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Five Decades of Productivity and Efficiency Changes in World Agriculture (1969–2013)

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Abstract: The present study applied the Färe–Primont index approach to estimate the total factor productivity (TFP) growth of world agriculture, covering the period 1969–2013. Overall, the world agricultural TFP grew at a rate of 0.44% p.a. This growth was mainly contributed to by technological progress and mix efficiency changes, while the contributions of technical efficiency and scale efficiency changes were negligible. TFP growth varied across regions, with South Asia at the top of the list (1.05% p.a.), and East Asia and the Pacific (0.18% p.a.) at the bottom. TFP components exerted differential influences amongst regions. For instance, mix efficiency played a dominant role in Sub-Saharan Africa, the Middle East and North Africa, whereas it was technical efficiency change in Latin America and the Caribbean region. The paper argues for region specific policy interventions emphasizing technical progress through investment in R&D and price and non-price interventions to improve economies of scope and scale of operation in the agricultural sector.

Keywords: total factor productivity; Fare-Primont index; technical; scale and mix efficiency changes; non-parametric linear programming

1. Introduction

Agriculture is not only a source of food, but also a source of vast employment and rural development; hence, its development and growth have always been and will remain one of the topmost priority agendas in the development arena, particularly for the policy makers in the least developed and developing countries. This is because food security is one of the prime goals of the governments of these countries. Agriculture has a pivotal role in poverty alleviation and economic development [1]. The nexus between agricultural productivity growth and poverty reduction is well documented in the literature [2,3]. Shane et al. [4] provided empirical evidence that gaining agricultural productivity is the most effective strategy for poverty alleviation. It is true that, at the global level, the sector has lost its previous importance, particularly in terms of contribution to GDP and employment generation. For example, in 2016, the agricultural sector merely contributed 4.00% to the global GDP, but the contribution is relatively much higher in low-income countries, amounting to an average of 30.00% of the national GDP. The contribution of agriculture to national economies has decreased over the years, as countries have moved upward to upper income classes. Still, 26.48% of the world's total employment is offered by this sector [5]. Through an extensive review of 25 reports on the incidence of the global food price hike that occurred during the end of the last decade, Abbott et al. [6] concluded that the hike was largely fueled by declining agricultural productivity, though Fuglie [7] did not find empirical evidence that agricultural TFP declined until 2006. This certainly advocates for more attention and investment in the agricultural sector, which was neglected by foreign aid donors and the governments of developing countries [3]. Therefore, it is very important that agricultural productivity growth should be undertaken as a long-term strategy to address such a crisis of poverty, hunger and malnutrition. Furthermore, higher agricultural productivity can promote non-agricultural sectors by diverting scarce resources (e.g., labor and capital) away from agriculture [8].

Increased productivity contributes to lowering food prices, which will certainly benefit the consumers, particularly the poor, since food expenses occupy a larger share of their total budget [9,10]. But, at the producer level, the effect varies largely depending on the level at which agricultural products are tradable, and the associated level of price elasticity of demand [11,12]. Furthermore, at the farm level, the effects vary depending on the individual farmers' access to resources, inputs and ability to adopt technology [11]. The debate on this productivity–price complex relationship is also mentioned as a critical factor hindering the development of agricultural capitalism in the literature explaining agrarian development history, particularly when the country lacks some comparative advantage in agriculture in the form of availability of ample productive land, advanced mechanization, specialized and intensive farming, and infrastructure, etc. [13].

The pioneering works on productivity analysis [14–16] were mostly confined to estimating partial productivity (land or labor productivity) while ignoring efficiency and technological changes [17]. The second generation studies were mostly cross-country analysis using production function and meta-production function approaches, including multiple inputs and outputs [18,19]. These studies explored the Food and Agriculture Organization of the United Nations Statistical Database (FAOSTAT) database and used index number approaches to estimate total factor productivity (TFP) growth [17]. TFP indices capture the effect of improvements in technology in the form of research and development, as well as investments in infrastructure, such as irrigation, roads and electricity [20]. Higher TFP does not only mean higher output from the available technology and given resource base, but also contributes to rural poverty reduction [21]. The approach has also been used to assess the sustainability of a specific agricultural production system [22] or crop [23].

A few studies have analyzed agricultural TFP growth at the global level [17,24–28], the majority of which adopted the Malmquist index (MI) [17,24–26]. The MI is not multiplicatively complete or transitive, and does not decompose TFP growth components into finer components, which are important in order to know the actual contributions of associated efficiency measures to TFP [29]. Moreover, like other simple index methods (i.e., Theil), the MI is biased and fails to satisfy transitivity or the axioms of the index number theory [8,29].

A contemporary method for computing a productivity index, which is based on two indices from Färe and Primont [30], known as Färe–Primont index (FPI), was proposed by O'Donnell [31]. The index specifies the production technology (through distance functions for both) without making any restrictive assumptions about the underlying production technology and returns to scale, firms' optimizing behavior, the market structure under which the firms operate and/or price information. In other words, it does not need the specification of any functional form of the underlying production technology, e.g., Cobb–Douglas or a more flexible translog, which is essential in a parametric approach. Most importantly, the index complies with all other regularity conditions of index numbers, including multiplicative completeness and transitivity [32]. Le Clech and Castejón [28] compared both MI and FPI on the same global database and concluded the superiority of the latter approach. Global TFP estimates using MI and growth accounting approaches are available in the works of Ludena et al. [25] and Fuglie [27], respectively. However, both Fuglie [27] and Le Clech and Castejón [28] used only one aggregate output, defined as the gross agricultural output at constant international dollars, which raises concerns as input and output aggregation have implications for productivity and efficiency measurements [25]. The aggregation of variables was not suggested as a preferred strategy [33] because the effects of the aggregation of input and output variables are ambiguous. For similar reasons, Rao and Coelli [34] suggested to avoid country level aggregation, where scale issues are a problem.

Given this backdrop, the present study aims to analyze agricultural productivity and associated efficiency measures at the global scale, covering large number of countries (i.e., 104 in total) for a 45-year period (1969–2013). The contribution of this study to the existing literature is two-fold. First, we have adopted the FPI approach proposed by O'Donnell [32], which circumvents all the methodological weaknesses identified above. Though this approach is adopted in a couple of earlier studies in estimating the productivity growth of world agriculture [27,28], we suspect that their results may be misleading due to the aggregation of output into a single index. Second, we have estimated and reported six finer TFP components (i.e., technical change, technical efficiency change, scale efficiency change, mix efficiency change, residual mix efficiency change and residual scale efficiency change) which were not reported in earlier studies. Thus, this study offers a greater insight on the sources of growth and enables us to draw a wider range of policy implications.

2. Materials and Methods

2.1. Measuring TFP and Its Different Components

Inspired by the theoretical superiority of the FPI [29,31,32] over other competitive index methods (e.g., Hicks–Moorsteen index (HMI) proposed by Bjurek, [35]), we adopt the FPI approach, which is developed with distance function as the aggregator function. Based on the economic connotations of related efficiencies, it is possible to decompose FPI into the product of technological progress (i.e., movements in the production frontier), technical efficiency (i.e., change is a measure of movements towards the frontier), scale efficiency (i.e., measures of movements around the frontier surface to capture economies of scale) and residual mix efficiency changes (i.e., measures of movements around the frontier surface to capture economies of scope), which are not sensitive to measurement units. That is, inputs and outputs can be measured either in physical quantities or in monetary values at constant prices, or a combination of both, because the computed results are ratios, which are unit free.

The FPI is based on two indices from Färe and Primont [30], and is defined as the ratio of an aggregate output (q) to an aggregate input (x):

$$TFP = \frac{Q(q)}{X(x)} \tag{1}$$

Following O'Donnell [31], the aggregated outputs and inputs can be estimated as

$$Q(q) = D_o(x_0, q, t_0) \tag{2}$$

$$X(x) = D_i(x, q_0, t_0) \tag{3}$$

The above two equations are Shephard output and input distance functions, respectively, which are in nature linearly homogenous, always positive and non-decreasing [36], and represent the production technology available in period t. The FPI score for firm i in period t relative to firm h in period s is [31]

$$TFP_{hs,jt} = \frac{D_0(x_0, q_{it}, t_0)}{D_0(x_0, q_{hs}, t_0)} \frac{D_1(x_{hs}, q_0, t_0)}{D_1(x_{it}, q_0, t_0)} \tag{4}$$

We have worked out the following finer measures of efficiency changes by decomposing output-oriented TFP changes, which are counterparts of the input-oriented technical efficiency measures (details of input-oriented TFP measures are available at [29]. The output-oriented technical efficiency, OTE, is defined as the maximum possible aggregate output produced while holding the input vector and output mix fixed (Figure 1). Other relevant output-oriented components are presented in Figure 1 [8,29,37,38]. These efficiency measures are defined and described with reference to two production frontiers: a mix-restricted production frontier (when the combination of outputs and inputs are supposed to be fixed) and unrestricted production frontier (when both input and output mixes are allowed to be different), where each point refers to a combination of aggregate input and output (Figure 1, adapted from [37,38]).

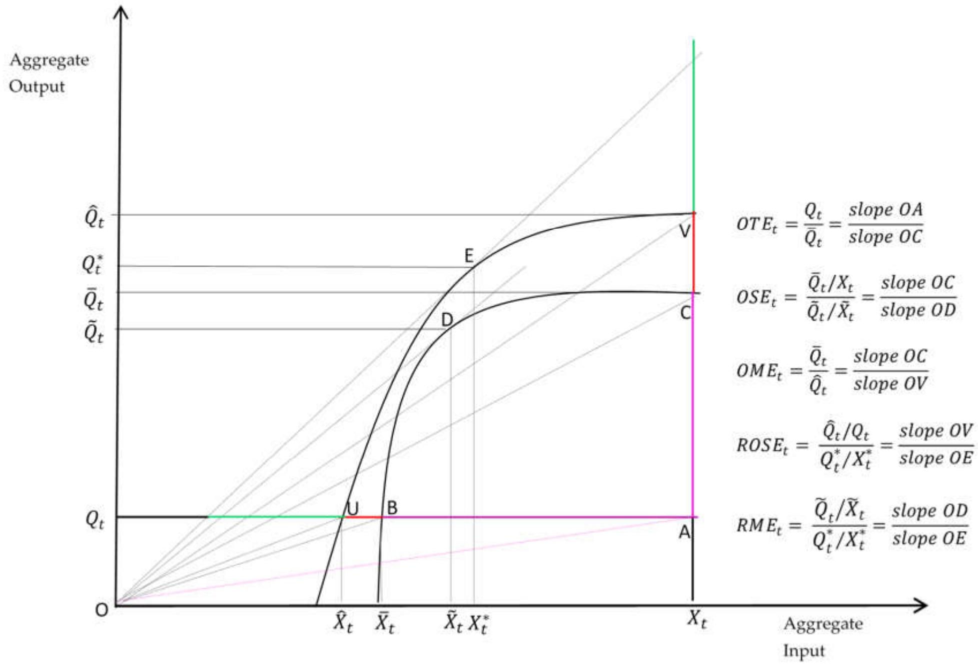

Figure 1. Technical, scale and mix efficiency of a multi-input multi-output firm.

The OTE estimates the productivity shortfall associated with operating below the production frontier; the OME defined by (6) measures productivity shortfalls associated with diseconomies of scope [8,29,37,38]. OME is the change in productivity when the assumptions about input and output mixes are relaxed, and is estimated as the ratio of restricted and unrestricted production function (i.e., *slope OCslope OV* in Figure 1) [29,37,38]. OSE (= *slope OCslope OD* in Figure 1) is the typical measure of output-oriented scale efficiency, which is the productivity difference between TFP at a technically efficient point and the maximum attainable TFP whilst holding the output and input mixes fixed [29,37]. The residual output-oriented scale efficiency, ROSE (= *slope OVslope OE* in Figure 1), is the difference between TFP at an output-mix-efficient point and the maximum possible TFP [29,37]. However, the term 'residual' here means that, although all points on the unrestricted frontier are mix efficient, each has different input and output mixes. Finally, residual mix efficiency, RME (= *slope ODslope OE* in Figure 1), allows probable changes in scale, estimated as the difference between TFP at a scale-efficient point and the maximum possible TFP [29,37,38].

The common measures of efficiency used in economic literature are derived as ratios of different TFP measures [31]. For instance, an alternative output-oriented measure can be shown as [37]:

$$TFPE_{nt} = OTE_{nt} \times OSE_{nt} \times RME_{nt} \tag{5}$$

$$TFPE_{nt} = OTE_{nt} \times OME_{nt} \times ROSE_{nt} \tag{6}$$

where output-oriented technical efficiency (OTE) is the conventional efficiency measure that measures the shortfall in productivity associated with operating below the production frontier, as noted by O'Donnell [32], i.e., the difference between aggregated output that a firm produces utilizing the given resource base at the maximum attainable output possible from that resource base. The output-oriented scale efficiency (OSE) and output-oriented mix efficiency (OME) account for productivity shortfalls associated with diseconomies of scope, which arises when a multiple output producing firm is less efficient than the specialized firms producing a single product. The measure of residual output-oriented scale efficiency (ROSE) is the ratio of TFP at a technically and mix-efficient point to the maximum TFP that is possible, where higher TFP is certainly a scale effect since the improvement is essentially a shift towards higher mix-efficient point along the unrestricted production frontier [37]. O'Donnell used the term residual since different points on the unrestricted frontier represents different input-output mixes, though all are mix-efficient [37]. The residual mix efficiency (RME) is the remaining component after accounting for pure technical and pure scale efficiency effects [31], which can be obtained as the difference in TFP between the point of MIOS (i.e., the optimal point on the restricted frontier) and the point where productivity is maximum (i.e., the optimal point on the unrestricted frontier), the difference between which is a mix effect [37].

Finally, following O'Donnell [8,29,37,38], the overall TFP can be estimated as

$$TFPE_{it} = \frac{TFP_{it}}{TFP_i^*} = OTE_{it}\ X\ OSME_{it} \tag{7}$$

O'Donnell [29,37] decomposes the multiplicatively complete TFP index when the output distance function is well-defined and the maximum TFP possible in each period is finite and non-zero. The resulting equation, where the first term on the right-hand side is a measure of technical change and the remaining terms indicate efficiency changes, can be written as

$$\begin{aligned} TFP_{ksit} &= \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{TFPE_{it}}{TFPE_{ks}}\right) \\ &= \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{OTE_{it}}{OTE_{ks}}\right)\left(\frac{OSME_{it}}{OSME_{ks}}\right) \end{aligned} \tag{8}$$

where TFP_i^* is the maximum TFP possible with the available technology and given input bundle, X_{it}; $\overline{Q}_{it} = Q_{it}/D_0(x_{it}, q_{it}, t)$ is the maximum aggregate output produced by keeping input vector and output mix fixed, and $\hat{Q}_{it}$ represents the maximum aggregate output that is produced when only the input vector is fixed and there are no restrictions on output mix.

We have used the *DPIN 3.0*, which uses a Data Envelopment Analysis (DEA) linear programming (LP) technique, to describe the production technology (and associated measures of productivity and efficiency) [31]. The details are available in the Appendix A. We have used eight output and six input variables to determine TFP. The input–output variables. along with their estimation techniques and sources. are available in Table 1.

Table 1. Output-input variables and their estimation procedures.

Variables	Estimation Procedure
Output	
Crops (output)	Eight output variables are included in TFP calculation: (i) cereals (includes rice, wheat, barley, maize, millet, sorghum, etc.); (ii) fibers (including agave fibers, bast fibres, cotton lint, ramie, sisal, manila fiber, jute, hemp tow waste, etc.); (iii) fruits (includes all types of fresh, citrus, tropical fruits such as apples, apricots, avocados, bananas, different types of berries and cherries, carobs, currants, dates, kiwi, grape, lemon and limes, mangoes, quinces, watermelon, etc.); (iv) pulses (includes all types of peas and beans, lentils, etc.); (v) oil crops (e.g., castor oil seed, coconuts, cottonseed, groundnuts, karite nuts, linseed, melon seed, mustard seed, palm, olives, palm kernels, poppy seed, rapeseed, safflower seed, sesame seed, soybeans, tung nuts, etc.); (vi) roots and tubers (includes cassava, chicory roots, potatoes and sweet potatoes, yams, etc.); (vii) cash crops (includes tea, coffee, gums, rubber, tobacco, etc.); and (viii) vegetables (all types, e.g., cauliflowers and broccoli, cabbages and other brassicas, lettuce and chicory, tomatoes, pumpkins, squash, gourds, cucumbers and gherkins, eggplants, green beans, carrots and turnips, okra, etc.). Cereals, roots and tubers, fibers and pulses are measured in physical quantity (i.e., metric tons). For the other four outputs (fruits, oil crops, cash crops, and vegetables), gross production value is used where 2004–2006 (1000 I$) is the base period.

Table 1. *Cont.*

Variables	Estimation Procedure
Inputs	
Machinery (HP)	Total horse power of all the agricultural machinery including tractors (40 HP) [39], combine harvesters and threshers (25 HP) [40], pedestrian controlled tractors (single axle tractors) (2 HP), ploughs (both reversible (0.864 HP) and non-reversible ploughs (0.576 HP) [41] and threshing machines (12 HP) [42].
Livestock (cattle equivalent animal power)	Livestock is the aggregate number of animals in 'cattle equivalents', and includes cattle, camels, water buffalos, horses and other equine species (asses, mules and hinnies), small ruminants (sheep and goats), pigs, and poultry species (chickens, ducks, and turkeys), with each species weighted by its relative size. The weights for aggregation are based on Hayami and Ruttan [43]: 1.38 for camels, 1.25 for water buffalo and horses, 1.00 for cattle and other equine species, 0.25 for pigs, and 0.13 for small ruminants.
Labour	Total economically active population (000) working in agriculture.
Gross cropped area	Gross cropped area (GCA) is the summation of the total area (000 ha) under all types of crops in a country in a year.
Fertilizer	Total consumption of the major three nutrients (N, P and K) in metric tons from all types of fertilizers (e.g., urea, single superphosphate, triple superphosphate, diammonium phosphate, muriate of potash, etc.) is estimated. Nutrient consumption figures for the years 2002-2013 were available in the FAOSTAT. For the earlier years, the physical quantities of different fertilizers were collected from the FAOSTAT, and were converted to actual nutrient quantity.
Irrigation	Proportion of land under irrigation is taken from the FAOSTAT. The missing information was filled by interpolation or extrapolation through the simple linear trend method.

Some manipulation tasks had to be undertaken because there were missing data points. Missing data were extrapolated using the average growth rate in Fuglie [44], and Rahman and Salim [45] used a standard linear trend interpolation model for the missing data. The following manipulation techniques were followed:

1. Data manipulation was performed only on the finalized output–input groups, e.g., cereals, pulses, etc. and not on individual crops. This was done to keep the level of adjustments to a minimum.
2. For countries with complete set of missing data for some of the input–outputs, an arbitrary scalar of 10 was inserted throughout so that we can still include the country in the analysis. As we followed non-parametric procedure, this scalar value has no influence on the calculation of the frontier whose values are invariably larger than 10 in all cases.
3. For interpolation of the missing data, the average annual change between two available data points was estimated and then that rate of annual change was applied to the missing years, which is a standard practice.
4. For extrapolation, we estimated the annual growth rate from the available data series. Then, that growth rate was applied from the actual data available next to the missing data point, to fill and create the extrapolated series.

While conducting the extrapolation (both for extrapolating backward or forward), if the extrapolated values went below 10 (as happens when negative growth rates were used to extrapolate the missing series), extrapolation was stopped at the year with the value nearest to the scalar 10. Then, that extrapolated value was replicated for the remaining missing years. This was done to avoid negative values when extrapolating missing data backwards, or even forwards with a negative growth rate estimated from actual data points, as by definition inputs and outputs cannot be negative in an economy.

Since we examine the differences and changes in TFP and its finer components across 104 countries over 45 years, technological heterogeneity across countries and over time is an important issue. Alvarez and del Corral [46] criticized the popular trend in the literature which assumes homogenous technology for all the producers, and applied a latent class model approach to empirically prove that such simplified assumptions result in biased estimates. Similarly, Cillero applied a latent class model to investigate the consequences of differences in production technology on Irish beef farms [47], whereas few studies have applied random parameter models [48,49]. A very similar one to ours is the work of Baráth and Fertő [50], who applied O'Donnell's FPI index framework and estimated TFP parameters and convergence to European agriculture. In the process, to acknowledge the productivity consequences of technological heterogeneity across European farms, the authors applied a cluster analysis. However, a cluster analysis requires additional information about farm production environments and weather conditions for grouping [50]. Since we are dealing with large number of countries covering a long period, gathering such information was difficult, and even after admitting the importance of technological heterogeneity, we had to proceed with the assumption of homogenous technology. However, further research acknowledging technological heterogeneity will provide more in-depth understanding of TFP dynamics.

2.2. The Study Countries and Time Period

We have selected those countries where agriculture contributed more than 4% of the total GDP, and/or countries where at least 4% of the total employment was in the agricultural sector in 2013. This resulted in a total of 137 countries. However, due to the unavailability of the required input–output data in the FAOSTAT database, only 104 countries could be included in the analysis (please refer to Appendix A Table A1 for the list of selected countries). The FAOSTAT reports input–output data from 1961. Many countries have several missing data for the earlier years (prior to 1969). Hence, for the sake of consistency, it was decided to cover 45 years (1969–2013).

3. Results

3.1. TFP Change and Its Components: Global Level Estimates

At the global level, the level of TFP, i.e., the ratio of aggregate output to aggregate input, was estimated at 0.20, implying that more aggregate inputs are needed to produce one unit of aggregate output, whereas the estimated technical efficiency of 0.91 implies that aggregate output could be increased by about 10% by removing inefficiency in production alone (Table 2). The estimated almost unitary values of pure technical and scale efficiency (0.97) scores, and the relatively lower values of the pure mix efficiency index (0.78), imply that world agriculture has done well in terms of pure technical and scale efficiencies, but lacks the ability to derive economies of scope by changing optimal input and output mixes (Table 2). The relatively lower residual mix efficiency, which is estimated to be 0.29 (Table 2), implies that countries are not doing well in terms of reaping the benefits of economies of scope. This suggests that there has been an upward shift in the production possibility frontier, most likely driven by innovation and the adoption of technologies, such as the Green Revolution technologies (i.e., a combination of high yielding varieties of rice/wheat/maize and inorganic fertilizers with supplementary irrigation and drainage controls) that created world-wide impact during 1980s, arguing that farmers are rationally adjusting the scale but lag behind in terms of deriving economies of scale. During the period under consideration, TFP grew at a rate of 0.44% p.a., which is relatively low (Figure 2). However, an important and encouraging feature is that world agriculture has maintained this growth rate of TFP for a period of four and half decades.

A summary of some influential related studies is presented in Table 3. To estimate TFP changes, Coelli and Rao [24], Ludena et al. [25], Ludena [26] and Headey et al. [17] applied MI. Ludena et al. [25], who incorporated three outputs (crops, ruminants and non-ruminants) and nine inputs (feed, animal stock, pasture, land under crops, fertilizer, tractors, milking machines, harvesters, threshers and labor) in their analysis of 116 countries and reported that, during the period 1961-2001, the annual TFP growth rate was 0.72%. Ludena [26] estimated that at the global level agricultural productivity growth rate was 1.7% p.a. between 1961 and 2007. The author included 26 Latin American and Caribbean countries and considered two outputs (crops and livestock), and five inputs (animal stock, land, fertilizer, tractors and labor). Headey et al. [17] used two outputs (crops and livestock) and five inputs (land, tractors, labour, fertilizer, and livestock) for 88 countries, and estimated the annual TFP growth to be 1.7% and 1.4%, according to the SFA and DEA model. Coelli and Rao [24] estimated a 2.1% annual growth rate in agricultural productivity for 93 countries over the period of 1980 to 2000.They considered two outputs (crops and livestock) and six inputs (area, tractor, labour, fertilizer, livestock and irrigation). Due to differences in methodology and the disaggregation of outputs into specific crop groups, our estimated figures are not comparable with the literature. The main source of difference may also be due to the aggregation of all types of outputs into one single index and/or use of livestock output in those studies.

Le Clech and Castejón [28] applied both MI and FPI using the same USDA-ERS database, and reported that TFP estimation is sensitive to the methods applied. The results are also sensitive to the time period covered. For instance, by applying the FPI index, Le Clech and Castejón [28] reported a 1.70% annual TFP growth rate during 1980–2000, which was reduced to 1.40% p.a. during the period 1975–2007, which they justified through lower growth rates prior to 1980. By applying the growth accounting method, Fuglie [27] estimated that the overall annual agricultural TFP grew by 0.18%, 0.60%, 0.62%, 1.65% and 1.84% during the periods 1961–1970, 1971–1980, 1981–1990, 1991–2000 and 2001–2009, respectively. Using MI, Nin-Pratt and Yu [51] noted that the overall annual TFP of Sub-Saharan African grew at an annual rate of 1.45%, with 1.06% growth in the first half of the period (1984–1995), which accelerated to 1.88% on average between 1996 and 2006.

There are two sources of differences in TFP growth rates between ours and the three mentioned studies above, though all utilized the FAOSTAT database. Firstly, the same time period and input-output items are not covered across the studies. Secondly, Fuglie [27] applied the 'growth accounting' approach, and converted all the crops and livestock items into a single output measured in constant prices. Le Clech and Castejón's [28] work is based on the data from Fuglie [27], with an update on later years supplied by the USDA-ERS. But such aggregation of output data may affect estimated values [25]. Finally, Nin-Pratt and Yu [51] employed MI to estimate TFP growth and used agricultural production as a single output.

The Green Revolution brought modern science to tackle the widening Asian food crisis in the 1960s. For this purpose, Bangladesh adopted several agricultural policies for robust technological progress, leading to the widespread farm-level dissemination of paddy-based GR technology packages. As a result, the growth in TFP was not uniform. Prior to 1985, TFP grew at a relatively slower pace, which then accelerated and went through several cycles of fluctuations (Table 3). Rahman [52] termed the era after 1985 as the mature stage of GR technology adoption. A similar pattern of TFP growth rate was observed not only in country specific studies for Bangladesh [45] and India [53], but also in regional level studies [54] for Asia, for Latin America and the Caribbean region [26] and at the global level [17,25,27].

Technological progress and mix efficiency changes were the two major drivers behind the growth in TFP (Figure 2). The dominant role of technology in agricultural development and growth is well documented in the literature [20,25,52]. The changes in both technical efficiency and scale efficiency were almost negligible, estimated to be 0.05% and 0.04% p.a., respectively (Figure 2). The implication is that, though world agriculture has managed to maintain positive change in technical efficiency and scale efficiency, the contribution of these two components to TFP growth are almost negligible.

3.2. TFP Change and Its Components: Regional Level Estimates

The estimated changes in TFP and its components for different regions are presented in Figure 3a–f, whereas the associated geomean and growth rates are presented in Figures 4 and 5 respectively. South Asia (SA) was the best performer in terms of TFP growth rate (1.05% p.a.), followed by the Middle East and North Africa (MENA; 0.70% p.a.), Sub-Saharan Africa (SSA; 0.66% p.a.), Europe and Central Asia (ECA; 0.57% p.a.) and Latin America and the Caribbean (LAC; 0.40% p.a.). East Asia and the Pacific (EAP) was the worst performer, with an annual TFP growth rate of only 0.18% p.a.

Coelli and Rao [24] reported that Asia recorded the highest TFP growth, followed by North America (consisting of USA and Canada), Australasia, Europe, Africa and South America. Avila and Evenson [55] also noted that Asia (2.21%) had the highest TFP growth, followed by LAC (1.85%) and Africa (1.44%) during the period of 1961–2001. However, this contrasts with Headey et al. [17] who observed that TFP growth was fastest in MENA and East Asian regions, unstable in LAC and SSA, and generally quite low in SA during the period 1970–2000. On the other hand, the TFP growth rate for SSA is consistent with Fuglie and Rada [56]. Their estimation of TFP growth for the region was 0.59%, while ours is 0.66%; a negligible difference of 0.07%. The present study estimated negligible decline in technical, scale and mix efficiency in SA, whereas technological progress was the main driver of TFP growth during 1969–2013. This result is partially consistent with Anik et al. [57], who reported that the four SA countries experienced little or no variation in technical, scale and mix efficiency changes during the period 1980–2013. The findings are also consistent with the findings of Rahman and Salim [45] on the TFP growth of Bangladeshi agriculture. This growth pattern of technological progress (0.23% p.a.) is similar for all other regions. Therefore, we did not find any evidence of global or regional technological regress. The principal source of TFP growth was efficiency change (or 'catch-up'). However, according to Fuglie [27], Africa was the continent with the highest TFP growth rate, followed by South America, North America, Australasia and Asia. Europe was at the bottom of the list. Baráth and Fertő [50] reported that, although there are considerable differences across countries, the agricultural TFP in the EU countries during 2004-13 showed a decreasing trend.

Mix efficiency is the major driver behind TFP growth in the SSA and MENA, implying that both regions successfully changed their input-output mixes through policy adjustment to derive economies of scope (Figure 3a–f). TFP in LAC was driven by technical efficiency change. Among all the regions, LAC was observed to have the highest annual growth rate (0.21% p.a.) of technical progress (Figure 3d). Lachaud et al. [58] also found that technological progress has been the key driver of agricultural productivity growth in LAC. They also stated that investment in R&D to facilitate access to the best available technologies is critical in the region, and investments in training and education to enhance the absorptive capacity of existing and/or new technologies are also important. Similarly, in the neighboring US states, technical progress was the major driver behind TFP change, with high and stable technical efficiency levels, but the scale-mix efficiency levels were relatively lower and fluctuating [29]. SA and EAP experienced declines in technical efficiency change, though the rate was negligible in SA (−0.01% p.a.) and high for EAP, estimated at −0.11% p.a. (Figure 3b,e). Both these regions also observed declining scale efficiency. Mix efficiency declined annually by 0.02% p.a. in SA, indicating the inability of the region to derive economies of scope (Figure 3b). These findings show that EAP and SA deviated from the available technological level; however, LAC moved closer to the available technological frontier.

Table 2. Global total factor productivity and efficiency levels (Geometric means 1969–2013).

Year	Max-TFP Level (TFP*)	Technical Efficiency Level (OTE)	Scale Efficiency Level (OSE)	Mix Efficiency Level (OME)	Residual Scale Efficiency Level (ROSE)	Scale-Mix Efficiency Level (OSME)	Total Factor Productivity Level (TFP)
1969	0.86	0.91	0.96	0.73	0.32	0.23	0.18
1970	0.86	0.90	0.96	0.73	0.31	0.23	0.18
1971	0.63	0.91	0.98	0.76	0.42	0.32	0.18
1972	0.65	0.90	0.97	0.75	0.42	0.31	0.18
1973	0.64	0.90	0.97	0.76	0.42	0.32	0.18
1974	0.66	0.91	0.97	0.75	0.41	0.31	0.19
1975	0.66	0.91	0.96	0.75	0.42	0.31	0.19
1976	0.66	0.91	0.97	0.75	0.41	0.31	0.19
1977	0.65	0.91	0.97	0.76	0.42	0.31	0.19
1978	0.66	0.90	0.97	0.77	0.41	0.31	0.19
1979	0.67	0.90	0.95	0.76	0.41	0.31	0.19
1980	0.73	0.88	0.96	0.77	0.38	0.29	0.19
1981	0.71	0.89	0.96	0.76	0.39	0.30	0.19
1982	0.69	0.89	0.97	0.79	0.39	0.31	0.19
1983	0.71	0.88	0.96	0.77	0.39	0.30	0.19
1984	0.70	0.89	0.96	0.78	0.40	0.31	0.19
1985	0.72	0.91	0.96	0.76	0.39	0.30	0.20
1986	0.69	0.91	0.97	0.78	0.41	0.32	0.20
1987	0.73	0.90	0.97	0.77	0.39	0.30	0.20
1988	0.72	0.92	0.97	0.76	0.40	0.30	0.20
1989	0.73	0.92	0.98	0.78	0.38	0.30	0.20
1990	0.71	0.92	0.97	0.78	0.39	0.30	0.20
1991	0.72	0.90	0.96	0.78	0.39	0.31	0.20
1992	0.74	0.89	0.96	0.77	0.38	0.29	0.19
1993	0.76	0.91	0.97	0.78	0.37	0.29	0.20
1994	0.77	0.91	0.97	0.78	0.36	0.28	0.20
1995	0.76	0.90	0.98	0.77	0.37	0.29	0.20
1996	0.78	0.92	0.98	0.79	0.36	0.29	0.21
1997	0.78	0.92	0.98	0.79	0.37	0.29	0.21
1998	0.78	0.92	0.98	0.78	0.36	0.28	0.20
1999	0.80	0.93	0.99	0.80	0.35	0.28	0.21

Table 2. *Cont.*

Year	Max-TFP Level (TFP*)	Technical Efficiency Level (OTE)	Scale Efficiency Level (OSE)	Mix Efficiency Level (OME)	Residual Scale Efficiency Level (ROSE)	Scale-Mix Efficiency Level (OSME)	Total Factor Productivity Level (TFP)
2000	0.82	0.93	0.99	0.77	0.35	0.27	0.20
2001	0.86	0.92	0.98	0.78	0.34	0.26	0.21
2002	0.82	0.91	0.98	0.78	0.33	0.26	0.20
2003	0.75	0.92	0.99	0.82	0.35	0.28	0.20
2004	0.86	0.92	0.98	0.80	0.32	0.26	0.20
2005	0.85	0.92	0.99	0.81	0.32	0.26	0.20
2006	0.84	0.92	0.99	0.80	0.33	0.27	0.20
2007	0.81	0.92	0.99	0.79	0.34	0.27	0.20
2008	0.83	0.92	0.99	0.80	0.34	0.27	0.21
2009	0.82	0.93	0.98	0.81	0.34	0.27	0.21
2010	0.84	0.94	0.99	0.81	0.33	0.27	0.21
2011	0.87	0.93	0.98	0.80	0.33	0.27	0.21
2012	0.87	0.93	0.98	0.82	0.33	0.27	0.22
2013	0.88	0.93	0.98	0.83	0.33	0.27	0.22
Geomean	0.75	0.91	0.97	0.78	0.37	0.29	0.20

Table 3. Selected studies of total factor productivity analysis.

Author(s)	Years Studied	Number of Countries	Chosen Method	Major Findings
Fuglie [7]	1961–2005	171	Multifactor productivity indices to estimate input cost shares	Globally agriculture output grew at about 2% p.a. with regional variations.
Headey et al. [17]	1970–2001	88	MI, SFA, DEA	TFP growth rate for the SFA and DEA models are 1.7% p.a. and 1.4% p.a. respectively.
Ludena et al. [25]	1961–2001	116	MI	Average annual agricultural TFP growth increased from 0.6% to 1.29% between 1961–1980 and1981–2001.
Fuglie [27]	1961–2009	171	Multifactor productivity indices to estimate input cost shares	Annually agricultural TFP grew by 0.18%, 0.60%, 0.62%, 1.65% and 1.84% during the periods 1961–70, 1971–80, 1981–90, 1991–00 and 2001–09 respectively.
Le Clech and Castejón [28]	1975–2007	93	MI and FPI	1.70% p.a. TFP growth rate during 1980–2000, which reduced to 1.40% p.a. during the period 1975–2007.
Nin-Pratt and Yu [51]	1984–2006	26	MI	TFP in Sub-Saharan Africa grew at an annual rate of 1.45%, with much faster rate between 1996 and 2006.
Avila and Evenson [55]	1962–2001	78	Growth accounting for cost shares	After 1981, annual TFP growth rates for all regions increased. During 1981–2001. Asia had the highest growth rate (around 2.5% p.a.) followed by LAC and Africa.

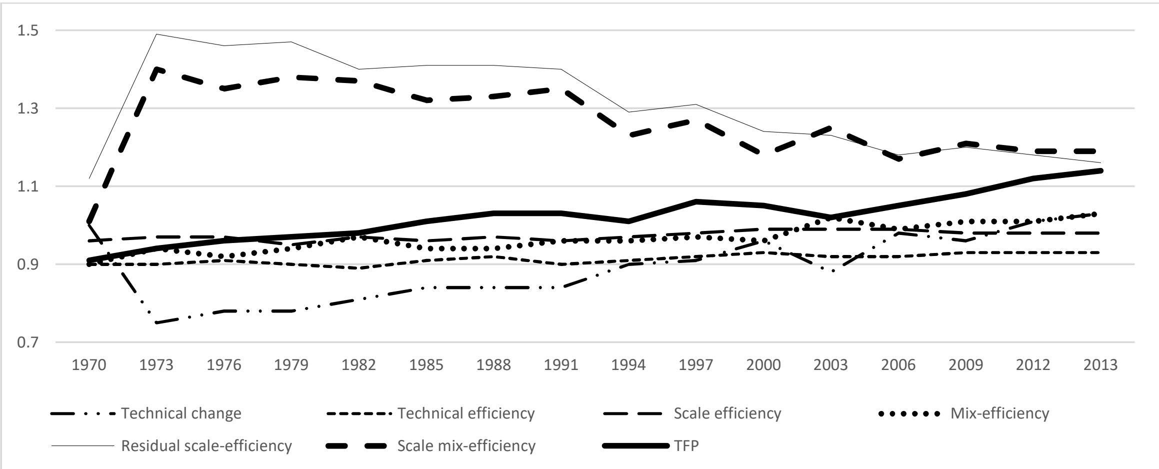

Figure 2. Global TFP change and its components during 1969–2013.

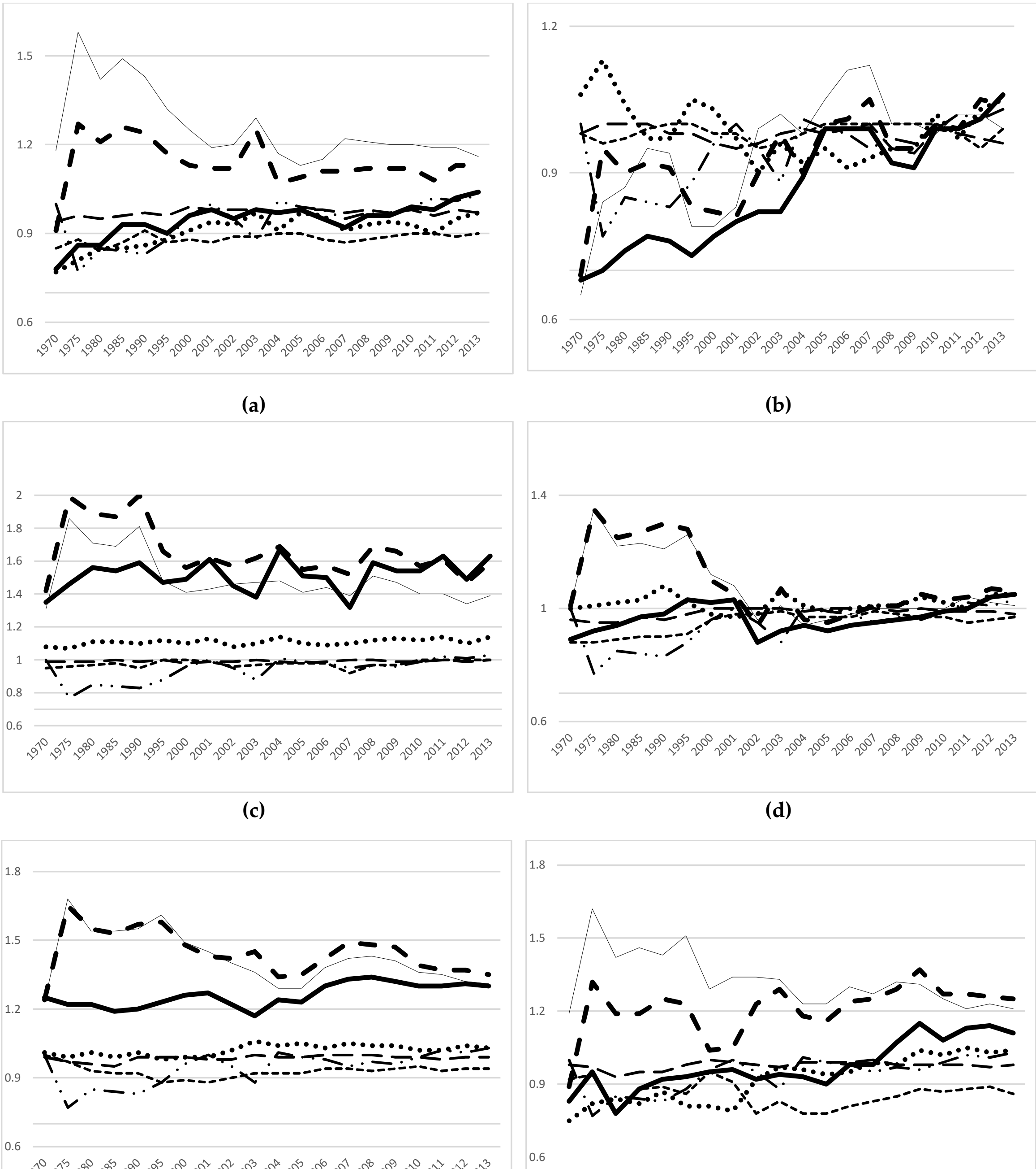

Figure 3. Changes in TFP and its components across regions during 1969–2013: (**a**) Sub-Saharan Africa; (**b**) South Asia; (**c**) Europe and Central Asia; (**d**) Latin America and the Caribbean; (**e**) East Asia and the Pacific; (**f**) the Middle East and North Africa.

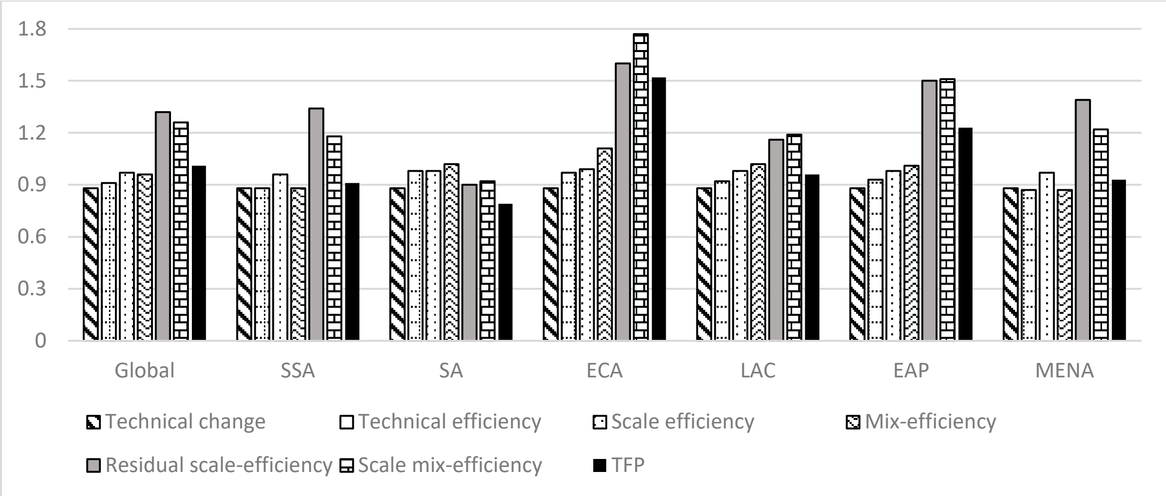

Figure 4. Geomean of TFP and its components.

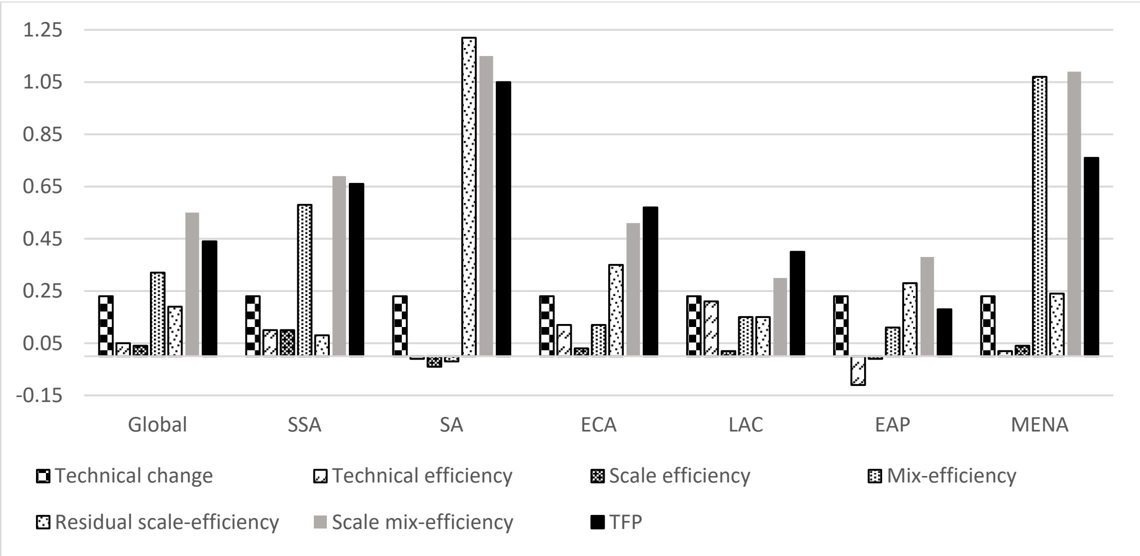

Figure 5. Growth rate (%) of TFP and its components.

4. Conclusions and Policy Implications

The present study assessed the productivity growth of world agriculture (104 countries) for a 45 year period (1969–2013) by applying the Färe–Primont TFP index to the FAOSTAT database. The study decomposed the TFP index into six finer components (i.e., technical change; technical, scale and mix efficiency changes; and residual scale and residual mix efficiency changes). The global level TFP was estimated at 0.20, technical efficiency level at 0.91, scale efficiency level at 0.97, mix efficiency level at 0.78, residual scale efficiency level at 0.37 and residual mix efficiency level at 0.29, respectively. The estimated levels imply that, although world agriculture has done well in terms of pure technical and scale efficiencies, there are deficiencies in the ability to derive economies of scope by changing input and output mixes to optimal levels. The annual TFP growth rate was estimated at 0.44% p.a. The growth rate varied over time, but accelerated after 1985. The major two contributors to TFP growth were technological progress and mix efficiency change, whereas the contributions of technical efficiency and scale efficiency changes were minimal.

Notable differences exist in regional TFP growth rates and their drivers. The highest TFP growth rate was observed in SA (1.05% p.a.), followed by MENA (0.70% p.a.), SSA (0.66% p.a.), ECA (0.57% p.a.) and LAC (0.40% p.a.). EAP was at the bottom of the list, with a growth rate of only 0.18% p.a. The TFP growth in SSA and MENA were largely driven by mix efficiency change, whereas it was technical efficiency change for LAC region. The LAC region is the world leader in terms of technical efficiency change. SA and EAP showed a declining trend in both technical efficiency and scale efficiency changes.

The estimated low level of TFP growth highlights that the sector needs special attention in order to fulfil the basic requirement of food and fibre for the growing global population. Appropriate economic-policy instruments have to be designed so that world agriculture can derive economies of scope by changing optimal input and output mixes. Several policy implications can be derived from the results of this study, though the specific prescription should be region specific, based on their respective TFP and efficiency performances. Firstly, policies for enhancing technical efficiency and scale efficiency changes in the form of increasing investment in R&D and human capital should be prioritized, particularly in EAP, MENA and SSA countries. Second, regions lagging behind in mix efficiency (e.g., SA) need to adopt both price (e.g., procurement programme, tax and/or subsidy, etc.) and non-price policies (e.g., agricultural extension and advisory services, etc.) so that farmers can utilise optimal input and output mixes. Third, policies for enhancing scale efficiency should be in the priority list of ECA and LAC countries. Countries should emphasize the rational allocation of agricultural inputs, particularly capital investment, so that they can avoid over-investment associated with adverse impacts from diseconomies of scale. Fourth, access to markets (both domestic and international) will help the producers in many instances, particularly against the odds associated with the reciprocal relationship between productivity and price.

Along with the bio-physical dimension, TFP has economic and social dimensions and is thus critical for the sustainability of any production system [59]. We could not incorporate this into our study since this is beyond the scope of the present study, but research on this dimension is highly required from both a policy and academic perspective. Additionally, we recommend an in-depth analysis of the potential determinants of differences across regions.

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Appendix A

DEA Estimation Technique

In DEA the (local) output distance functions in period t demonstrating the available technology can be expressed as [60]

$$D_0(x_{it}, q_{it}, t) = (q_{it}\alpha)/(\gamma + x_{it}\beta) \tag{A1}$$

The output-oriented solution requires the unidentified parameters of the input oriented technical efficiency to diminish technical efficiency: $OTE_{it}^{-1} = D_0(x_{it}, q_{it}, t)^{-1}$. The resulting linear program is

$$D_0(x_{it}, q_{it}, t)^{-1} = OTE^{-1} = \underset{\alpha,\gamma,\beta}{min} \left\{\gamma + x'_{it}\beta : \gamma l + X'\beta \geq Q'\alpha; q'_{it}\alpha = 1; \alpha \geq 0; \beta \geq 0\right\} \tag{A2}$$

where Q is a $J \times M_t$ matrix of observed outputs, X is a $K \times M_t$ matrix of observed inputs, t is an $M_t \times 1$ unit vector, and M_t denotes the number of observations used to estimate the frontier in period t [31]. To calculate Färe–Primont aggregates, *DPIN 3.0* uses a variant of this LP that begins by solving the following [31]:

$$D_0(x_0, q_0, t_0)^{-1} = \underset{\alpha,\gamma,\beta}{min} \left\{\gamma + x'_0\beta : \gamma l + X'\beta \geq Q'\alpha; q'_0\alpha = 1; \alpha \geq 0; \beta \geq 0\right\} \tag{A3}$$

Following this, the aggregated outputs and inputs of the FPI can be derived as [25]

$$Q_{it} = \left(q'_{it}\alpha_0\right)/\left(\gamma_0 + x'_0\beta_0\right) \tag{A4}$$

$$X_{it} = \left(x'_{it}\eta_0\right)/\left(q'_0\Phi_0 - \delta_0\right) \tag{A5}$$

where α_0, β_0, Φ_0 and η_0 are solved at sample mean vectors as representative output and input vectors. According to O'Donnell [46], the Färe–Primont TFP index is:

$$TFP_{hs,it} = \frac{D_0(x_0, q_{it}, t_0)}{D_0(x_0, q_{hs}, t_0)} \frac{D_1(x_{hs}, q_0, t_0)}{D_1(x_{it}, q_0, t_0)} \tag{A6}$$

The representative technology in this LP is the technology achieved under the assumption of no technical change, which permits the technology to demonstrate variable returns to scale (VRS). In a case where technology is assumed to exhibit constant returns to scale (CRS), *DPIN 3.0* sets $\delta = 0$ [61].

In DEA, there is an issue of the curse of dimensionality. Although our sample size is much larger than the rule of thumb dictates (i.e., max $\{k > 3\ [m+n];\ k > m * n\}$) [57], there may be issues related to using too many inputs and outputs. Therefore, in order to check the robustness and stability of our results, we conducted a sensitivity analysis by reducing the number of outputs to five by aggregating fruits, vegetables, oilseeds and cash crops into one cash value output, and inputs to five by adding livestock inputs (after converting into horsepower) with the machinery input. The results show very little difference in TFP levels over time (see Figure A1). Therefore, we are confident that using a large number of inputs and outputs did not pose any problems, because we had very large sample size to begin with. The curse of dimensionality is more of an issue if the number of samples is relatively small.

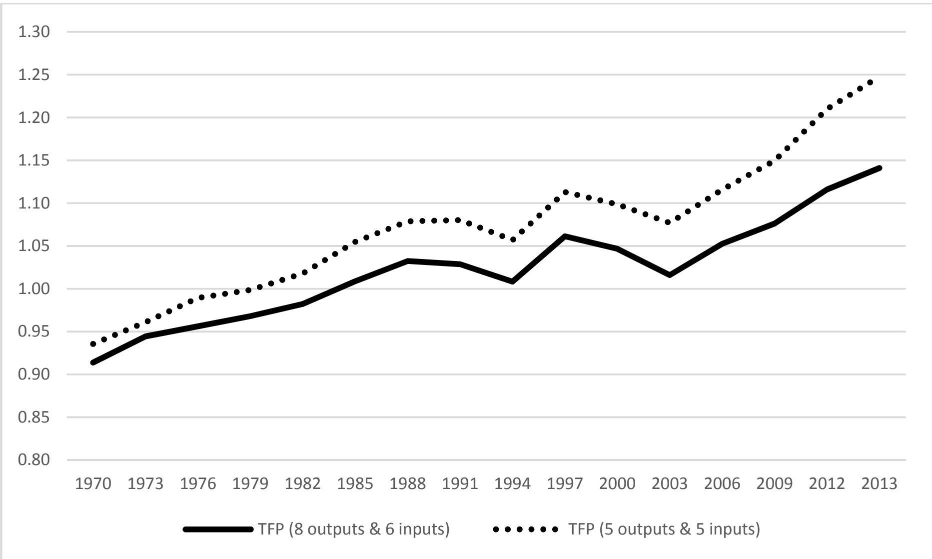

Figure A1. Comparison of TFP with a reduced number of inputs and outputs with the original specification.

Table A1. Countries and regional groupings included in the TFP Analysis.

Sub-Saharan Africa		**Latin America & Caribbean**		**Asia Pacific**
Angola	Madagascar	Argentina	Paraguay	Cambodia
Benin	Malawi	Belize	Peru	China
Burkina Faso	Mali	Bolivia (Plurinational State of)	Suriname	Fiji
Burundi	Mauritania	Brazil	Uruguay	Indonesia
Côte d'Ivoire	Mauritius	Chile	Venezuela (Bolivarian Republic of)	Japan
Cabo Verde	Mozambique	Colombia		Lao People's Democratic Republic
Cameroon	Namibia	Costa Rica		Malaysia
Chad	Niger	Cuba		Mongolia
Comoros	Nigeria	Dominican Republic		Myanmar
Congo	Rwanda	Ecuador		New Zealand
Democratic Republic of the Congo	Senegal	El Salvador		Papua New Guinea
Gambia	Sierra Leone	Guatemala		Philippines
Ghana	Somalia	Guyana		Republic of Korea
Guinea	South Africa	Haiti		Solomon Islands
Guinea-Bissau	Swaziland	Honduras		Thailand
Kenya	Togo	Jamaica		Timor-Leste
Lesotho	Uganda	Mexico		Tonga
Liberia	Zambia	Nicaragua		Viet Nam
	Zimbabwe			
Europe and Central Asia		**Middle East and North Africa**		**South Asia**
Albania	Romania	Algeria	Syrian Arab Republic	Afghanistan
Austria	Spain	Egypt	Tunisia	Bangladesh
Bulgaria	Turkey	Iran (Islamic Republic of)	Yemen	Bhutan
Greece		Lebanon		India
Hungary		Morocco		Nepal
Poland		Saudi Arabia		Pakistan
Portugal				Sri Lanka

Table A2. Descriptive statistics of the input–output variables.

Variables	**Mean**	**Std. Dev.**	**Min**	**Max**
Cereals	10,933,066.1	2,982,856.6	6,014,337.9	16,959,814.5
Fibres	161,367.4	36,565.3	107,535.2	242,209.8
Fruits	1,181,295.0	515,139.0	566,133.5	2,274,134.9
Oil Crops	652,304.2	337,381.3	240,776.8	1,380,743.8
Pulses	604,543.4	355,082.0	186,726.8	1,387,817.0
Roots and Tubers	365,519.3	60,982.9	285,664.1	534,843.8
Cash crops	235,466.6	69,551.0	131,359.5	379,155.1
Vegetables	971,000.4	578,093.1	334,212.7	2,144,484.0
Machinery	4,698,743.2	2,444,382.8	1,120,998.3	10,281,803.7
Livestock	11,288,780.5	1,468,453.2	8,818,822.2	13,659,008.8
Gross cropped area	7,673,161.3	860,742.1	6,448,045.2	9,499,882.1
Labour	24,901.9	2953.6	18,805.0	27,969.8
Fertilizer	503,866.8	447,353.8	58,365.9	1,366,817.0
Irrigation	18.8	3.8	13.0	24.8

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