Determinants of Technical Efficiency in Agricultural Production among Sub Saharan African Countries

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Abstract: *Climate change has led to a decline in agricultural production due to erratic weather patterns, compromised crop yields and population pressure on arable land. Sub-Saharan Africa is most vulnerable to climate change due to its geographical location, increase in population, destruction of the forests and other agricultural malpractices. This is a threat to livelihoods, food systems, and increase in malnutrition and shocks in food prices. This study examines the influence of climatic factors on the technical efficiency of agricultural production in Sub Saharan Africa using time series data for 25 years from 1991 to 2015 selected from nine countries. The data envelopment analysis estimates technical efficiency with input variable as agricultural land and output variable as agricultural value-added. The panel data analysis response variable is the technical efficiency scores. Predictor variables were population, forest area, temperature, rainfall, and greenhouse gases. In the last 25 years, there has been an increase in population, agricultural land, temperature, and greenhouse gases with a decrease in forest area and rainfall. Temperature, forest area, and greenhouse gases showed significant influences on the technical efficiency of agricultural production. The intricate nature of climate change requires significant efforts to reverse the trend being observed and boost agricultural production efficiency.*

Keywords: Climate change, greenhouse gases, panel analysis, Sub-Saharan Africa, technical efficiency

1. Introduction

The last two decades have witnessed a drastic change in climatic conditions that have led to a decline in food production. Climate change is taunted to increase the frequency and intensity of disasters, disruption of food production and livestock rearing. This has raised concern among public policymakers and interest groups due to uncertainty in food security and agricultural sustainability (Eniko *et al*., 2018). Climate change is one of the several changes affecting food systems and this varies between regions and the different social groups within a region. The threat of global food shortage is evident due to a number of factors: population pressure, water scarcity, land degradation, frequent droughts, declining soil fertility, lack of credit facilities, poor agronomic practices, poor seed quality, pests, weeds and incidence of diseases (Abera *et. al*., 2018; Nsiah and Fayissa, 2019; Popp *et. al*., 2019). African is already overburdened with food insecurity, poverty and low adaptive capacity but climate change is projected to increase the vulnerability and burden (Muller *et. al*., 2011). The models that derive the relationship between environmental conditions and production systems project a continued decline in crop yields due to climate change (Ray *et. al*., 2019) with traditional rain-fed agriculture facing more climate-related risks (Eniko *et al*., 2018).

Smallholder systems in Africa will be the most compromised in agriculture production due to little adaptive capacity to climate change (Muller *et. al*., 2011). In Asia and Latin-America, there is improved food security that has also reduced the prevalence of undernourishment (Popp *et. al*., 2019). Smallholder farmers account for 80% of all the farms in SSA employing 175 million directly and 70% of the smallholder farmers being women. Subsistence farming is a key employer with 76 % of the population in Botswana, 85% in Kenya and 90% in Malawi depending on agriculture (AGRA, 2014). The future impacts and exposure to climate variability and extremes are expected to increase with time (FAO, 2018). Food systems are changing rapidly due to globalization and urbanization with an increasing population (Gregory *et al*., 2005; Nsiah and Fayissa, 2019). This is compounded by the expected growth of 22% in the SSA population by the year 2050 projected to be 1.5 billion (Nsiah and Fayissa, 2019) and an additional of 2.4 billion people in the world by 2050 (Islam and Wong, 2017). The rate of population growth exceeds the agricultural production due to declining land size, climate change and other vulnerabilities facing farmers (Nsiah and Fayissa, 2019). Worldwide, 821 million people are undernourished, with 237 million in SSA and 257 million are in Africa (Islam and Wong, 2017; FAO, 2018).

The risks for African agriculture and food production are due to anthropogenic climate change with statistical, process-based and econometric models indicating negative and positive impacts on agriculture. The underlying assumptions in the climate change projections and its impact on food production are greenhouse gas emissions, biophysical and socio-economic conditions. Climate change has increased the global mean annual air temperature by 0.74 °C and atmospheric greenhouse gases during the last 100 years (Tokunaga, *et al*., 2015). The vulnerability of the African continent to the effects of climate change are already evident, with predictions indicating that Africa is warmer compared to the global average. Temperature and rainfall are two key determinants of agricultural production and food security (Abera *et. al*., 2018). Climate change is worsening agricultural production in Africa due to erratic weather patterns and extreme weather events that decrease the average yields (AGRA, 2014).

The agricultural production technical efficiency (TE) study found that agricultural land, arable land, rural population, average precipitation, land under cereal production and economically active population working in the agricultural sector, access to credit and agricultural research influence TE (Nsiah and Fayissa, 2019). An estimated 2.7 million hectares can be irrigated, but only 11% was equipped for irrigation in 2001 (FAO, 2018). A survey from 28 among 47 countries in SSA indicated that 75% of the labour force worked in household enterprises and the agricultural sector (FAO, 2018) with households that are food secure being TE and productive (Oyetunde-Usman and Olagunju, 2017). The future maize yields in Ethiopia are either increasing or decreasing based on the region (Abera *et. al*., 2018) while Ngango and Kim (2019) noted that coffee production TE in Rwanda depends on technological adoption.

An input-oriented Data Envelopment Analysis (DEA) employed to examine the TE of maize production in northern Ghana noted that efficiency can further be boosted through formal and informal educational platforms to educate the farmers on improved cultivation practices. The DEA employed various variables, fertilizer consumption, household size, household labor, maize plot size, age of respondent, among other variables (Abdulai *et. al*., 2018). The mean difference between food secure and insecure households TE is 0.035 and was found to be statistically significant among the agriculture households in Nigeria (Oyetunde-Usman and Olagunju, 2017). A study on the African agriculture and food production TE found that it has decreased significantly over time (Ogundari, 2014). The employment of the right combination of productive resources to achieve food sustainability is important for African countries (Abdulai *et. al*., 2018). The technically efficient food producers are more food secure to non-technically significant producers. African countries need to continue making agriculture a critical component as it's the principal source of food, livelihood and a channel to reduce poverty and attain food security (Ogundari, 2014).

A panel data analysis model was used to estimate the impact of global warming-induced climate change on agricultural production in Japan. The results indicated that rising precipitation and temperature and decreasing solar radiation reduced rice production in Japan. A dynamic panel analysis on rice, vegetable and potato showed a decline in production. An increase of a degree in mean annual temperature reduces rice production by 5.8% and 3.9%, and potato production by 5% and 8.6% in the short and long term, respectively (Tokunaga *et al*., 2015). In Burkina Faso, an increase in temperature reduced the production of millet, maize and sorghum while an increase in rainfall and precipitation increased the production of the cereals (Nana, 2019).

The goal of this study was to assess and identify the climatic factors that influence technical efficiency of agricultural production in SSA through the DEA model and panel data analysis. Climatic risks are changing the agricultural production landscape in SSA with a reduction in crop yields to cater for the increasing population. An analysis of the relationship between the environmental conditions and production system is important to understand the influence of climatic risks on agricultural production efficiency. The intent is to understand to what extent climatic conditions are influencing the agricultural sustainability and food systems in SSA. We found no similar study that has considered agriculture value-added and agricultural land size in estimating TE among SSA countries and use of forest area as a predictor variable in panel data analysis. Forest cover is key in absorbing greenhouse gases while agricultural value-added is an indicator of the interplay between the inputs and outputs in the agricultural production systems.

2. Materials and Methods

The two-step DEA model was applied to estimate the agricultural production TE among the selected countries in SSA. The first step is to estimate the efficiency scores on agricultural production. The second step performs the panel data analysis to estimate which climate variables have an influence on the agricultural production TE scores. The study covers a period of 25 years from 1991 to the year 2015 with countries sampled from SSA. The DEA input variable is agricultural land and the output variable is the agricultural value-added, with data sourced from FSP (2020). The five climate change variables are forest area from World Bank portal (World Bank (2020)) while rainfall, temperature, population and greenhouse gases are from climate watch data (CWD, 2020). The study has two input/output variables. Therefore at least 8 Decision-Making Units (DMU) were required as indicated by Ntwiga (2020). The study population has 28 SSA countries with an overall food security score of between 34.3 and 67.3% (Economist Intelligent Unit, 2020). A total of top 9 DMUs with no missing data points were selected from the 28 countries to form the study sample. The countries include Benin (BEN), Botswana (BWA), Burkina Faso (BFA), Cameroon (CMR), Ethiopia (ETH), Ghana (GHA), Kenya (KEN), Mali (MLI) and Nigeria (NGA) (Economist Intelligent Unit, 2020).

The efficiency scores were analyzed using DEA. Then, the results were assessed using descriptive statistics and econometrics model. The influence of climatic factors on TE of agricultural production was estimated using regression panel analysis. The efficiency scores summary statistics were grouped into four periods; 1991-2000, 2001-2010, 2011-2015 and 1991-2015. The purpose was to check if any significant changes can be attributed to these time segments compared to the overall period. In the determinant of TE, four models were derived where model M1 was the two-dimensional variables panel analysis. Model M2 and M3 captured one-way effect controlling for the year and country, respectively while M4 captured two-way effects controlling for both year and country.

2.1. Variables definition and measurement

The DEA input and output variables resulted to the TE scores as the output variable. In the panel analysis, the TE scores were the response variable and climate factors were the predictor variables.

The study variables and their descriptions for step one DEA model and the step two-panel analysis are presented in Table 1. In the DEA model, the input and output variables estimate the TE of agricultural production. In the panel data analysis, the efficiency scores are the response variable, while the five climate change variables are the predictor variables. The goal is to assess the influence of the climatic factors on TE of the agricultural production in SSA.

Table 1: Data Envelopment Analysis and panel regression models variables

Variable Name	Description
Agricultural land (AL) – Input variable	Percentage of total land that is arable, used for permanent crops, and used for permanent pastures
Agriculture value-added (AVA) - Output variable	Net output for the agriculture sector, forestry, hunting, cultivation of crops, fishing and livestock production, after adding up all outputs and subtracting intermediate inputs (Value added is outputs minus inputs)
Forest Area (FA)	Land under natural/planted trees (5 meters), whether productive or not
Greenhouse Gases (GHG)	Total including land-use change and forestry/agriculture
Population (POP)	People living in the country as defined by the national statistics office
Rainfall (RN)	Average annual rainfall observed in the country
Temperature (TP)	Average annual temperature observed in the country

2.2. Data envelopment analysis

The non-parametric DEA technique was applied to estimate the efficiency scores of a DMU relative to other DMU. The Charnes, Cooper and Rhodes (CCR) model is the basic DEA technique with the Constant Return to Scale (CRS), which assumes no significant relationship between the scale of operations and efficiency (Charnes, *et al*., 1978). A modification of CRS by (Banker *et al*., 1984) became the Banker, Charnes and Cooper (BCC) model which accommodates the variable return to scale (VRS). The TE entails overall TE estimated by the CRS. In the DEA, an efficient frontier is created that evaluates the efficiency of a DMU and is designed to maximize the relative efficiency of each DMU. The efficiency score is estimated as the ratio of weighted outputs to weighted inputs for each variable of every DMU in order to maximize its efficiency score (Ntwiga, 2020; Abel and Bara, 2017). Weights were determined by solving the following linear programming problem.

$$Maximize \quad h_k = \frac{\Sigma_{r=1}^{s} u_r y_{rk}}{\Sigma_{i=1}^{m} v_i x_{ik}} \qquad [1]$$

$$\boldsymbol{Subject\ to}: \quad \frac{\Sigma_{r=1}^{s} u_r y_r}{\Sigma_{i=1}^{m} v_i x_i} \leq \mathbf{1} \qquad [2]$$

$v_i \geq 0;\ u_r \geq 0;\ r = 1 \ldots s;\ \ i = 1..m$

Where,

y_{rk} is the output for the r^{th} country at k^{th} year with weight u_r

x_{ik} is the input for the i^{th} country at k^{th} year with weight v_i

s and m are the number of countries for the output and input variables respectively;

k is the number of years

h_k is the efficiency score to be maximized

The maximal efficiency score is equal to 1 and the lower values indicate relative inefficiency of analyzed objects (Ntwiga, 2020). We apply the output-oriented DEA model to estimate the efficiency scores of agricultural land used to produce agriculture value addition.

2.3. Panel data analysis

The panel regression model response variable is the TE scores with the predictor variables being GHG, FA, POP, RN and TP as explained in Table 1. The panel data comprises of nine countries from SSA, with 25 annual data points for five predictor variables and one response variable. The equation for the panel model is indicated below.

$$TE_{it} = \alpha + \beta_i FA_{it} + \psi_i GHG_{it} + \psi_i Ln(POP_{it}) + \theta_i RN_{it} + \rho_i TP_{it} + \epsilon_{it} \qquad [3]$$

Where,

TE_{it} is the TE scores of country i and time t

FA_{it}, GHG_{it}, POP_{it}, RN_{it} and TP_{it} represent the forest cover, greenhouse gases, population, rainfall and temperature in country i at time t, respectively

3. Results and Discussion

The results were analyzed in two steps. Efficiency scores of two-dimensional variables, individual and time period, were computed using DEA. Then, the panel data of computed efficiency score regressed on the explanatory variables to find the determinants of TE. The descriptive statistics provide the summary statistics for the variables in Table 1. The diagnostic tests for the panel data comprising nine countries, for 25 years with five predictor variables were performed and the data did not exhibit multi-collinearity but heteroscedasticity and autocorrelation were observed. The panel AR package and function (Panel Regression with AR (1) Prais-Winsten correction and panel-corrected standard errors) in R statistical software were used to correct for heteroscedasticity and autocorrelation.

Table 2 presents the summary statistics for the nine countries based on the mean, standard deviation and percentage change of the two DEA variables (AVA and AL) and the five-panel regression model variables (GHG, FA, POP, RN and TP). Nigeria had the highest GHG production on average in the 25 years followed by Cameroon and Ethiopia. The ratio of AVA to AL was an indicator for the TE with Benin having a ratio of one-to-one, Botswana had a ratio of one-to-fourteen and Ethiopia's ratio was one-to-less than one. These ratios indicated the efficiency levels with Ethiopia being more TE based on the selected variables among the nine countries in the sample. The average temperature did not vary much across the nine countries during these 25 years but major variations were observed in mean rainfall amounts. The highest average rainfall was observed in Cameroon, followed by Ethiopia, Nigeria and Benin. Nigeria had the highest population, followed by Ethiopia, Kenya and Ghana. Cameroon had the highest forest area, then Benin and Ghana with Mali having the lowest forest area.

The variables summary for the 25 years among the nine countries indicates a decrease in forest area, rain and agriculture value addition with an increase in population, greenhouse gases, agricultural land and temperature. This is a paradox as population increase requires more food that led to agricultural land increase that increases agricultural production and in the process of reducing forest cover. The increase in greenhouse gases and temperature and reduction of rainfall complicates the agricultural production due to the compound nature of climate change. Nsiah and Fayissa (2019) observed that the SSA population is expected to increase by 22% to 1.5 billion by 2050, to exceed agricultural production and declining agricultural land. This study noted that population increase far exceeds the growth in agricultural land which will further lead to food security vulnerabilities in the short and long term. An increase in temperature by 1.37% is similar to observations by FAO (2018) that Africa is becoming warmer compared to the rest of the globe. On average, among the nine countries between 1991 and 2015, forest cover had reduced by 20.85%, rainfall by 17.49% and agricultural value-added by 23.06% while the population, greenhouse gases, agricultural land, temperature increased by 90.81, 46.94, 14.93, 1.37%, respectively which agrees with the sentiments from Tokunaga *et al*. (2015).

Table 2: Summary statistics of variables in DEA and panel analysis

Variable	Statistic	BEN	BWA	BFA	CMR	ETH	GHA	KEN	MLI	NGA	Mean
FA	Mean	43.87	22.18	21.51	45.39	13.39	39.53	7.21	4.64	13.08	
	SD	3.70	1.61	1.51	3.43	0.89	0.92	0.49	0.48	3.31	
	%	-24.25	-21.17	-20.29	-21.91	-16.52	7.88	-4.22	-28.68	-58.44	-20.85
GHG	Mean	21.89	66.66	29.92	192.47	134.89	40.81	51.24	32.09	402.48	
	SD	1.84	29.48	4.68	21.07	25.95	13.70	41.02	6.00	30.21	
	%	26.59	117.6	59.73	52.13	70.96	46.74	-55.50	87.23	16.97	46.94
POP	Mean	7.65	1.81	13.00	16.88	73.42	20.81	34.74	12.43	134.75	
	SD	1.65	0.23	2.78	3.28	15.21	3.86	7.02	2.74	25.48	
	%	105.4	55.94	100.12	89.33	100.5	83.40	95.36	101.9	85.40	90.81
RN	Mean	87.68	31.56	66.28	131.06	67.30	95.97	55.96	26.55	95.29	
	SD	8.58	6.53	5.90	8.97	5.78	8.80	12.87	3.10	7.56	
	%	-25.50	-36.25	-8.21	-11.81	8.86	-22.93	-47.83	6.51	-20.22	-17.49
TP	Mean	27.87	22.27	28.68	24.91	23.13	27.60	25.20	28.87	27.25	
	SD	0.31	0.38	0.30	0.24	0.35	0.26	0.70	0.35	0.31	
	%	2.95	5.37	1.95	1.50	4.17	2.71	-9.95	1.89	1.71	1.37
AL	Mean	28.15	45.68	39.29	19.71	34.47	63.99	47.57	31.70	76.76	
	SD	4.31	0.12	3.82	0.52	5.51	4.86	0.65	2.44	2.91	
	%	64.47	0.39	26.7	6.56	-28.91	23.43	2.8	28.2	10.75	14.93
AVA	Mean	28.89	3.24	35.41	17.44	49.10	35.75	29.28	37.88	31.43	
	SD	4.18	0.93	2.72	3.29	7.21	7.76	2.79	2.89	7.17	
	%	-27.74	-49.37	8.07	-35.26	-36.05	-53.93	18.34	1.6	-33.2	-23.06

Note: Percent (%) was the change of the variable from the year 1991 to 2015

Forest area = FA, Greenhouse gases = GHG, Population = POP, Rain = RN, Temperature =TP, agricultural land = AL, agricultural value-added = AVA

In table 3, Ethiopia had generally the highest average efficiency scores followed by Mali and the lowest efficiency scores were observed in Botswana as indicated in Table 3. In the 25 years, the efficiency scores in descending order of country were Ethiopia (0.971), Mali (0.816), Benin (0.708), Burkina Faso (0.617), Cameroon (0.598), Kenya (0.420), Ghana (0.378), Nigeria (0.277) and Botswana (0.047). The difference between Ethiopian and Botswana TE was about 92.4%, which is a wide margin for TE of agricultural production of the two countries. TE of Kenya, Ghana, Botswana and Nigeria were below 50% during the segmented period. The major difference was observed between the country with the lowest and highest TE ranging between 4.7% and 97.1%. Between 1991 and 2015, the overall change in TE showed a decline. Highest negative change in TE was observed in Ghana, followed by Benin and

Botswana while the highest positive change was observed in Kenya and Ethiopia.

Generally, the technical efficiency of agricultural production among the selected countries is decreasing trend with an average of 3.6%. The percentage change of efficiency between 1991 and 2015 ranged from -47.97% to 60.47%. Similar sentiments were also noted by Ogundari (2014) where TE in Africa has decreased drastically over time.

Table 3: DEA Technical efficiency scores of Sub-Saharan countries in the last 25 years

Variable	Statistic	BEN	BWA	BFA	CMR	ETH	GHA	KEN	MLI	NGA
1991-2000	Mean	0.801	0.051	0.558	0.599	0.947	0.409	0.376	0.771	0.252
	SD	0.138	0.009	0.057	0.122	0.113	0.042	0.037	0.073	0.030
	Min	0.585	0.043	0.442	0.407	0.694	0.353	0.327	0.674	0.214
	Max	1.000	0.068	0.634	0.844	1.000	0.482	0.443	0.905	0.297
2001-2010	Mean	0.664	0.043	0.671	0.604	1.000	0.402	0.424	0.790	0.333
	SD	0.038	0.006	0.045	0.068	0.000	0.065	0.044	0.037	0.065
	Min	0.587	0.033	0.595	0.509	1.000	0.330	0.363	0.743	0.248
	Max	0.719	0.051	0.731	0.703	1.000	0.490	0.484	0.858	0.459
2011-2015	Mean	0.608	0.045	0.627	0.582	0.961	0.269	0.499	0.961	0.218
	SD	0.035	0.003	0.017	0.033	0.058	0.023	0.035	0.049	0.009
	Min	0.582	0.042	0.603	0.539	0.870	0.245	0.454	0.896	0.211
	Max	0.666	0.049	0.639	0.626	1.000	0.306	0.552	1.000	0.233
1991-2015	Mean	0.708	0.047	0.617	0.598	0.971	0.378	0.420	0.816	0.277
	SD	0.120	0.008	0.069	0.087	0.077	0.074	0.060	0.092	0.065
	Min	0.582	0.033	0.442	0.407	0.694	0.245	0.327	0.674	0.211
	Max	1.000	0.068	0.731	0.844	1.000	0.490	0.552	1.000	0.459
	%	-38.76	-29.70	18.90	-15.31	25.40	-47.97	60.47	10.48	-15.92

Note: SD = Standard deviation, Min = minimum value, max = maximum value
Percent (%) is the change of the variable from the year 1991 to 2015

The results presented in Table 4 highlights only the countries whose results are statistically significant. Model 1 showed that a unit increase in temperature and forest area increased the technical efficiency by 3% and 0.7%, respectively while a unit increase in greenhouse gases decreased technical efficiency by 0.03%. The predictor variables explained 73.94% variations in the efficiency. In model 2, a unit increase in greenhouse gases decreased efficiency by 0.054%, while a unit increase in temperature and forest area increased efficiency by 3.1 and 0.84%, respectively. Controlling for the year significantly increased the magnitude of temperature and forest area and reduced the magnitude of greenhouse gases in influencing efficiency. When the year 1992 is compared to that of 1991, technical efficiency was reduced by 4.5%. The influencing efficiency of temperature change was 3.01% in Model 1 while 3.11% in Model 2. Similarly, the influencing efficiency of forest area change was 0.663 % and 0.835% in Model 1 and 2, respectively, in Table 4. The influencing efficiency of greenhouse gases in model 1 was 0.034 while in model 2 it was 0.054 as indicated in Table 4. The predictive power of the model 1 (73.94%) had been reduced to 66.22% in model 2 after controlling for the year. The changes from year to year reduced the predictive power of the model.

In model 3, the one-way effect of the country, there is an increase in efficiency by 0.882% when forest area increases by one unit. Compared to Benin, technical efficiency of Botswana and Ghana has been reduced by 43.56% and 32.8%, respectively. On the other hand, technical efficiency of Ethiopia and Mali has been increased by 44.28% and 49.96%, respectively with an overall R-squared of 89.68%. In model 4, the two-way effect of country and year showed that a unit increase in forest area significantly increased efficiency by 1.58%. Controlling for the year showed significant changes on the influence of predictor variables on technical efficiency in agricultural production from the year 2002 to 2015.

AGRA (2014) observed that an increase in greenhouse gases in the last 100 years, which has worsened agricultural production in Africa due to erratic weather patterns. The study found an increase in the greenhouse gases and temperature and they reduced and increased TE respectively in the last 25 years. Muller *et al*. (2011) noted that temperature and rainfall changes are the two major determinants of agricultural production. On the other hand, rainfall did not influence the technical efficiency significantly although the rainfall amount declined in the last 25 years. The technical efficiency of agricultural production in selected countries was decreasing in the last 25 years with an average of 3.6%. Population increase far exceeds the growth in agricultural land which will further lead to food insecurity in the short and long term.

Table 4: Panel data analysis results of five selected variables

Variables	Model 1	Model 2	Model 3	Model 4
Greenhouse gases	−0.0003 **	−0.0005 *	−0.0003	−0.0004
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Rain	0.0003	0.0006	0.0003	0.0002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Temperature	0.0302 ***	0.0311 ***	0.0013	−0.0104
	(0.0068)	(0.0078)	(0.008)	(0.0094)
Forest Area	0.0066 **	0.0084 ***	0.00882 *	0.0158 **
	(0.0020)	(0.0021)	(0.0041)	(0.0057)
Population	−0.0004	0.0010	0.0017	0.0012
	(0.0008)	(0.0010)	(0.0008)	(0.0007)
Factor (Year) 1992		0.0455 *		
		(0.0211)		
Factor (Year) 1993				−0.0596 *
				(0.0247)
Factor (Year) 2002				0.09997 **
				(0.0316)
Factor (Year) 2003				0.0992 **
				(0.0318)
Factor (Year) 2004				0.0897 **
				(0.0331)
Factor (Year) 2005				0.0803 *
				(0.0332)
Factor (Year) 2010				0.0753 *
				(0.0365)
Factor (Year) 2013				0.0768 *
				(0.0380)
Factor (Year) 2014				0.0758 *
				(0.0383)
Factor (Year) 2015				0.0816 *
				(0.0391)
Factor (country) BWA			−0.4356 ***	−0.3548 **
			(0.1191)	(0.1461)
Factor (country) ETH			0.4428 ***	0.6362 **
			(0.1299)	(0.1708)
Factor (country) GHA			−0.3280 ***	−0.3073 *
			(0.0680)	(0.1534)
Factor (country) MLI			0.4996 **	0.8005 **
			(0.1764)	(0.2417)
Constant term	−0.4263 *	−0.5572 *	0.2671	0.2606
	(0.1974)	(0.2211)	(0.3306)	(0.3966)
R-squared	0.7394	0.6622	0.8968	0.9388
Wald statistic	53.39 ***	101.01 ***	3133.41 ***	2603.31 ***
Total Obs.	225	225	225	225

Significance codes: '*' 0.05, '**' 0.01, '***' 0.001

4. Conclusions and Recommendation

A significant decrease in technical efficiency of agricultural production has been observed in selected SSA countries with an average downward trend of 23.06% for the last 25 years. Temperature and forest cover had a significant and positive influence on efficiency and greenhouse gases had a significant and negative influence on efficiency. Rainfall and population changes did not significantly influence technical efficiency. In the last 25 years, technical efficiency declined while greenhouse gases, temperature and agricultural land increased due to population pressure and climate change. The increase in population and agricultural land reduced forest coverage with climatic changes influencing rainfall amount. The agricultural value addition decreased during this period, an indication that farmers are becoming less efficient in adding value to agricultural production even in the face of climatic risks and population increase. The paradox observed was, the increase in population increased greenhouse gases and agricultural land and reduced forest cover that in turn reduced climatic mitigation with an increase in temperature and reduction in rainfall.

Therefore, there is need for concerted efforts to increase agricultural value addition and adopt more efficient agricultural practices. This will reduce deforestation, have sustainable agricultural food production for the increasing population and deal with the adverse effects of climate change in SSA countries.

Conflict of Interest

The author declares no conflict of interest.

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