improving agricultural productivity. Advisors, researchers, and policymakers need to identify and tackle the factors influencing farmers' technical, allocative, and economic efficiency to enhance overall productivity.

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