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Total Factor Productivity Growth in Agriculture, Adjusted for Greenhouse Gas Emissions: Trends in Developed and Developing Countries over the 1992-2016 period

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Total Factor Productivity Growth in Agriculture, Adjusted for Greenhouse Gas Emissions: Trends in Developed and Developing Countries over the 1992-2016 period

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Abstract

In the coming decades, the demand for agricultural products will become increasingly pressing, while the quantity and quality of natural resources will decline. The challenge is to implement policies that encourage environmentally sustainable agricultural productivity growth. Assessing their effectiveness will require adequate information. This study proposes to use a Malmquist productivity index to analyse the evolution of agricultural productivity in time under the condition of minimizing greenhouse gas emissions. Empirical application concerns a selection of developed and developing countries, over the period 1992-2016.

1 Introduction

The growth in the total world population of the last century has led to a substantial rise of food demand. Although a slowdown of global population growth is foreseen for the next century, significant and persistent increases are expected in Africa and South Asia, with consequent higher pressure on food demand in the next future [FAO, 2018]. Considerable improvements in agricultural productivity are thus needed to meet the increasing food demand, but such improvements cannot ignore the increasing negative impacts of agriculture on environment. In particular, agriculture, forestry and other land use (AFOLU) activities accounted for around 13% of carbon dioxide (CO2), 44% of methane (CH4), and 81% of nitrous oxide (N2O) emissions from human activities globally during 2007-2016, representing 23% of total net anthropogenic emissions of greenhouse gas (GHGs) emissions [Shukla et al., 2019].

The challenge is to put in place policies that foster environmentally sustainable agricultural productivity growth, and assessing the effectiveness of such difficult endeavor requires an adequate information base.

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Productivity is conventionally measured using index numbers. However, data on prices of all output and inputs are difficult to track and prices on pollutants like nutrients or GHGs emissions do not exist. The distance function approach can help overcome such problems as it requires data only on quantities of inputs, outputs and pollutants.

This paper proposes to use data envelopment analysis (DEA) to derive a total factor productivity index adjusted for greenhouse gas emissions (TFP_E). require data on prices of all outputs and inputs and the price information for bad outputs does not exist. The distance function approach can help overcome such problems as it requires data only on quantities of inputs, outputs and pollutants.

The basic assumption is that emissions are caused by the inputs used in the production process[1]. Thus, for a given level of production, a reduction in emissions is achieved either by improving productivity (i.e., minimizing input use) or by choosing the least polluting combination of inputs. However, only by combining both minimizations can a sustainable increase in agricultural productivity be achieved.

TFP_E is defined as a Malmquist productivity index where technical efficiencies are substituted by environmental efficiencies. Instead of minimizing inputs use, this procedure also minimizes the amount of CHGs emissions due to the inputs use. The index is inspired to the nutrient oriented TFP index developed by Hoang and Coelli [Hoang and Coelli, 2011]. In the literature, other methods have been proposed to develop environmental TFP indexes based on DEA. To give some examples, Kumar [2006], Zhang et al. [2011], Chang-Gil and Kim [2015], Oude Lansink and Dakpo [2015] develop a Malmquist-Luemberger index [Chung et al., 1997, Färe et al., 2001], where the frontier is computed by maximizing good outputs while minimizing undesirable outputs, given the inputs. Other authors develop input-oriented Malmquist indexes where negative externalities are minimized instead of inputs [Kuosmanen, 2014, Kortelainen, 2008].

The empirical application includes a selection of developed and developing countries, over the period 1992-2016. Selected countries are the top 47 agricultural producers in the world, which accounted for roughly 90% of the world agricultural output in 2016. Data come from FAOSTAT [Faostat, 2021] and USDA [USDA, 2021] databases.

The paper is structured as follows. Section 2 describes the methodology, section 3 contains the description of data used in the empirical analysis, and the results are presented in Section 4. Section 5 includes concluding remarks.

2 Methodology

In this paper, a Malmquist index is computed to monitor changes in total factor productivity once constrained to the minimization of GHGs emissions (TFP_E). The first subsection illustrates how technical, environmental, and environmental allocative efficiencies are derived at each time point for each production unit. The second subsection describes how TPF_E is derived.

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[1] This assumption is also supported by the fact that GHG emissions from agriculture are obtained precisely considering activities related to the use of land, livestock, fertilizers and energy [H.S. et al., 2006].

2.1 Efficiency measures

Let us consider a panel of country-level observations where k identifies the country and t denotes the time when the observation is made. We denote the input and output vectors for the k-th country at time t by $x_{kt} = (x_{kt1}, \ldots, x_{ktn})$ and $y_{kt} = (y_{kt1}, \ldots, y_{ktm})$, respectively. The pair (x_{kt}, y_{kt}) constitutes the production set for the k-th country at time t, provided that the output y_{kt} over the 1992-2016 period can be physically produced by making use of the bundle x_{kt}, and it is denoted by $\mathcal{P}^{kt}$. Formally:

$$\mathcal{P}^{kt} = \{(x_{kt}, y_{kt}) \in \mathbb{R}^n \times \mathbb{R}^m : \ (x_{kt}, y_{kt}) \text{ is feasible}\} \tag{1}$$

Furthermore, the production technology is assumed to be convex, with free disposal in inputs and outputs and with constant returns to scale (CRS). It is worth reminding that CRS assumption is necessary when dealing with aggregate data [Coelli and Rao, 2005] and when measuring productivity change through Malmquist indices (see, e.g. [Grifell-Tatj and Lovell, 1995]).

Using DEA, it is possible to measure the efficiency of the production plan (x_{kt}, y_{kt}) in terms of its distance from the frontier. In this study, we use input-oriented DEA to compute environmental efficiencies. Note that input and output orientations provide the same efficiency scores when, like in this paper, a constant returns-to-scale (CRS) technology is assumed.

For any production set (x_{kt}, y_{kt}) we define the input-oriented distance function

$$d_t(x_{kt}, y_{kt}) = \min\{\theta \in [0,1] : \ (\theta x_{kt}, y_{kt}) \in \mathcal{P}^{kt}\} \tag{2}$$

The input distance function represents the maximum proportional contraction of the input vector x_{kt} so the output vector y_{kt} can be obtained given the reference technology available at time t. It takes value 1 when the production process (x_{kt}, y_{kt}) is fully technically efficient, otherwise it takes values lower than 1. This distance function thus measures technical efficiency and we let $\tilde{x} = d_t(x_{kt}, y_{kt})x_{kt}$ the input bundle corresponding to full technical efficiency.

Following the approach proposed in Hoang and Coelli [2011], we introduce the definition of *environmental efficiency* (EE), with the purpose of assessing how technically efficient agricultural systems behave in terms of reduction of GHGs emissions. Let $a'x_{kt}$ the amount of GHGs emissions generated by the k-th country at time t to produce y_{kt}, where $a > 0$ is a vector representing the GHGs emissions by unit of inputs.

Borrowing from the standard method used to identify the combination of inputs which minimizes costs [Farrell, 1957], it is possible to minimize $(a'x)$, i.e. the total amount of GHGs emissions due to the inputs use and define *Environmental Efficiency* (EE) as:

$$\text{EE} = \frac{a'x^*}{a'x} \tag{3}$$

where x^* is the input combination which minimizes the GHGs emissions, whereas x is the observed mix of inputs. This measure compares the minimal feasible GHGs emissions to the emissions actually observed. EE efficiency is equal to 1 when the production process is environmentally efficient (i.e., when $x = x^*$), otherwise it takes value lower than 1. In a similar fashion we define *Technical Efficiency* (TE) as

$$\text{TE} = \frac{a'\tilde{x}}{a'x} \tag{4}$$

Finally, we define the *Environmental Allocative Efficiency* (EAE) as:

$$\text{EAE} = \frac{a'x^*}{a'\tilde{x}} \tag{5}$$

EAE compares the amount of emissions produced by the less polluting input mix x^* with the amount of emissions produced by the technically efficient plan $\tilde{x}$. EAE is equal to 1 when the process is allocative efficient (i.e., when $x^* = \tilde{x}$), otherwise it takes values lower than 1. EAE can be estimated as the ratio EE to TE.

From Equations (3), (4) and (5), it follows that:

$$\text{EE} = \text{TE} \cdot \text{EAE} \tag{6}$$

This decomposition, proposed in Hoang and Coelli [2011], replicates *mutatis mutandis*, the one proposed for cost efficiency (e.g. Maniadakis and Thanassoulis, 2000). To be environmentally efficient, a production unit must be both technically and environmentally allocative efficient (TE = EAE = 1). In other words, it must be able to choose the right mix of inputs and use them in a technical efficient manner. An environmental efficiency less than 1 may be due to an excessive use of inputs (TE < 1) and/or to a wrong input mix (EAE < 1).

2.2 Environmental productivity change and its decomposition

The total factor productivity change between two time points s and t for the k-th country is defined as:

$$\text{TFP}_{s,t} = \sqrt{\frac{\text{TE}_{t,s}}{\text{TE}_{s,s}} \cdot \frac{\text{TE}_{t,t}}{\text{TE}_{s,t}}} \tag{7}$$

This formula is in fact the geometric mean of two TFP indices: one evaluated with respect to the technology at time s, and the other with respect to the technology at time t.

Following Färe et al. [1994], the index can be rewritten as:

$$\text{TFP}_{s,t} = \frac{\text{TE}_{t,t}}{\text{TE}_{s,s}} \cdot \sqrt{\frac{\text{TE}_{s,s}}{\text{TE}_{s,t}} \frac{\text{TE}_{t,s}}{\text{TE}_{t,t}}} \equiv \text{EFF}_{s,t} \cdot \text{TECH}_{s,t} \tag{8}$$

The first factor, called *efficiency change* (EFF), shows the change in the relative position of an observation with respect to the frontier. In other words, it accounts for the production unit capacity of catching up the best performers (leaders). The second factor, called *technical change* (TECH), represents the shift of the frontier due to a technological progress (inward shift) or regress (backward shift). An increase in productivity yields a value of TFP greater than 1.

TFP_E is defined as a Malmquist index, where technical efficiencies are replaced by environmental efficiencies. Specifically, it is defined as:

$$\text{TFP\_E}_{s,t} = \sqrt{\frac{\text{EE}_{t,s}}{\text{EE}_{s,s}} \cdot \frac{\text{EE}_{t,t}}{\text{EE}_{s,t}}} \tag{9}$$

In line with the decomposition of EE proposed in Equation (6) and following Hoang and Coelli [2011], we can express TFP_E as the product of TFP and *Environmental Allocative*

Efficiency Change (EAEC):

$$\begin{aligned} \text{TFP\_E}_{s,t} &= \text{TFP}_{s,t} \cdot \text{EAEC}_{s,t} = \\ &= \text{TECH}_{s,t} \cdot \text{EFF}_{s,t} \cdot \text{EAEC}_{s,t} \end{aligned} \tag{10}$$

The decomposition in (10) allows one to identify the causes of a change in the environmental total factor productivity change. Change may be explained in terms of technological change (progress or regress of the frontier), catching up and choosing the less pollutant inputs mix. The EAEC can be interpreted as a sort of environmental adjustment coefficient for TFP, allowing to convert a measure of technical productivity change to a measure of environmental productivity change.

3 Description of data and some preliminary descriptive statistics

The present study analyses the evolution of TFP and TFP_E for 47 agricultural systems over the period 1992-2016. These countries are the top 47 agricultural producers in the world, which accounted for roughly 90% of the world agricultural output in 2016.

Output and inputs data were downloaded from the USDA database on agricultural total factor productivity growth [USDA, 2021] with the only exception of data on land (1000 ha) that was taken from the Faostat database [Faostat, 2021], along with data on GHGs emissions. For what concerns output, we considered gross agricultural productions expressed in thousand constant 2004-2006 international dollars ($1000). Input data include proxies of the main productive factors used in agriculture, namely farm labour, agricultural land, livestock, farm machinery and fertilizers. The choice of these inputs is in line with other studies dealing with national agricultural systems productivity (eg. Coelli and Rao, 2005, Hoang and Coelli, 2011). In particular we drew land data from the Faostat database In particular, from USDA database we drew: the total number of animals, equating the cattle equivalents (1000 heads); the total number of economically active persons engaged or seeking work in Agriculture, hunting, fishing or forestry (1000 persons); the total stock of farm machinery expressed in “40-CV tractor equivalents”; metric tonnes of N, P2O5, and K2O nutrients for fertilizer consumption; the ‘Utilized agricultural area’.

Faostat publishes estimates of GHGs emissions (in kilotonnes of CO2 equivalents) by type of agricultural activity that generates them. In particular, the following domains are distinguished [Faostat, 2021]:

- Crop residues: nitrous oxide (N2O) emissions from the decomposition of nitrogen in crop residues left on managed soils.
- Emissions from rice cultivation: methane gas production from the anaerobic decomposition of organic matter in paddy fields.
- Burning crop residues: methane (CH4) and nitrous oxide (N2O) gases produced by the combustion of crop residues burnt on-site
- Organic soils: nitrous oxide (N2O) and carbon dioxide (CO2) emissions associated with the drainage of organic soils.

- Fires: methane (CH4), nitrous oxide (N2O) and carbon dioxide (CO2) from biomass burning in a range of vegetation types (forest, savanna, tropical forests) and from fires in organic soils.
- Emissions from net forest conversion
- Enteric Fermentation: methane gas produced in digestive systems of ruminants and to a lesser extent of non-ruminants.
- Manure applied to soils or left on pasture: direct and indirect nitrous oxide (N2O) emissions from nitrogen (N) of manure added to agricultural soils or left by grazing livestock on pasture
- Manure management: methane (CH4) and nitrous oxide (N2O) emissions from aerobic and anaerobic processes of manure decomposition.
- Synthetic Fertilizers: nitrous oxide gas from synthetic nitrogen additions to managed soils.
- Energy: carbon dioxide, methane and nitrous oxide gases associated with fuel burning and generation of electricity used in agriculture

We assume that the first six domains account for GHGs emissions related to land use. Consequently we calculate the overall amount of emissions attributable to land input as the sum of emissions produced in the six domains (variable $GHGs.land$). Furthermore, we define the variable $GHGs.livestock$ as the sum of the following three domains, as these directly or indirectly account for livestock-related emissions. Finally, variable $GHGs.fertilizers$ corresponds to GHGs emissions contained in the Synthetic fertilizers domain, while $GHGs.machinery$ is equal to GHGs emissions of the Energy domain.

Coefficients a (see Section 2.1) are computed as the ratio of GHGs emissions attributed to each input and the total quantity of input used in production.

Table 1 shows annual average values of output, inputs, and total GHGs by country. Table 2 compares average annual productivities across countries where productivities are computed as production by input unit. Figure 1 shows average emissions by output in the observed countries over the 1992-2016 period. We see that values are sensibly different across countries, ranging from 1.47 of Italy to 27.03 of Tanzania tonnes per thousand constant 2004-2006 international dollars.

Finally, Figure 2 focuses on the a coefficients. The figure compares each country's position relative to the others in terms of the pollutant intensity of their inputs. Country inputs have lower pollutant intensity in terms of emissions when the country is represented by a small (coefficient associated with fertilizers) and light (coefficient associated with machinery use) bubble placed close to the lower left corner (coefficients associated with land and animals).

4 Results

In the countries taken as a whole, during the period 1992-2016, environmental efficiency recorded an average score equal to 0.362 (geometric mean)[2] (see Table 3). These values

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[2] Or an arithmetic mean of 0.42.

indicate that the same level of output could have been produced with 63.8 % lower emissions of GHGs. In particular, reductions up to 55.7% could have been obtained by using a less pollutant mix of inputs.

Figure 3 displays the evolution of efficiencies. We observe that technical efficiencies are stable over the period with a slight decrease during the last four years. Conversely, environmental efficiencies increase all over the period with the only exception of the last year. The trend of environmental efficiencies is driven by that of environmental allocative efficiencies.

Countries efficiencies do not seem to converge towards the frontier (see Figure 4). Indeed, although the mean of the environmental efficiencies increase over time, so does the standard deviation. Technical efficiencies trend is stable both in terms of mean and standard deviation.

Results show considerable differences among the efficiencies levels of countries, as shown in Figure 5, where the deviations from the mean are shown. The most virtuous countries are in the top right panel, the least virtuous in the bottom left panel.

Finally, Figure 6 shows the cumulative growth of TFP_E and its components 10 during the observed period. Results show that the increase of TFP_E is driven by technological progress (TECH), followed by improvement in the choice of less pollutant inputs (EAEC). In contrast, agricultural systems show (on average) difficulties in catching up the leaders, as shown by the trend of the EFF variable whose value remained unchanged over the period.

5 Conclusions

The transition towards sustainable agri-food systems is compelling and adequate information is required to assess the effectiveness of policies aimed at supporting sustainable agricultural productivity growth. In this paper we propose to apply the methodology developed in Hoang and Coelli [2011] to compute an index that can monitor changes in the efficiency of top agricultural producers with respect to the use of inputs and thereby generation of GHGs emission. Indeed, the frontier is represented by those production processes that for a given level of output minimize inputs use and GHGs emissions. The use of the DEA has the strong advantage of not requiring knowledge of the output, inputs and emissions prices, which are seldom available. The method used in this paper could be extended by considering sequential frontiers beside contemporaneous frontiers, to avoid implausible levels of technical regress and to obtain more stable production frontiers [Thirtle et al., 2003, Nin et al., 2003, Alene, 2010, Chaudhary, 2016] . The empirical application concerns the agricultural production of 47 countries from 1992 to 2016. Globally, environmental total factor productivity increased by approximately 70% in the period considered driven mainly by technological progress (37%), and improvement in environmental allocative efficiency (28%). Conversely, on average, countries' agricultural systems failed to catch up with the best performers, recording an increase of only 1.2% from 1992 to 2016.

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Table 1: Production, inputs and emissions average levels by country, over the 1992-2016 period - geometric mean.

COUNTRY	OUTPUT	LABOUR	LAND	FERTILIZERS	LIVESTOCK	MACHINERY	GHGs.livestock	GHGs.fertilizers	GHGs.machinery	GHGs.land
Algeria	5682073	1274	40515	99365	5477	108971	8811	222	234	722
Argentina	35383551	1190	126379	956458	49589	276098	114007	3002	14145	124618
Australia	24428602	371	417358	2100916	33799	345593	104063	5110	6642	109469
Bangladesh	16502887	26840	9301	1517756	26595	116539	38447	5665	2322	59141
Belarus	6644722	479	9024	998779	5215	74869	13661	1957	2436	30569
Brazil	107584865	13381	230450	8111790	182893	873078	411039	11933	20393	1320255
Canada	25994773	363	60174	2842284	14878	804865	35907	10066	14657	177562
Chile	6991486	804	15561	447120	5165	55031	10196	1414	711	1746
China	423840983	311975	525664	39318663	276820	6125161	359510	142380	100524	184215
Colombia	12459157	3605	43632	671165	26074	23411	56800	2163	3135	91264
Côte d'Ivoire	5548949	2867	20167	79585	1876	8119	2803	167	344	39350
Denmark	6848574	88	2671	333446	4193	121585	9125	1240	2270	2075
Egypt	18694955	6249	3440	1281694	11536	98452	17097	5948	4092	6103
France	42326524	959	29470	3797144	23357	1230190	63588	12404	12591	10322
Germany	35165329	833	16985	2557627	18896	995054	51575	9605	8876	16373
Ghana	5104032	4260	13449	28308	2246	2312	3758	69	438	21363
Greece	8413341	644	7967	382804	2531	262691	6655	1276	1790	2336
India	191898678	224225	180322	19436077	290633	3702418	458706	70099	35507	172307
Indonesia	47515874	40204	49975	3554628	28746	56607	39831	12543	5404	962167
Iran	21656620	4080	55008	1239955	21244	290132	30031	4484	13303	5149
Italy	32152971	1029	14653	1331728	10091	1325959	27619	4065	9018	5466
Japan	18799823	2989	4894	1287031	8673	2558070	11852	2645	25032	18243
Kazakhstan	7530500	2350	215472	73205	8828	75883	17313	223	3085	6844
Kenya	5713933	6472	27103	158615	17381	14313	30513	399	345	5469
Korea, Republic	9915218	1950	1892	666316	5206	471686	6913	1846	9251	9273
Malaysia	11586492	1582	7278	1494922	2974	53278	3175	2567	1375	79695
Mexico	32092273	7135	104249	1732092	47016	280442	81155	6367	9907	23489
Morocco	6838715	3914	30428	380429	7568	49029	10764	1113	1706	812
Myanmar	13431818	13192	11425	115191	15404	40311	31870	519	473	178031
Netherlands	12958290	245	1921	364228	7280	151198	17839	1572	9496	3195
New Zealand	9457926	156	12790	784266	12640	81587	42249	1291	1624	2125
Nigeria	30541492	17886	66809	272959	24725	19444	42519	834	1542	64300
Pakistan	32379454	19820	36165	3232569	63497	405133	104680	13843	1748	19511
Peru	6513476	4052	23224	273078	9914	13511	20261	1034	900	87515
Philippines	18258107	11483	11621	704947	9345	575168	15334	2695	895	57189
Poland	20666795	2589	16476	1698313	10410	1546536	22747	5275	17207	18201
Romania	9845958	3277	14303	438746	6506	189418	14354	1540	1055	2774
Russian Federation	49840205	7063	216464	1994110	36207	640917	91930	6124	24944	146596
South Africa	11179227	958	97202	753546	16449	90351	26570	2240	4398	12805
Spain	31225959	958	28633	1859434	13828	754613	32409	5446	6936	3560
Tanzania	6116263	13488	35548	46607	17611	17479	30355	189	137	133854
Turkey	33347218	6386	39651	1978823	17330	965284	28769	7342	20602	3178
Ukraine	23826218	4206	41500	916158	12229	418001	29535	3324	7293	19408
United Kingdom	18433439	407	17322	1737808	15486	450258	43770	6234	2299	8468
United States	220193763	2426	412323	19844296	113502	4473457	269026	62275	55774	208150
Uzbekistan	9151260	3669	26564	677838	7781	178475	17393	2917	2895	1333
Viet Nam	21843892	24751	9331	1936665	13592	134493	21053	6018	1438	46960

Table 2: Productivity by type of input. Average values over the 1992-2016 period-geometric mean.

COUNTRY	labour	land	livestock	fertilizers	machinery
Algeria	4461.12	140.25	1037.42	57.18	52.14
Argentina	29741.92	279.98	713.54	36.99	128.16
Australia	65806.30	58.53	722.75	11.63	70.69
Bangladesh	614.85	1774.23	620.54	10.87	141.61
Belarus	13861.67	736.37	1274.23	6.65	88.75
Brazil	8040.03	466.85	588.24	13.26	123.22
Canada	71587.67	431.99	1747.21	9.15	32.30
Chile	8699.73	449.31	1353.73	15.64	127.05
China	1358.57	806.30	1531.11	10.78	69.20
Colombia	3456.25	285.55	477.85	18.56	532.20
Côte d'Ivoire	1935.27	275.15	2957.44	69.72	683.45
Denmark	77854.68	2563.89	1633.49	20.54	56.33
Egypt	2991.84	5435.33	1620.54	14.59	189.89
France	44151.66	1436.26	1812.18	11.15	34.41
Germany	42216.65	2070.37	1860.96	13.75	35.34
Ghana	1198.03	379.51	2272.46	180.30	2207.18
Greece	13062.45	1056.01	3324.32	21.98	32.03
India	855.83	1064.20	660.28	9.87	51.83
Indonesia	1181.88	950.80	1652.98	13.37	839.40
Iran	5307.35	393.70	1019.41	17.47	74.64
Italy	31252.01	2194.26	3186.20	24.14	24.25
Japan	6289.99	3841.35	2167.61	14.61	7.35
Kazakhstan	3204.25	34.95	852.98	102.87	99.24
Kenya	882.92	210.83	328.75	36.02	399.21
Korea, Republic	5085.12	5239.77	1904.63	14.88	21.02
Malaysia	7323.11	1591.98	3895.62	7.75	217.47
Mexico	4497.64	307.84	682.58	18.53	114.43
Morocco	1747.04	224.75	903.60	17.98	139.48
Myanmar	1018.19	1175.60	871.96	116.60	333.21
Netherlands	52960.67	6745.61	1779.97	35.58	85.70
New Zealand	60457.88	739.49	748.24	12.06	115.92
Nigeria	1707.54	457.15	1235.25	111.89	1570.71
Pakistan	1633.71	895.33	509.93	10.02	79.92
Peru	1607.56	280.46	656.99	23.85	482.10
Philippines	1590.03	1571.18	1953.87	25.90	31.74
Poland	7982.28	1254.36	1985.25	12.17	13.36
Romania	3004.68	688.40	1513.34	22.44	51.98
Russian Federation	7056.96	230.25	1376.52	24.99	77.76
South Africa	11670.02	115.01	679.61	14.84	123.73
Spain	32596.13	1090.54	2258.15	16.79	41.38
Tanzania	453.45	172.05	347.29	131.23	349.93
Turkey	5221.56	841.02	1924.20	16.85	34.55
Ukraine	5665.13	574.13	1948.34	26.01	57.00
United Kingdom	45252.17	1064.19	1190.30	10.61	40.94
United States	90766.87	534.03	1940.00	11.10	49.22
Uzbekistan	2494.18	344.49	1176.04	13.50	51.27
Viet Nam	882.54	2340.93	1607.17	11.28	162.42

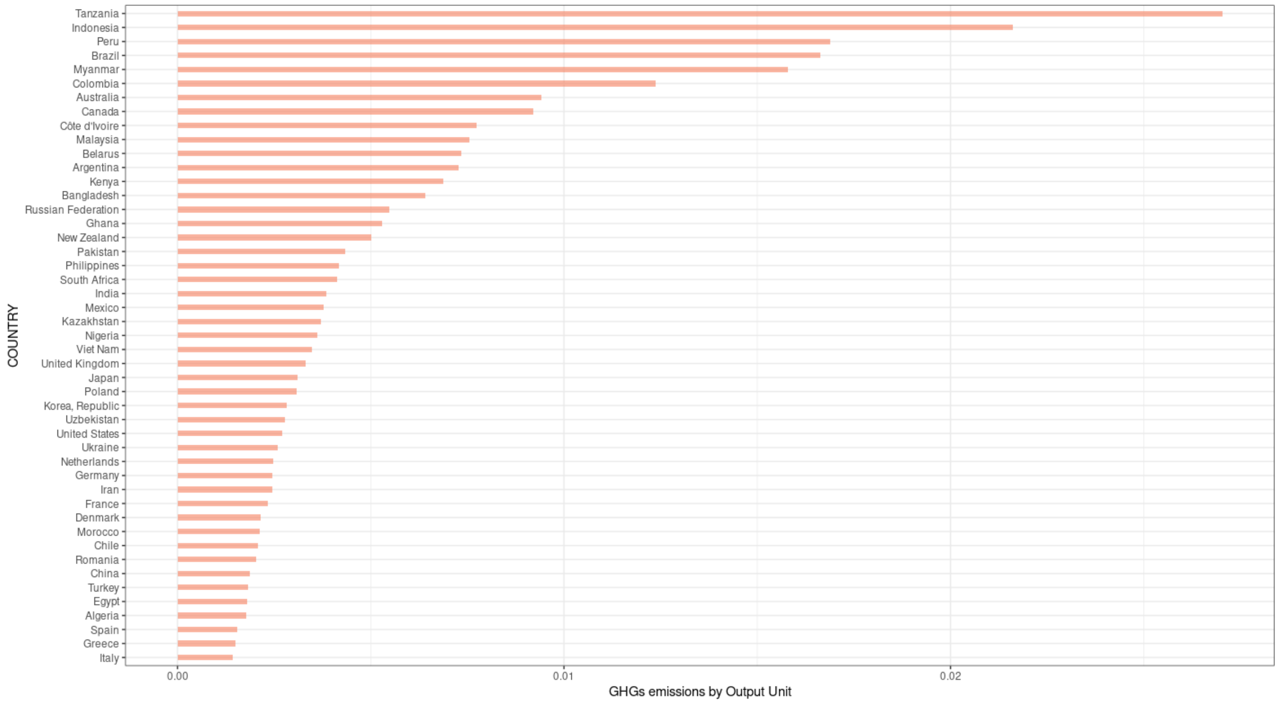


Figure 1: GHGs emissions by unit of production value averaged over the period 1992-2016 (kilotonnes of CO2 eq. per 1000 international dollars of production).

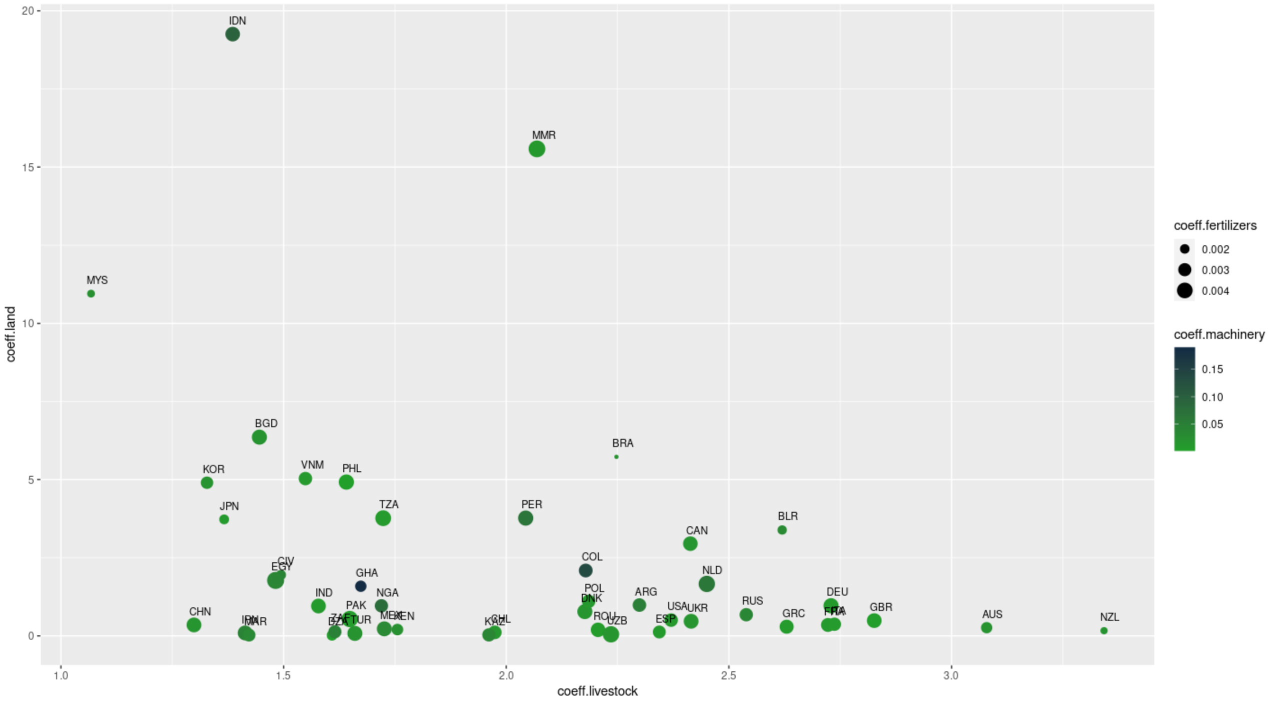
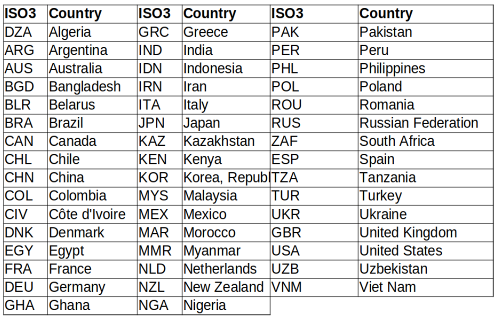


Figure 2: GHGs emissions by input unit, avarage values over the period 1992-2016



ISO3	Country	ISO3	Country	ISO3	Country
DZA	Algeria	GRC	Greece	PAK	Pakistan
ARG	Argentina	IND	India	PER	Peru
AUS	Australia	IDN	Indonesia	PHL	Philippines
BGD	Bangladesh	IRN	Iran	POL	Poland
BLR	Belarus	ITA	Italy	ROU	Romania
BRA	Brazil	JPN	Japan	RUS	Russian Federation
CAN	Canada	KAZ	Kazakhstan	ZAF	South Africa
CHL	Chile	KEN	Kenya	ESP	Spain
CHN	China	KOR	Korea, Republ	TZA	Tanzania
COL	Colombia	MYS	Malaysia	TUR	Turkey
CIV	Côte d'Ivoire	MEX	Mexico	UKR	Ukraine
DNK	Denmark	MAR	Morocco	GBR	United Kingdom
EGY	Egypt	MMR	Myanmar	USA	United States
FRA	France	NLD	Netherlands	UZB	Uzbekistan
DEU	Germany	NZL	New Zealand	VNM	Viet Nam
GHA	Ghana	NGA	Nigeria		

Table 3: Summary statistics of environmental, technical and environmental allocative efficiencies (EE,TE, EAE) in top agricultural producers of the world, over the 1992-2016 period

Efficiency	Geometric mean	Arithmetic mean	Standard deviation
EE	0.362	0.42	0.22
TE	0.816	0.84	0.18
EAE	0.443	0.50	0.21

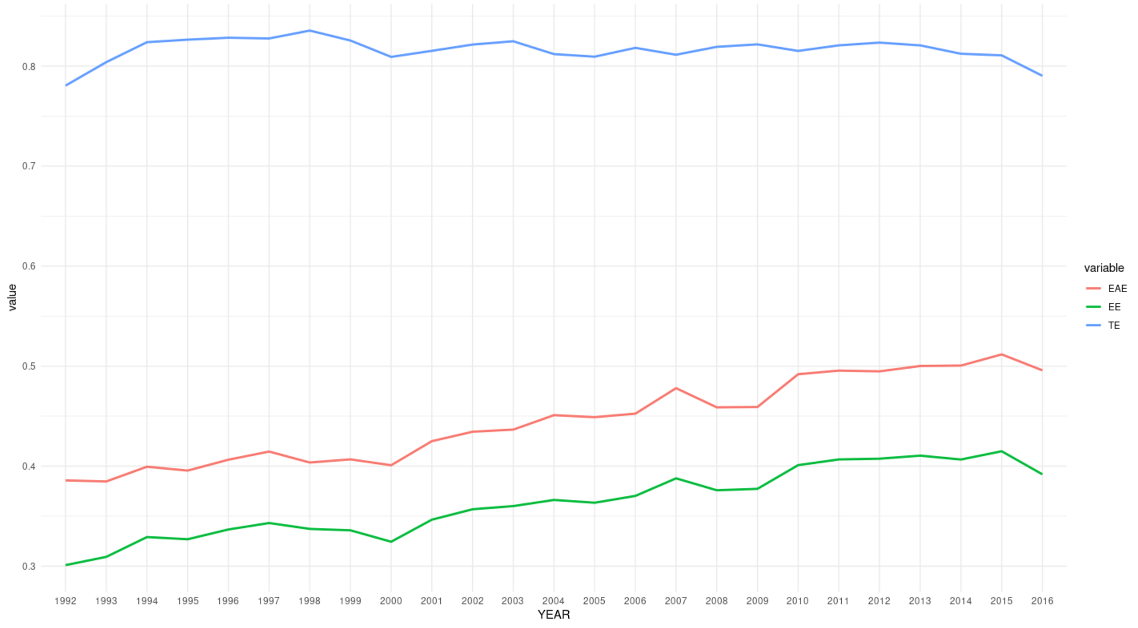


Figure 3: Evolution of environmental, technical, and environmental allocative efficiencies (EE, TE, EAE) in the observed countries, over the period 1992-2016.

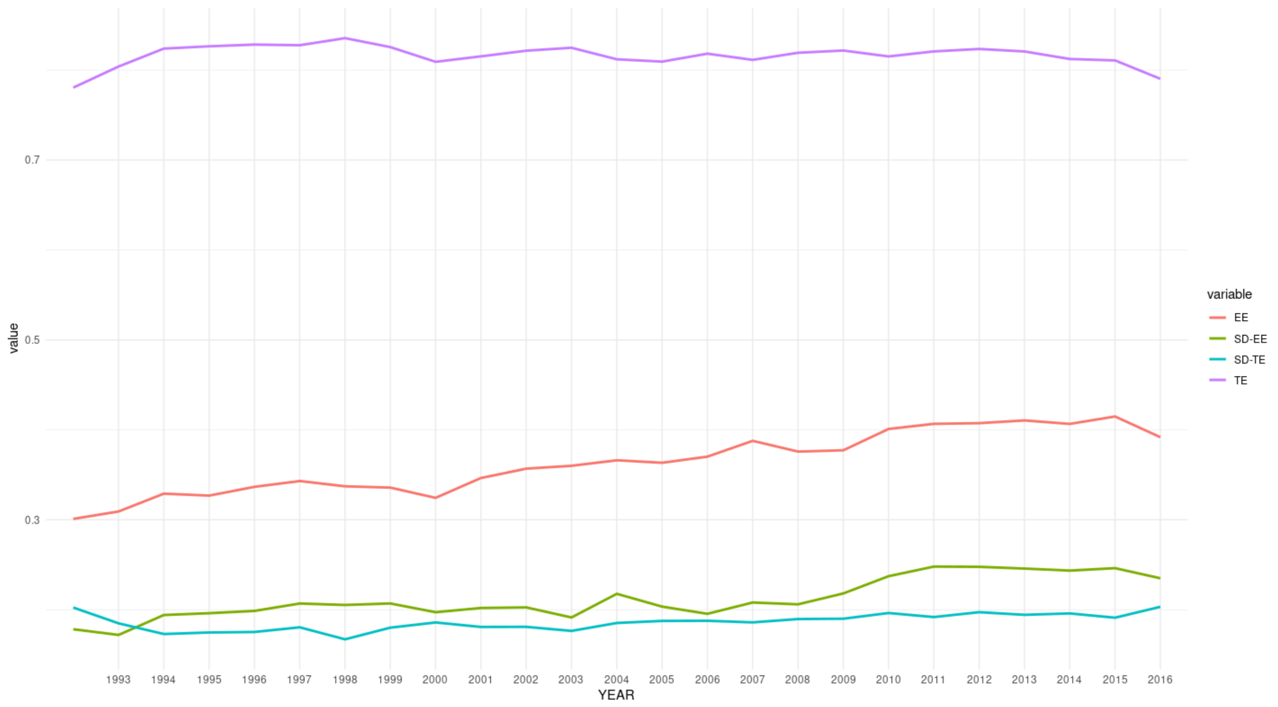


Figure 4: Evolution of mean and standard deviation of technical efficiencies (TE) and environmental efficiencies (EE) over the 1992-2016 period. In case of convergence, the annual means should approach 1 over time, while their standard deviation should decline [Shestalova, 2003]

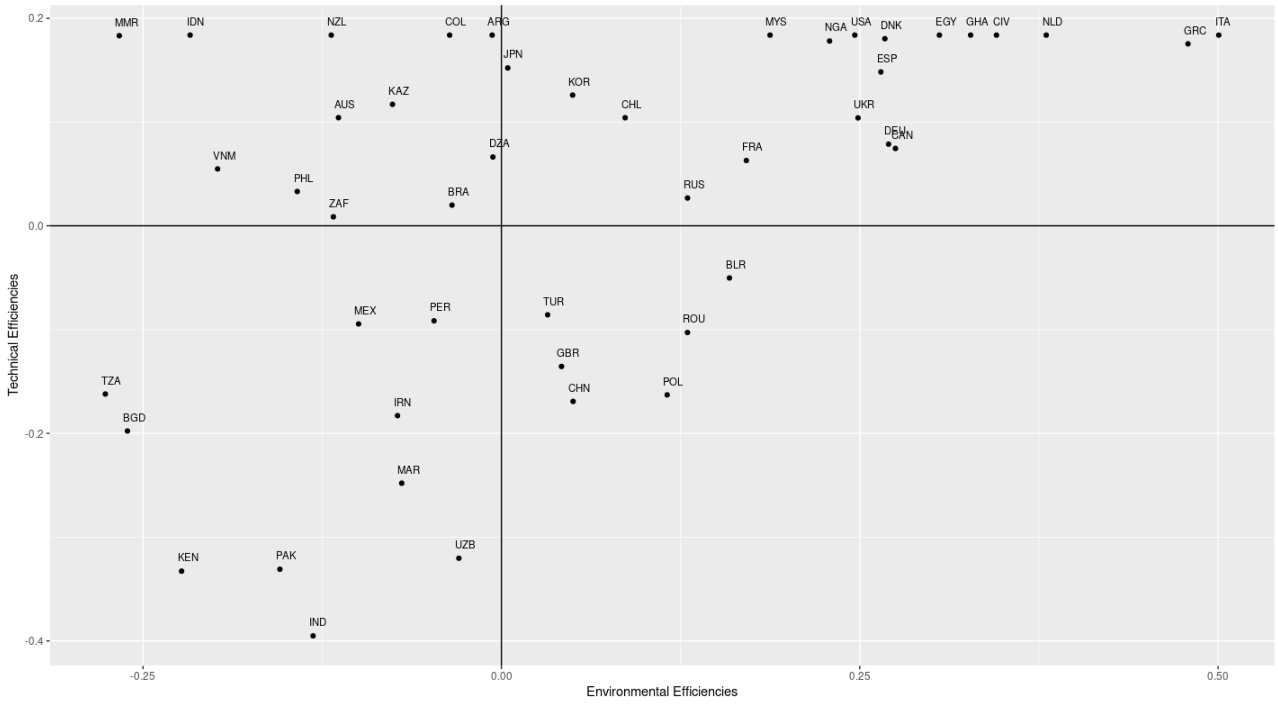


Figure 5: Technical and Environmental efficiencies by country. Deviations from the mean. Average value over the 1992-2016 period

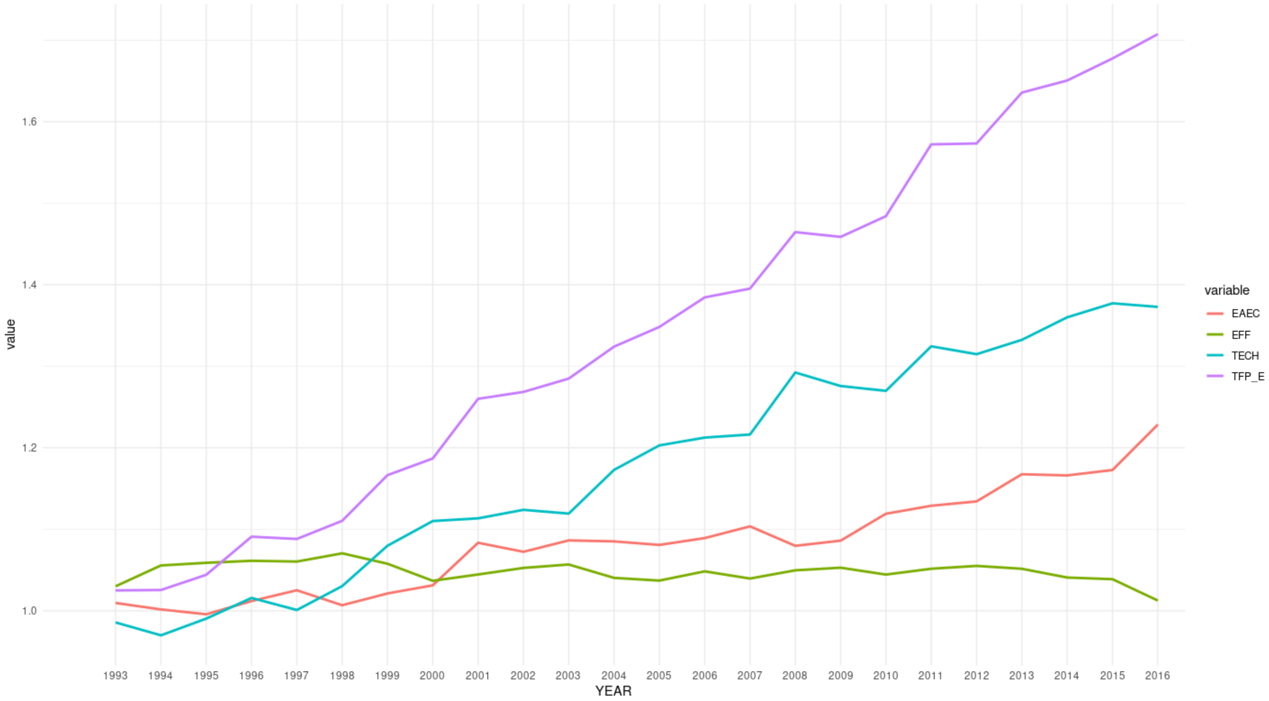


Figure 6: Evolution of environmental total factor productivity change (TFP_E) and its components: technical change (TECH), efficiency change (EFF), environmental allocation efficiency change (EAEC). Top 47 agricultural producers, 1992-2016. Fixed base indices, 1992 = 1