Productivity growth and the effects of R&D in African agriculture

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Abstract

This paper measures and compares total factor productivity growth in African agriculture under contemporaneous and sequential technology frontiers over the period 1970–2004. The paper further investigates the sources of agricultural productivity growth using a fixed-effects regression model and a second-degree polynomial distributed lag structure for agricultural research. The conventional estimates show an average productivity growth rate of only 0.3% per year over the period 1970–2004. In contrast to conventional measures, however, the improved measures under sequential technology show that agricultural productivity grew at a higher rate of 1.8% per year. Technical progress, rather than efficiency change, was the principal source of productivity growth. Agricultural research has turned out to have positive and significant impacts on productivity. The estimated productivity elasticity with respect to agricultural research is 0.04 and suggests that doubling research investments would lead to a 4% increase in total factor productivity. Consistent with the induced intensification hypothesis, population pressure has a positive and significant effect on agricultural productivity. We find a negative and significant relationship between rainfall variability, confirming that drought is a major constraint to agricultural production in Africa.

Key words: Productivity growth; Sequential technology; R&D; Africa.

1. Introduction

Agricultural productivity growth has long been recognized as the key to overall economic growth. Measuring and explaining productivity growth in agriculture has thus been the focus of much agricultural and development economics research. A growing volume of empirical work has investigated the trends and sources of agricultural productivity growth in developing countries in general (e.g., Fulginiti and Perrin, 1993, 1997, 1998; Trueblood and Coggins, 1997; Nin et al., 2003; Coelli and Rao, 2005) and in African countries in particular (e.g., Block, 1994; Frisvold and Ingram, 1995; Thirtle et al., 1995; Lusigi and Thirtle, 1997; Nkamleu, 2004; Fulginiti et al., 2004). While there is ample evidence showing substantial productivity growth in Asian countries, much of the evidence relating to African agricultural productivity points to poor aggregate performance (e.g., Thirtle et al., 1995; Trueblood and Coggins, 1997; Nkamleu et al., 2004). Nkamleu et al. (2004), for example, measured agricultural productivity in 16 African countries for the period 1970–2000 and found that total factor productivity declined in the 1970s and 1980s and showed only slight improvement after 1990s, with an average growth rate of 0.1% per year.

Recent empirical work has demonstrated, however, that traditional Malmquist index measures are based on an inappropriate representation of the underlying technology that typically understates productivity (Nin et al., 2003; Thirtle et al., 2003). An important feature of the traditional approach is that, in general, it attributes productivity stagnation or decline to technological regress, whereas productivity growth is attributed to efficiency improvement (Nin et al., 2003). However, it has been demonstrated that measured technical regress is actually the consequence of a contemporaneous reference technology where current-period technology is assumed to be unavailable for production in subsequent periods. The contemporaneous technology frontier is unstable, moving back and forth, and possibly intersecting, thereby introducing implausible levels of technical regress (Thirtle et al., 2003).

Explaining spatial and temporal productivity differentials has been an important component of research measuring agricultural productivity. However, there is no strong econometric evidence and many studies often resorted to identifying the correlates of productivity—such as policy reforms (e.g., Fulginiti and Perrin, 1993, 1999; Block, 1994), population pressure (e.g., Frisvold and Ingram, 1995; Lusigi and Thirtle, 1997), and institutions (Fulginiti et al., 2004; Nkamleu, 2004). Lack of data on research expenditures and inadequate specification of the length and shape of agricultural research lag have also undermined efforts to examine the effects of agricultural research on productivity in African agriculture. The objective of this paper is to estimate and explain total factor productivity (TFP) growth in African agriculture under sequential technology over the period 1970–2004. First, the paper applies the sequential Malmquist index approach (Nin et al., 2003; Thirtle et al., 2003) and compares the results with the traditional Malmquist indexes. Second, the paper assesses the relative impacts of R&D on productivity using a polynomial distributed lag structure in a fixed-effects regression model of total factor productivity.

2. Methods and data

2.1. The Malmquist TFP index

The Malmquist TFP index measures the TFP change between two data points—such as for a given country in two adjacent time periods—by calculating the ratio of the distances of each data point relative to a common technology. Following Färe et al

(1994), the output-oriented Malmquist TFP change index between period *t* (the base period) and period *t*+1 is given by

$$M_o = (y^t, x^t, y^{t+1}, x^{t+1}) = \left(\frac{D_o^t(y^{t+1}, x^{t+1})}{D_o^t(y^t, x^t)} \times \frac{D_o^{t+1}(y^{t+1}, x^{t+1})}{D_o^{t+1}(y^t, x^t)} \right)^{1/2} \qquad (1)$$

where the notation D_o^{t+1} (x^{t+1}, y^{t+1}) represents the distance from the period *t*+1 observation to the period *t* technology. A value of M_o greater than one will indicate positive TFP growth from period *t* to period *t*+1 while a value less than one indicates a TFP decline. Note that Eq. (1) is, in fact, the geometric mean of two TFP indexes. The first is evaluated with respect to period *t* technology and the second with respect to period *t*+1 technology.

An equivalent way of writing the Malmquist TFP index is

$$M_o = (y^t, x^t, y^{t+1}, x^{t+1}) = \frac{D_o^{t+1}(y^{t+1}, x^{t+1})}{D_o^t(y^t, x^t)} \left(\frac{D_o^t(y^{t+1}, x^{t+1})}{D_o^{t+1}(y^{t+1}, x^{t+1})} \times \frac{D_o^t(y^t, x^t)}{D_o^{t+1}(y^t, x^t)} \right)^{1/2} \qquad (2)$$

where the ratio outside the square brackets measures the change in the output-oriented measure of technical efficiency between periods *t* and *t*+1. The remaining part of the index in Eq. (2) is a measure of technical change. It is the geometric mean of the shift in technology between the two periods, *t* and *t*+1.

2.1.1. The contemporaneous Malmquist TFP index

The Malmquist TFP index defined above can be constructed with respect to either the contemporaneous or sequential technology frontiers. Following Färe et al. (1994), the required distance measures for the contemporaneous Malmquist TFP index are calculated using linear programming (LP) formulated with respect to the contemporaneous technology frontier. For the *i*-th country, we need to calculate four distance functions to measure the TFP change between period *t* and *t*+1. This requires solving the following four LP problems:

$$\underset{\theta_{1i},\lambda_i}{\text{Maximize}}\,[D_o^t(x^t, y^t)]^{-1} = \theta_{1i},$$
$$\begin{aligned} \text{subject to } & -\theta_{1i} y_{im}^t + \sum_{i=1}^{52} y_{im}^t \lambda_i \geq 0, \quad m = 1,2,\ldots,M \\ & x_{in}^t - \sum_{i=1}^{52} x_{in}^t \lambda_i \geq 0, \qquad n = 1,2,\ldots,N \\ & \lambda_i \geq 0, \end{aligned} \tag{3}$$

$$\underset{\theta_{2i},\lambda_i}{\text{Maximize}}\,[D_o^{t+1}(x^{t+1}, y^{t+1})]^{-1} = \theta_{2i},$$
$$\begin{aligned} \text{subject to } & -\theta_{2i} y_{im}^{t+1} + \sum_{i=1}^{52} y_{im}^{t+1} \lambda_i \geq 0, \quad m = 1,2,\ldots,M \\ & x_{in}^{t+1} - \sum_{i=1}^{52} x_{in}^{t+1} \lambda_i \geq 0, \qquad n = 1,2,\ldots,N \\ & \lambda_i \geq 0, \end{aligned} \tag{4}$$

$$\underset{\theta_{3i},\lambda_i}{\text{Maximize}}\,[D_0^t(x^{t+1}, y^{t+1})]^{-1} = \theta_{3i},$$
$$\begin{aligned} \text{subject to } & -\theta_{3i} y_{im}^{t+1} + \sum_{i=1}^{52} y_{im}^t \lambda_i \geq 0, \quad m = 1,2,\ldots,M \\ & x_{in}^{t+1} - \sum_{i=1}^{52} x_{in}^t \lambda_i \geq 0, \qquad n = 1,2,\ldots,N \\ & \lambda_i \geq 0, \end{aligned} \tag{5}$$

$$\underset{\theta_{4i},\lambda_i}{\text{Maximize}}\,[D_o^{t+1}(x^t, y^t)]^{-1} = \theta_{4i},$$
$$\begin{aligned} \text{subject to } & -\theta_{4i} y_{im}^t + \sum_{i=1}^{52} y_{im}^{t+1} \lambda_i \geq 0, \quad m = 1,2,\ldots,M \\ & x_{in}^t - \sum_{i=1}^{52} x_{in}^{t+1} \lambda_i \geq 0, \qquad n = 1,2,\ldots,N \\ & \lambda_i \geq 0, \end{aligned} \tag{6}$$

where λ is an $N\times1$ vector of peer weights and θ is a scalar. The LPs for the contemporaneous Malmquist TFP index were solved using the software DEAP 2.1 (Coelli, 1996).

2.1.2. The sequential Malmquist TFP index

Unlike the contemporaneous Malmquist TFP index that relies on the assumption that successive production sets are essentially unrelated to one another, the premise of the sequential Malmquist TFP index is the fact that past production techniques would also be available for current production activities (Nin et al., 2003). The required distance measures for the sequential Malmquist TFP index are calculated using linear programming (LP) formulated with respect to the sequential technology frontier. For the *i*-th country, we need to calculate four distance functions to measure the TFP change between period t and t+1. This requires solving the following four LP problems:

$$\begin{aligned}
&\underset{\theta_{1i},\lambda_i^{t'}}{\text{Maximize}}\,[D_o^t(x^t, y^t)]^{-1} = \theta_{1i},\\
&\text{subject to } -\theta_{1i}y_{im}^t + \sum_{t'=1}^{t}\sum_{i=1}^{52} y_{im}^{t'}\lambda_i^{t'} \geq 0, \quad m = 1, 2, \ldots, M\\
&\qquad x_{in}^t - \sum_{t'=1}^{t}\sum_{i=1}^{52} x_{in}^{t'}\lambda_i^{t'} \geq 0, \qquad n = 1, 2, \ldots, N\\
&\qquad \lambda_i^{t'} \geq 0,
\end{aligned} \tag{7}$$

$$\begin{aligned}
&\underset{\theta_{2i},\lambda_i^{t'}}{\text{Maximize}}\,[D_o^{t+1}(x^{t+1}, y^{t+1})]^{-1} = \theta_{2i},\\
&\text{subject to } -\theta_{2i}y_{im}^{t+1} + \sum_{t'=1}^{t+1}\sum_{i=1}^{52} y_{im}^{t'}\lambda_i^{t'} \geq 0, \quad m = 1, 2, \ldots, M\\
&\qquad x_{in}^{t+1} - \sum_{t'=1}^{t+1}\sum_{i=1}^{52} x_{in}^{t'}\lambda_i^{t'} \geq 0, \qquad n = 1, 2, \ldots, N\\
&\qquad \lambda_i^{t'} \geq 0,
\end{aligned} \tag{8}$$

$$\begin{aligned}
&\underset{\theta_{3i},\lambda_i^{t'}}{\text{Maximize}}\,[D_0^t(x^{t+1}, y^{t+1})]^{-1} = \theta_{3i},\\
&\text{subject to } -\theta_{3i}y_{im}^{t+1} + \sum_{t'=1}^{t}\sum_{i=1}^{52} y_{im}^{t'}\lambda_i^{t'} \geq 0, \quad m = 1, 2, \ldots, M\\
&\qquad x_{in}^{t+1} - \sum_{t'=1}^{t}\sum_{i=1}^{52} x_{in}^{t'}\lambda_i^{t'} \geq 0, \qquad n = 1, 2, \ldots, N\\
&\qquad \lambda_i^{t'} \geq 0,
\end{aligned} \tag{9}$$

$$\begin{aligned}
&\underset{\theta_{4i},\lambda_i^{t'}}{\text{Maximize}}\,[D_o^{t+1}(x^t, y^t)]^{-1} = \theta_{4i}, \\
&\text{subject to } -\theta_{4i} y_{im}^t + \sum_{t'=1}^{t+1}\sum_{i=1}^{52} y_{im}^{t'}\lambda_i^{t'} \geq 0, \quad m = 1,2,\ldots,M \\
&\qquad x_{in}^t - \sum_{t'=1}^{t+1}\sum_{i=1}^{52} x_{in}^{t'}\lambda_i^{t'} \geq 0, \qquad n = 1,2,\ldots,N \\
&\qquad \lambda_i^{t'} \geq 0,
\end{aligned} \tag{10}$$

The LPs for the sequential Malmquist TFP index were solved using the solver MINOS5 of the General Algebraic Modeling System (GAMS).

2.2. Explaining agricultural productivity

Measuring agricultural productivity and explaining cross-country agricultural productivity differentials has been an important area of agricultural and development economics research (e.g., Hayami and Ruttan, 1985; Evenson and Pray, 1991; Craig et al., 1997). As there are no explicit theoretical models of TFP growth in agriculture, Evenson and Pray (1991) proposed a two-stage approach where the productivity indexes are first constructed and then explained by the productivity-changing factors using regression. Using a double-log specification, the empirical model of agricultural TFP used in this study is given as

$$\begin{aligned}
\ln(TFP) = {} & \beta_0 + \sum_{j=0}^{16}\beta_{1(j)}\ln(\text{R\&D})_{t-j} + \beta_2\ln(\text{Literacy}) \\
& + \beta_3\ln(\text{Land quality}) + \beta_4\ln(\text{Population pressure}) \\
& + \beta_5\ln(\text{Infrastructure})_{t-1} + \beta_6\ln(\text{Gov expenditure})_{t-1} \\
& + \beta_7\ln(\text{Trade}) + \beta_8\ln(\text{Rainfall}) + \beta_9\ln(\text{Rainfall variability}) \\
& + \beta_{10}(t) + \beta_{11}(t)^2 + e
\end{aligned} \tag{11}$$

where $\beta_{1(0)} + \beta_{1(1)} + \ldots + \beta_{1(16)} = \beta_1 = \beta_{(R\&D)}$; t and t^2 represent the time trend and are included to effectively de-trend the variables; and e is the random error term.

Agricultural R&D expenditures per hectare of agricultural land were included in the TFP equation with a formally determined length and shape to account for the fact that R&D investments generate a flow of benefits over time. Using the criterion of maximum adjusted R^2, a lag length of 16 years was chosen.

Regarding the shape of the R&D lag, a second-order polynomial distributed lag (PDL) was imposed on the coefficients based on the inverted U hypothesis where the impact of R&D first rises and then falls (Alston et al., 1995). The PDL was specified such that

$$\alpha_j = \lambda_0 + \lambda_1 j + \lambda_2 j^2 , \qquad j = 0,1,....,16 \tag{12}$$

so that the PDL specification for R&D becomes

$$\begin{aligned} \sum_{j=0}^{J} \alpha_j \ln(\text{R\&D/ha})_{t-j} &= \sum_{j=0}^{16} (\lambda_0 + \lambda_1 j + \lambda_2 j^2) \ln(\text{R\&D/ha})_{t-j} \\ &= \lambda_0 \sum_{j=0}^{16} \ln(\text{R\&D/ha})_{t-j} + \lambda_1 \sum_{j=0}^{16} j \times \ln(\text{R\&D/ha})_{t-j} \\ &+ \lambda_2 \sum_{j=0}^{16} j^2 \times \ln(\text{R\&D/ha})_{t-j} \end{aligned} \tag{13}$$

The PDL specification for R&D implies that it is only necessary to estimate three parameters (i.e., λ_0, λ_1, and λ_2) so that the respective seventeen parameters of the lag distribution (α_js) can be derived from these estimates using Eq. (12). The standard errors of the seventeen parameters were derived from those of the three coefficient estimates using the *delta* method (Greene, 2000). End-point constraints were imposed to rule out implausible negative lag coefficients (Ravenscraft and Scherer, 1982). The constraints are imposed such that $\alpha_{-1} = \alpha_{J+1} = 0$, implying that $\lambda_0 = -\lambda_2 (J+1)$ and $\lambda_1 = -\lambda_2 J$. Imposing the end-point constraints reduces Eq. (13) to

$$\sum_{j=0}^{J} \alpha_j \ln[\text{R\&D/ha}]_{t-j} = \lambda_2 \sum_{j=0}^{16} (j^2 - 16j - 17) \ln(\text{R\&D/ha})_{t-j} \tag{14}$$

In the restricted PDL specification, only λ_2 needed to be estimated, with the remaining two coefficients derived using the above relations as $\lambda_0 = -17\lambda_2$ and $\lambda_1 = -16\lambda_2$.

2.3. Data sources

Panel data on output and conventional agricultural inputs (land, labor, fertilizer, and machinery) for the 52 African countries for the period 1970–2004 were accessed from the FAOSTAT database (FAO, 2007). Agricultural output is measured as the volume of agricultural production in millions of 1999–2001 international dollars. Agricultural land is measured as the sum of arable land and land under permanent crops and permanent pastures in thousand hectares. Agricultural labor is measured as thousands of economically active persons engaged in agriculture. Fertilizer is defined as tons of plant nutrients—consisting of nitrogen, phosphorous, and potash—used in agriculture. Farm machinery is defined as the number of agricultural tractors.

Data on R&D expenditures (millions of international dollars) were available for 27 countries and for the period 1980–2001 from IFPRI's (International Food Policy Research Institute) Agricultural Science and Technology Indicators database. A land quality index created by Peterson (1987) was used that indexes land quality at the national level as a function of historic precipitation and the share of a country's land area devoted to pasture and crops. A comprehensive data set on historical annual and monthly rainfall in all African countries was obtained from Jefferson and O'Connell (2004). Data on the rest of the variables were obtained from Africa Development Indicators (World Bank, 2006).

3. Results

3.1. Country-specific and regional productivity growth

The conventional estimates show that the aggregate productivity growth in African agriculture was only 0.3% per year over the period 1970–2004 (Table 1). The poor aggregate performance is due to agricultural productivity decline in over one-third of SSA countries. The estimates show that only five experienced agricultural productivity growth rates of over 2% per year. With a rate of growth of only 0.1% per year, the performance of SSA agriculture implied by the conventional approach is poor and suggests stagnation of agricultural productivity in the region. Consistent with available evidence, the results further show that technical regress explains much of the stagnation of productivity growth in African agriculture. Fulginiti and Perrin (1997), for example, reported technical regression in a group of 18 developing countries over the period 1961–1985.

Insert Table 1 here

In sharp contrast to conventional measures, the improved measures of productivity under sequential technology show that African agricultural productivity grew at a much higher rate of 1.8% per year over the period 1970–2004 (Table 2). In SSA, agricultural productivity grew at a comparable rate of 1.6% per year. Four countries (Egypt, Ethiopia, Mauritius, and South Africa) defined the production technology frontier in the vicinity of their input–output mixes, indicating that these countries led the technological innovation process. Egypt was particularly important because it remained on the frontier consistently throughout the period. As the only fully efficient country throughout the period, Egypt naturally shows no efficiency gains and its productivity growth rates are attributable entirely to technological progress.

Insert Table 2 here

3.2. Annual and periodic productivity growth

There are marked periodic differences between conventional and improved measures productivity growth, efficiency change, and technical progress (Table 3). Consistent with past empirical work, the conventional measures demonstrate negative agricultural productivity growth in the 1970s (-0.9% per year) and a recovery to positive growth during the 1980s (1.4% per year). While productivity decline during the 1970s is attributable to technological regress (-1.1% per year), technical progress (1.5% per year) was the principal source of recovery of productivity during the 1980s. The new measures under sequential technology, on the other hand, demonstrate positive productivity growth in all three periods: 1970s (1.4% per year), 1980s (1.7% per year), and during 1991–2004 (2.1% per year). Unlike the conventional estimates, the improved measures thus demonstrate sustained increases in productivity growth over the years, with an impressive annual growth rate of over 2% achieved during and after the 1990s. This is consistent with recent economic recovery in Africa as evidenced by stronger agricultural GDP growth rates reported in the World Development Report 2008 (World Bank, 2007). With technological improvement at a rate of over 1.8% per year in each period, productivity growth during 1970s, 1980s, and 1990s is attributable to technical progress alone, whereas efficiency change stagnated at best.

Insert Table 3 here

3.3. Cumulative productivity growth

The relative importance of technical progress and efficiency change as sources of productivity growth can be further demonstrated using cumulative productivity growth, efficiency change, and technical progress. The conventional cumulative rates of efficiency change were positive for much of the period after late 1970s, whereas positive cumulative rates of technical progress were observed only after late 1980s (Fig. 1). Over the period 1970–2004, the cumulative rates of technical progress and efficiency change were only 4.3% and 7.5%, respectively. It is interesting to note that the major drought year of 1983–84 appears to have marked effects on technical progress rather than on technical efficiency. This confirms that the conventional approach accounts for the adverse effects of weather in terms of technical regress when in fact it would be more reasonable to interpret the effects of weather as deterioration in technical efficiency. Given the confounding effect of weather conditions and the implied sensitivity of conventional measures, past empirical work may thus have underestimated technical progress in African agriculture.

Insert Figure 1 here

Cumulative productivity growth trends under sequential technology closely follow cumulative technical change trends, whereas technical efficiency exhibited negative growth throughout the period (Fig. 2). Relative to the conventional measures of efficiency change, which are unstable and sensitive to weather conditions, the cumulative rates of efficiency change under sequential technology are more stable and robust. The new approach based on sequential technology accounts for the adverse effects of weather in terms of efficiency decline rather than technical regress. Over the period 1970–2004, the cumulative rates of productivity growth, efficiency change, and technical progress were about 57%, -4%, and 64%, respectively. The results thus confirm that technical progress is the major source of productivity growth in African agriculture.

Insert Figure 2 here

3.4. Determinants of productivity growth

Table 4 presents the fixed-effects regression estimates of the determinants of total factor productivity in African agriculture. The fixed-effects model was applied to the pooled cross-sectional, time series data to account for unobserved country-specific conditions influencing productivity differentials. The model fits the data reasonably well, with about 74% of the variation in total factor productivity explained by R&D and other variables included in the model. Agricultural R&D, population pressure, and weather variability have a significant influence on total factor productivity.

Insert Table 4 here

The polynomial distributed lag structure for R&D means that the model estimates the productivity elasticities of R&D for individual years as well as the aggregate elasticity for all years. The trends implied by the individual elasticities confirm that the R&D lag has an inverted U shape. Consistent with the decomposition of productivity growth showing technological progress as the major driver of productivity growth, R&D has turned out to have a positive and significant aggregate effect on productivity growth in African agriculture. The estimated aggregate productivity elasticity with respect to R&D is 0.04, implying that a 1% increase in R&D investments raises total factor productivity by 0.04%. This is much lower than the land productivity elasticity of 0.36 with respect to R&D in African agriculture (Thirtle et al., 2003), but it derives from the fact that partial productivity measures, particularly land productivity, are much higher than total factor productivity. It should be noted that, although the estimated total factor productivity elasticity of R&D appears to be small where doubling R&D expenditures would only lead to a 4% increase in agricultural (total factor) productivity, the implied absolute effect is very large.

Corroborating the induced intensification hypothesis, population pressure has turned out to have positive and significant effects on agricultural productivity. This is in agreement with Lusigi and Thirtle's (1997) finding that total factor productivity in African agriculture increases with increasing population pressure on agricultural land. Finally, the results demonstrate that temporal rainfall variability, rather than rainfall amount, has significant negative effects on agricultural productivity. This confirms that, in African agriculture, rainfall distribution is more critical and is a better proxy for drought than total amount of rainfall. The negative and significant productivity elasticity of rainfall variability confirms that weather is one of most critical constraints to agricultural production in Africa.

4. Conclusions

This paper measures and compares total factor productivity growth in African agriculture under contemporaneous and sequential technology frontiers over the period 1970–2004. In contrast to conventional measures showing an average productivity growth rate of only 0.3% per year, the improved measures under sequential technology show that African agricultural productivity grew at a higher rate of 1.8% per year. SSA agricultural productivity also grew at a comparable rate of 1.6% per year. The results demonstrate that technical progress, rather than efficiency change, was the principal source of productivity growth in African agriculture. Given the inherent weaknesses of the conventional approach where the adverse effects of weather and other shocks are attributed to technical regress, past studies may have underestimated the true rate of technical progress in African agriculture. Since early 1990s, agricultural productivity grew at an impressive rate of over 2% per year and this is consistent with recent economic recovery in Africa as evidenced by stronger agricultural GDP growth rates following improved macroeconomic conditions and commodity prices.

Agricultural R&D has turned out to have a positive and significant influence on total factor productivity in African agriculture. This is consistent with the productivity decompositions showing technological progress as the major driver of productivity growth. Overall, the estimated productivity elasticity with respect to R&D suggests that doubling R&D investments would lead to a 4% increase in total factor productivity in African agriculture. That is, doubling R&D investments would nearly double current average productivity growth rates. Consistent with the induced intensification hypothesis, population pressure has a positive and significant effect on agricultural productivity. That is, total factor productivity in African agriculture increases with increasing population pressure on agricultural land. Finally, the results demonstrate that weather variability has a negative and significant effect on agricultural productivity. This only reinforces the fact that drought is a major constraint to agricultural production in Africa. Therefore, public investments aimed at containing the effects of drought would have considerable payoffs.

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Table 1. Conventional Malmquist measures of productivity growth, efficiency change, and technical progress in African agriculture

Country	TFP growth	Efficiency change	Technical progress
		Percent	
Republic of Congo	3.6	2.9	0.7
Libya	3.0	3.2	–0.2
Central African Republic	2.8	1.0	1.8
Djibouti	2.7	2.2	0.5
Benin	2.3	1.1	1.2
South Africa	2.1	1.2	0.9
Algeria	1.9	1.0	0.9
Burkina Faso	1.7	2.0	–0.3
Swaziland	1.7	0.0	1.7
Tunisia	1.7	0.3	1.4
Angola	1.6	1.7	–0.1
Morocco	1.6	0.2	1.4
Nigeria	1.6	0.0	1.6
Cote d’Ivoire	1.4	0.5	0.9
Gabon	1.3	0.6	0.7
Kenya	1.2	0.1	1.1
Tanzania	1.1	1.4	–0.3
Egypt	1.0	0.0	1.0
Sierra Leone	1.0	1.5	–0.5
Zambia	1.0	–0.4	1.4
Malawi	0.8	0.9	–0.1
Uganda	0.8	0.0	0.8
Mauritius	0.7	0.0	0.7
Cameroon	0.6	0.0	0.6
Guinea	0.6	–0.7	1.3
Liberia	0.5	1.9	–1.4
Togo	0.5	–0.5	1.0
Cape Verde	0.4	0.0	0.4
Equatorial Guinea	0.3	0.6	–0.3
Mali	0.2	0.4	–0.2
Ghana	0.1	0.1	0.0
Madagascar	0.1	0.0	0.1
Sudan	0.1	–0.4	0.5
Zimbabwe	0.1	–1.8	1.9
Chad	0.0	–0.4	0.4
Botswana	–0.3	–1.0	0.7
Somalia	–0.3	0.4	–0.7
Mauritania	–0.4	–0.3	–0.1
Senegal	–0.5	–0.8	0.3
Guinea Bissau	–0.7	–1.3	0.6
Sao Tome and Principe	–0.9	0.0	–0.9
Niger	–1.0	–2.1	1.1
Mozambique	–1.2	–1.2	0.0
Gambia	–1.3	–0.4	–0.9
Burundi	–1.9	0.0	–1.9
Lesotho	–1.9	–3.0	1.1
Rwanda	–2.3	0.0	–2.3
Namibia	–2.6	0.0	–2.6
Seychelles	–2.6	0.0	–2.6
Democratic Republic of Congo	–2.9	0.0	–2.9
Comoros	–3.6	0.0	–3.6
Ethiopia	–4.3	–2.5	–1.8
Mean	0.3	0.2	0.1
North Africa	1.8	0.9	0.9
Sub-Saharan Africa	0.1	0.1	0.0

Table 2. Sequential Malmquist measures of productivity growth, efficiency change, and technical progress in African agriculture

Country	TFP growth	Efficiency change	Technical progress
		Percent	
Cape Verde	5.7	0.2	5.5
Republic of Congo	5.4	4.2	1.2
Seychelles	5.0	0.6	4.4
Rwanda	4.8	0.1	4.7
Central African Republic	4.6	1.0	3.7
Egypt	4.4	0.0	4.4
Uganda	4.2	–0.1	4.2
Mauritius	4.0	0.1	3.9
Tunisia	4.0	0.7	3.3
Algeria	3.9	1.5	2.4
Djibouti	3.8	0.6	3.3
South Africa	3.8	0.1	3.7
Libya	3.7	1.7	2.0
Equatorial Guinea	3.1	2.1	0.9
Benin	2.9	0.4	2.6
Nigeria	2.8	0.3	2.5
Gabon	2.1	1.1	1.1
Morocco	2.1	0.0	2.1
Cameroon	2.0	0.0	1.9
Malawi	2.0	1.3	0.8
Sudan	1.9	0.7	1.2
Kenya	1.8	–2.2	4.1
Mauritania	1.7	–0.3	2.0
Angola	1.6	1.0	0.7
Swaziland	1.6	–0.8	2.4
Somalia	1.4	0.2	1.3
Liberia	1.3	1.1	0.2
Guinea Bissau	1.2	–0.4	1.6
Sierra Leone	1.1	0.6	0.5
Zambia	1.1	–1.0	2.2
Chad	1.0	–0.2	1.2
Ghana	0.9	0.5	0.4
Senegal	0.8	–0.9	1.8
Tanzania	0.8	–1.4	2.1
Togo	0.8	–0.3	1.1
Zimbabwe	0.8	–1.7	2.6
Ethiopia	0.7	–1.3	2.0
Gambia	0.6	–1.0	1.7
Niger	0.6	–1.0	1.6
Burkina Faso	0.4	–1.8	2.2
Botswana	0.3	–0.3	0.6
Guinea	0.3	–0.4	0.7
Madagascar	0.1	–0.9	1.0
Mali	0.1	–1.2	1.3
Namibia	0.1	0.0	0.1
Comoros	–0.5	–1.8	1.3
Lesotho	–0.6	–3.4	2.8
Mozambique	–0.6	–1.1	0.5
Democratic Republic of Congo	–0.7	–0.9	0.1
Sao Tome and Principe	–0.8	–0.3	–0.5
Cote d'Ivoire	–0.9	0.5	–1.4
Burundi	–1.4	–2.2	0.8
Mean	1.8	–0.1	1.9
North Africa	3.6	0.8	2.8
Sub-Saharan Africa	1.6	–0.2	1.8

Table 3. Annual productivity growth, efficiency change, and technical progress in African agriculture

Year	Conventional Malmquist			Sequential Malmquist		
	TFP	Efficiency change	Technical progress	TFP	Efficiency change	Technical progress
				Percent		
1971	0.4	2.0	–1.6	1.6	–1.9	3.5
1972	–3.1	–1.1	–2.0	–0.3	–2.4	2.1
1973	–3.5	–4.6	1.1	0.3	–1.0	1.3
1974	1.8	1.0	0.8	–0.1	–1.5	1.4
1975	–1.0	–2.0	1.0	1.4	–0.4	1.8
1976	0.3	1.3	–1.0	1.0	–1.2	2.2
1977	–2.8	0.0	–2.8	3.5	2.6	0.9
1978	1.2	1.8	–0.6	2.6	0.8	1.8
1979	0.4	3.9	–3.5	3.3	0.7	2.5
1980	–2.8	–0.8	–2.0	–1.0	–2.9	1.9
1981	4.0	0.2	3.8	3.4	1.8	1.6
1982	0.3	–0.9	1.2	2.3	–0.9	3.2
1983	–2.2	–1.0	–1.2	1.3	–0.4	1.7
1984	–0.3	4.4	–4.7	0.3	–1.3	1.5
1985	4.8	–2.8	7.6	1.9	0.2	1.7
1986	3.2	4.4	–1.2	3.2	1.7	1.5
1987	–2.8	–1.5	–1.3	0.8	–1.5	2.3
1988	6.8	–3.8	10.6	4.2	0.8	3.5
1989	1.9	–0.1	2.0	1.8	0.5	1.3
1990	–1.5	0.5	–2.0	1.4	–0.1	1.5
1991	1.6	2.7	–1.1	4.0	1.8	2.2
1992	–2.1	–9.8	7.7	0.8	–5.3	6.0
1993	8.4	9.5	–1.1	0.1	–1.3	1.4
1994	2.1	3.2	–1.1	2.1	0.4	1.7
1995	–8.5	–7.4	–1.1	2.2	0.1	2.1
1996	4.1	0.5	3.6	4.0	1.1	2.9
1997	–0.7	5.4	–6.1	2.5	1.4	1.0
1998	–0.7	–0.2	–0.5	1.6	0.9	0.7
1999	–0.1	0.1	–0.2	3.9	2.8	1.1
2000	–0.4	–3.2	2.8	0.8	–2.0	2.8
2001	0.9	3.2	–2.3	2.3	1.4	0.8
2002	–2.8	0.2	–3.0	–0.5	–1.3	0.8
2003	4.0	2.5	1.5	2.8	2.0	0.8
2004	0.9	–0.1	1.0	0.7	0.0	0.7
Periodic means						
1970–1980	–0.9	0.2	–1.1	1.4	–0.5	1.9
1981–1990	1.4	–0.1	1.5	1.7	–0.3	2.0
1991–2004	0.5	0.5	0.0	2.1	0.3	1.8
1970–2004	0.3	0.2	0.1	1.8	–0.1	1.9

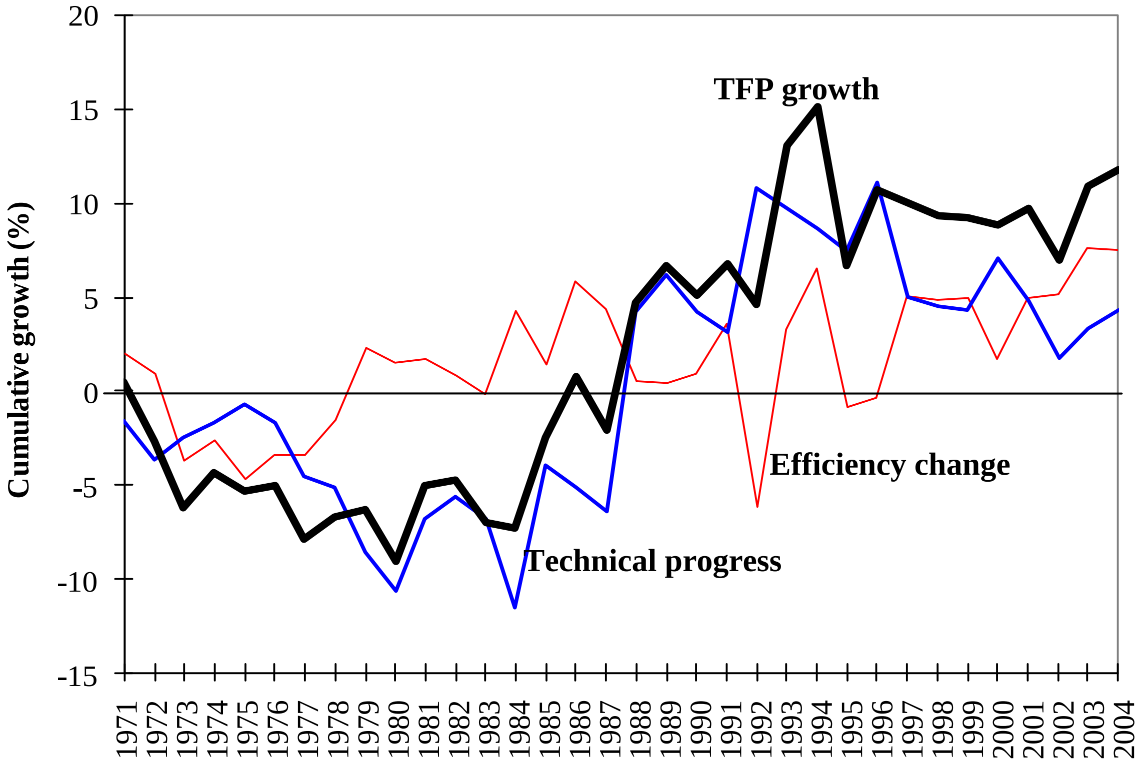

Fig. 1. Conventional measures of cumulative productivity growth, efficiency change, and technical progress in African agriculture.

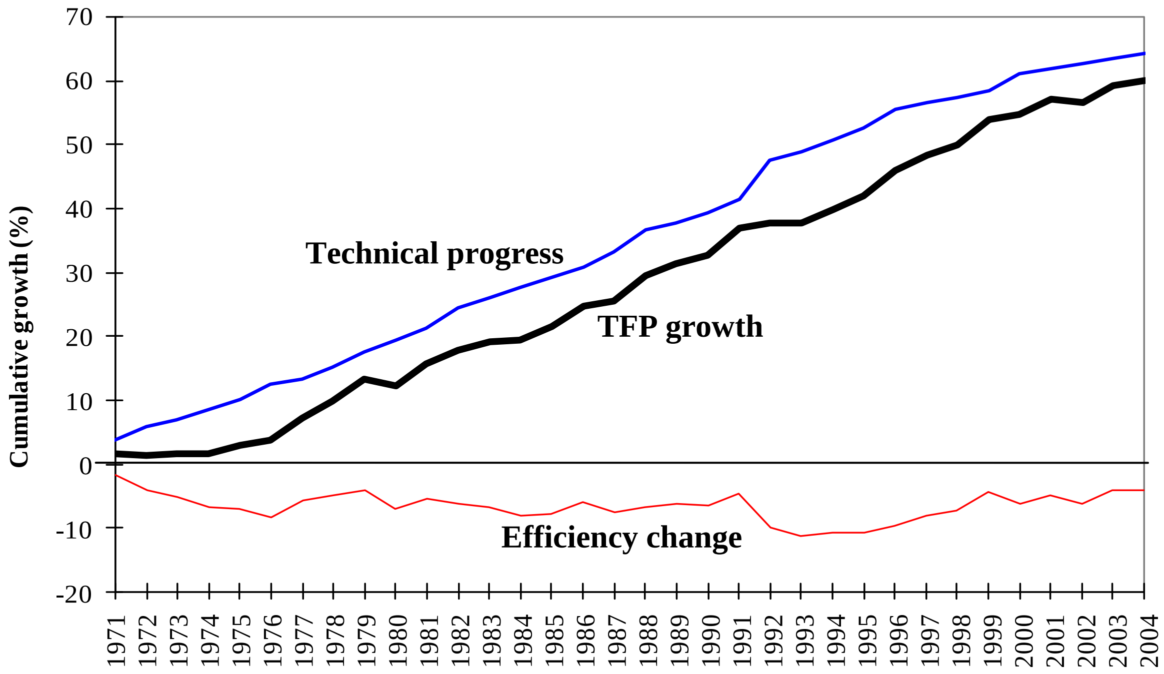

Fig. 2. Sequential measures of cumulative productivity growth, efficiency change, and technical progress in African agriculture.

Table 4. Parameter estimates of the fixed-effects regression model of productivity in African agriculture

Variable	Parameter	Estimate	*t*-value
R&D (t)	$\beta_{1(0)}$	0.0007	3.78***
R&D ($t-1$)	$\beta_{1(1)}$	0.0013	3.78***
R&D ($t-2$)	$\beta_{1(2)}$	0.0019	3.78***
R&D ($t-3$)	$\beta_{1(3)}$	0.0024	3.78***
R&D ($t-4$)	$\beta_{1(4)}$	0.0027	3.78***
R&D ($t-5$)	$\beta_{1(5)}$	0.0030	3.78***
R&D ($t-6$)	$\beta_{1(6)}$	0.0032	3.78***
R&D ($t-7$)	$\beta_{1(7)}$	0.0034	3.78***
R&D ($t-8$)	$\beta_{1(8)}$	0.0034	3.78***
R&D ($t-9$)	$\beta_{1(9)}$	0.0034	3.78***
R&D ($t-10$)	$\beta_{1(10)}$	0.0032	3.78***
R&D ($t-11$)	$\beta_{1(11)}$	0.0030	3.78***
R&D ($t-12$)	$\beta_{1(12)}$	0.0027	3.78***
R&D ($t-13$)	$\beta_{1(13)}$	0.0024	3.78***
R&D ($t-14$)	$\beta_{1(14)}$	0.0019	3.78***
R&D ($t-15$)	$\beta_{1(15)}$	0.0013	3.78***
R&D ($t-16$)	$\beta_{1(16)}$	0.0007	3.78***
R&D	β_1	0.0410	3.78***
Literacy (% of adult population that is literate)	β_2	0.006	0.440
Land quality (Peterson Index)	β_3	0.030	1.320
Population pressure (Labor per ha of agricultural land)	β_4	0.027	2.440**
Infrastructure (Gross fixed capital formation as % of GDP)	β_5	–0.016	–0.730
Government expenditure (% of GDP)	β_6	0.021	0.720
Trade (% of GDP)	β_7	0.017	0.720
Rainfall (millimetre/year)	β_8	–0.035	–1.370
Rainfall variability (coefficient of monthly variation)	β_9	–0.036	–1.770*
Time trend	β_{10}	0.003	0.130
(Time trend) ^{2}	β_{11}	–0.001	–0.720
Constant	β_0	0.308	0.960
Model fit	R^2	0.74	

*** Significant at 1% probability level; ** Significant at 5% probability level; * Significant at 10% probability level.