Agricultural productivity growth in African agriculture over the last six decades

Abstract
This paper compares agricultural productivity growth, specifically, the impact of agricultural mechanization on total factor productivity and cereal yields, across African countries using contemporaneous and sequential Malmquist index approaches. Contemporaneous approach findings indicate that agricultural productivity grew by 1% annually over 1961–2014, while sequential technology measures show much higher growth of 1.7%. The highest growth rates were experienced since the 2000s due to technical progress. Regression analysis indicates that mechanization, research and development, weather conditions, and population pressure influence African agricultural productivity. Climate-smart options to sustain crop yields in countries relying heavily on rain-fed agriculture are critical. The transfer of knowledge from countries with high-level productivity might enhance productivity in "laggard" countries.

Keywords: Mechanization, total factor productivity (TFP), Malmquist TFP index, technical change, technological progress.

1. Introduction

The quest to sustainably manage food systems and increase agricultural productivity to meet the growing demand of the population, especially in developing and less developed countries, remains a critical pursuit for both policy makers and the academic community (Fears et al. 2019). Increasing agricultural productivity is essential to achieving several sustainable development goals (SDGs) related to enhancing food, fiber, and energy security (FAO 2018; Kopittke et al. 2019), especially in areas of Africa where the prevention of hunger, the provision of adequate nutrition, and the alleviation of poverty require urgent action (Tittonell and Giller 2013; Van Ittersum et al. 2016). Yet the landscape of the continent is heterogeneous, as is the potential to close yield gaps through modernization and institutional reform. For instance, Baumüller et al. (2020) describe the current state of the agricultural sector in Africa and its potential to contribute, if yields gaps are closed, to food and nutrition security.

Van Dijk et al. (2017) decompose the yield gap (that is, the gap between actual and (theoretical) potential yield) into four components: technical inefficiency, allocative inefficiency, socio-economic (dis)incentives, and technological limitations, with the technological yield gap being the most relevant. Therefore, access to modern inputs and technologies is the key to improved agricultural productivity (van Dijk et al. 2017; McArthur and McCord 2017). Some countries have been able to induce a high level of agricultural productivity by means of infrastructural development, while ineffective institutions and difficulty in market access have kept several countries suffering from poor yields and low incomes (Benin 2016).

Though agricultural mechanization is on the rise in Africa, the continent's farming systems remain the least mechanized globally (Sims et al., 206; Daum & Birner, 2020). For example, FAO estimates that the Africa has less than two tractors per 1,000 hectares of cropland on average compared to about 10 tractors per 1,000 hectares in South Asia and Latin America. The range is varied across the continent – from 1.3 per square kilometer in Rwanda to 43 per square kilometer in South Africa, compared with 128 per square kilometer in India and 116 per square kilometer in Brazil (Sims et al., 2016).

Mechanization is thought to improve agricultural labor productivity – a major determinant of farmers' incomes and subsequently food and nutrition security (Fuglie and Rada, 2013). The replacement of manual labor and animal traction with mechanical power would change the face of African farming and rural areas such as is seen in regions (such as Europe and North America) that are now highly mechanized (Jansen, 1969). There is a large body of literature that documents the benefits of farm mechanization in reducing drudgery and improving labor productivity and crop yields (Sims et al. 2016; Malabo Montpellier Panel 2018; Adu-Baffour et al. 2019; Kirui 2019; Daum et al. 2020). Other studies have also recently allayed fears that farm mechanization may lead to unemployment in a largely agrarian population and land expansion at the cost of forests and savannah (Daum and Birner 2020). Further, acknowledge that agricultural mechanization enhances the farm power available to farmers and may have other agronomic, environmental, and socioeconomic effects beyond the scope of this paper.

Several studies have highlighted the role of climate, infrastructure, labor productivity, and fertilizer in boosting agricultural productivity in Africa, neglecting the importance of mechanization to agricultural growth (Van Loon et al. 2020; Takeshima et al. 2020; Takeshima & Liu 2020). Therefore, this study addresses this research niche. To derive the set of policies and close yield gaps in Africa, an assessment of agricultural productivity across the continent was first conducted. Then, key factors influencing agricultural productivity differences were assessed to demonstrate the relevance of a particular set of measures, including mechanization, to enhance productivity in the lagging regions. To assess the effects of these variables on agricultural productivity, we use two indicators: total factor productivity (TFP) and cereal yields. While cereal yield is what matters for production and food security, TFP is a relevant and popular method for evaluating productivity in multi-input and multi-output production systems. TFP links all factors (e.g., land, labor, capital, and other material resources) employed in production to total output and facilitates a meaningful comparison between spatial units. Therefore, TFP growth illustrates the potential of the agricultural sector to unlock its full production potential. In this study, changes in TFP over time and between countries are assessed by applying Malmquist indices based on both conventional (i.e., contemporaneous) and improved (i.e., sequential) technological approaches and panel data for the 1961–2014 period. The importance of influential factors such as mechanization, climate, labor abundance, and research and development (R&D) expenditures on TFP growth are examined using regression analysis. The details of the methods employed, and the data used are provided in Section 3 after a comprehensive review of the literature on TFP growth assessment and a demonstration of this study's main contributions. Section 4 provides the key findings regarding TFP changes over time across Africa and the regression model's results. We summarize the main outcomes and present key conclusions in the final section.

2. Literature review

Agriculture is Africa's most important economic activity – it provides employment for about two-thirds of the working population (Jayne et al., 2017; Woldemichael et al., 2017) and contributes an average of a quarter of GDP (in sub-Saharan Africa) and about 30 percent of the value of exports in participating countries (AGRA, 2018; Goedde et al., 2019). More than 60 percent of the population of SSA is smallholder farmers producing on very low productivity (Goedde et al., 2019). Boosting African agricultural productivity would require utilization of cost-effective and high-quality agricultural inputs, irrigation, mechanization, and agrochemicals for crops, livestock, fisheries, and aquaculture (Mamo Panel, 2018). This study put special focus on agricultural mechanization. Successful mechanization practices are needed to improve the capacity of smallholders and other operators to grow, store, process, transform and transport their crops and products.

The existing literature on agricultural productivity is quite broad; however, only a few studies have concentrated on African countries and examined the sources of agricultural productivity. They have focused mainly on explanations of agricultural growth as a result of either technological progress or changes in efficiency. For instance, Nin-Pratt and Yu (2009) showed that the recovery in agricultural development in Sub-Saharan countries that occurred between 1984 and 2003 resulted from improved efficiency. In addition, Nin-Pratt (2016) distinguished between African countries with lower or higher output and input per worker and concluded that agricultural productivity growth occurred mostly due to efficiency gains, while technological progress played a greater role in the productivity growth in the latter. By contrast,Mohamed et al. (2016) decomposed agricultural growth in 10 African countries into technical change, efficiency change, and scale effects, and demonstrated that only technical change exhibited a positive effect on agricultural productivity. Changes in the level of input use intensity might explain these outcomes. Unlike these studies, we look into the sources of growth for all African countries using both the contemporaneous production set and a sequential production set as detailed in the next section.

Recent studies have attributed agricultural productivity changes to various factors. Policy interventions are considered to be one of the main contributing factors during the 1980–1990 period (Nin-Pratt and Yu 2009). In addition, trade policy changes contributed to the recovery of agricultural productivity in African countries after the mid-1980s (Alene 2010). Unlike both Nin-Pratt and Yu (2009) and Alene (2010) we estimate both contemporaneous and sequential Malmquist because we believe that there is a certain form of dependence between production sets across time. We also include additional sets of variables such as cumulative effects of agricultural R&D and agricultural expenditure and quality of labor (proxied by literacy level) in the assessment of determinants of agricultural productivity.

Improvements in trade contributed to over 30% of the growth in agricultural gross domestic product (GDP) during 2006–2008 in SSA countries (Fuglie 2011). Furthermore, research shows that a strong correlation exists between macroeconomic policies associated with Structural Adjustment Program (SAP) intensification on agricultural productivity and agricultural growth in 33 African countries (Ojede et al. 2013). The importance of colonial-era institutions is also evident: an assessment of 41 SSA countries demonstrated that former British colonies exhibited greater TFP growth than former Portuguese colonies (Fulginiti et al. 2004).

R&D investment is also a key contributor to agricultural growth. R&D expenditure positively affects productivity growth in many African countries (Lusigi and Thirtle 1997; Lusigi et al. 1998; Alene 2010). Moreover, lags exist between R&D expenditures and the time in which they affect agricultural productivity - the maximum effect of R&D occurs around 10 years after the initial investment (Alene 2010). Furthermore, production R&D elasticity is estimated at approximately 0.2, suggesting that doubling R&D expenditures could increase productivity by 20% 10 years later (Block 2014). Additionally, R&D returns depend on the size of a country's agricultural sector; returns to research decline according to size of the country, with larger agricultural research spending being expected to obtain higher returns in agricultural productivity gains (Fuglie and Rada 2011).

Factor accumulation (e.g., fertilizer use, growing population, increased yields) can be considered another source of agricultural improvement in Africa (Nin-Pratt and Yu 2009; Avila and Evenson 2010). The use of fertilizer is found to explain approximately 51% of African agricultural growth, and its influence was especially significant during the 1970s and 1980s (Nkamleu 2013). Other studies have shown that input intensification And the availability of agricultural land coupled with input intensification increase both TFP and agricultural GDP (Fuglie 2010). The contribution of land, although positive, is marginal and tends towards zero. Population pressure on productive land also significantly contributes to faster agricultural growth (Lusigi and Thirtle 1997).

The quality of labor has also received attention in previous research. Several studies have shown that agricultural productivity is positively linked to improvements in the quality of the labor force (proxied by progress in education and training) (Avila and Evenson 2010; Fuglie and Rada 2011; Block 2014). On the macro level, the quality of the labor force measured in terms of per capita education expenditure is estimated to be a significant determinant of agricultural growth (Lusigi et al. 1998). Furthermore, Nkamleu (2013) demonstrated that increase in labor productivity contributed to increasing African agricultural growth during the 1990s, surpassing the effects of other factors.

African agricultural production is almost entirely rain-fed. The use of irrigation is limited—only approximately 6% of cultivated areas in Africa are under some form of irrigation (MaMo Panel 2018; Houdret et al. 2017). As such, productivity relies on weather conditions, especially rainfall and temperature. Alene (2010) demonstrated a strong and positive relationship between annual rainfall and agricultural productivity, with an elasticity of 0.17. There is also evidence of short- and long-run relationships between per-capita GDP growth and temperature and rainfall in Africa (Lanzafame 2012).

Fuglie and Rada (2011) found that civil strife was a significant constraint to agricultural development, because conflict degrades social constructions, reduces labor availability in rural areas, and causes the destruction of the infrastructure that serves sustainable food production. Yet, contrary to expectations, infrastructural development, especially road expansion, is found to be negatively associated with agricultural growth (Fuglie and Rada 2011; Block 2014). Theoretically, an improved infrastructure would lead to lower transport costs and increased input and output market access, which would be expected to increase output. High-level inequality at the subnational level, as reflected through high-level transport density and the development of capital cities as well as a lack of attention to investment in rural areas, might explain these unexpected results. The lack of sufficient data and incorrectly specified models may also explain these variations.

A review of the literature only produced one study by Avila and Evenson (2010) that quantified the implications of farm mechanization on agricultural growth for the whole of Africa. Unlike their study, we use more up-to-date data that captures the period in which agricultural growth is perceived to have picked across Africa. Our study also goes beyond estimating the sources of growth to include the different drivers of yield for specific cereals. Elsewhere in the literature, some attention (however limited) has been accorded to the significance of farm machinery on agricultural growth in other developing countries. For example, Salam (1981) also estimated that the number of tractors and tube-wells has contributed significantly to agricultural productivity in Pakistan. Similarly, in China the amount of motorized equipment has been linked to increased agricultural growth (Zhou and Zhang 2013). Moreover, machinery elasticities have shown a positive and increasing effect over time, implying their growing influence on Chinese agriculture (Gong 2018). A more recent study found limited technological change and slow growth in efficiency in South African wine grape production between 2005–2015 (Conradie et al. 2019). Furthermore, technology spillovers were found to be significant source of productivity growth in South African Agriculture (Khatri et al. 2000). Other studies in South Asia have not discovered a significant effect of the level mechanization on agricultural growth (Anik et al. 2017). Other important determinants of agricultural growth in developing countries include general investment in agriculture (Chand et al. 2011; Rahman and Salim 2013), infrastructural investments such as road density, electricity supply (Chand et al. 2011), and irrigation investment (Chand et al. 2011). Factor inputs such as fertilizer, land, labor, and human capital development (e.g., literacy and education) are also significant determinants (Zhou and Zhang 2013; Rahman and Salim 2013). Natural disasters are shown to slow agricultural growth (Gong 2018).

The contributions of this study are thus, to fill the research gap identified by the preceding review. We aim to quantify the implications of farm mechanization on agricultural growth. To achieve this, we begin by computing and comparing the TFP growth in African agriculture over the 1961–2014 period under the contemporaneous and improved sequential technology approaches. We consequently examine the sources of agricultural productivity growth with a special focus on the role of mechanization. Another contribution relates to the estimation of the determinants of selected cereal (e.g., wheat, rice, barley, and maize) yields at both the continental and regional levels over the 2000–2014 period. This is particularly important because it provides further corroborating evidence on the significant influence of selected variables on TFP growth.

3. Methodology

Our econometric strategy proceeds in two parts. In the first part, following the work of Evenson and Pray (1991) and Fuglie (2018), we use a two-stage approach to assess the impact of various factors on TFP growth. First, TFP indices are constructed using the Malmquist approach. Then, the impact of various technical and institutional factors influencing TFP changes over time and across African countries are evaluated using regression analysis. In the second part, we empirically examine the contribution of fixed and variable inputs to increased productivity among staple crops, proxied by cereal yields per hectare, using cross-country-cross-commodity panel data. Calculation and analysis sequences are briefly described in Figure 1. The details of the methods used are provided in the following subsections.

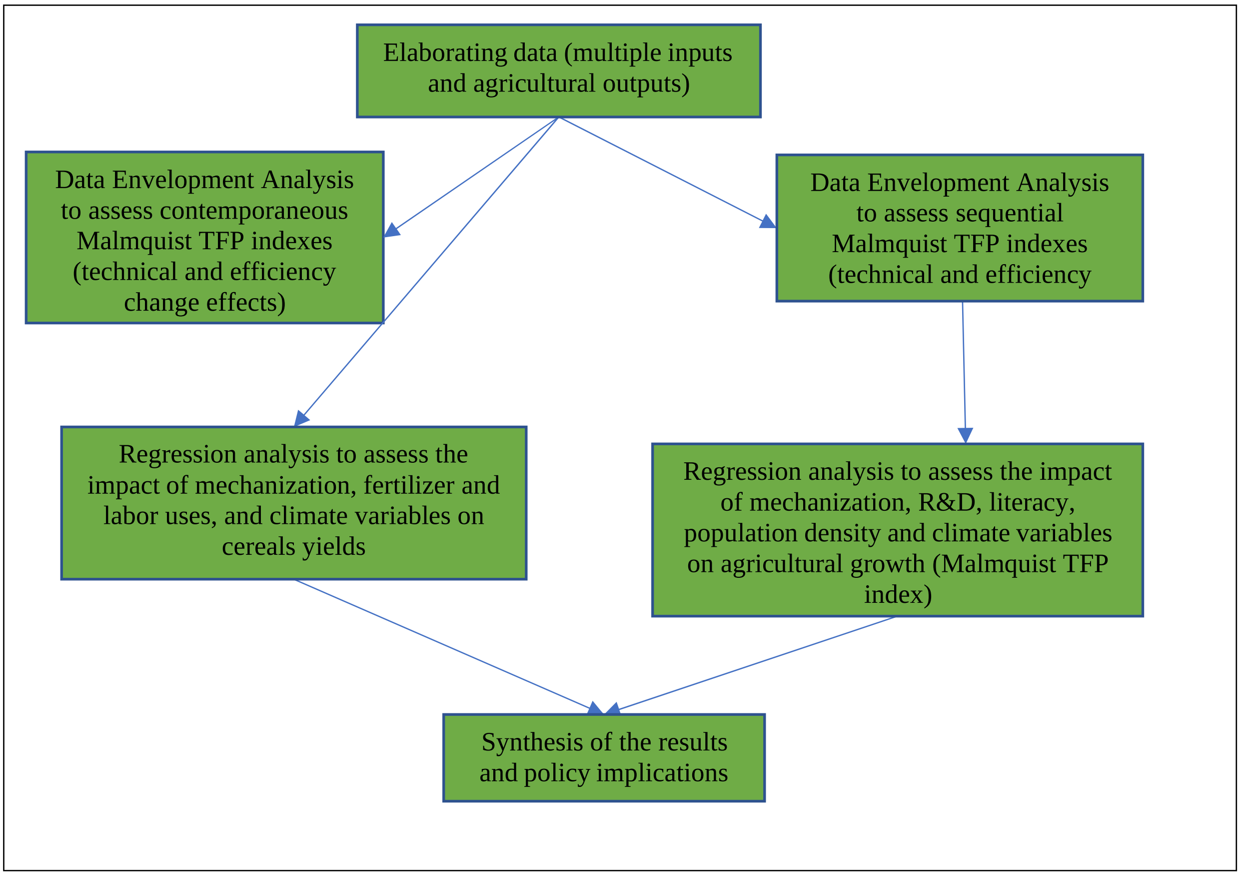


Figure 1. Steps of applying and integrating Data Envelopment Analysis and econometric approaches to estimate the impact of mechanization on agricultural productivity
Source: Authors' creation

3.1 The Malmquist TFP index

The Malmquist TFP index is a well-established measure for productivity growth and decomposition (Färe et al. 1994; Coelli and Rao 2005; Kohl et al. 2019). This index enables the technological, efficiency, and scale change effects that enhance TFP growth to be separately assessed. The index has been broadly applied since information on the quantities of inputs and outputs sufficient for the calculations were made available; assessments using alternative approaches require additional information on prices and behavioral assumptions (cost-minimizing or revenue-maximizing; Färe et al. 1994). This approach is therefore particularly relevant in the case of African agriculture where the markets (land and labor) are not well-developed and information on prices and decision-making attitudes is lacking (Barrett et al. 2012). Chang and Luh (2000) posited that TFP decomposition is essential in characterizing and comparing growth patterns between countries. From a policy perspective, TFP decomposition is useful for policy makers because they can monitor technologicalprogress (improvement or stagnation) and the impact of technological and institutional policymeasures over time (Kalirajan et al. 1996).

The underlying assumption when applying data envelopment analysis (DEA) to calculate the Malmquist productivity index is that one can construct a best practice frontier for each time period as a reference technology. Tulkens and Eeckaut (1995) and Nin et al. (2003) described two possible ways for constructing the frontier of the production set—a contemporaneous production set and a sequential production set. Under the contemporaneous production approach, successive production sets are fundamentally unrelated. In contrast, the sequential production set assumes that there is a certain form of dependence between production sets across time.

3.2 Which factors influenced agricultural productivity?

Beyond the measurement and decomposition of productivity growth, this study provides an assessment of the correlates of African agricultural productivity growth between 2000- 2014. Differing from previous studies, we consider a comprehensive set of factors related withinput availability, access to supply chains, environmental changes, and institutional variables. Therefore, the regression analysis includes wide range of variables such as mechanization, agricultural expenditures per worker [1]climate variables (temperature and rainfall), agricultural labor per unit of arable land (as a proxy for population pressure), and literacy level (as a proxy quality of labor). Since the estimation of TFP growth rates for the 2000-2014 period is based on a set of variable and fixed inputs, we do not employ the same regression type. Instead, we explore how mechanization, fertilizer intensity and the labor-land-ratio in 2000 are associated with average TFP growth between 2000-2014. Specifically, the empirical specification applied to assess the determinants of agricultural productivity in this study is as follows:

$$
\begin{aligned}
(TFP)_{i2000-2014} = {} & \beta_0 + \beta_1 \ln(\text{Mechanization}/ha)_{i2000} + \beta_2 \\
& \ln(\text{Rainfall})_{i2000-2014} + \beta_3 \ln(\text{Temp})_{i2000-2014} + \beta_4 \\
& \ln(Fertilizer\ /ha)_{jt} + \beta_5 \ln(\text{Labor/ha})_{i2000-2014} + \\
& \beta_6\, \text{Literacy}_{i2000} + \beta_7 \ln(\text{AgExp})_{i2000-2014} + e_{it}
\end{aligned}
\tag{1}
$$

Subscripts 2000-2014 imply that 15-year averages are used; $\beta_1, \beta_2, \ldots, \beta_7$ are slope coefficients of the regression equation; i stands a cross-sectional unit, Mechanization is the number of machinery (1000 metric horsepower (CV) Equivalent) per hectare, Fertilizer/ha is total chemical and organic N fertilizer use per hectare, AgExp stands for central government agricultural expenditures; Literacy is the literate population share, Rainfall and Temperature are measures as the annual levels as compared to long-term averages. e is a random error term. Given that TFP is calculated through production sets, the results need to be interpreted with caution and equation (1) should not be interpreted as a production function, but it will only reveal correlations.

3.3 Regression analysis of the factors influencing cereal yields

After having analyzed how mechanization and other components contributed to TFP growth, we are interested in understanding how these inputs are the driving factors underlying cereal yield growth. Specifically, we aim to determine the contribution of agricultural mechanization on yield growth. We start following the modelling approach of McArthur and McCord (2017) who include technological inputs as drivers of yield growth. The model is illustrated as follows:

[1] Central government agricultural expenditures per worker and agricultural R&D are highly correlated and cannot appear in a single equation. Given that the expenditure data is more complete, we have not considered agricultural R&D.

$$\ln(Yield)_{ijt} = \beta_1 \ln(Mechanization)_{jt} + \beta_2 ln(\frac{Labor}{ha}.)_{jt} + \beta_3 ln(Fertilizer\ /ha)_{jt} + u_{ijt} \quad (2)$$

Where we observe the i[th] crop in country j at time t. u_{ijt} comprises the random error e_{ijt} and the time-invariant constant $\bar{u}_j$. By accounting for country fixed effects, we ensure that the results are not driven by any unobserved heterogeneity of the panel units. Notably, while yieldis measured for each crop separately, all inputs are not available at crop level.

The model differs from McArthur and McCord (2017) in two ways. First, we choose a log-log specification, that addresses outliers, after inspecting the data. Second, we do not divide the number of tractors -the mechanization indicator- by area. We argue that machinery is in a sense non-rival since, unlike fertilizer, it can be used as input on different fields. To account for dynamics t is the sandwich year of a 3-years moving average of the dependent and independent variables.

Although we test for unit roots in the panel, using the Phillips–Perron test, and reject that ln($Yield)_{ijt}$ has a unit root at 1% probability of error. In this model, we consider the change in agricultural yields, $\Delta Yield_{ijt} = Yield_{ijt} - Yield_{ijt-1}$ instead of levels (also the changes for all independent variables). Last, to better account for dynamics, we follow Haile et al (2013) and Magrini et al. (2018) and model yield as a function of its own lag. A dynamic model is justified by the persistence of the dependent variable, but also theoretically grounded through naive expectations (Haile et al., 2013) We believe that for mechanization this model could be more appropriate as benefits of mechanization (e.g., land preparation after harvesting) may only utilize after several years.

$$\text{Ln}(\,Yield)_{ijt} = \beta_1\ln\,(Yield)_{ijt-1} + \beta_2\ln\,(Mechanization)_{ijt} + \beta_3\,ln(Labor/ha)_{ijt} + \beta_5\,ln(Fertilizer/ha)_{ijt} + \beta_6\,\,ln(Rainfall)_{it} + \beta_7\,\,ln(Rainfall)^2_{it} + \,\beta_8\,\,ln(Temp)_{it}\, + \,\beta_9\,\,ln(Temp)^2_{it} + u_{ijt} \quad (3)$$

Where $ln(Rainfall)^2_{it}$ and $ln(Temp)^2_{it}$ are measures of rainfall and temperature variability and are computed as the standard deviation of monthly deviations from the long-term averages. As compared to equation (1), we do not consider agricultural expenditures per worker and adult literacy as explanatory variable. This is motivated by two issues. First, agricultural expenditures and adult literacy data series have several missing gaps which affect the dynamic panel estimation. Second, both variables are more likely to affect yield and productivity growth in the long-term, but less likely in the contemporaneous and first lag period.

There is another source of endogeneity because $Yield_{ijt-1}$ is not only correlated with u_{ijt-1}, but also with u_{ijt} . Therefore, the regressor $Yield_{ijt-1}$is correlated with u_{ijt} and both the within estimator and difference estimator become inconsistent unless $T \rightarrow \infty$, the so-called Nickell-bias (Nickell 1981). In addition, other explanatory variables may be predetermined by $Yield_{ijt-1}$, e.g., last year's change in yield is correlated with input use (labor, tractors,fertilizer) for the current period and therefore the input use variables are also correlated with Δu_{ijt-1} (Roodman, 2009A).

As proposed by Anderson and Hsiao (1981), lagged differences can also serve as instruments at the cost of losing one or more periods of observation. Yet, the Anderson–Hsiao estimator could lack efficiency for not using all available instruments. Blundell and Bond (1998) therefore proposed making use of all available moment conditions to estimate a system of equations to estimate the coefficients of Equation (3). The validity of the set of instruments needs to be tested using the Hansen Test or the Sargan Test for overidentifying restrictions. The system GMM estimator potentially suffers from inconsistency due to the use of too many instruments (Roodman, 2009A). This problem can be solved by limiting the number of instruments to the most relevant instruments. In lacking a valid external instrument, we focus on internal gmm instruments. Therefore, the model may be subject to weak instrumentation.

4. Data

The data used for the TFP estimation in this study are retrieved from the United States Department of Agriculture, Economic Research Service. These consist of 1961–2015 annual time series (panel) data on agricultural production (crops and livestock) and conventional agricultural inputs (land, labor, fertilizer, and machinery and animal feed inputs) for the 53 African countries for the 1961–2015[2] period from the Food and Agriculture Organization of the United Nations (FAO). These data were chosen because they contain the input and output data required to construct agricultural TFP indices and subsequently assess the determinants of TFP. The data are modified or supplemented with data from other sources—especially from national statistical agencies—when they are considered to be more accurate or up-to-date.

Agricultural output is measured as the volume of agricultural production at constant 2004–2006 average international prices measured in thousands of dollars. International commodity prices are used to aggregate the agricultural production of 189 crop and livestock commodities to facilitate cross-country comparative analyses of productivity. This output measure is equivalent to a Paasche Quantity Index in which annual quantities vary and end-period prices are fixed. FAO gross agricultural output is used for the output series. Total agricultural land is measured as the sum of arable land and land under permanent cultivation and pasture in thousands of hectares (ha). Agricultural labor is measured as the number of economically active adults engaged in agriculture (as provided by the International Labor Organization (ILO)). Fertilizer is defined as the plant nutrients—e.g., nitrogen, phosphorous, and potash—used in agriculture and measured in metric tons (as obtained from the International Fertilizer Association (IFA)). Farm machinery is defined as the total stock of farm machinery in “40-CV tractor equivalents” (CV = metric horsepower), aggregating the number of two-wheel tractors, four-wheel tractors, and combine-harvesters and threshers. The weights are assumed asfollows: two-wheel tractors average 12 CV, four-wheel tractors average 40 CV, and combine-harvesters average 20 CV. Data is from the FAO, except for two-wheel tractors, which were compiled from national sources. Historical weather data (monthly rainfall and temperature) were obtained from Jefferson and O’Connell.

In the assessment of the determinants of agricultural productivity changes and agricultural yield growth, we have used data from four sources. First, the updated USDA TFP data set for the number of machinery (1000 metric horsepower) and the labor-land ratio. Second, the FAOSTAT data for cereal yields, namely wheat, maize, barley, rice, sorghum, and millet as well as fertilizer use by nutrient, namely nitrogen (N) and potassium (K). Third, the World Development Indicators of the World Bank provided data on the rate of adult literacy (as a slack proxy of the quality of labor in the absence of actual data on the quality of labor). Data on agricultural expenditures (measured per agricultural worker) were also obtained from FAO.

[2] See https://www.ers.usda.gov/data-products/international-agricultural-productivity.aspx for additional details.

Rainfall and temperature data until 2020 is taken from the World Bank's Climate Change Knowledge Portal.

5. Results and Discussion

5.1 Productivity growth estimates

We present the aggregate conventional and sequential Malmquist indices of productivity growth and their components (efficiency change and technical progress) for African regions in Table 1. The findings indicate that under contemporaneous technology (conventional Malmquist), African agriculture grew by 1.1% per year over the 1961–2014 period. Regionally,[3] Northern African countries experienced the highest growth at about 3.1% annually, followed by . Southern at about 1.6%, Eastern Africa 0,9%, Western Africa 0.8% and Central Africa 0.7%.

Table 1. Productivity growth estimates (average & range) in Africa, 1961–2014

	Conventional Malmquist Index			Sequential Malmquist Index		
	TFP	Efficiency Change	Technical Progress	TFP	Efficiency Change	Technical Progress
Africa (Average	1.121	0.185	0.941	1.664	0.185	1.479
East Africa	0.856 -0.85-3.07	0.026 -1.18-1.33	0.843 0.28-1.79	1.648 0.10-5.14	0.026 -1.18-1.33	1.623 0.61-4.96
Central Africa	0.686 -0.58-1.67	−0.220 -1.12-0.72	0.921 0.51-1.32	1.136 -0.63-2.51	−0.220 -1.12-0.72	1.369 0.52-2.04
North Africa	3.111 0.53-7.13	1.493 -0.06-2.39	1.586 0.60-3.91	3.178 0.52-7.17	1.493 -0.06-3.03	1.670 0.59-4.05
Southern Africa	1.551 -0.09-2.52	0.472 -0.16-1.20	1.074 0.08-2.39	2.472 0.44-3.97	0.472 -0.16-1.20	1.977 0.60-3.72
West Africa	0.785 -0.93-3.35	0.009 -1.34-1.93	0.784 0.39-1.40	1.183 -0.89-3.76	0.009 -1.34-1.93	1.178 0.46-2.46

Source: Authors' compilation based on USDA and FAO data.

At the individual country level, Libya (7.1%), Tunisia (4.2%), Cape Verde (3.4%), Seychelles (3.1%), Algeria (2.9%), South Africa (2.5%), and Morocco (2.5%) reported growth of 2.5% or more, while Burkina Faso, Comoros, DRC, Burundi, Gambia, Equatorial Guinea, Namibia, Sao Tome, and Uganda reported negative growth over the same time period. the rest of the countries combined reported average annual growth of about 1%. In summary, estimates calculated using the conventional approach suggest agricultural productivity stagnation in Africa. This is consistent with earlier findings by Alene (2010), which indicated stagnation in SSA agriculture, and by Fulginiti and Perrin (1997), which demonstrated regression in 18 low-income countries.

Table 1 shows that agriculture grew at a much higher rate of about 1.7% peryear over the 1961–2014 period under sequential technology. Northern and Southern Africa experienced faster growth with average growth rates of 3.2% and 2.3%, respectively, while Eastern Africa experienced growth of about 1.6%, and Western and Central Africa a paltry 1.2% and 1.1%, respectively. Eighteen countries experienced an annual growth rate of at least2%, with five of these countries over 4% including Libya (7.2%), Reunion (5.1%), Djibouti (4.4%), Tunisia (4.2%), and Eswatini (4.0%). Conversely, three countries reported negative productivity growth rates, largely due to waning technical efficiency.

[3] The countries were grouped into the different regions based on the official UN classification: https://cies2018.org/wp-content/uploads/List-of-Countries-by-Region-UN-Annex-II.pdf.

The leading countries in terms of technical progress—Djibouti, Libya, Reunion France, Eswatini, and South Africa— all report annual technical progress of at least 3.5%, implying that these countries led in technological innovation processes. Similarly, efficiency gains were reported in Libya, Tunisia, Cape Verde, and Morocco.

These findings align with earlier studies such as Headey et al. (2010), Nin-Pratt and Yu (2008), and Alene (2010). Headey et al. (2010) measured agricultural TFP growth rates in 22 SSA countries over the 1970–2001 period while Alene (2010) estimated agricultural TFP for the whole of Africa for the 1971–2004 period. They found average annual growth rates of 2% and 1.8%, respectively. Other studies, however, discovered a higher growth rate of about 7.7% per year (Nin-Pratt et al. 2012) for the 2001–2010 period and approximately 7% annually since 2005 (AGRA 2017), propelled mainly by the expansion of cropped areas and commodity price surges.

5.2 Annual productivity growth estimates

Table 2 presents the conventional and the sequential Malmquist estimates of annual and periodic productivity growth and its components. There are noticeable differences between the conventional and sequential measures of productivity growth. On average, African agriculture grew annually by 1.1% and 1.7% under contemporaneous technology and under sequential technology, respectively.

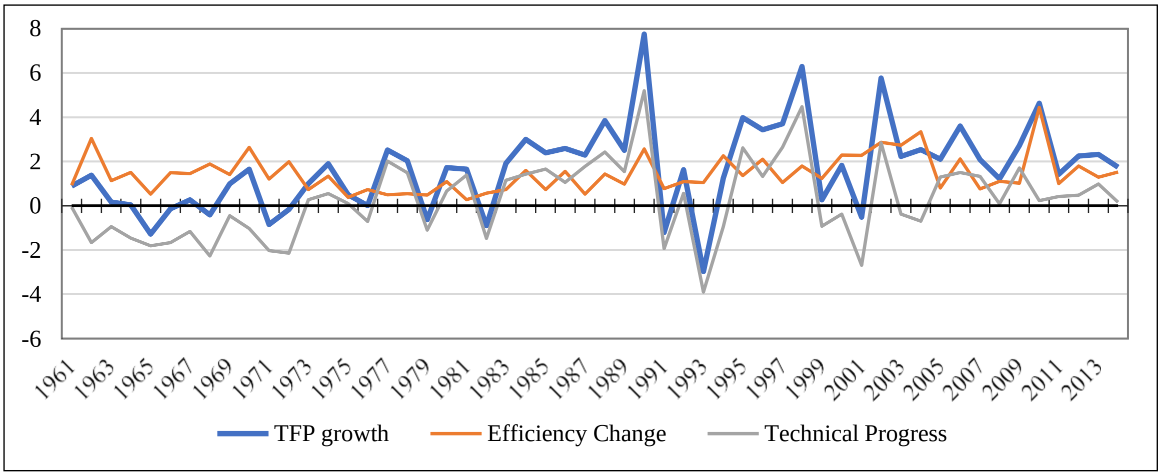
Table 2. Annual agricultural productivity growth estimates over decades

Year	Conventional Malmquist			Sequential Malmquist		
	TFP	Efficiency Change	Technical Progress	TFP	Efficiency Change	Technical Progress
1961-2014	1.12	0.94	0.18	1.66	1.48	0.18
1961-1970	0.25	1.06	−0.81	0.53	1.33	−0.81
1971-1980	0.55	0.57	−0.02	0.84	0.86	−0.02
1981-1990	1.63	0.77	0.86	2.00	1.13	0.86
1991-2000	1.44	0.96	0.50	1.82	1.33	0.50
2000-2010	1.76	1.36	0.41	2.71	2.30	0.41
2010-2014	1.00	0.83	0.16	2.59	2.41	0.16
2000-2014	1.56	1.22	0.34	2.68	2.33	0.34

Source: Authors' compilation based on USDA and FAO data.

The assessments based on the conventional approach showed negligible agricultural productivity growth in the 1960s (0.3% annually) and 1970s (0.7% annually), with the decline primarily due to the lack of technological progress (−0.8% and –0.02% yearly, respectively). Some recovery began in the 1980s (1.6% per year), followed by a slight dip in the 1990s (1.4% annual growth) during the structural adjustment period. The major source of recovery in the 1980s was technical progress, and efficiency gains in the 1990s and 2000s (Figure 2). Under the conventional measures, the highest rate of growth was experienced in the 2000s (1.8% annually). This is contrary to earlier studies such as Alene (2010), who demonstrated that under the conventional approach, the growth of the 1980s was sustained into the 1990s and beyond. Nevertheless, our findings are consistent with available evidence such as that of the World Bank (2007) showing that African agricultural growth has been on an upward trend due to improved macroeconomic conditions.

Conversely, the improved estimates using the sequential approach indicate augmented and sustained growth over the years. The 1960s experienced the lowest growth (0.5% annually), but growth has been on an upward trend since that time, except for the 1990s, when there was a slight slowdown. Annual growth rates for the subsequent decades were 0.8% for the 1970s, 2% for the 1980s, 1.8% in the 1990s, 2.71% during the 2000s, and 2.59% in the 2010–2014 period. Over the period2000–2014, agriculture grew at an average of about 2.7% annually. These findings are consistent with the economic recovery narrative in Africa, marked by growth in agricultural GDP due mainly to improved prices of agricultural goods and a better macroeconomic environment (World Bank 2007).

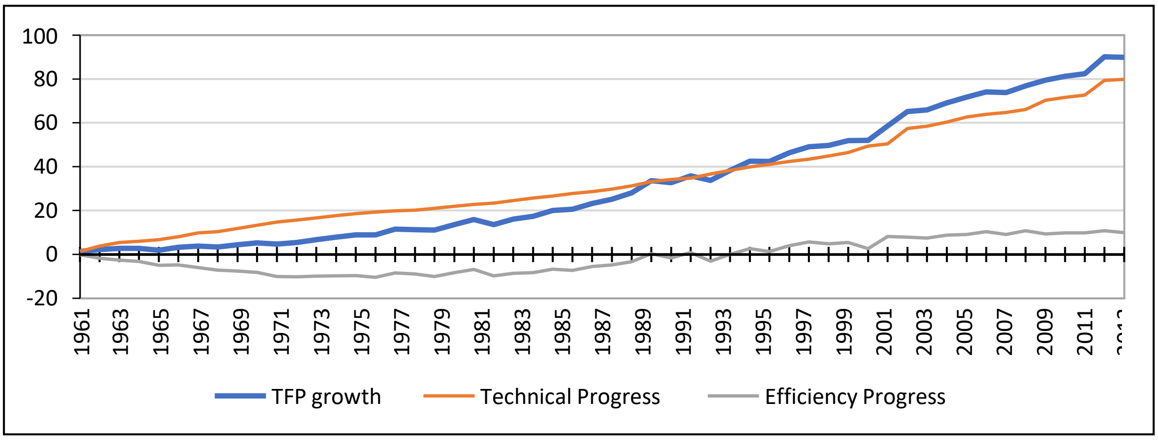


Source: Authors' compilation based on USDA and FAO data.

Figure 2. Annual agricultural productivity growth, efficiency change, and technical progress in Africa using conventional Malmquist TFP index (1961–2014)

5.3 Cumulative productivity growth

The cumulative values of technical progress and efficiency change can be used to demonstrate their relative importance as sources of productivity growth. Figure 3 presents the productivity changes based on the improved (sequential) Malmquist index method. Sequential Malmquist measures are considered progressive because unlike the conventional measures, they are not susceptible or sensitive to the confounding effects of weather conditions. The adverse effects of the weather are more accurately accounted for as efficiency deterioration instead of technical decline. Figure 3 presents cumulative TFP growth, efficiency change, and technical progress for the 1961–2014 period. The estimates calculated under the sequential technology assumption evidently show that cumulative TFP growth is closely interwoven with cumulative technical efficiency. Markedly, cumulative technical change remained negative in the first three decades (1961–1990)—this can be categorized as the period of decline (1961–1980) and the beginning of recovery (1981 onwards). Cumulative technical change became positive and continued increasing beginning in 1991, and by 2014, cumulative technical change reached 10%.



Source: Authors' compilation based on USDA and FAO data.

Figure 3. Cumulative sequential agricultural productivity growth, efficiency change and technical progress in African agriculture (1961–2014)

5.4 Correlates of agricultural productivity growth

To examine the sources of agricultural productivity growth, we estimate the model in Equation (1) using a cross-sectional OLS regression (Table 3A). We present the results of three different estimations with different set of explanatory variables in Table 3B. We also depict the relationship between TFP and selected covariates (mechanization, fertilizer, literacy, agricultural expenditure and rainfall) in Figure 4. The results from the Africa-wide model specification show that, among the production inputs, the level of agricultural mechanization (per ha) in 2000 is the only variable that is significantly correlated with TFP growth between 2000-2014 (Table 3B). We observe no correlation with fertilizer intensity and the labor-land ratio. This finding accords with earlier studies that showed that the number of tractors (Zhou and Zhang 2013) or the level of mechanization (Anik et al. 2017; Gong 2018) contributed significantly to agricultural productivity. Specifically, the results indicate that the elasticity of agricultural productivity with respect to mechanization is around 0.2. This implies that a 10% increase in the number of machines per hectare in 2000 is associated with a productivity about 2% more TFP growth between 2000-2014.

Table 3A. Correlated of TFP growth between 2000-2014

	Africa (pooled)	East Africa	West Africa	North Africa	Southern Africa	Central Africa
Ln(Mechanization)	0.174*	0.063*	-0.019	0.013	0.511**	-0.508
Ln(labor/ha)	-0.042	-0.081	0.017	0.184*	-0.107*	0.066
Ln(labor/ha^2)	0.002	0.003	-0.002	-0.010**	0.006**	-0.003
Ln(R&D)	-0.062	-0.123	-0.056	0.000	-0.041	-0.039
Ln(Ag_Exp)	0.023*	0.044*	0.011**	0.218*	0.000	0.029
Ln(literacy)	0.051	0.058	0.102	0.044	0.078	0.132
Weather variables	Yes	Yes	Yes	Yes	Yes	Yes
constant	2.585***	3.575**	4.266**	7.87	0.17	6.65
Year_dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	386	81	53	58	42	34
p-value	0.000	0.000	0.000	0.000	0.001	0.000

Note: Single, double, and triple asterisks (*,**,***) indicate statistical significance at the 10%, 5%, and 1% level.
Source: Authors' compilation based on USDA and FAO data.

Table 3B. Correlates of average TFP growth between 2000-2014

	TFP growth	TFP growth	TFP growth
Ln(Mechanization_2000)	0.24*	0.196+	0.21+
labor/ha_2000	-0.028	0.044	0.047
Ln(Fertil/ha_2000)	-0.14	-0.08	-0.078
Ln(Ag_Exp)		0.42***	0.407***
Ln(literacy_2000)		-0.29**	-0.32**
Weather variables	No	No	Yes
constant	1.012***	4.306***	4.299***
N	46	46	46
R^2	0.08	0.30	0.31

Note: Plus sign, single, double, and triple asterisks ($^+$,*,**,***) indicate statistical significance at the 15%, 10%, 5%, and 1% level. Source: Authors' compilation based on USDA and FAO data.

On the other hand, both adult literacy (as indicator for education) and agricultural expenditures per worker are significantly correlated with TFP growth. First, adult literacy is negatively correlated with TFP growth. This implies that countries with higher levels of education experienced lower TFP growth between 2000-2014. The effect suggests a convergence in TFP growth across African countries with respect to the returns from education. Countries with lower adult literacy in 2000 were able to generate additional returns from educational improvement which are likely to positively affect TFP growth. Besides, the average agricultural expenditure allocations per worker were significantly correlated with agricultural productivity. The elasticity implies that a 10% increase in agricultural expenditures per workers were associated with 4% increases in average annual agricultural productivity growth.

Population pressure on agricultural land is positively associated with agricultural growth in the Northern Africa region but shows an opposite effect in the Southern Africa region. A 10% increase in agricultural labor per unit of agricultural land increases productivity by about 1.8% per year in Northern Africa but reduces productivity by 1.1% per year in Southern Africa. This finding might imply that Southern African countries (except South Africa) has a low incentive to increase land productivity through the adoption of yield-enhancing technologies due to land abundance. On the other hand, following the population-induced innovation hypothesis, population pressure on already limited arable land is contributing to increasing agricultural productivity in Northern Africa.

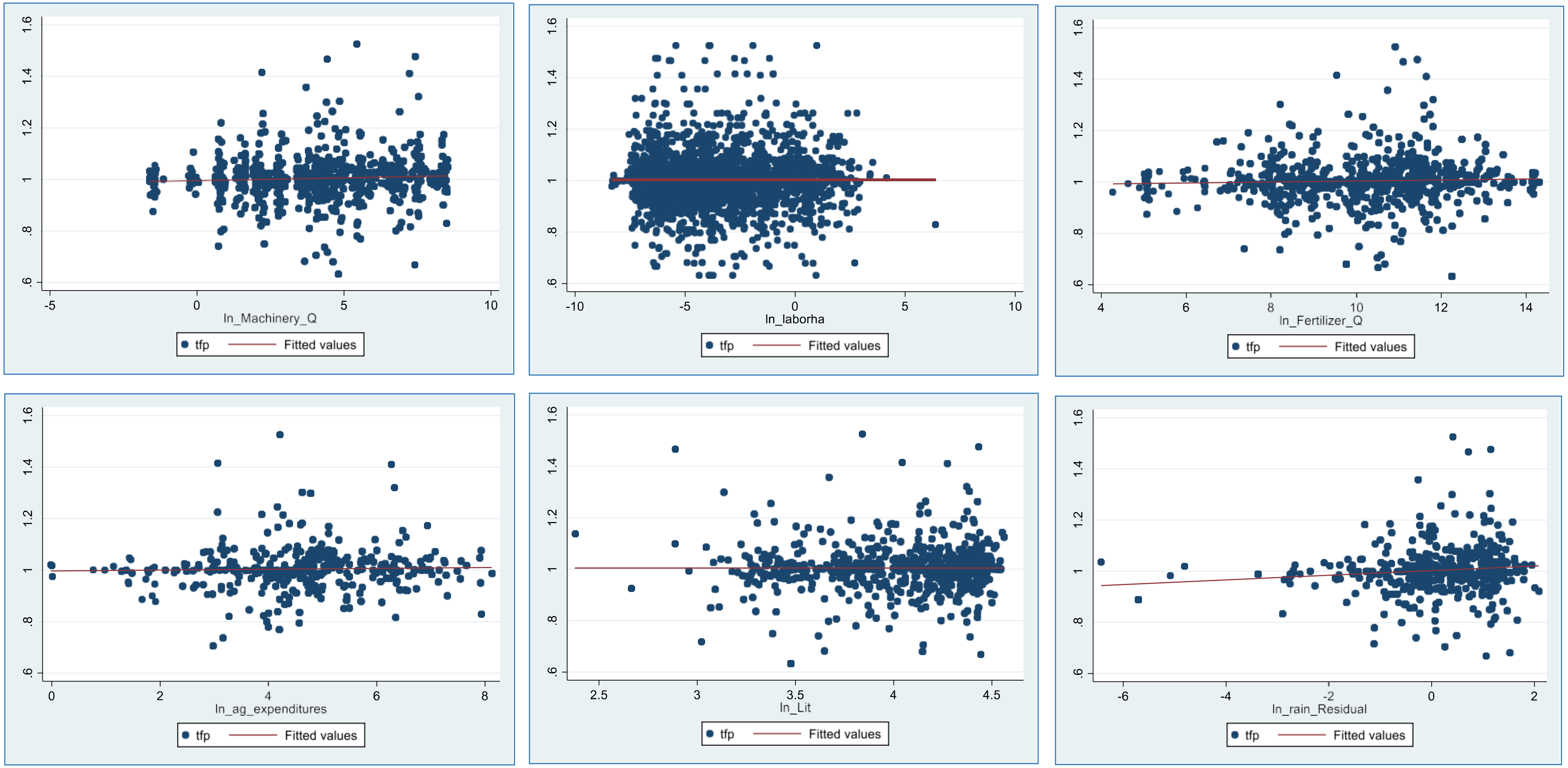


Figure 4. Relationship between TFP and various covariates (i.e., capital, labor, fertilizer, machinery, and land).
Source: Authors’ compilation based on USDA and FAO data.

5.5 Determinants of cereal yields: Does mechanization matter?

We estimated the determinants of agricultural productivity for selected cereals at the continental level and at the regional level over the 2000–2020 period. These supplementary assessments serve as complimentary for the findings on the determinants of TFP growth. The mean total yields of wheat, rice, maize, barley, millet and sorghum between 2000 and 2020 were 2.1, 2.5, 1.7, 2.1, 0.8, and 1.1 tons per ha, respectively. This varied between regions according to crop. We depict the relationship between the outcome variable (yield) and various factors of production (capital, labor, fertilizer, machinery, and land) in Figure 5. As expected, there is a strong, positive relationship between cereal yield and capital and between cereal yield and the intensity of fertilizer used. The relationship between yield and tractor use is also positively sloping. The size of (arable) land area is the only variable that exhibits a negative relationship with cereal yield. This implies that the source of growth starting in the 2000s is no longer attributable to agricultural land expansion but to input intensification.

The estimated results of the relationship between cereal yield and various inputs are presented in Table 4. In Column (1) we present a parsimonious model replicating McArthur and McCord (2017). Columns (2), (3) and (4) present the dynamic panel model using the system GMM estimator but with different variables for fertilizer intensity. In Column (2), we use total chemical fertilizer, in column (3) total nitrogen fertilizer, and in column (4) total potassium fertilizer. We include the results of the standard specification tests for dynamic panel regressions in Table 4. The details are presented in the notes of the table. To avoid instrument proliferation, we collapse the instruments following Rodman's (2009B) suggestion. Here, the number of instruments is reduced using a principal component method. As long as the number instruments is smaller than the number of cross-sectional units, instrument proliferation is limited, which is the case for all models.

Table 4. The effect of mechanization on agricultural yields in Africa

	FE		**sysGMM**		**sysGMM**		**sysGMM**	
	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E.
Ln(Yield)	na		0.924	0.044	0.984***	0.062	0.924***	0.048
Ln(Mech)	**0.144*** **	**0.046**	**0.069*** **	**0.025**	**0.051** **	**0.026**	**0.078*** **	**0.025**
Ln(Labor/ha)	0.001	0.001	-0.003***	0.000	-003***	0.000	-0.003***	0.000
Ln(Fertil/ha)	0.039***	0.009	0.014*	0.008				
Ln(N/ha)					0.009	0.008		
Ln(K/ha)							0.015**	0.007
Weather variables	No		Yes		Yes		Yes	
Year dummies	No		Yes		Yes		Yes	
N	1,464		4,080		4,190		4,080	
N(instruments)	na		111		111		111	
N(groups)	221		217		217		217	
p>AR (2)	na		0.128		0.076		0.107	
p>Sargan Test	na		0.000		0.000		0.000	
p>Hansen Test	na		0.858		0.819		0.925	
p>Diff-in-Hansen Test	na		0.995		0.28		0.989	

Note: Plus sign, single, double, and triple asterisks ($^{+}$,*,**,***) indicate statistical significance at the 15%, 10%, 5%, and 1% level. For columns (2), (3) and (4) two-step robust standard errors, incorporating the Windmeijer (2005) correction, are in parentheses. Diff-in-Hansen test shows p-values for the validity of instruments for the endogenous variables. To address the problem of serial correlation of second order only deeper lags (starting from lag 3) are used as instruments.
Source: Authors' compilation based on USDA and FAO data.

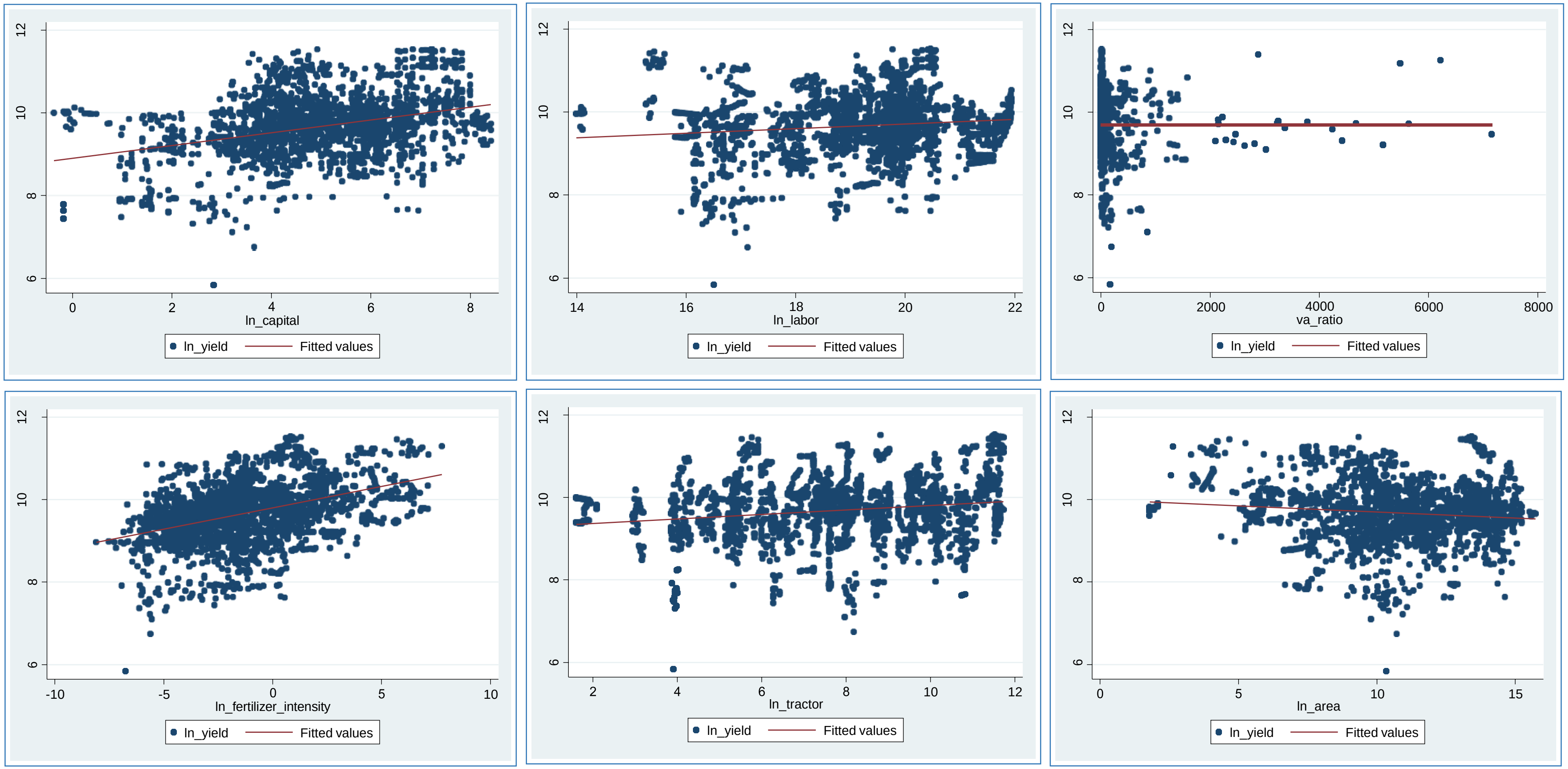


Figure 5. Relationship between Yield and various factors of production (i.e., capital, labor, fertilizer, machinery, and land).
Source: Authors' compilation based on USDA and FAO data.

In all models, the coefficients of all inputs have the expected sign and are, in most cases, significantly different from zero. Of particular interest is the relationship between cereal yield and the use of farm machinery. The findings indicate that increasing the number of machines by 1% increases the cereal yield by 0.08% across the different specifications. In the long-run, considering the dynamics of the benefits from mechanization, the effect increases to around 0.8%. However, it is important to note that due to diminishing returns, we do not expect that growth rates in machinery use could have similar effects in the future. This corroborates our findings from the previous section—mechanization (technological progress) is a key driver of agricultural productivity in Africa, although the magnitude of influence might vary from region to region.

Other significant variables include labor, fertilizer use, and weather (rainfall). Specifically, agricultural labor per ha is negatively and significantly related to cereal yield in the overall model. The implication is important for African agriculture where farm preparations prior to planning are often done mechanically (by tractors), but subsequent operations and crop husbandry practices (such as weeding to harvesting) still depend heavily on manual labor. Without proper crop husbandry practices, the gains of mechanized farm preparations would be wasted. A decrease in the labor-land ratio is, however, an indicator for increasing labor productivity. The sign of the effects is in accordance with McCord (2017).

As expected, input intensification—particularly fertilizer—is positively and significantly associated with cereal yield in the overall model, supporting the findings by McArthur and McCord (2017). Specifically, doubling fertilizer was associated with long-run yield growth of around 13%. This figure is very similar to what McArthur and McCord (2017) report using a linear model specification.

Indeed, the literature shows that access to modern inputs and technologies and factor accumulation (such as fertilizer, land, labor, irrigation and human capital development) are key to improving agricultural productivity (Nin-Pratt and Yu 2009; Avila and Evenson 2010; Nkamleu 2013; Houdret et al. 2017; van Dijk et al. 2017; McArthur and McCord 2017; MaMo Panel 2018; Takeshima & Liu 2020; Takeshima et al. 2020). Furthermore, weather significantly contributed to variations in cereal yields. This further corroborates the importance of rainfall as a limiting factor in Africa's predominantly rain-fed agriculture as shown in Van Loon et al. (2020), Takeshima et al. (2020) and Takeshima & Liu (2020). The sequential technology credence gains more traction in the Eastern and Southern African regions where previous yield has a positively significant effect on the subsequent yield. Although positive, the implications of the previous yield are not significant in the overall specification or in the Central, Northern, and Western African regions.

6. Conclusions and implications

The findings of this study show that the annual agricultural productivity growth in Africa using conventional and sequential Malmquist indices was 1% and 1.7%, respectively, during the period between 1961 and 2014. Furthermore, the cumulative TFP growth is closely interwoven with cumulative technological change. Growth in African agricultural productivity has been particularly remarkable over the last 15 years. Sequential index-based calculations provide an augmented and sustained annual growth rate during the 2000–2014 period. This is consistent with the economic recovery narrative in Africa, marked by growth in agricultural GDP due to improved fundamentals and an improved macroeconomic environment.

The assessment of the sources of agricultural productivity growth, the results indicate that enhanced mechanization and agricultural expenditure allocations could facilitate TFP growth. In particular, the elasticity of agricultural productivity with respect to mechanization is 0.2, implying that a 10% increase in machinery increases productivity by 2%. Generous policies toward the agricultural sector such as increasing the allocations of total expenditures on agriculture have a positive effect in increasing TFP. Therefore, increasing allocations to the agricultural sector – in line with Malabo Declaration – could further thrust TFP growth if such allocations are directed to key investments such as mechanization. It is also important to highlight the importance of weather-related variables (especially rainfall) in determining TFP growth in Africa. This finding points to the importance of rainfall as a limiting factor in Africa's predominately rain-fed agriculture. Perhaps additional investments in irrigation might mitigate some of the effects of low and unreliable rainfall.

The supplementary assessments on the determinants of agricultural productivity for selected cereals (wheat, rice, barley, and maize) provide further corroborating evidence on the significant influence of selected variables on TFP growth. Increased use of modern inputs, including mechanization, is found to be an integral part of the agricultural transformation process. Given that current adoption rates of machineries in Africa are very low, deepening mechanization remains an important target for many nations. In this regard, it is important to explore options to introduce context specific machines, for instance for use on hilly land. This might include providing incentives for small-scale, affordable, and appropriate mechanical technological options (like small tractors) for smallholder farmers. The experience from South Asia has shown that establishing a rental market for machineries, which also generates employment, could circumvent capital constraints in African agriculture (Hassan & Kornher 2020). Partnership between public and private sector agents would be instrumental in achieving higher levels of mechanization. Each of these groups have clear and specific roles to play; while the public sector is mandated with providing the enabling environment, private sector agents could provide the required equipment and services.

Structural drivers of productivity, such as agricultural R&D spending and education variables, however, remain key drivers of technological change. In fact, these variables are themselves drivers of machinery use, fertilizer development and labor productivity, as well as the appropriate use of improved technologies. Therefore, the findings of this study highlight the importance of the investment in technological change to transform the African agricultural sector.

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