Climate, environment and socio-economic drivers of global agricultural productivity growth

Rahman, Sanzidur ORCID logoORCID: https://orcid.org/0000-0002-0391-6191, Anik, Asif Reza ORCID logoORCID: https://orcid.org/0000-0002-0461-6094 and Sarker, Jaba Rani (2022) Climate, environment and socio-economic drivers of global agricultural productivity growth. Land, 11 (4). 512. ISSN 2073-445X doi: https://doi.org/10.3390/land11040512
Available at https://centaur.reading.ac.uk/104456/

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Climate, Environment and Socio-Economic Drivers of Global Agricultural Productivity Growth

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Abstract: Growth in total factor productivity (TFP) indicates the sustainable and/or judicious use of scarce resources, including non-renewables. This paper identifies sources of growth in global agricultural TFP and its finer components, ranging from climate, production environment, and socio-economic factors, using a panel data of 104 countries, covering a 45-year period (1969–2013); and, finally, projects changes in TFP from increased climate variability. The results revealed that global agricultural productivity grew consistently at a rate of 0.44% p.a., driven by technological progress and mix-efficiency change, with negligible contributions from technical- and scale-efficiency changes; albeit with variations across regions. Both long-term and short-term climatic factors and the natural production environment significantly reduce global agricultural productivity, whereas a host of socio-economic factors have a significant but varied influence. The projected increased level of future climate variability will significantly reduce future agricultural productivity. Policy implications include investments in crop diversification, education, agricultural spending, number of researchers, and country specific R&D.

Keywords: Färe–Primont TFP index; technical-, scale- and mix-efficiency changes; climate change; socio-economic factors; determinants; multivariate Tobit model

Citation: Rahman, S.; Anik, A.R.; Sarker, J.R. Climate, Environment and Socio-Economic Drivers of Global Agricultural Productivity Growth. *Land* **2022**, *11*, 512. https://doi.org/10.3390/land11040512

Academic Editor: Marta Debolini

Received: 10 March 2022
Accepted: 31 March 2022
Published: 1 April 2022

1. Introduction

Technological change is an important factor in economic growth and development. Historical experience suggests that technology, by raising the productivity of factors (e.g., labor, capital, land, and other natural resources), plays an important role in economic growth [1]. The major technological breakthrough in agricultural history was the development of high-yielding modern varieties of rice and wheat, which are highly responsive to inorganic fertilizers, pesticides/insecticides, effective soil management, and water control [2]. The overwhelming belief in the pursuit of this 'high-input payoff' model of agricultural development, known as the 'green revolution' (GR), is due to its potential for increasing food-grain productivity and employment, as well as income; thereby, alleviating poverty and hunger [3]. However, this pioneering scientific method-based modern agriculture has overlooked the sustainability of this input-intensive production system. In fact, GR technology enabled rapid global food-grain output growth by bringing more land under cultivation, as well as by increasing the efficiency of the inputs used, but not by increasing total factor productivity (TFP) growth [4,5], which can contribute towards the sustainability of the production system [6]. The modern agricultural production process does not adequately address sustainability issues and increasing environmental concerns, including biodiversity loss, greenhouse gas emissions, and reduced availability of fertile soils and clean water [7–9]. Since the mid-1980s, there has been reduced returns from different inputs, which Singh [10] characterized as high input-use and a decelerating productivity growth phase for India. The concern is even greater today because, to meet global food requirements, production needs to increase 2.5 fold by 2050 [11].

There is a need for sustainable intensification of the agricultural production system that does not require trade-offs between productivity and other ecosystem services [11–13]. In other words, the global food production system requires TFP growth, which will ensure increased productivity, while maintaining the sustainability of the system and contributing towards poverty reduction [14–16]. Exploration of agricultural TFP, not only provides information about the diversity of agricultural growth, but increased TFP can ensure increased agricultural production, while reducing environmental externalities, which is also important for increasing the resilience and ensuring sustainability of the farming system [6]. Moreover, given the changing nature of climate and weather, concerns about their effects on agriculture and livelihoods are increasing globally [17,18]. Therefore, TFP growth in agriculture has become more critical than ever.

Researchers believe that agricultural productivity growth is the most effective long-term strategy to tackle the problems of poverty, hunger, and malnutrition [19], which are amenable through devising policies and investments in agriculture [20]. Abbott et al. [21] noted that the global spike in food prices during 2008–2009 was largely due to declining agricultural productivity and cereal crop failure in food exporting economies, which are likely to be repeated more frequently and with higher intensity in the future, owing to increasing anomalies in climate, weather events, and other factors; thereby, threatening agricultural sustainability [22,23]. However, the declining yield trend can be addressed through adjusting production systems, technology, and/or input combinations. In this respect, examination of TFP change is appropriate, because it allows decomposition of total production growth into various components (technology, efficiency, and scale changes) and enables identification of specific sources of productivity growth, thereby leading to better policy prescriptions [24]. Increased TFP has implications beyond national boundaries and can help in achieving internationally set development targets, including the sustainable development goal (SGD). For instance, to attain SDG2 (zero hunger) there is a target of doubling productivity in smallholder farms by 2030. TFP growth will also help in achieving sustainability related SGD targets, viz. SGD 12 (responsible consumption and production) targeting the strengthening of scientific and technological capacities (i.e., use of modern technologies in production); SDG 13 (climate action) focusing on resilience and adaptive capacity to climate-related hazards and natural disasters (i.e., climate change adaptation in production); and SDG 15 (life on land), which is aimed at ensuring conservation, restoration, and sustainable use of ecosystems.

Conventionally, agricultural policies, whether designed at the regional or country level, are targeted at attaining higher productivity, so that enough food is produced [25]. Most Asian countries have followed the Asian path of productivity growth, where land productivity increased faster than labor productivity in the early period, followed by fairly rapid growth of labor productivity, even after the mid-1980s [26]. On the contrary, the Common Agricultural Policy of the European Union focused on mechanization of agriculture to boost labor productivity, as labor supplies were relatively scarce in these economies. Japan followed the European path (i.e., increasing labor productivity), which is closely related to an increase in farm size and mechanization. Although the policies of various regions were different, the goal was to increase total agricultural productivity. There are examples of support policies, such as innovation policies related to agriculture, captured in the OECD's classification as part of the General Services Support Estimate (GSSE), and other policies (environmental regulations or taxes), which may also influence producers' decision-making and ultimately influence productivity and sustainability outcomes in agriculture [27]. African farmers faced more discriminatory agricultural policies than in other parts of the world [28]. Nevertheless, different agricultural policies in Sub-Saharan Africa, e.g., national and international agricultural research investment policies, economic policy reforms, and irrigation investments, had a positive and significant effect on total factor productivity [29].

Literature is available which provides valuable insights on the effects of climate change on agricultural production (e.g., [18,24,30–32]) and productivity (e.g., [33,34]). However, research on climate change and TFP is confined to a specific region or country, e.g., Ryan [35], Mullen and Cox [36], and Salim and Islam [33] focused on a specific Australian region. Liang et al. [37] explored impacts on US agriculture, whereas Kunimitsu et al. [38] studied the effects in Japan. Furthermore, there are limitations in terms of the scope of analysis, content coverage, methodology applied, and identification of determinants of agricultural productivity [20]. Although climate, weather, agro-ecological and socio-economic factors influence agricultural land use change and/or production [30,31], the exact nature and magnitude of their influence on productivity and efficiency is not clear. Lobell and Field observed that the literature did not duly emphasize climate change effects on agriculture, despite the increasing trend in surface temperature rise over the past few decades [30]. The dominant trend in the literature is to model changes in crop production, as explained by different climatic variables (mainly rainfall and temperature) and natural factors (soil quality) only (e.g., [22,30,31,39]), but they do not consider the influence of socio-economic and other factors [40]. Some even proxied weather by rainfall only while exploring the impact of climate change on farm cost (e.g., [35]) or TFP (e.g., [34]). Mullen and Cox [37] explained TFP variations in Australian broadacre agriculture through time trends, which is an even more distant proxy. In their subsequent work, Mullen and Cox [41] used pasture growth based on rainfall data to supplement weather. Most importantly, the TFP measures used in these studies have their own limitations. For instance, Liang et al. [37] used Wang et al.'s [42] estimates for US agriculture, where TFP was defined simply as the ratio of output to input. In the case of Western Australia, Salim and Islam [33] used TFP measured through the Tornqvist index method, whereas Kunimitsu et al. [38] applied the Tornqvist–Theil index for paddy production in Japan. Mullen and Cox [36] adopted the Divisia indices of aggregate output to aggregate input. All these are biased measures and do not possess the required features of multiplicative completeness or transitivity, and the scope to decompose estimated TFP growth into finer components of associated efficiency measures is limited [43].

Finally, and most importantly, the aforementioned studies lack a holistic approach, as none has explicitly explored the impacts of climate change, the production environment, and relevant socio-economic factors together, which are driving global agricultural productivity and efficiency changes over time and, hence, carry little interest in the policy arena. Rather, efforts are limited to exploring the impact of climatic variables only along with research and development (e.g., [33,37]). Alternatively, TFP-focused global-level studies did not try to explain the growth factors, particularly climatic factors. Avila and Evenson [44] and Fuglie [4] concentrated only on technology and human capital index to explain TFP growth, and Fuglie [4] admitted that due to 'left-out' variables (such as, climate change, production environment, and other socio-economic factors), the results may suffer from omitted variable bias. Furthermore, the future possible effect of the changing climate and associated anomalies on TFP is yet to be explored in the literature. Although, Anik et al. [45] circumvented all of the aforementioned weaknesses and provided an estimate of global agricultural TFP growth and efficiency changes, they did not attempt to identify the determinants and/or drivers of these changes, which is important for policy purposes. They also did not conduct any predictive analysis regarding future climate variability on agricultural TFP.

Given these backdrops, the main objectives of the present study were to (a) jointly identify the influences of climate change, natural production environment, and socio-economic factors on global agricultural productivity growth and its finer components (i.e., technical-, scale-, and mix-efficiency changes); and (b) predict the effect of future climate variabilities on global agricultural productivity. To achieve these objectives, we used the TFP and efficiency estimates of Anik et al. [45], which are based on a panel data of 104 countries, covering a 45-year period (1969–2013). Our study revealed three important insights and/or contributions to the existing literature: (i) established linkages, including magnitude and direction, amongst climate, production environment and socio-economic factors with global agricultural productivity and its efficiency components; (ii) identified synergies amongst agricultural productivity and various efficiency components; and (iii) provided the magnitude and direction of agricultural TFP change from future climate variabilities.

Although we explored different potential dimensions of agricultural productivity, due to a lack of the necessary data covering a long time-series for the majority of the countries investigated in this study, we could not explore two potential dimensions. The first one is related to waste management in agriculture from the viewpoint of the circular economy and the bioeconomy. While agriculture is both a cause and effect of climate change, it also contributes to climate change mitigation and resilience, since all the inputs from its production process are not lost, and the concept of circular economy addresses this. Although several notable related works are available (e.g., [46,47]), more rigorous work regarding these themes aimed at exploring the linkages, and possible policy options are suggested for future research.

Another crucial research area is related to the role of agricultural trade in TFP growth. Trade can enable a country to explore markets beyond its own geography and gain through comparative advantages originating from various factors, including natural and bio-physical factors and the institutional culture and skills that farmers possess over time. Edwards [48] noted that countries having greater trade barriers experienced slower productivity growth. Farmers of a middle-income country producing traditional and non-traditional crops, and those producing only traditional crops, are facing different international trade effects on crop yields [49]. They also revealed that exporting channels include international technology and knowledge spillovers because of trade and also gains in productivity, due to product specialization in trade. In global market exports, the EU countries held comparative advantages in exporting products of animal origin, whereas the US had comparative advantages in the exports of cereals, preparations of cereals, oilseeds, oleaginous fruits, and meat products [50]. Future studies focusing on the linkages between international trade, comparative advantages of an individual country, and TFP growth in agriculture could unpack new insights and knowledge on the subject matter.

2. Methodology

2.1. TFP Index and Its Components

We utilized the estimated values of TFP, technical-, scale-, and mix-efficiency indices from Anik et al. [45], who applied O'Donnell's [51] Färe–Primont index (FPI) approach, and produced estimates of TFP and its six finer components (i.e., technical change, technical efficiency change, scale efficiency change, mix efficiency change, residual mix efficiency change, and residual scale efficiency change). The advantage of the FPI method is that it only requires specification of the production technology (i.e., output and/or input distance functions), and it is free from any restrictive assumptions related to the nature of production technology, optimizing behavior of the firms, structure of markets and prices, and it also satisfies the condition of multiplicative completeness and transitivity of index number theory [52]. Anik et al. [45] constructed all relevant input and output variables, using the FAOSTAT database to estimate output oriented TFP and efficiency changes for 104 countries where agriculture contributed at least 4% of the GDP and/or 4% of total employment, covering a period of 45 years (1969–2013).

The estimation used eight outputs and five inputs, which circumvented aggregation issues, a common concern in global level TFP studies [53,54]. The panel-data series used in this study covered the period 1969–2013. This is because, prior to 1969, many data points were missing for most of the variables for many countries. In addition, although data from FAOSTAT for production inputs and outputs are available up to 2018 (i.e., prior to COVID-19, since data from the pandemic period are not considered as normal years), other data variables used to identify determinants of TFP change and its components are not available for most of the countries in the sample. Moreover, we believe that, since our study covers a historically long period of 45 years covering 137 countries, adding another 5 years of data, with incomplete information, would not have any discernible impact on the main conclusions and policy implications drawn from this study.

2.2. Determinants of TFP Change and Its Components: A Multivariate Tobit Analysis

Having the estimates of TFP and efficiency change indices in hand, which are censored in nature, we applied a multivariate Tobit model (MVTOBIT) to identify the determinants/drivers jointly influencing agricultural TFP and its efficiency components. Furthermore, the model enables testing correlations between error terms of different equations, which ultimately will inform how countries substitute or compliment TFP and its efficiency components. The general form of the model can be written as

$$Y_{it}^{*} = \gamma' X_{it} + \mu_{it} \tag{1}$$

where Y_i^* is the estimated value of TFP or its various components (log transformed) for country i in year t; x_{ijt} is the vector of different explanatory variables j of country I in time t; ε_i is the error. In any equation, Y_i^* equals the actual level of TFP of its components (Y_i); whereas for other countries, Y_i^* is an index reflecting potential score, such that

$$\begin{aligned} Y_{it} &= Y_{it}^{*} \quad if\ \gamma' X_{it} + \mu_{it} > 0 \\ &= 0 \quad\ \ if\ \gamma' X_{it} + \mu_{it} < 0 \end{aligned} \tag{2}$$

We developed four equations for TFP change index (dTFP) and its output-oriented components: technical efficiency change index (dOTE), scale efficiency change index (dOSE), and mix-efficiency change index (dOME). The general form of the four equations can be written as

$$\begin{gathered} dTFP_{it}^{*} = \gamma' X_{dTFP_{it}} + \mu_{dTFP_{it}} \\ dTFP_{it} = Maximum\left(dTFP_{it}^{*}, 0\right)\ (the\ usual\ Tobit\ specification\ as\ in\ 2) \\ dOTE_{it}^{*} = \gamma' X_{dOTE_{it}} + \mu_{dOTE_{it}} \\ dOTE_{it} = Maximum\left(dOTE_{it}^{*}, 0\right)\ (the\ usual\ Tobit\ specification\ as\ in\ 2) \\ dOSE_{it}^{*} = \gamma' X_{dOSE_{it}} + \mu_{dOSE_{it}} \\ dOSE_{it} = Maximum\left(dOSE_{it}^{*}, 0\right)\ (the\ usual\ Tobit\ specification\ as\ in\ 2) \\ dOME_{it}^{*} = \gamma' X_{dOME_{it}} + \mu_{dOME_{it}} \\ dOME_{it} = Maximum\left(dOME_{it}^{*}, 0\right)\ (the\ usual\ Tobit\ specification\ as\ in\ 2) \end{gathered} \tag{3}$$

A list of the explanatory variables and their estimation procedures are presented in Table 1.

2.3. Predicting Future TFP under Different Climatic Scenarios: A Sensitivity Analysis

Using the parameter estimates of the aforementioned MVTOBIT model, we predicted change in global agricultural TFP up to 2033. The predict command available in STATA 16 software enables both in-sample and out-of-sample forecasting. The out-of-sample prediction process requires forecasting explanatory variables, which we did for each country, using the annual compound growth rate estimated as the parameter β in $lnY = \alpha + \beta t$ (where y is the relevant explanatory variable and t is time) of the existing in-sample data. The assumption is that the explanatory variables will follow the same rate of growth in the future as experienced over the past 45 years (1969–2013). Therefore, the projected values of the explanatory variables can be considered as the natural change over the next 20 years (2014–2033) and provide us with the counterfactual scenario. This is because, along with this natural growth rate of explanatory variables, we assumed additional changes in climatic variables and developed four different models. The first of these is the 'counterfactual model', where we assumed the natural growth rate for all the explanatory variables, including climate variables. In the second model (Model 2), to capture the impact of increased rainfall and temperature variabilities, we imposed a 1% additional change in total rainfall and mean temperature variabilities annually on top of the counterfactual model. In the third model (Model 3), we imposed a 0.1% additional change in LTP and LTT annually, on top of the counterfactual model. In the final model (Model 4), we incorporated changes in Models 2 and 3, simultaneously, on top of the counterfactual model. All other remaining explanatory variables followed the natural growth rate, as explained previously.

Table 1. Definition and construction of the determinants.

Variables	Description of Variables
	Technology enhancing variables
Researcher	Agricultural researchers defined as '000 FTEs, collected from IFPRI's ASTI database.
Spending	Total agricultural spending, defined as share of Agricultural GDP, collected from IFPRI's ASTI database.
	Institutional capacity variables
Literacy	Log of literacy rate defined as share of people aged 15 years and above, collected from World Bank Data Bank (https://data.worldbank.org/indicator/SE.ADT.LITR.ZS; accessed on 21 February 2021). The data are available for different time periods for different countries. The standard interpolation method was applied to fill missing data.
Employment	Log of employment in agriculture, defined as share of total employment. The standard interpolation method was applied for missing years. A constant value of 4% (minimum threshold level for a country to be selected as a sample in our analysis) was applied to those countries where the method was not applicable because they had only one or no observations.
Economic openness	Log of trade, which is the sum of exports and imports of goods and services, measured as share of total GDP. Information compiled from the World Bank's national accounts data and OECD National Accounts data files.
	Socio-economic variables
Crop diversification	Log of Herfindahl index of crop diversification, which is constructed using land area under the different crops available at FAOSTAT. A zero value means complete diversification, and a value of 1 means complete specialization.
Dummy for income category (base = upper-middle income countries)	Based on GNI per capita. World Bank classifies countries into four categories, and three dummy variables are used: dummy for low income country (=1 for countries belonging to low income category, 0 otherwise); dummy for low-middle income country (=1 for low-middle income category countries, 0 otherwise); and dummy for high income country (=1 for the high income category, 0 otherwise).
	Agro-ecological and physical location variables
Elevation	Log of mean elevation (meters above sea level), available at https://www.pdx.edu/econ/country-geography-data; accessed on 7 June 2020.
Dummy for country's location in a typical weather regime (base = temperate zone)	The countries were classified into three broad typical weather regimes, and dummies for two regimes were used. These are dummy for arid and semiarid regions (=1 if the country belongs to arid and semi-arid region, 0 otherwise), and dummy for tropical sub-tropical regions (=1 if the country belongs to tropical and sub-tropical region, 0 otherwise). Some countries fall into multiple categories. The classification is available at: https://www.cia.gov/library/publications/the-world-factbook/fields/284.html; accessed on 17 December 2018
Climatic variables	Under this category four variable are used. The first four are climatic variables used to represent climate change and are constructed by exploring the World Bank's Climate Change Knowledge Portal (https://climateknowledgeportal.worldbank.org; accessed on 3 April 2020); whereas the fifth one represents the impact of climate change, and was collected from The International Disaster Database (available at: https://www.emdat.be; accessed on 25 March 2020).

Table 1. *Cont.*

Variables	Description of Variables
Long-term-precipitation–LTP (mm)	As climate is the average weather over a long period of time [39] and as the IPCC [55] considered 30 years as an example of a long time-period, a 30-year moving average (starting from 1901) of total annual rainfall was used, in logarithmic form.
Rainfall variability (mm)	Log of standard deviation of monthly rainfall per year is estimated using monthly total rainfall data.
Long-term-mean-temperature–LTT (0C)	Similarly to LTP, a log of the 30-year moving average (starting from 1901) of mean annual temperature is used as a measure of climate change.
Temperature-variability (0C)	The annual temperature variability is estimated as the difference between monthly maximum and minimum average temperature.
Regional dummy (base = Middle East and North Africa (MENA))	The countries belonged to six different regions, and, therefore, five dummies were constructed. These are dummy for Sub-Saharan Africa (SSA) = 1 if the country belongs to SSA, 0 otherwise; dummy for South Asia (SA) = 1 if the country belongs to SA, 0 otherwise; dummy for Latin America and Caribbean (LAC) =1 for LAC countries, 0 otherwise; dummy for East Asia and the Pacific (EAP) =1 if the country belongs to EAP, 0 otherwise; and dummy for Europe and Central Asia (ECA) = 1 if the country belongs to ECA, 0 otherwise.
Year	An integer variable represents time, t = 1 for 1969, 2 for 1970, and so forth.

3. Results

3.1. Global Agricultural TFP Change and Its Components

The estimated global agricultural TFP indices and its various components are presented in Table 2. The global TFP grew annually at a rate of 0.44%, and the estimated level was 0.20. The global technical efficiency level was estimated 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.

Table 2. Total factor productivity and efficiency levels in global agriculture.

TFP and Its Components	Geometric Mean	Growth Rate (%)
Max-TFP level	0.75	0.23
Technical efficiency level	0.91	0.05
Scale efficiency level	0.97	0.04
Mix-efficiency level	0.78	0.32
Residual scale efficiency level	0.37	0.19
Scale–mix efficiency level	0.29	0.55
Total factor productivity level	0.20	0.44

The geometric mean of agricultural TFP and its components across regions and different categories are presented in Table 3. At the global level, the geometric mean of the TFP change index for the last four and half decade was 1.014, meaning the output increased at a higher rate than inputs. For the other three TFP components, i.e., technical-, scale-, and mix-efficiency changes, the index values remained less than unitary. The TFP change index values across all the categories are statistically significant.

3.2. Climate, Production Environment, and Socio-Economic Drivers of Productivity Change

Table 4 presents the joint estimates of the determinants of the TFP change and its three efficiency components by applying the MVTOBIT model. The key hypothesis in this multivariate analysis is that the 'correlation of the disturbance term between any pair of equations is zero $\left(i.e.\ \rho_{jk} = 0\right)$'. We found all correlations to be positive and significantly different from zero. This implies that complementary relationships exist amongst TFP and its three efficiency components, i.e., growth in TFP or any of its components is associated with growth in another component. The signs associated with the time variable imply that technical-, scale-, and mix-efficiency grew significantly over time.

Table 3. Geometric mean of TFP change and its components for different categories.

Country Categories	TFP Change Index *	Technical Efficiency Change Index	Scale Efficiency Change Index	Mix-Efficiency Change Index
Income classes				
Low income countries	1.001	0.940	0.980	0.944
Low middle income countries	0.975	0.879	0.965	0.947
Upper-middle income countries	1.105	0.916	0.978	1.041
High income countries	1.236	0.963	0.995	1.012
Production environment: land elevation				
Low elevation (185.39 MASL)	0.851	0.901	0.964	0.942
Medium elevation (503.19 MASL)	1.147	0.914	0.977	0.959
High elevation (1252.73 MASL)	1.068	0.921	0.981	0.981
Production environment: weather regime/zone				
Arid and semiarid	0.975	0.892	0.968	0.859
Tropical and subtropical	1.083	0.915	0.976	0.979
Temperate	0.803	0.922	0.972	1.017
Region/geographic location				
SSA	0.913	0.881	0.964	0.878
SA	0.791	0.981	0.982	1.015
ECA	1.516	0.975	0.991	1.109
LAC	0.964	0.922	0.979	1.024
EAP	1.231	0.926	0.979	1.006
MENA	0.928	0.868	0.967	0.874
Global	1.014	0.912	0.974	0.960

Note: * We conducted a one-way ANOVA test and found that the TFP change index across all the categories was significantly different at a 1% level of significance.

3.2.1. Socio-Economic Factors Explaining TFP Growth and Its Components

The negative signs on the coefficient of the Herfindahl index of crop diversification imply that crop diversification positively contributed towards TFP growth, technical-, and mix-efficiency changes. A 1% increase in crop diversity index will increase the likelihood of an increase in TFP, technical-, scale-, and mix-efficiency by 0.585%, 0.031%, and 0.074%, respectively (Table 4).

To understand whether the growth in TFP and its three components across countries belonging to different income classes is different, countries were categorized into four income classes, following the World Bank classification. Except for the mix-efficiency change index, high-income countries had the highest index values compared to the other three income classes (Table 3). However, the econometric analysis revealed that, compared to the upper-middle income countries, low-income countries attained significantly higher growth in TFP and its three components, and that the high-income countries experienced significantly higher technical- and scale-efficiency growth. However, for low-middle income countries, the mix-efficiency change was significantly lower than for the upper-middle income countries (Table 4).

Table 4. Joint estimation of the determinants of TFP change and its components.

Variables	MVTOBIT (Marginal Effects)			
	TFP Change Index	**Technical Efficiency Change Index**	**Scale Efficiency Change Index**	**Mix-Efficiency Change Index**
Technology enhancing variables				
Spending	0.043 ***	0.006 *	0.002 *	−0.003
Researcher	0.006	0.005 ***	0.0003	0.010 ***
Institutional capacity variables				
Literacy	0.010	−0.019 ***	0.003 *	0.021 ***
Employment	0.023 ***	0.004 ***	−0.001	0.007 ***
Economic openness	0.004	−0.002 **	0.002 ***	0.0003
Socio-economic variables				
Crop diversification	−0.585 ***	−0.031 **	−0.007	−0.074 ***
Income class dummy (base = upper-middle income countries)				
Low income	0.112 ***	0.031 ***	0.015 ***	0.030 ***
Low middle income	0.016	−0.003	0.001	−0.011 *
High income	0.024	0.033 ***	0.008 ***	0.009
Production environment and weather regime dummy (base = temperate zone)				
Land elevation	0.046 ***	−0.024 ***	0.006 ***	−0.051 ***
Square of land elevation	−0.003 ***	0.002 ***	−0.0002 *	0.005 ***
Arid and semiarid	0.126 ***	0.006	0.005 ***	−0.015 ***
Tropical and subtropical	0.203 ***	0.015 ***	0.006 ***	0.045 ***
Climatic variables				
LTP	0.016	−0.021 ***	0.004 ***	0.004
Rainfall variability	−0.139 ***	0.002	−0.004 ***	−0.051 ***
LTT	−0.056 ***	−0.011 ***	−0.002	−0.013 ***
Temperature variability	−0.021 ***	−0.011 ***	−0.002 *	−0.017 ***
Region/Geographic location dummy (base = MENA)				
SSA	0.068 ***	−0.004	−0.010 ***	0.011
SA	0.047 *	0.030 ***	−0.004	0.063 ***
ECA	0.301 ***	0.074 ***	0.009 ***	0.103 ***
LAC	0.146 ***	0.054 ***	0.0005	0.081 ***
EAP	0.260 ***	0.045 ***	−0.002	0.073 ***
Year	0.0002	0.0004 ***	0.0001 ***	0.0003 *
Model diagnostic				
LR χ^2 (92)	2547.31 ***			
Log likelihood	248.36			
ρ_{12}	0.329 ***			
ρ_{13}	0.223 ***			
ρ_{14}	0.345 ***			
ρ_{23}	0.098 ***			
ρ_{24}	0.356 ***			
ρ_{34}	0.243 ***			
N	4680			

Note: ***, ** and * indicate significance at 1%, 5% and 10% level respectively.

3.2.2. Role of Technology-Enhancing and Institutional Capacity Variables in TFP Change and Its Components

The positive sign on the coefficient of employment variable in the TFP, technical-, and mix-efficiency change model implies that a 1% increase in the quantity of agricultural labor increases the likelihood of an increase in TFP, technical-, and mix-efficiency efficiency change by 0.023%, 0.004%, and 0.007%, respectively (Table 4). Our results reveal that a 1% increase in the adult literacy rate increases the likelihood of a 0.003% and 0.021% increase in scale- and mix-efficiency change, while technical efficiency is likely to be reduced by 0.019% (Table 4). Contrary to the common notion of the efficiency-enhancing role of education, in many instances empirical literature was inconclusive about the relationship between the two, while some noted a negative relationship [56,57]. A commonly mentioned reason is the wider livelihood domain beyond agriculture, which is more likely to be explored by educated farmers.

To capture the impact of economic openness on TFP and its associated components, an explanatory variable, defined as the ratio of trade (sum of exports and imports of goods and services) with GDP was included. The coefficient on this variable has a positive sign in the scale efficiency change equation, but negative sign in the technical efficiency change equation (Table 4). The implication is that the likelihood of enhancing scale efficiency is significantly higher in open economies.

Agricultural spending (measured as the share of agricultural GDP) positively increases the likelihood of TFP growth, technical-, and scale-efficiency improvements. Similarly, increase in the number of agricultural researchers increases the likelihood of an increase in technical- and mix efficiency changes (Table 4).

3.2.3. Climate, Agroecology, and Weather Regimes as Drivers of TFP and Its Components

We incorporated four variables to represent climate change: two of these are to capture the long-term change in climate, i.e., a 30-year moving average of annual mean temperature (LTT) and annual total rainfall (LTP), whereas the remaining two capture annual variations in total rainfall and mean temperature.

Among these four variables used to represent climate change, except the LTP variable in the scale-efficiency equation, all coefficients have negative signs, especially where the effect is significant. The estimated marginal effects with the variable LTP imply that a 1% increase in LTP is associated with a likelihood of 0.021% reduction and 0.004% increase in the technical- and scale-efficiency change indices, respectively. We also found that a 1% increase in LTT is associated with the likelihood of a 0.056%, 0.011%, and 0.013% decrease in TFP, technical-, and mix-efficiency change indices, respectively, which is in-line with Rahman and Anik's [58] findings about agriculture in Bangladesh. Moreover, climatic vulnerability, in the form of increasing LTP and LTT, creates risk and uncertainty, which can negatively contribute to efficiency. Annual mean temperature and total rainfall variations have severe implications on agriculture, as expected. Except for rainfall variation in the technical efficiency change equation, both variables have a significant growth reducing role across equations, with relatively higher marginal effects of variation in annual total rainfall (Table 4). Increasing precipitation within the growing season may cause crop loss, particularly in tropical and sub-tropical countries that are prone to flood. Within a certain temperature range, crop growth is positively and linearly related with temperature. However, beyond the base and the upper threshold temperature, growth is affected, and the relationship is inverse for temperature between optimum and a ceiling levels [59]. Increasing temperature in the growing season has an adverse effect on yield [60].

Based on the mean elevation of the landscape, the countries were divided into three categories, and countries belonging to the medium elevation category had the highest level of TFP change, whereas the high elevation countries had the highest technical-, scale-, and mix-efficiency changes (Table 3). To further investigate the dynamics between land elevation and agriculture performance, we included land elevation and squared land elevation as explanatory variables and found a significant negative effect of both across four equations. With increasing land elevation, TFP first increases. However, as land elevation increases at an increasing rate, the TFP level then reduces. A similar pattern was observed with the scale-efficiency change model. However, the relationship was opposite for the technical- and mix-efficiency change models (Table 4).

Based on weather regime, we classified the countries into three categories, and the descriptive statistics presented in Table 3 show that the arid and semiarid region was the worst performing. The econometric analysis shows that, compared to the temperate zone, the likelihood of growth in TFP and its three efficiency components is significantly higher in the tropical and subtropical zone. The arid and semiarid region also showed significantly higher TFP and scale-efficiency changes than the temperate region, although the mix-efficiency change was relatively higher in the temperate zone than the arid and semiarid zones (Table 4).

3.2.4. TFP and Its Components across Regions

TFP and its three different components have regional patterns. Among the regional dummies, except for scale-efficiency change in SSA, all showed a positive effect, especially where the effect is significant, implying that the likelihood of increase in TFP and its efficiency components is significantly higher in these regions compared to the base region, MENA (Table 4).

3.3. Predicting Impact of Future Climate Change on TFP: Sensitivity Analysis

Table 5 presents predicted TFP based on parameter estimates of the MVTOBIT model up to 2033, under four different climatic scenarios. For all four models, the predicted TFP in 2033 is significantly higher compared to the baseline year of 2013, but the TFP increases more in the counterfactual model, where no additional climate variabilities are assumed. The bottom two rows of Table 5 show the mean-differences in TFP between the counterfactual and other three models, which shows that with any additional climatic variabilities, the TFP reduces significantly from its natural rate of change, i.e., the counterfactual model.

Table 5. Predicted changes in TFP index under different scenarios.

Year/Time-Period	TFP Change Index			
	Counterfactual Model [1]	**Model 2** [2]	**Model 3** [3]	**Model 4** [4]
Terminal year, 2013	1.038			
Projected final year, 2033	1.102	1.098	1.102	1.098
% change from 2013 to 2033	+6.20	+5.75	+6.19	+5.74
t-test statistics	5.201 ***	4.766 ***	5.192 ***	4.757 ***
Mean difference with the counterfactual model (%)	Not applicable	−0.431	−0.009	−0.440
t-test statistics	Not applicable	48.949 ***	29.052 ***	49.680 ***

Note: [1] changing at the same rate as observed from 1969 to 2013. [2] 1% additional change in annual rainfall and temperature variabilities on top of the counterfactual model. [3] 0.1% additional change in LTP and LTT annually, on top of the counterfactual model. [4] combined changes in Models 2 and 3, on top of the counterfactual model. *** indicate significance at 1% level.

4. Discussion

Although the estimated annual TFP growth rate was below a modest level (Table 2), an important and encouraging feature of this rate is that global agriculture has maintained this positive rate of growth over four and half decades, which certainly contributed towards enhancing global food security. The econometric analysis also confirmed that, over the years, TFP and its three efficiency components increased significantly (Table 4). Meanwhile, the estimated high values of technical- and scale-efficiency indices, and relatively lower values of mix-efficiency index, imply that global agriculture has performed well, in terms of operating at a technically efficient and optimal scale, but lacked the ability to derive economies of scale, by changing optimal input and output mixes (Table 2). The estimated geometric mean of TFP change index implies that during the last four and half decades, global agricultural output increased at a higher rate than the input growth, which is encouraging. However, the estimated less than unitary values for the three efficiency components imply that global agriculture is not only incapable of optimizing economies of scale and judiciously deciding on input-output mixes, it also failed to enhance technical efficiency to its maximum level; along with notable regional differences (Table 3). The existence of notable regional differences is further confirmed by the significant effects of production environment (i.e., land elevation and weather regime) and regional dummies in the econometric analysis (Table 4).

Farming is sensitive to topography, as both climatic variables (precipitation and temperature) and associated changes are related to elevation and extreme topography and can severely affect plant growth [61]. For instance, low temperature at higher elevation can progressively increase plant duration [62]. Farm management practices become complex and different at higher elevation as the topography is also complex [63]. Alternatively, at mid-elevations, precipitation and temperature are likely to be at a level that is optimal for crop growth [61], and we observed relatively higher TFP change index values for countries located at medium elevation level (Table 3). These dynamisms can probably explain the positive sign in the TFP change index, where, as elevation increases at an increasing rate, TFP reduces (Table 4).

Weather regime dummies significantly influence changes in TFP and its three efficiency components. Sachs [64] highlighted the importance of physical geography while explaining growth differences across regions. Compared to the tropics, the yield of major agricultural crops is higher in the temperate zone [65]. However, when it comes to inputs, except for labor, use of other inputs (e.g., fertilizer, machinery) is much lower in the tropics [65], as is the level of agricultural technology use [64].

Similarly, regional dummies are critical in explaining changes in TFP and its efficiency components, as is evident from Tables 3 and 4. The positive associations with regional dummies imply that the TFP in MENA has changed at a relatively lower rate than in other regions, except for technical efficiency for the SSA region. The findings in the literature about regional patterns are mixed. For instance, while Fuglie [5] noted that SSA has the lowest agricultural TFP growth, Headey et al. [20] observed that SSA has been doing remarkably better in recent years. Ludena et al. [53] noted that the TFP for MENA between 1981 and 2000 was much lower than the LAC, SSA, and SA regions.

The growth reducing role of increasing temperature (Table 4) is consistent with the literature, reporting increasing temperature as a major threat to agricultural production and yield [31,66]. Zhao et al. [67] analyzed historical trends in production and climatic variables and demonstrated the impact of increasing temperature on agricultural production. Finally, they argued for the importance of understanding temperature impacts while formulating agricultural policies. Our econometric analysis also confirmed a growth reducing role for both temperature and rainfall variabilities (Table 4), which is in line with previous literature. For instance, Lansigan et al. [68] discussed the different short- and long-term agronomic impacts of climatic variability. Such variabilities do not only have bio-physical impacts, but also contribute to associated risks and uncertainties (e.g., shifting dates of plantation and other farming activities). Pest and disease infestations vary according to seasonal variations in weather parameters [69]. Most importantly, although climatic variations are forcing changes in agricultural cycle [70] and the literature argues for proper forecasting [68] and adaptive strategies [70], farmers fail to cope properly with environmental changes [70]. The forecasted TFP under different climatic scenarios presented in Table 5 implies that, although agricultural TFP will increase in the future following past growth patterns, any additional changes in climate are likely have a significant growth-reducing role.

In such situations, agricultural spending for R&D becomes critical, as we observed in our results (Table 4). However, globally there has been a relatively low allocation to this sector, which is an unfortunate trend, given the proven positive effect of investment in R&D in enhancing food security and employment. For instance, Rahman and Salim [71] found a positive impact of R&D expenditure on technical change, technical- and scale-efficiency changes, and TFP in Bangladesh, which is also consistent with the findings of Coelli et al. [72]. Anik et al. [16] highlighted the importance of technology capital through investments in R&D, to obtain a higher level of agricultural productivity growth in South Asia.

Crop diversification significantly contributes in increasing TFP, technical-, and mix-efficiency changes (Table 4). In the literature, there is ample empirical evidence that crop diversification positively contributes to farming efficiency [73] and income [74], while reducing variability in income [75]; and that it ultimately can contribute to agricultural growth [76]. The strategy further helps in building resilience against a changing climate [77].

The importance and role of labor and its productivity in agricultural growth and development is repeatedly mentioned in many countries' policy documents (e.g., [78,79]). We also found that increasing employment in agriculture positively contributes to TFP growth, technical-, and mix-efficiency change (Table 4). However, in general, for several reasons, including the increasing use of agricultural technology and mechanization that leads to increased labor productivity, and the growth in the non-farming sector creating more lucrative job opportunities beyond the farm sector, employment in agriculture is showing a downward trend globally, which again points towards the need to enhance agricultural productivity through R&D. Furthermore, our results for the literacy variable establish the importance of human capital development, which is possible through education. However, we also saw a negative influence of literacy on technical efficiency (Table 4). In fact, the nexus between education and agricultural productivity and efficiency is ambiguous [57]. For instance, while some observed a production, profitability, and efficiency enhancing role of education (e.g., [58,80]), Hasnah et al. [81] reported a negative relationship.

5. Conclusions and Policy Implications

Globally, the agricultural sector was successful in maintaining a modest level of positive TFP growth rate, mainly through reaping the benefits of technological progress and deriving economies of scale by optimally changing input and output mixes. There were many more factors, including natural resources, that led to the concentration of production and specialization. The revealed complementary relationships amongst TFP and its three efficiency components imply that growth over time in TFP, or any of its components, is associated with growth in another component. This insightful finding is a methodological improvement, which is not found in the conventional literature exploring determinants of TFP. For instance, the land-rich and resourceful Central Asian countries specialized in grain and cotton production [82], and African countries concentrated on traditional agricultural products (e.g., cocoa, coffee, cotton, fish and fish products, fruits, legumes, and tea, etc.) [83]. However, it failed to improve regarding technical efficiency changes and the ability to operate at an optimal scale, although the actual levels of technical and scale efficiency were quite high at the beginning but became stagnant over time. A wide range of climate, production environment, and socio-economic factors exert significant and varied influences on TFP growth and its efficiency components. Climatic variables have a robust effect across models, particularly the variation in annual mean temperature and annual total rainfall. Alarmingly, future TFP projections show that any incremental variabilities in climatic variables will have a further growth-reducing effect.

Therefore, based on the observations of the varied performance of TFP and its components and findings from the econometric analysis, the following policy implications are suggested: At the strategic level, the main thrust should be geared towards technological progress and mix-efficiency improvements, while special attention needs to be paid to remove stagnancy in pure technical and scale efficiency changes at the global level. First, investment in agriculture, particularly in R&D activities needs to increase, which has been on the decline in many economies. Second, research and extension organizations have a vital role to play in promoting crop diversification, through identifying and developing appropriate crop diversification portfolios suited to each agro-ecology and its socio-economic settings. Third, the above two strategies need to be backed up with a favorable institutional and policy environment, particularly given that the existing low institutional efficiency and low adoption rate of innovative agricultural technologies remains a worldwide phenomenon [84]. Enhanced institutional efficiency will specifically contribute to a higher scale- and mix-efficiency. Fourth, due to its undisputed role, investment is needed in education, particularly in the developing economies and focusing on agriculture. Finally, there is strong evidence that increasing temperature and volatility in climatic variables are adversely affecting TFP growth. Therefore, given the regional variations in TFP performance, country and region-specific research and policies to mitigate and adapt to climate change should have topmost priority. Although various climate-smart agricultural technologies are being developed and advocated, their adoption is subjected to several socio-economic, political, and institutional constraints [85,86]. Crop insurance may be an effective instrument, and has been suggested across different agricultural settings, including pastoral regions of Kenya and other East African countries [87]. While, the Indian policy of banning conventional urea, and producing neem-coated urea only, is a successful example of enhancing both nitrogen use efficiency and farm efficiency [88], the recent Sri Lankan policy of banning fertilizers and agro-chemicals has created an economically and politically chaotic situation [89].

Governments, alone, may not be capable of bringing about the required changes in the agricultural future; rather, international donors, development partners, and private sectors need to contribute as well. Furthermore, individual farmers and/or farm managers in their respective countries also have an important role to play by implementing the economic optimization of their production process, by adopting appropriate/modern technologies and improving technical, scale, and mix-efficiencies, while acknowledging the limitations posed by climate change and the natural production environment within which they are operating.

Author Contributions: Conceptualization, S.R. and A.R.A.; methodology, S.R. and A.R.A.; software, A.R.A.; formal analysis, A.R.A.; data collection, A.R.A. and J.R.S.; data curation, A.R.A. and J.R.S.; writing—original draft preparation, A.R.A. and J.R.S.; writing—review and editing, J.R.S.; supervision, S.R.; All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

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