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Agricultural productivity in the presence of undesirable output: The case of African agriculture

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Abstract

The motivation for this study stems from two major concerns that are interlinked. First, the on-going food security crisis of African countries. Second, the negative impact greenhouse gas (GHGs) emissions from agriculture have on future food production which worsens the food insecurity problem. The conundrum SSA faces is the need to increase food output through productivity growth while minimizing GHG emissions. To measure changes in productivity growth and GHG emissions, this study evaluates agricultural performance of 18 African countries by utilizing the Malmquist-Luenberger index to incorporate good and bad outputs for the years 1980 to 2012. The empirical evidence demonstrates that productivity is overestimated when not considering bad outputs in the production model. The analysis will also provide a better understanding of the effectiveness of previous mitigation methods which would then allow for appropriate course of action to achieve the twin objectives of increasing agriculture productivity while reducing GHG emissions.

Key words: Malmquist-Luenberger index; efficiency change; technical change; scale efficiency; good output; bad output; methane; carbon dioxide; nitrous oxide; mitigation; adaptation

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1. Introduction

On 23rd August 2013, the delegates meeting on African Food security and Adaptation unanimously declared to end Africa's food hunger crisis by the year 2025 through an Ecosystems Based Approach (EBA). This approach is based on developing sustainable food production systems that would also enable farmers to adapt to climate change (UNEP, 2013). The declaration emerged because of the growing food crises in many African countries and due to the deteriorating natural environment which has a major impact on agricultural production.

Food insecurity is an ongoing problem for many African countries attributed to frequent droughts and low food output that does not correspond with the heightened food demands. In recent years, food insecurity has reached critical levels as reported in the food insecurity and global hunger index (GHI) reports (FAO, IFAD, and WFP., 2014, Singh et al. 2016, Harrigan, 2014). The hunger levels worldwide remain high with close to one billion people being food insecure and malnourished (Misselhorn et al. 2012). Some fifty two countries are identified to have a serious or 'alarming' GHI values in the 2015 GHI report, majority being located in Africa and South Asia thus making food security a major concern for policy makers (Von Grebmer et al. 2015).Thus, in order to avert the food insecurity crises and also meet the global demand for food, efforts that will double food output by 2050 such as through improved productivity become necessary (Pratt and Yu, 2008). Increased agricultural productivity efforts such as intensification also has the benefit of reducing pressure on marginal lands (Baiphethi and Jacobs, 2009).

However, intense cultivation can lead to unintended costs for example due to loss of biodiversity, emission of greenhouse gases (GHG) and loss of soil nutrients. It is well-documented that agricultural activities such as land cultivation or deforestation discharges substantial amounts of GHGs such as methane (CH_4), carbon dioxide (CO_2) and nitrous oxide

(N_2O) to the atmosphere (Sonnemann et al. 2012, Benioff et al. 2013, Jia et al. 2012, Cole et al. 1997, IPCC 2001, Paustian et al. 2004, Ciais et al. 2013). Sejian and Naqvi (2012) noted that agriculture contributed 25.5% of global GHG emissions, of which 60% are from anthropogenic sources and 18% from animal husbandry. Tubiello et al. (2014) observed that Africa is the third largest GHG emitter in agriculture and accounts for 15% of global agriculture GHG. AGRA (2014) projected that African agriculture GHG emissions will increase by 30% between 2010 and 2030. Agriculture GHG emissions emanate mainly from ruminant enteric fermentation, poor manure management, poor management of agricultural soils and through rice farming which leads to nitrogen loss, energy loss and loss of organic matter thus undermining efficiency and productivity (Gerber et al. 2013). Clay (2011), Thornton (2012) and Vermeulen et al. (2012) raised concerns that the focus on raising farm output has increased the carbon footprint of agriculture and led to increasing frequency and severe weather events which affects farm output. The impact on food security from extreme weather events would thus require farmers to switch to farming practices that are adaptive and mitigate climate change such as drought resistant crops.

The extant literature on agriculture productivity is vast with the bulk focusing on good outputs only. Standard measures of productivity ignore bad outputs although the production process described earlier yields both good outputs such as food, fibre and other raw materials and bad outputs or by-products such as GHGs, toxic wastes and soil erosion. To achieve sustainable long-term growth in agriculture, the production model must incorporate good output and bad output simultaneously in the estimation.

To measure productivity change the study utilises the Malmquist-Luenberger index (henceforth MLI), developed by Chung, Färe, and Grosskopf (1997). The MLI estimates the directional distance function hence allowing bad outputs to be incorporated in the production function. In the literature several studies employ the MLI to assess productivity at firm level or across countries. Such studies[1] include Jeon and Sickles (2004); Yörük and Zaim (2005); Oh (2010) and Oh and Heshmati (2010) on OECD countries; Kumar (2006) and Kumar and Managi (2010) on developed and developing countries; Pathomsiri et al. (2008) and Yu et al. (2008) on the airport sector; Lee et al. (2015) on airlines; Färe et al. (2001) and Weber and Domazlicky (2001) on manufacturing; Zhang et al. (2011) on China's provinces; He et al. (2013) on iron and steel industry; Färe et al. (2007) and Wang et al. (2013) on energy. For agriculture, only a handful of studies exist in the last fifteen years. These studies include Ball et al. (2001); Kuosmanen (2005); Färe et al. (2006); and Piot-Lepetit and Le Moing (2007). To the best of our insight, no studies exist for African agriculture that incorporate both good and bad outputs. In the absence of empirical evidence, it makes it difficult for policy-makers to ascertain how the degrading ecosystems due to bad outputs from agriculture is likely to impact negatively on future food production. It also makes it difficult to put in place feasible approaches that would help mitigate and help farmers adopt better farming practices. The current study thus aims to measure African agriculture TFP while incorporating bad outputs using the ML index. The study uses carbon dioxide, nitrogen oxide, and methane to represent bad outputs and crop and livestock output to represent good outputs.

This study becomes important in the wake of the 2015 Paris climate change talks that emphasized on the world shifting towards a low carbon pattern in the energy, transport, agriculture and forestry systems. Incorporating emissions in the measurement of agricultural performance of African agriculture will thus provide the real productivity change because it considers how farmers allocate the scarce resources to produce more food while minimising the bad outputs. Progress is being made by many countries to cut down on emissions. For example, countries such as the US are making efforts to promote "climate smart agriculture" while Australia farmers are practising the Carbon Farming Initiative (CFI) that reduces

[1] For brevity purpose, we list several studies here mainly to illustrate the adaptability of the ML index.

emissions and or captures and holds carbon in the soils or vegetation. In African countries, such as Malawi and Zambia are promoting "climate smart agriculture" through agroforestry and conservation agriculture to promote small holder productivity agricultural systems (Kaczan et al. 2013).

Thus, incorporating bad outputs would provide policy makers in Africa with useful information in determining appropriate mitigation and adaptation approaches in changing conditions of farming practices and ecosystems. Incorporating bad outputs will help answer the questions whether there are differences in productivity when accounting for bad outputs in African agriculture and whether some countries are more productive when emissions are accounted for.

The paper is divided into the following sections: Section 2 outlines the Malmquist luenberger productivity index. Section 3 and 4 provides the data sources and the results of the analysis respectively. The conclusion and policy recommendations are provided in section 5.

2. Empirical model: Malmquist Luenberger productivity index

Estimating TFP change of African agriculture is based on the framework developed by Chung, et al. (1997). The approach adopts the directional distance function to represent the production technology which models the reduction of bad outputs while expanding on production of good outputs. The other advantages of utilizing the directional distance function framework over other frameworks include the fact that the framework does not require the designation of a specific function form neither information on the shadow prices. The input-output distance function in respect to period t and t+1 is specified as follows:

$$\vec{D}_0^{t+1}(x^t, y^t, b^t : g) = \sup\{\beta : (y^t, b^t) + \beta g \in P(x^t)\} \tag{1}$$

where $\vec{D}$ represents the directional output distance function which represents the production technology while "g" denotes the vector of directions for scaling the outputs, and g = (y, -b).

In this case, y denotes good outputs while b denotes bad outputs thus g = (1, -1) which implies the good outs expand while bad outputs are reduced. β denotes the rate at which the good outputs and bad outputs can expand or contract respectively. For more details see (Chung, et al., 1997; Färe, Grosskopf, & Pasurka Jr, 2001; Färe, et al., 2007; Kumar, 2006).

The Malmquist-Luenberger index for period t and t+1 given the number of DMUs, is as follows:

$$ML_t^t = \frac{[1+\overrightarrow{D_0}^{t}(x^{t}, y^{t}, b^{t}; y^{t}, -b^{t})]}{[1+\overrightarrow{D_0}^{t}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})]} \tag{2}$$

$$ML_t^{t+1} = \frac{[1+\overrightarrow{D_0}^{t+1}(x^{t}, y^{t}, b^{t}; y^{t}, -b^{t})]}{[1+\overrightarrow{D_0}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1} - b^{t+1})]} \tag{3}$$

The geometric mean of equations 2 and 3 yields the Malmquist Luenberger productivity index as follows:

$$ML_t^{t+1} = [\frac{(1+\overrightarrow{D_0}^{t}(x^{t}, y^{t}, b^{t}; y^{t}, -b^{t})) \qquad (1+\overrightarrow{D_0}^{t}(x^{t}, y^{t}, b^{t}; y^{t} - b^{t}))}{(1+\overrightarrow{D_0}^{t}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}))(1+\overrightarrow{D_0}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1} - b^{t+1}))}]^{1/2} \tag{4}$$

The ML index for each period is thus decomposed into efficiency and technical change components as follows;

$$MLEFFCH_t^{t+1} = [\frac{(1+\overrightarrow{D_0}^{t}(x^{t}, y^{t}, b^{t}; y^{t}, -b^{t}))}{(1+\overrightarrow{D_0}^{t}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}))}]^{1/2} \tag{5}$$

$$MLTECH_t^{t+1} = [\frac{(1+\overrightarrow{D_0}^{t+1}(x^{t}, y^{t}, b^{t}; y^{t}, -b^{t}))\ (1+\overrightarrow{D_0}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}))}{(1+\overrightarrow{D_0}^{t}(x^{t}, y^{t}, b^{t}; y^{t}, -b^{t}))\ (1+\overrightarrow{D_0}^{t}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}))}]^{1/2} \tag{6}$$

The efficiency change represents the output changes between the periods while technical change represents the shift in the technology frontier.

If $x^t = x^{t+1}, y^t = y^{t+1},$ and $b^t = b^{t+1}$ it implies that there are no feasible changes in input or output quantities between periods, suggesting that the ML_t^{t+1} TFP index is equal to

1 (Färe, Grosskopf, & Pasurka Jr, 2001). When TFP improves, the ML_t^{t+1} TFP index becomes greater than one and vice versa when a decline occurs. A $MLTECH_t^{t+1}$ score of greater than one suggests a positive change of the production frontier in favour of good output while decreasing the bad output and vice versa. A $MLEFFCH_t^{t+1}$ score that is greater than one suggests that the firm's performance is located nearer to the frontier in period t+1 while a score less than one suggests that the performance of the firm is located further from the frontier.

The Malmquist Luenberger index is computed by solving the four distance functions specified in the linear programme. Subject to the time periods (denoted as t….T) and number of countries (denoted as k = 1……...K), the input-output model is specified as follows:

$$P(x) = (y, b): \sum_{k=1}^{K} z_k y_{km}^t \geq y_{km}^t \qquad m = 1, \dots \dots \dots, M \qquad (7)$$

$$\sum_{k=1}^{K} z_k^t b_{kj}^t = b_j^t \qquad j = 1, \dots \dots \dots, J$$

$$\sum_{k=1}^{K} z_k^t x_{kn}^t \leq x_n^t \qquad n = 1, \dots \dots \dots, N$$

$$z_k \geq 0 \qquad k = 1, \dots \dots \dots, K$$

The output set satisfies the assumption of CRS which indicates that inputs and outputs will be increasing at the same rate and under the assumption that inputs are strongly disposable:

$$\mathrm{P}(\lambda \mathrm{x}) = \lambda \mathrm{P}(\mathrm{x}), \lambda > 0 \qquad (8)$$

$$x' \geq \mathrm{x} \Rightarrow \mathrm{P}(x') \supseteq \mathrm{P}(\mathrm{x})$$

The assumption for the inputs and good outputs inequalities is that of free disposability while it will be costly to dispose of bad outputs. The Malmquist Luenberger index is computed using the directional distance functions by solving the following four linear programme problems:

$$\overrightarrow{D_0^t}(\mathrm{x}^{\mathrm{t,k'}}, \mathrm{y}^{\mathrm{t,k'}}, b^{t,\mathrm{k'}};\ y^{t,\mathrm{k'}}, -b^{t,\mathrm{k'}}) = \mathrm{Max}\,\beta \qquad (7)$$

Subject to:

$$\sum_{k=1}^{K} z_k^t y_{km}^t \geq (1+\beta)\, y_{\mathrm{k'm}}^t \qquad m = 1, \dots \dots \dots, M \qquad (10)$$

$$\sum_{k=1}^{K} z_k^t b_{ki}^t = (1-\beta)\, b_{\mathrm{k'i}}^t \qquad j = 1, \dots . \dots \dots, J$$

$$\sum_{k=1}^{K} z_k^t x_{kn}^t \leq x_{\mathrm{k'n}}^t \qquad n = 1, \dots \dots \dots, N$$

$$z_k^t \geq 0 \qquad k = 1, \dots \dots \dots, K$$

In this study, a two-year window reference technology is employed whereby for example the frontier for 1981 would be constructed using data for 1980 and 1981 and so forth. For comparison two models are computed i.e. one model with only good output and the other with jointly estimates good and bad output.

3. Data sources

The study utilises data from Food and Agriculture Organization of the United Nations statistical database (FAOSTAT, 2014) to analyse TFP of African agriculture for eighteen African countries. The concepts and measurement used by the FAO remain consistent across countries thus allowing international comparison. A balanced[2] panel dataset that covers the period from 1980 to 2012 was used for the following countries: Burundi, Cameroon, Côte d'Ivoire, Gabon, Gambia, Ghana, Kenya, Libya, Madagascar, Malawi, Mozambique, Niger, Nigeria, Sudan (former), Tanzania, Togo, Tunisia and Zambia. Thirty-six other African countries are excluded due to technical requirement for a balanced panel of data.

The output variables consisted of crop and livestock output which represent the good output; and three bad outputs which include carbon dioxide, methane and nitrous oxide

[2] Balanced data refers to the fact that all countries have data for all years

emissions. The disaggregation of the data into crop and livestock output is an advantage since it gives performance benchmarks that are more accurate than the aggregated which sometimes gives potentially misleading and even inaccurate estimates (Zhu, 2016). Crop and livestock output was based on gross production value expressed in constant 2005 international dollars as provided in Rao (1993) detailed description and assessment of the data aggregation. The bad outputs were the agriculture GHG measured in metric tonnes. The FAOSTAT GHG data is based on country-level estimates following FAOSTAT activity data computed using Tier 1 which complies with the 2006 Intergovernmental Panel on Climate Change (IPCC) Guidelines for National GHG Inventories. The four inputs consist of land, labour, farm capital and materials (fertilizer). Land is the number of hectares of land (which include amount of arable land, land under permanent crops and land under pasture). Labour is defined as the total population that actively participates and earn either a wage, salary, commission, piece rate or pay in kind in agriculture. Gross capital stock is defined as the total physical assets for land development, livestock (fixed assets and inventory), machinery and equipment and livestock structures measured in 2005 constant prices. This study uses capital stock as an input instead of tractors the reason being, there is low tractor use among small-scale farmers in Africa and the FAO data does not provide a balanced panel dataset in almost all countries due to missing values. To compare across countries, the data was deflated using the World Bank purchasing power parity conversion factors. Gross capital stock however ends in 2007. To estimate 2008 to 2012 capital stock figures, we follow (Kumar, Stauvermann, & Samitas, 2016) and extrapolate annual growth rates for agriculture value added for each country as a proxy for capital growth. Agriculture value added were drawn from Worldbank (2014) database. The annual growth in agriculture was used because the patterns of growth of farm capital stock for each country seemed very close to the annual growth rate for the agriculture value added trends. Fertilizer is the quantity of all fertilisers used measured in tonnes.

The summary statistics of the data used is provided in Table 1. The Malmquist Luenberger index were obtained using the Max DEA pro version 6.0 program. CRS assumption to the production technology in most cases is imposed when using an aggregate of different countries since capturing the difference in scale becomes irrelevant (Coelli & Rao, 2005). Thus, since the countries endowments' such as the land size, population and the available natural resources remain as given hence could not be deciding factors, the CRS assumption to the underlying technology was more appropriate than the VRS assumption. CRS was also preferred because Malmquist-type TFP estimates tend to be biased under VRS technology as observed by Grifell-Tatjé and Lovell (1995).

Table 1: Descriptive statistics (1980-2012 average)

Variable	Mean	Min	Max	STDEV
Crops (2005 international $)	2,851,025.0	51,834.0	33,900,000.0	5,109,033.0
Livestock (2005 international $)	777,653.6	16,415.0	5,516,586.0	1,016,063.0
CO_2 emissions (1,000 metric tons)	14,925.4	86.9	110,220.3	20,541.7
CH_4 emissions (1,000 metric tons of CO_2 equivalent)	7,963.4	30.2	59,866.2	11,297.2
N2O emissions (1,000 metric tons CO_2 equivalent)	6,813.9	55.6	50,094.2	9,330.9
Capital stock (2005 international $)	186,764.0	53.7	4,056,013.0	470,965.7
Total agricultural land (1,000 ha)	26,673.1	495.0	136,698.0	29,971.4
Total agricultural population (1,000)	4,263.9	60.0	17,851.0	3,928.1
Fertilizer (metric tons)	211,621.6	100.0	62,151,574.0	2,549,453.0

Source: FAOSTAT (2014).

4. Results

4.1 Productivity change

Table 2 presents productivity change estimates for five models. Model 1 presents the standard Malmquist productivity index (MI). Model 2 presents the MLI when CO_2 is considered. Model 3 presents the MLI when CH_4 is considered. Model 4 presents the MLI when N_2O is considered. Model 5 presents the MLI when all three bad outputs are considered. We include MI to show the discrepancy in estimating productivity when bad outputs are not considered. All the models registered positive productivity change. Model 1 exhibited an increase of 1.5%. Models 2, 3 and 4 had positive average annual productivity changes of 0.3%, 1.2%; and 1.2%, respectively. Model 5 showed an average annual productivity change of 1.4%. These estimates show that agriculture output can be increased while reducing GHG emissions at the same rate.

The annual change in model 1 varied across countries. In model 1, majority (fourteen) of the countries experienced positive change which is consistent with studies such as Alene, 2010; Avila and Evenson, 2010; and Nin-Pratt and Yu, 2012. Only four countries (Burundi, Gabon, Niger and Zambia) exhibited negative change. In models 2, 3 and 4; we observe that the number of countries exhibiting increasing MLI falls to ten, twelve, and eleven, respectively. Under model 5, twelve countries exhibited increasing MLI.

Countries such as Cameroun, Gambia, Kenya, Malawi and Tanzania exhibited positive productivity change when bad output was incorporated in all the models due to positive shift in technical change while Gabon, Libya and Madagascar experienced negative productivity change when bad output was considered in all the models which suggests the countries' lack of initiative of adopting technology to curb emissions. For example, Tanzania's vision 2025 spells out its agenda for agriculture growth and managing of resources as a key driver to sustainable agriculture (URT, 2001., 2003). The Tanzanian agriculture sector development strategy promote conservation agriculture to make land more productive. Several programmes initiated by the governments such as reforestation, agroforestry, protecting the water catchments and improved land husbandry have helped the countries curb land degrading activities (Shetto & Lyimo, 2001). The top rice producing countries in Africa Madagascar recorded a decline in TFP change in the presence of CH_4 emissions which suggests high CH_4 emissions from the paddy fields. Livestock remains the largest contributor of N_2O emissions which emanate from paddocks, ranges, and pastures (Hickman et al., 2011). Thus, countries such as Sudan (Former) that has the 2nd largest livestock herd after Ethiopia had declined TFP change in the presence of N_2O emissions due to high emissions from the livestock sector. Libya and Tunisia with known high global CO_2 emission also had declined TFP change in the presence of CO_2 emissions.

4.2 Efficiency and technical change

The MI and MLI efficiency and technical change components of productivity are presented in Table 2. In model 1, average technical change was 1.9% while efficiency change was -0.4% indicating the former as the main driver for MI growth. Decomposing efficiency change into pure technical efficiency and scale efficiency, we observe no change in scale efficiency although pure technical efficiency declined by 0.4% which suggest failure to use inputs efficiently. We note that Ghana, Malawi, Mozambique and Tanzania regressed in pure technical efficiency. As noted by Pauw and Thurlow (2011), Tanzania's output growth was attributed to land expansion driven by large-scale farmers especially after the 1990s. Chilonda et al. (2011) noted that agriculture land productivity in Mozambique declined between 2002 and 2008 due to little or no change in yield although the land area under farming increased (Benson, Mogues, & Woldeyohannes, 2014).

For models 2, 3, 4 and 5; technical change on average improved by 0.3%, 1.1%, 1.2%, and 1.3%, respectively, while efficiency change remained constant for all four models. We observe that pure technical efficiency was the main driver for the declining efficiency change while scale efficiency improved suggesting countries attempting to adopt technology and/or mitigation activities. Madagascar has been identified as one country which practises conservation. Instead of replenishing the nitrogen losses that occur through erosion, leaching or harvest with external nitrogen inputs, it uses supplementary feed (nitrogen inputs) to increase dairy output. Tanzania in its ‘Vision 2025’ identifies managing resources as a key driver to achieving sustainable agriculture productivity (URT, 2001., 2003). Since the late 1980s, the Tanzanian government has implemented programmes aimed at improving land productivity such as reforestation, agroforestry, protecting the water catchment areas and encouraging better land husbandry (Shetto and Owenya, 2007).

Table 2: Malmquist index (MI) and Malmquist Luenberger index (MLI) and its components across countries

Country	**Model 1: MI**					**Model 2: MLI (CO_2 emissions)**					**Model 3: MLI (CH_4 emissions)**				
	effch	tech	pech	sech	proch	effch	tech	pech	sech	proch	effch	tech	pech	sech	proch
Burundi	1.000	0.972	1.000	1.000	0.972	1.000	1.005	1.000	1.000	1.005	1.000	1.005	1.000	1.000	1.005
Cameroon	1.000	1.036	1.000	1.000	1.036	1.000	1.008	1.000	1.000	1.008	1.000	1.056	1.000	1.000	1.056
Côte d'Ivoire	1.000	1.023	1.000	1.000	1.023	1.000	0.981	1.000	1.000	0.981	1.000	1.006	1.000	1.000	1.006
Gabon	1.000	0.983	1.000	1.000	0.983	1.000	0.955	1.000	1.000	0.955	1.000	0.936	1.000	1.000	0.936
Gambia	0.984	1.024	1.000	0.984	1.008	0.997	1.020	0.743	0.997	1.016	0.997	1.032	0.731	0.997	1.029
Ghana	0.998	1.009	0.997	1.001	1.007	1.000	0.988	0.973	1.000	0.988	1.001	0.987	0.977	1.001	0.988
Kenya	1.000	1.011	1.000	1.000	1.011	1.000	1.035	1.000	1.000	1.035	1.000	1.137	1.000	1.000	1.137
Libya	1.000	1.038	1.000	1.000	1.038	1.000	0.982	1.000	1.000	0.982	1.000	0.970	1.000	1.000	0.970
Madagascar	1.000	1.026	1.000	1.000	1.026	1.000	0.930	0.977	1.000	0.930	1.000	0.998	0.974	1.000	0.998
Malawi	1.010	1.017	1.007	1.003	1.027	1.006	1.002	0.907	1.000	1.008	1.005	1.005	0.928	1.000	1.010
Mozambique	0.974	1.040	0.971	1.004	1.013	0.998	1.005	0.744	1.002	1.003	1.000	1.005	0.740	1.003	1.005
Niger	1.000	0.995	1.000	1.000	0.995	1.000	1.047	1.000	1.000	1.047	1.000	0.905	1.000	1.000	0.905
Nigeria	1.000	1.049	1.000	1.000	1.049	1.000	1.018	1.000	1.000	1.018	1.000	1.048	1.000	1.000	1.048
Sudan (former)	1.000	1.033	1.000	1.000	1.033	1.000	1.034	1.000	1.000	1.034	1.000	0.935	1.000	1.000	0.935
Togo	1.010	1.012	1.000	1.010	1.023	1.008	0.982	0.813	1.008	0.989	1.007	1.006	0.821	1.007	1.014
Tunisia	1.000	1.037	1.000	1.000	1.037	1.000	0.945	1.000	1.000	0.945	1.000	1.000	1.000	1.000	1.000
Tanzania	0.982	1.023	0.981	1.002	1.005	0.997	1.132	0.932	1.005	1.129	0.997	1.214	0.929	1.005	1.210
Zambia	0.975	1.019	0.978	0.997	0.994	0.999	1.000	0.691	1.003	0.999	0.999	1.000	0.690	1.004	1.000
Geomean	**0.996**	**1.019**	**0.996**	**1.000**	**1.015**	**1.000**	**1.003**	**0.926**	**1.001**	**1.003**	**1.000**	**1.011**	**0.926**	**1.001**	**1.012**

Note: effch = efficiency change; tech=technical change; pech=Pure technical efficiency change; sech = scale efficiency change; and proch= productivity change.

Table 2: Continued

Country	Model 4: MLI (N_2O emissions)					Model 5: MLI (CO_2, CH_4 & N_2O)				
	effch	tech	pech	sech	proch	effch	tech	pech	sech	proch
Burundi	1.000	1.004	1.000	1.000	1.004	1.000	1.004	1.000	1.000	1.004
Cameroon	1.000	1.061	1.000	1.000	1.061	1.000	1.132	1.000	1.000	1.132
Côte d'Ivoire	1.000	1.010	1.000	1.000	1.010	1.000	1.004	1.000	1.000	1.004
Gabon	1.000	0.993	1.000	1.000	0.993	1.000	0.964	1.000	1.000	0.964
Gambia	0.997	1.009	0.756	0.997	1.005	0.998	1.028	0.819	0.998	1.026
Ghana	1.000	0.976	0.972	1.000	0.976	1.000	1.002	0.985	1.000	1.002
Kenya	1.000	1.110	1.000	1.000	1.110	1.000	1.118	1.000	1.000	1.118
Libya	1.000	0.973	1.000	1.000	0.973	1.000	0.978	1.000	1.000	0.978
Madagascar	1.000	0.968	0.982	1.000	0.968	1.000	0.985	0.987	1.000	0.985
Malawi	1.007	1.001	0.885	1.000	1.007	1.004	1.004	0.944	1.000	1.008
Mozambique	0.998	1.005	0.748	1.002	1.002	0.998	1.004	0.796	1.001	1.003
Niger	1.000	0.979	1.000	1.000	0.979	1.000	0.892	1.000	1.000	0.892
Nigeria	1.000	1.027	1.000	1.000	1.027	1.000	1.037	1.000	1.000	1.037
Sudan (former)	1.000	0.961	1.000	1.000	0.961	1.000	0.973	1.000	1.000	0.973
Togo	1.008	1.003	0.800	1.008	1.011	1.006	1.005	0.855	1.006	1.011
Tunisia	1.000	1.001	1.000	1.000	1.001	1.000	0.996	1.000	1.000	0.996
Tanzania	0.998	1.154	0.926	1.006	1.152	0.998	1.147	0.947	1.004	1.145
Zambia	0.999	0.999	0.693	1.003	0.998	1.000	0.999	0.758	1.003	1.000
Geomean	**1.000**	**1.012**	**0.925**	**1.001**	**1.012**	**1.000**	**1.013**	**0.946**	**1.001**	**1.014**

4.3 Comparing productivity change between MI and MLI models

Table 3 presents the difference in productivity change between MI and MLI models which indicate how TFP changes when including CO_2, CH_4, N_2O or the three gases in the production function. A positive (negative) change between the MI and MLI estimates indicates a(an) decline (increase) in TFP or increase (decrease) in the bad outputs. The TFP change difference involved subtracting TFP change of bad output from TFP change of good output.

Comparing Model 1 versus the other models, TFP declined by 1.2%, 0.2% and 0.2% in the presence of CO_2, N_2O and CH_4 emissions respectively which imply that TFP change when good output only was factored was more than when considering bad output in the analysis. Cameroun, Côte d'Ivoire, Libya, Madagascar, Togo and Tunisia had the highest TFP change decline when factoring CO_2 in the analysis with a gap of 2.8%, 4.2%, 5.6%, 9.6%, 3.4% and 9.2%, respectively. The results reaffirm the findings of Canadell et al. (2009) that countries like Libya remain top CO_2 emitters in Africa. Burundi, Kenya, Niger and Tanzania had the highest TFP change increase of 3.3%, 2.4%, 5.2% and 12.4% respectively when considering CO_2 which suggests that these countries are low CO_2 emitters.

Comparing Model 1 versus Model 3, 4 and 5 exhibited similar outcomes in productivity change gap. Only six countries had positive TFP change when including N_2O and CH_4 emissions in the analysis with Libya, Niger and Sudan (Former) showing the highest TFP decline of 6.8%, 9% and 9.8% respectively in the presence of N_2O emissions. In the presence of CH_4 emissions, Libya, Madagascar and Sudan (Former) had the highest productivity decline of 6.5%, 5.8% and 7.2% respectively, while when including the three bad outputs in the analysis, Libya, Niger and Sudan (Former) had the highest productivity change decline of 6%, 10.3% and 6% respectively.

4.4 Comparing technical change and efficiency change between MI and MLI models

Examining Model 1 and Model 2, technical change revealed a positive gap in many of the countries when including CO_2 with a decline of 1.6%. The results thus imply a negative shift in production possibilities frontier towards producing more bad output and less good output. The efficiency change improved by 0.4% although pure technical efficiency declined by 6.4% when factoring CO_2 emissions. Comparing Model 1 with models 3 and 4, technical change showed a positive gap of 0.6% each, efficiency change improved by 0.4% while pure technical efficiency change declined by 6.4 and 6.5% in each model respectively. Comparing Model 1 and Model 5, the technical change indicated a positive gap of 0.4% with 0.4% improvement in efficiency change while pure technical efficiency declined by 4.7%.

The results suggest that increased emissions (CO_2, CH_4 and N_2O) contributed to declining technical change and pure efficiency change. Efficiency change improved in all the models which was attributed to improved scale efficiency change whereas pure technical efficiency change worsened. The decline in pure technical efficiency indicates that there is a direct link between GHG emissions and efficient resource use. The declining technical change imply that countries may not be adopting technologies that reduce emissions. Livestock production systems (including producing and processing of feeds) and ruminants' enteric fermentation are identified as the two primary sources of agriculture greenhouse gases which contribute immensely to the sector's emissions by approximately 45 and 39 percent respectively (Gerber et al., 2013). Hence interventions to reduce greenhouse gases should target on technologies and measures that enhance livestock productivity. In countries, such as Ghana, Zambia and Malawi, synthetic nitrogen fertilizer is applied intensively because of their national fertilizer subsidy programmes to small-scale farmers. As noted by Crawford, Jayne, and Kelly (2006), subsidized inputs crowd out the private sector deliveries and discourages investments into new private fertilizer sales networks. Subsidized inputs are also misallocated due to overuse which does not raise crop productivity.

Table 3: Comparison of mean productivity changes between ML and MLI models

Country	Model 1 vs Model 2					Model 1 vs Model 3					Model 1 vs Model 4				
	effch	tech	pech	sech	proch	effch	tech	pech	sech	proch	effch	tech	pech	sech	proch
Burundi	0.000	-0.033	0.000	0.000	-0.033	0.000	-0.033	0.000	0.000	-0.033	0.000	-0.032	0.000	0.000	-0.032
Cameroon	0.000	0.028	0.000	0.000	0.028	0.000	-0.020	0.000	0.000	-0.020	0.000	-0.025	0.000	0.000	-0.025
Côte d'Ivoire	0.000	0.042	0.000	0.000	0.042	0.000	0.017	0.000	0.000	0.017	0.000	0.013	0.000	0.000	0.013
Gabon	0.000	0.028	0.000	0.000	0.028	0.000	0.047	0.000	0.000	0.047	0.000	-0.010	0.000	0.000	-0.010
Gambia	-0.013	0.004	0.257	-0.013	-0.008	-0.013	-0.008	0.269	-0.013	-0.021	-0.013	0.015	0.244	-0.013	0.003
Ghana	-0.002	0.021	0.024	0.001	0.019	-0.003	0.022	0.020	0.000	0.019	-0.002	0.033	0.025	0.001	0.031
Kenya	0.000	-0.024	0.000	0.000	-0.024	0.000	-0.126	0.000	0.000	-0.126	0.000	-0.099	0.000	0.000	-0.099
Libya	0.000	0.056	0.000	0.000	0.056	0.000	0.068	0.000	0.000	0.068	0.000	0.065	0.000	0.000	0.065
Madagascar	0.000	0.096	0.023	0.000	0.096	0.000	0.028	0.026	0.000	0.028	0.000	0.058	0.018	0.000	0.058
Malawi	0.004	0.015	0.100	0.003	0.019	0.005	0.012	0.079	0.003	0.017	0.003	0.016	0.122	0.003	0.020
Mozambique	-0.024	0.035	0.227	0.002	0.010	-0.026	0.035	0.231	0.001	0.008	-0.024	0.035	0.223	0.002	0.011
Niger	0.000	-0.052	0.000	0.000	-0.052	0.000	0.090	0.000	0.000	0.090	0.000	0.016	0.000	0.000	0.016
Nigeria	0.000	0.031	0.000	0.000	0.031	0.000	0.001	0.000	0.000	0.001	0.000	0.022	0.000	0.000	0.022
Sudan (former)	0.000	-0.001	0.000	0.000	-0.001	0.000	0.098	0.000	0.000	0.098	0.000	0.072	0.000	0.000	0.072
Togo	0.002	0.030	0.187	0.002	0.034	0.003	0.006	0.179	0.003	0.009	0.002	0.009	0.200	0.002	0.012
Tunisia	0.000	0.092	0.000	0.000	0.092	0.000	0.037	0.000	0.000	0.037	0.000	0.036	0.000	0.000	0.036
Tanzania	-0.015	-0.109	0.049	-0.003	-0.124	-0.015	-0.191	0.052	-0.003	-0.205	-0.016	-0.131	0.055	-0.004	-0.147
Zambia	-0.024	0.019	0.287	-0.006	-0.005	-0.024	0.019	0.288	-0.007	-0.006	-0.024	0.020	0.285	-0.006	-0.004
Geomean	**-0.004**	**0.016**	**0.064**	**-0.001**	**0.012**	**-0.004**	**0.006**	**0.064**	**-0.001**	**0.002**	**-0.004**	**0.006**	**0.065**	**-0.001**	**0.002**

Note: effch = efficiency change; tech=technical change; pech=Pure technical efficiency change; sech = scale efficiency change; and proch= productivity change.

Table 3: Continued

Country	Model 1 vs Model 5				
	effch	tech	pech	sech	proch
Burundi	0.000	-0.032	0.000	0.000	-0.032
Cameroon	0.000	-0.096	0.000	0.000	-0.096
Côte d'Ivoire	0.000	0.019	0.000	0.000	0.019
Gabon	0.000	0.019	0.000	0.000	0.019
Gambia	-0.014	-0.004	0.181	-0.014	-0.018
Ghana	-0.002	0.007	0.012	0.001	0.005
Kenya	0.000	-0.107	0.000	0.000	-0.107
Libya	0.000	0.060	0.000	0.000	0.060
Madagascar	0.000	0.041	0.013	0.000	0.041
Malawi	0.006	0.013	0.063	0.003	0.019
Mozambique	-0.024	0.036	0.175	0.003	0.010
Niger	0.000	0.103	0.000	0.000	0.103
Nigeria	0.000	0.012	0.000	0.000	0.012
Sudan (former)	0.000	0.060	0.000	0.000	0.060
Togo	0.004	0.007	0.145	0.004	0.012
Tunisia	0.000	0.041	0.000	0.000	0.041
Tanzania	-0.016	-0.124	0.034	-0.002	-0.140
Zambia	-0.025	0.020	0.220	-0.006	-0.006
Geomean	**-0.004**	**0.004**	**0.047**	**-0.001**	**0.000**

4.5 Hypothesis testing

Table 4 provides the results of a Kruksal Wallis Test that tests the null-hypothesis of whether productivity measures and its components between the MI and MLI models remains the same across countries. The MI and the MLI productivity changes seem not to be different since the results fail to reject the null hypothesis in all the models. The null hypothesis is also not accepted for the efficiency change and scale efficiency components for all the models. However, the results reject the null hypothesis that pure technical efficiency remains the same across countries for the CO_2 and CH_4 included models while for technical change measure, the null hypothesis is rejected in the in CO_2 and N_2O models. This implies that the difference in productivity growth rates between the MI and MLI measures for these models depend on respective growth of the good and bad outputs with efficiency and technical change explaining the change. Considering GHG emissions are due to poor manure management, burning, manure and synthetic fertilizer application and inefficient energy use it is not surprising that when these activities are not handled efficiently, resources will be shifted towards production of bad outputs.

Table 4: Hypothesis testing using Kruskal Wallis test of the means (by countries)

	Model 2		**Model 3**		**Model 4**		**Model 5**	
Null hypothesis	**p value**	**Result**	**p value**	**Result**	**p value**	**Result**	**p value**	**Result**
MLI=MI	0.117	Accepted	0.282	Accepted	0.114	Accepted	0.217	Accepted
MLPECH=MPECH	0.043	Rejected	0.043	Rejected	0.051	Accepted	0.061	Accepted
MLTECH=MTECH	0.037	Rejected	0.093	Accepted	0.038	Rejected	0.090	Accepted
MLEFFCH=MEFFCH	0.619	Accepted	0.358	Accepted	0.606	Accepted	0.450	Accepted
MLSECH=MSECH	0.970	Accepted	0.740	Accepted	0.970	Accepted	1.000	Accepted

Note: MLI=Malmquist Luenberger Index; MLPECH = Malmquist Luenberger Pure technical efficiency; MLTECH = Malmquist Luenberger Technical Change; MLEFFCH = Malmquist Luenberger Efficiency Change; MLSECH = Malmquist Luenberger Scale Efficiency; MI=Malmquist Index; MPECH = Malmquist Pure technical efficiency; MTECH=Malmquist Technical Change; MEFFCH= Malmquist Efficiency Change and MSECH = Malmquist Scale Efficiency.

5. Conclusions

This study employed the MLI to measure the agricultural productivity of 18 African countries by incorporating good and bad outputs. From the analysis, the Malmquist index which does not consider bad output in the production model was found to overestimate the productivity growth rates. The results also suggest African countries were not successful in raising productivity and reducing GHG emissions.

In terms of policies, the analysis from the study provide the following. Policies that educate farmers to use appropriate amounts of synthetic fertilizers and encourage efficient use of nutrients (manure and fertilizer) to help reduce N_2O. Policies that improves manure management practices and help recover and recycle nutrients include appropriate storage, management and application of manure. Policies aimed at efficient use of energy such as reducing fossil fuel use and adopting cleaner energy (i.e. solar uptake) can contribute towards mitigation of GHG emissions. Policies that encourage adopting improved crop varieties and livestock breeds can also reduce GHG emissions. Appropriate technologies and practices such as the use of safe feeding technologies directed at animal and herd farming can reduce methane gas emissions. Policies that encourage better water and fertilizer management practises e.g. the system of rice intensification (SRI) in rice cultivation which aims to grow rice using less water, fertilizer and pesticides can help to reduce the emissions from rice farms. Lastly, government efforts should aim at packaging subsidies such as seed and fertiliser subsidies in a way that will promote their efficient use and sustain an efficient input market.

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