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Effects of carbon dioxide emissions on agricultural production indexes in East African community countries: Pooled mean group and fixed effect approaches

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ABSTRACT

The ongoing climate change threat brought by the increase of carbon dioxide (CO_2) emissions in the atmosphere has rekindled global activism to address its detrimental effects on agricultural production with the maximum tenacity. The current study, consequently, examines the causal effect between CO_2 emissions and agricultural production indexes while controlling for renewable energy consumption, arable land and governance, using data spanning from 1996 to 2019. The study applied pooled mean group/Autoregressive distributed lag and fixed effect approaches and tested for the causality between the variable of interest using the Dumitrescu and Hurlin Granger non-causality test. The long-run equation shows that CO_2 emissions, renewable energy consumption, labour force and arable land size have positive effects on the crop production index. Whereas, renewable energy consumption, labour force, arable land size and governance positively affect the livestock production index. While no causality exists between CO_2 emissions and crop production index. However, the effects of governance and the size of arable land on agricultural production remained inconclusive. To achieve the UN Sustainable Development Goal of zero hunger for their people, East African Community countries need to commercialize agricultural production and embrace more eco-friendly farming techniques.

1. Introduction

Anthropogenic greenhouse gas emissions have been key drivers of climate change since the 1950s [1]. Thus, it endangers the sustainable exploitation and use of natural resources for both the present and future generations [2]. Besides, carbon dioxide (CO_2) is one of the greenhouse gases with a significant contribution to climate change, and it continues to receive renewed interest from the research community [3–6]. The quality of the environment is affected by increased consumption of materials in several ways, including global warming, depletion of resources, increased contamination of the environment, and a decline in plant and animal diversity [7]. The greatest strategy for preventing catastrophic repercussions of climate change on the earth is to keep temperature below 1.5 °C. However, the continuous increase in the global temperature means that we are still off course from achieving our goal [8]. An accelerated rise in carbon dioxide emissions causes global warming, and climate change, which threatens food production [9]. Agriculture especially livestock production is a significant contributor to global warming [2,10] and at the same time, both crops and livestock are the most impacted sectors by climate change [11]. Extreme arid conditions, which are becoming common as a result of climate change, reduce crop output by immobilizing nutrients and allowing the salt to build up in the soil, making it unhealthy, saline, and ultimately sterile [12]. The decline in crop production becomes more catastrophic when the increase in CO_2 emissions is in the absence of carbon fertilization [13]. However, agriculture provides for society's fundamental requirement for food production, but it should be accomplished without endangering global food security or ecological services [14]. Crop and livestock production is likely to decrease in the face of unprecedented climate change [10]. The pressure on agriculture stems from human

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activities that compromise the quality of the environment and reduce the limited arable land for livestock production [15]. The agricultural sector exerts a positive influence on the environment and plays a fundamental role in reducing carbon emissions through green investment in tree planting and afforestation [2,16].

The impact of global warming triggered by the increasing CO_2 emissions has a disproportionate incidence across the world regardless of which country contributes more to environmental degradation with Europe and the United States of America being the biggest contributors to global CO_2 emissions [10]. Sub-Saharan Africa has suffered severely and will continue to suffer the impact of climate change due to its weak adaptation and response to global warming coupled with an increased level of poverty [17]. The weak response to climate change shock has led to the loss of human lives, crops, and livestock and a decrease in income [18]. The East African Community (EAC) countries are not exceptional and the relationship between both the climate and way of life is quite profound in East Africa. Rural lifestyles in East Africa are extremely susceptible to climate volatility, such as changes in planting season settings, since the region relies significantly on rain-fed agricultural production [19]. In addition, 40 % of the EAC's GDP is derived from agriculture, and 80 % of East Africans depend on it for their livelihood. All the East African countries experienced food shortages in 2003 - 04 because of the weather, making them particularly susceptible to the consequences of climate change on their farming [19].

The empirical studies show inconclusive results on the causal effect of CO_2 emissions on the agricultural sector. A study by Appiah et al. [4] shows the feedback causality between CO_2 emissions and crop production index both in the short and long run for the panel data for Brazil, India, China and South Africa. Besides a study conducted with specific reference to Nigeria by [20] using Autoregressive distributed lag, Vector autoregressive and Granger causality approaches show a one-way causality running from CO_2 emissions to agricultural productivity. In addition, a study by Ayyildiz and Erdal [9] in selected 184 countries across the world from 1984 to 2014 shows a bidirectional causality between CO_2 emissions and Crop Production Index (CPI) in the short-run for lower-middle, upper middle and high-income countries. Sarkodie and Owusu [21] used time series data from 1960 to 2013 and found a bidirectional causality between crop production index and CO_2 emissions and a unidirectional causality running from the Livestock Production Index (LPI) to CO_2 emissions for the case of Ghana. A study by Pata [2] on the case of BRICS countries for the period of 1971–2016 confirms the two-way causality between agriculture and environmental pollution. The study indicates that agriculture is a victim to and a contributor to environmental pollution. Agriculture contributes to carbon emissions through farming methods such as the burning of the farmlands, draining of wetlands, use of agrochemicals, raring of ruminant animals that produce methane and use of fossil energies in the production process.

Energy is an important input in agricultural production. Energy consumption is required in the ploughing of land, making of fodder, pumping of water for irrigation, harvesting and drying of crops, grinding of grains and other agricultural activities. The studies have produced varying results on the causal effect between energy consumption and agricultural production. A study by Appiah et al. [4] using time series data for Brazil, India, China and South Africa based on Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS) and Pooled Mean Group (PMG) between 1971 and 2013 found livestock production index to Granger cause energy consumption in both the short and long run. Doğan [22] for China found no causality between renewable energy consumption and agricultural production in the case of China. In addition, Waheed et al. [23] found no causality between renewable energy consumption and per-worker agricultural value added in Pakistan. In the case of Portugal, Leitão and Balogh [24] found a unidirectional between energy running from consumption and crop production index and the causality. Leitão and Balogh's study was modelled based on ARDL, Autoregressive Integrated Moving Averages (ARIMA), Granger causality and Newey standard error regression techniques using time series data from 1960 to 2015.

A study conducted by Lio and Liu [25] in 127 selected countries across the globe using structural equation techniques and ordinary least squares with the panel-corrected standard errors shows that countries with better governance frameworks experienced higher agricultural output than their counterparts with weaker institutional frameworks even when the same amount of input factors are used. Therefore, the role of governance is pivotal in the promotion of agricultural production and is critical in providing incentives to farmers and regulating the market to ensure that quality products are produced Bethwell et al. [26]. However, the effect of governance on economic growth is not uniform across countries. Pruntseva et al. [27] show that government intervention in agricultural production by providing subsidies, lowers agricultural productivity. The negative effect of government expenditure on agricultural production is attributable to the market distortion by the governments through its intervention. For the recent literature, methodological developments and conclusions related to the study see Table 1.

First, the study is novel since it addresses the causal effect of CO_2 emissions on crop and livestock production. Many existing studies examine the effects of agricultural activities on CO_2 emissions and pay less attention to how CO_2 emission affects livestock and crop production [9,22,33,34]. To the best of our knowledge, this is the first study in EAC countries that examines how CO_2 emissions affect agricultural production from crop and animal perspectives. Examining the effect of CO_2 emissions on agricultural indexes will go a long way in determining the appropriate intervention in crop and livestock production in the face of global warming. The study controls for the effect of governance and renewable energy consumption within the EAC countries, which are key in climate change mitigation and adaptation.

Secondly, we contribute to the literature on carbon dioxide emissions and agricultural production indexes by applying a pooled mean group which allows short-run coefficient, error variances, and the speed of adjustment to vary across units, and the long-run slope coefficients are restricted to be homogeneous [35]. The PMG estimator under long-run slope homogeneity becomes more efficient and quite robust to outliers and the choice of lag order in its estimation. The approach captures the cross-sectional dependence of errors that occur due to spatial effect, interaction with socioeconomic networks, and omitted common factors of the cross-sectional units [36]. It also captures heterogeneity between countries under investigation since ignoring slope heterogeneity and assuming homogeneous slope coefficients in the panel data model may lead to invalid results on the effects of CO_2 emissions on agricultural production indexes. Previous studies [2,25,31] ignored testing for cross-sectional dependence, spatial effect, and heterogeneity. Similarly doing separate ordinary least-squares regression analysis for each country, while neglecting cross-sectional dependency decreases efficiency improvements [37].

The remaining section of this paper is as follows: section two provides the theoretical underpinning for the modelling, section three shows the material and methods followed to arrive at the results, section four presents the results and discussions of the study and lastly, section five presents the conclusion and policy implications.

2. Theoretical framework

The basic framework for studying agricultural production is built from the production theory. The theory shows that any production is a function of the input factors with capital (K) and labour (L) playing critical roles. The basic production equation for agricultural production is therefore expressed as follows:

$$A = f(\mathrm{K},\ \mathrm{L}) \tag{1}$$

where A measures agricultural production in terms of crop production

Table 1
Summary of related literature.

Sn	Author	Country	Period	Methodology	Conclusion
1	[25]	Selected 127 countries	1998, 2000 &2002	OLS-PCSE and SEM	Better governance has a positive effect on agricultural performance.
2	[28]	Selected 173 countries across the world	1975–2007	Between-group analysis and ANOVA test	Countries with lower-quality governance embrace the expansion of agricultural land rather than yield. While countries with high-quality governance prefer reducing the size of agricultural land and increasing agricultural productivity (yield).
4	[20]	Nigeria	1961–2010	ARDL, VAR, and Granger causality	CO_2→AGP AGP↛ CO_2
5	[29]	Tunisia	1980–2011	Johansen-Juselius cointegration, VECM	In the SR AVA↔ CO_2, AVA →REC, CO_2 →REC and in the LR AVA ↔ CO_2, AVA↔REC with AVA exerting a positive effect on CO emissions and REC pivotal in CO_2 emissions reduction.
6	[21]	Ghana	1960–2013	ARDL Granger causality	CPI ↔ CO_2 LPI →CO_2
7	[4]	Brazil, India, China, and South Africa.	1971–2013	FMOLS, DOLS, and PMG	In the SR, CO_2↔LPI, LPI→EC; In the LR CO_2↔ CPI, EC↔CO_2, EC→CPI, LPI→CO_2, LPI→EC
8	[23]	Pakistan	1990–2014	ARDL	REC has a negative effect on CO_2 emissions, while AGRIC and forest planting positively affect CO_2 emissions
9	[22]	China	1971–2010	FMOLS. DOLS, CCR	AGRI has positive effect on CO_2
10	[30]	Pakistan	1961–2014	Johansen cointegration and ARDL	AVA→Per capita CO_2 AVA has a positive effect on Per capita CO_2 Land under cereal crops has a positive effect on Per capita CO_2
11	[31]	West African countries (15 ECOWAS countries)	1990–2015	Panel Quintile Regression	AGRIC has a positive effect on per capita CO_2 emissions
12	[32]	China, Russia, India, Brazil, Mexico, Indonesia, Turkey (E7)	1990–2014	OLS, FMOLS, DOLS, VECM	AVA has a positive on CO_2 emissions, and REC has a negative effect on CO_2 emissions. In the SR REC→ CO_2 and both SR and LR AVA↔CO_2 emissions
13	[24]	Portugal	1960–2015	ARDL, ARIMA, Granger causality, Newey West standard error regression	EC, CPI and agricultural land use have positive effects on CO_2 emissions. Agriculture land use→ CPI CO_2 →EC EC →CPI LPI ↛ CO_2
14	[2]	Brazil, Russia, India, China, and South Africa (BRICS)	1971–2016	The Fourier ADL cointegration test and bootstrap FTY causality test.	AGIC↔ CO_2 REG →CO_2
15	[9]	Selected 184 countries classified as low-income, lower-middle-income, upper-middle income and high-income countries,	1998–2014	Dynamic common correlated effects technique	CPI has a positive on CO_2 emissions in lower-middle-income countries LPI has a positive effect on CO_2 emissions in all the classified categories except in low-income countries. CO_2↔CPI in the SR in low-income countries. CO_2→CPI in the SR in lower-middle-income countries and the LR→LPI→CO_2, CO_2→CPI and CPI →LPI LPI→CO_2 in the SR in upper-middle-income countries, and LR LPI →CO_2 and LPI→ CO_2 in the LR in high-income countries.

Notes: SR is Short-Run, LR: is Long-Run, LPI: is the livestock production index, CPI: is the crop production index, CO_2 is carbon dioxide, AGRIC: is agricultural output, AVA: is agriculture value-added, REC: is the renewable energy consumption, ARDL: is Autoregressive Distributed Lag, ADL: is autoregressive distributed lag, FMOLS: is fully modified ordinary least squares, DOLS: is dynamic ordinary least squares, PMG: is the pooled mean group, OLS-PCSE: is ordinary least squares with panel corrected standard errors, SEM: structural Equation model, VAR: is vector autoregressive, VECM: vector error correction model, ARIMA: is an autoregressive integrated moving average, FTY: is Fourier Toda Yamamoto, E7: is emerging seven countries, ↔: is bidirectional causality, →: is unidirectional causality, ↛: no causality.

index and animal production index, K is capital and L is labour. Following the neoclassical Cobb-Douglas production function, the output is expressed as:

$$A = \theta K^{\alpha} L^{\beta} \tag{2}$$

where θ denotes the total factor, which after productivity is normally attributed to technological progress, α and β are output elasticities showing the share of capital and labour in the production of output. The neoclassical production function makes a restrictive assumption of constant returns to scale, where $\alpha+\beta = 1$. The Cobb-Douglas production function in Eq. (2) is modified as follows:

$$A = \theta K^{\alpha} L^{\beta} E^{\gamma} \tag{3}$$

where E denotes energy consumption in the production of output and Eq. (3) is referred to as the augmented production function [38]. For the parameters to exhibit constant returns to scale, $\alpha+\beta+\gamma = 1$ [39]. Romer [40] in his endogenous growth theory and Lucas [41], show that the contribution of labour is overestimated in the neoclassical production and argues for the inclusion of knowledge acquisition or human capital accumulation in the production of output. Therefore, this justifies the inclusion of renewable energy consumption variables in our Cobb-Douglas Production function.

3. Materials and methods

3.1. Data

To examine the effect of CO_2 emissions on agricultural production (A) in constant 2015 US$, we used the World Bank data spanning from 1996 to 2019 (24 years dataset) for the EAC countries. The study covered 6 countries in the EAC regional block. These countries include Kenya, Uganda, Tanzania, Rwanda, Burundi, and the Democratic Republic of the Congo (DRC). South Sudan is excluded from the study given that its data points are few to provide meaningful and comprehensive analysis. However, DRC is included in the study although is a new member of EAC countries due to its geographical boundary with earlier member countries of EAC. Besides, DRC is among the member countries of the Great Lake Region where Uganda, Burundi, Tanzania, and Kenya are members. The geopolitical and trade relationship between these countries has existed for a long time.

We disaggregated agricultural production into crop production index (CPI), and Livestock production index (LPI). The crop production index displays annual agricultural output to the base period of 2014–2016 when agricultural commodity prices were stable. Other than fodder crops, all crops are included to avoid double counting. The underlying data in international US $, normalized to the base year 2014–2016, are used to produce regional and income group aggregates for the FAO's production indices. The Livestock Production Index comprises all types of meat and milk, dairy items like cheese and eggs, honey, raw silk, wool, and hides and skins. To control for the omitted variable bias, we added the arable land as a percentage of total land (ARL) and governance (GOV). To fill up the missing values in the data required for governance between 1996 and 2001 since the governance indicators we computed biannually, we followed Danish et al. [42] and applied a linear interpolation method. The fact that linear interpolation does not produce an overshoot, in contrast to cubic interpolation, makes it superior to the latter [43]. In general, cubic interpolation with a small number of points performs worse for smooth functions than linear interpolation. In addition, linear interpolation is more user-friendly than cubic interpolation. Table 2 presents the variables, definitions and sources of data used in the study.

3.2. Empirical model specifications

The model for our study is based on production theory [46,47]. Eq. (3) is modified to include CO_2 emissions as our explanatory variable and assesses the role of governance on agriculture expressed as follows:

$$A = \theta K^{\beta_1} L^{\beta_2} E^{\beta_3} C^{\beta_4}\ G^{\beta_4}\ X^{\beta_5} \tag{4}$$

where A stands for a vector of agriculture production, composed of the crop production index (2014–2016 = 100) and animal production index (2014–2016 = 100). Besides, θ is technological progress which is assumed to be constant, and K is capital stock measured as Gross capital formation (constant 2015 US$). While L is labour measured as labour total, E is Renewable Energy Consumption measured as a percentage of total final energy consumption C is CO_2 emissions is measured in kiloton, G is governance measured as an average of governance indicators, and X is arable land as percent of land area. Using the modified Eq. (4), the empirical model for determining the effect of CO_2 emissions on agricultural production is expressed in Eq. (5).

$$lnA_{it} = \alpha_i + \mu_i\zeta_t + lnk_{it} + lnlbr_{it} + \vartheta_3 lnrec_{it} + \vartheta_4 co_{2it} + \vartheta_5 lngov_{it} + lnal_{it} + u_{it} \tag{5}$$

$$u_{it} = \delta_i F_t + \varepsilon_{it}$$

where ***lnA*** stands for ***ln(A)***; ***lnk*** stands for ***ln(K)***;***lnlbr*** stands for ***ln***(L); ***lnrec*** stands for ln(*E)*; ***co*$_2$** stands for ln(C); ***lngov*** stands for ln(G); ***lnal*** stands for ln(X). *i* and *t* stand for individual countries and time respectively. In addition, α_i denotes country-specific intercept, in other words, it represents a time-invariant nuisance parameter. While ζ_t is observed such as world price shocks, global financial crises, global business cycles, and other global shocks. The unobserved common factor is denoted by F_t with a heterogeneous factor loading δ_i and serially uncorrelated with zero mean and constant variance, and $\varepsilon_{it} \sim \text{iid}(0,\ \sigma_\varepsilon^2)$.

3.3. Cross-sectional dependency

Macroeconomics panel data exhibit cross-sectional dependence (CD) in many cases making unit root test to have size distortions [48]. The CD errors occur due to spatial effect, interaction with socioeconomic networks, and omitted common factors of the cross-sectional units [36]. The conventional estimation method, such as random effects, and fixed

Table 2
Variable description and data sources.

Variables	Definition	Data sources
lncpi	Log of Crop production index (2014–2016 = 100)	WDI [44]
lnlpi	Log of Livestock Production Index (2014–2016 = 100)	WDI [44]
lnk	Log of Gross capital formation (constant 2015 US$)	WDI [44]
lnlbr	Log of the Labour force, total	WDI [44]
lnrec	Log of Renewable energy consumption (% of total final energy consumption)	WDI [44]
lnCO_2	Log of CO_2 emissions kt (kiloton)	WDI [44]
lngov	Log of Political Stability and Absence of Violence/ Terrorism, Voice and Accountability, Regulatory Quality, Control of Corruption, Government Effectiveness, rule of law, and control of corruption (ps+va+rq+ge+rl+cc)/6	WGI [45]
lnarl	Log of Arable land (% of land area)	WDI [44]

Source: Authors' construction.

effects, can produce inconsistent parameter estimates and misleading inferences in the presence of CD [49,50]. The study tested for cross-sectional dependence in panel data because the choice of appropriate methods will depend on its occurrences. The LM test [51,52] for cross-sectional dependence is key when $T > N$ since it produces more consistent and reliable results. The LM test is defined as follows:

$$LM = T\left(\sum_{i=1}^{N-1}\sum_{j=1+1}^{N}\widehat{\rho}_{ij}^{2}\right) \tag{6}$$

where T is the time in years, N is the number of cross-sectional units and ρ_i is the cross-sectional correlation error estimate of country i and j.

The study used Pesaran's [53] CD test due to its robustness in dealing with structural breaks and the non-normality of errors. In addition, the CD applies to a wide range of panel data such as non-stationary models, and heterogeneous/homogeneous dynamic models (Hoyps and Saradifis, 2006). Pesaran's [53] CD test is also suitable for panel data with small T and N dimensions and small T and large N dimensions [54]. Pesaran's [53] CD test statistic is as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\widehat{\rho}_{ij}\right) \sim N(0,1)i,j = 1,2,3,\dots,N \tag{7}$$

where $\widehat{\rho}_{ij} = \widehat{\rho}_{ji} = \frac{\sum_{t=1}^{T} e_{it}e_{jt}}{\sum_{t=1}^{T}(e_{it})^{1/2}(e_{jt})^{1/2}}$

Where $\widehat{\rho}_{ij}$ is the sample estimate of the pairwise correlation of residuals (e_{it}) derived from the ordinary Least square estimation.

3.4. Panel unit root

The cross-sectional dependence tests guide the selection of either first-generation or second-generation unit root tests. Ignoring these tests leads to inconsistent and biased results [53,55]. In the presence of cross-sectional independence and homogeneous slope coefficients, a panel unit root test developed by [56] (henceforth LLC) will apply.

The application of panel unit root tests such as Maddala and Wu [57], Levin et al. [56], and Im et al. [58] are restrictive in macroeconomics and not appropriate where there is cross-section dependence and the presence of international shocks [55,59]. Pesaran [60] proposed cross-sectionally Augmented DF (CADF) statistics as follows:

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i \overline{y}_{t-1} + \omega_i \Delta\overline{y}_{it} + \mu_{it} \tag{8}$$

where $\overline{y}_{t-1} = N^{-1}\sum_{i=1}^{N} y_{i,t-1};\ \Delta\overline{y}_{it} = N^{-1}\sum_{i=1}^{N}\Delta y_{i,t}$

Cross-sectionally augmented version of IPS test statistic (CIPS) is expressed as:

$$CIPS(N,T) = t - bar = N^{-1}\sum_{i=1}^{N} t_i(N,T) \tag{9}$$

where $\mathrm{t_i(N,\ T)}$ is CADF (t) statistic of β_i of OLS regression. Augment. The null hypothesis is there exists cross-sectional independence in the series versus the alternative of cross-sectional dependency in the series.

3.5. Panel co-integration

After establishing that the stationarity of the parameters exists at least at the first difference. We apply panel cointegration tests, which investigate the existence of a long-term relationship or cointegration between variables in a panel dataset. The study adopts the Westerlund cointegration test [61] that takes into account both the time series dynamics and the cross-sectional heterogeneity or differences between entities as in the case of our data. For the robustness check, the study applies Kao's residual cointegration test developed by Kao (999) which shows cross-section specific intercepts and homogeneous coefficients on the first-stage explanatory variables.

3.6. Model estimation

The PMG allows short-run coefficient, error variances, and the speed of adjustment to vary across units, and the long-run slope coefficients are restricted to be homogeneous [35]. The long-run equilibrium correlations between variables are similar across countries due to arbitrage conditions or common technologies, and solvency constraints or budgets influencing all the cross-sectional units [35]. The assumptions of short-run dynamic slope coefficients allow dynamic specifications to differ across groups [35]. The PMG estimator under long-run slope homogeneity becomes more efficient and quite robust to outliers and the choice of lag order in its estimation than the mean group estimators. The error-correction term of the estimated PMG model is denoted as follows:

$$\Delta CPI_{it} = \lambda_i\left(CPI_{i,t-1} - \theta_{ij}^{'}X_{i,t}\right) + \sum_{j=1}^{p-1}\varphi_{ij}^{*}\Delta \mathrm{CPI}_{i,t-j} + \sum_{j=0}^{q-1}\delta_{ij}^{*'}\Delta \mathrm{X}_{i,t-j} + \mu_i + \upsilon_{i,t} \tag{10}$$

where *CPI* is the crop production index and *X* is a vector of explanatory variables. The parameter λ_i is the coefficient of error correction term (ECT), which after estimating the model, should be negative and statistically significant so that any short-run shock from any of the independent variables can be restored in the long run. If $\lambda_i = 0$, then there will be no evidence for a long-run association, $\theta_i^{'}$ contains long-run coefficients between the variables and μ_i is the group-specific effect [62]. In the absence of the long-run relationship in the case of LPI model using Kao and Westerlund cointegration tests, the ARDL/PMG model would be inappropriate. It is therefore appropriate to estimate the LPI model using the fixed effect (FE) elevated with Driscoll and Kraay standard errors [63]. Thus, controlling for serial correlation, heteroscedasticity, and cross-sectional dependence which is a common problem in panel data [64].

3.7. Causality

A clear understanding of the direction of causality between CO_2 emission and its determinants are important in designing CO_2 emission-specific policies [65]. Dumitrescu and Hurlin [66] developed a causality test in an extension of the Granger causality test (1969), which assumes slope homogeneity and intercept to be the same. To account for slope heterogeneity that always exists in the macroeconomic panels, Dumitrescu and Hurlin (DH henceforth) developed a heterogeneous panel Granger non-causality test [66], and all the variables are considered to be endogenous. The DH test detects the bivariate based causality in the panel regression equation expressed as:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K}\gamma_i^{(k)}y_{i,t-k} + \sum_{k=1}^{K}\vartheta_i^{(k)}x_{i,t-k} + \epsilon_{i,t} \text{ with } i = 1,\ \dots, N \text{ and } t = 1\dots T \tag{11}$$

$$x_{i,t} = \alpha_i + \sum_{k=1}^{K}\vartheta_i^{(k)}x_{i,t-k} + \sum_{k=1}^{K}\gamma_i^{(k)}y_{i,t-k} + \epsilon_{i,t} \text{ with } i = 1,\ \dots, N \text{ and } t = 1\dots T \tag{12}$$

$$K \in \mathbb{N}^{+} \ and\ \vartheta_i = \vartheta_i^1,\dots,\vartheta_i^K,\ \vartheta_i = \gamma_i^1,\dots,\gamma_i^K$$

where $y_{i,t}$ and $x_{i,t}$ denote observations of two pairwise stationary variables to be used in the study at a time with N individual in T Period. In the estimation, the lag order K is identical for all the individual units determined by the information criterion. The coefficients are time-invariant but are allowed to vary across groups and α_i is the individual fixed effect and the panel is balanced.

The study estimation phases are illustrated in Fig. 1.

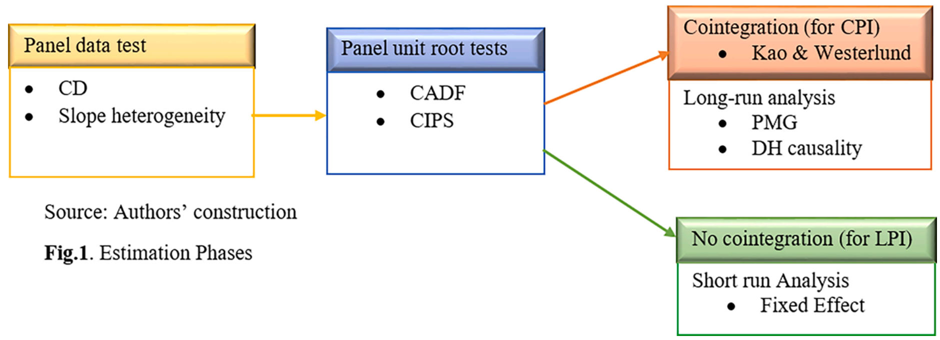

Fig. 1. Estimation phases.

4. Results and discussion

4.1. Descriptive statistics

The study analyzed the effect of CO_2 emissions on agricultural production and control for the effect of labour, capital, renewable energy consumption, governance and arable land. The agricultural production is split in terms of crop production index and life stock production. We examined six countries who are members of EAC from 1996 to 2019 with 144 observations. Table 3 reports the behavior of the variables used in the study.

The results show that the mean and median of the log of crop production index, log of livestock production index, log of capital, log of labour, log of renewable energy consumption, log of CO_2 emissions, log of governance, log of arable land are not significantly different from each other. Besides, their standard deviations are also small. Therefore, we can conclude that all six countries are almost at the same level of economic development. The correlation between the variables under-study is depicted in Table 4. There is a link between crop production and livestock production and the relationship is statistically significant at 1 %. In addition, the study shows that gross capital formation is not associated with the crop production index in EAC countries but is positively related to livestock production and statistically significant at a 1% level. Labour is negatively associated with crop production and statistically significant at 1% while it is positively associated with livestock production index and also statistically significant at 1%. There is no correlation between renewable energy consumption and livestock production, while renewable energy consumption is negatively associated with crop production. In addition, there is a weak negative correlation between CO_2 emissions and crop production and CO_2 emissions have a positive association with livestock production and are statistically significant at 1%. In addition, there is a negative association between CO_2 emissions and renewable energy consumption statistically significant at 1%. Good governance is positively correlated with crop production and statistically significant at 1% but it has no association with livestock production.

The size of arable land is positively correlated with crop production and negatively correlated with livestock production. The pairwise correlation coefficients among the variables under investigation are moderate since most coefficients are below 0.6. This implies that there is no possibility of multicollinearity in our estimated models.

4.2. Cross-section dependency

Cross-sectional dependence (CD) is a common feature of macroeconomic panel data, which causes size distortions in unit root tests [48]. We examined the possibility of cross-sectional dependency in our variables using Breusch-Pagan LM, Pesaran scaled LM, bias-corrected scaled LM and Pesaran CD tests. The results of different tests are reported in Table 5.

The null hypothesis of cross-sectional independence is rejected at a 1 per cent level of significance and we can conclude that there is a significant level of dependence among EAC countries because the majority of tests indicated cross-sectional dependence. This result is expected since EAC countries share borders and there is a lot of intra-regional trade.

4.3. Panel unit root test results

The existence of cross-sectional dependence and slope heterogeneity shows that panel unit root tests for cross-sectional independence such as those developed by Levin et al. [56] become biased and inefficient [67] and restrictive in macroeconomics and not appropriate where there is cross-section dependence and the presence of international shocks [55, 59]. We, therefore, applied the [60] proposed cross-sectionally Augmented DF (CADF) statistics and a cross-sectionally augmented version of the IPS (CIPS) test statistic. The results of the panel cointegration tests are reported in Table 6. The null hypothesis states that there is the existence of a panel unit root in the series versus the alternative hypothesis of the presence of stationarity in the series. The log of capital and labour are stationary at least at the first difference using both CADF and CIPS. All the variables are stationary at the first difference, which implies that the variables are either I(0) or I(1) which makes them ideal for running PMG/ARDL models.

4.4. Panel cointegration

We used the panel cointegration tests developed by Kao [61,68] to determine whether there is non-spurious long-run cointegration among the variables. The cointegration tests developed by Kao and Westerlund offer a comprehensive framework for panel cointegration testing. Table 7 shows the existence of long-run cointegration in model 1 for CPI as reflected by six separate test statistics, each with a probability value

Table 3
Descriptive statistics.

Statistics/Variables	lncpi	lnlpi	lnk	lnlbr	lnrec	lnCO_2	lngov	lnarl
Mean	4.420	4.344	21.591	16.153	4.493	7.626	0.787	2.822
Maximum	4.995	4.890	23.777	17.247	4.588	10.011	0.962	3.870
Minimum	3.549	3.399	18.617	14.774	4.221	5.012	0.433	1.084
Std. Dev.	0.336	0.309	1.410	0.747	0.079	1.322	0.136	0.899
Observations	144	144	144	144	144	144	144	144

Table 4
Correlation matrix.

Correlation	LNCPI	LNLPI	LNK	LNLBR	LNREC	$LNCO_2$	LNGOV	LNARL
LNCPI	1							
	—							
LNLPI	0.265[a]	1						
	(0.001)	—						
LNK	0.069	0.509 [a]	1					
	(0.414)	(0.000)	—					
LNLBR	−0.293 [a]	0.508 [a]	0.873 [a]	1				
	(0.000)	(0.000)	(0.000)	—				
LNREC	−0.203 [b]	−0.121	−0.397 [a]	−0.169 [b]	1			
	(0.015)	(0.149)	(0.000)	(0.042)	—			
$LNCO_2$	−0.141[c]	0.400 [a]	0.919 [a]	0.878 [a]	−0.552 [a]	1		
	(0.091)	(0.000)	(0.000)	(0.000)	(0.000)	—		
LNGOV	0.335 [a]	−0.089	0.355 [a]	−0.050	−0.487 [a]	0.292 [a]	1	
	(0.000)	(0.287)	(0.000)	(0.549)	(0.000)	(0.000)	—	
LNARL	0.638 [a]	−0.238 [a]	−0.449 [a]	−0.789 [a]	−0.018	−0.561 [a]	0.503 [a]	1
	(0.000)	(0.004)	(0.000)	(0.000)	(0.833)	(0.000)	(0.000)	—

Note: The figures in the parentheses are p-values.
[a] Denotes a 1 % statistical level of significance.
[b] Denotes a 5 % statistical level of significance.
[c] Denotes a 10 % statistical level of significance.

Table 5
Cross-sectional dependence tests.

Test	cpi	lpi	lnk	lnlbr	lnrec	$lnCO_2$	lngov	lnarl
Breusch-Pagan LM	146.08[a]	225.73 [a]	291.31 [a]	355.19 [a]	176.41 [a]	243.9[a]	109.55 [a]	237.08 [a]
Pesaran scaled LM	23.93 [a]	38.47 [a]	50.45 [a]	62.11 [a]	29.47 [a]	41.79[a]	17.26 [a]	40.55 [a]
Bias-corrected scaled LM	23.80 [a]	38.34 [a]	50.32 [a]	61.98 [a]	29.34 [a]	41.66[a]	17.13 [a]	40.42 [a]
Pesaran CD	8.33 [a]	14.49 [a]	16.89 [a]	18.85 [a]	12.54 [a]	15.47[a]	8.91 [a]	15.20 [a]

[a] denotes a 1 % level of significance and indicates the rejection of the null hypothesis of no cross-sectional dependence.

Table 6
Panel unit root test.

Variables	CADF		CIPS	
	Level	Δ	Level	Δ
lncpi	−1.460	−2.875[a]	−2.180	−5.497 [a]
lnlpi	−0.364	−2.092	−0.691	−3.939 [a]
lnk	−2.445[b]		−2.753 [a]	
lnlbr	−2.459[b]		−2.460 [b]	
lnrec	−1.983	−2.885[a]	−1.143	−3.046 [a]
$lnCO_2$	−2.262	−2.966[a]	−1.567	−3.716 [a]
lngov	−1.729	−4.252[a]	−1.719	−4.377 [a]
lnarl	−1.445	−2.196	−1.548	−3.017 [a]

Note: Critical values are −2.21(10 %), −2.33(5 %),−2.57(1 %). The deterministic chosen: constant.
Δ Denotes the first difference. CADF is computed using a t-bar statistic.
[a] Denotes 1 % statistical significance.
[b] Denotes 5 % statistical significance.

Table 7
Panel cointegration tests for EAC countries (model 1).

Kao and Westerlund panel cointegration tests	Statistics	P-value
lnCPI=*f*(lnCPI+lnK+lnLBR+lnrec+$lnCO_2$+lnGOV+lnARL)		
Kao panel cointegration test		
Modified Dickey-Fuller	−4.4448	0.000
Dickey-Fuller	−3.4003	0.000
Augmented Dickey-Fuller	−1.5359	0.062
Unadjusted modified Dickey-Fuller	−5.0770	0.000
Unadjusted Dickey-Fuller	−3.5517	0.000
Westerlund panel cointegration test		
Variance ratio	−1.6441	0.050

Table 8
Panel cointegration tests for EAC countries (model2).

Kao and Westerlund panel cointegration tests	Statistics	P-value
lnLPI=*f*(lnCPI+lnK+lnLBR+lnrec+$lnCO_2$+lnGOV+lnARL)		
Kao panel cointegration test		
Modified Dickey-Fuller	−0.3944	0.3466
Dickey-Fuller	−0.2587	0.3979
Augmented Dickey-Fuller	0.0801	0.4681
Unadjusted modified Dickey-Fuller	−0.5995	0.2744
Unadjusted Dickey-Fuller	−0.3872	0.3493
Westerlund panel cointegration test		
Variance ratio	−0.9258	0.1773

thereby making it suitable for the long-run model estimation and Granger causality tests. Nonetheless, Table 8 depicts that the long-run relationship does not exists in the model 2 for LPI, since all the six distinct statistics are statistically insignificant, making it only possible to estimate short run model.

4.5. Estimation results

The existence of I(0) and I(1) in the series, cross-sectional dependency and cointegration in our models allow us to estimate the PMG/ARDL models. The result for the empirical model 1 is reported in Table 9. For the short-run analysis, only labour is statistically significant at 10 percent, and it has a negative effect on crop production. This is probably because the marginal product of labour in the agricultural sector is zero implying that an additional increase of labour in the agricultural sector without augmenting labour with skill and capital leads to a fall in production. The gross capital formation, renewable energy consumption, CO_2 emissions, governance, and the size of arable land do not have a significant effect on crop production in the short run. However, the coefficient of error correction term, which is the speed of

Table 9
Regression estimates for CPI (Model1).

Dependant variable: cpi variables	pmg/ardl			p-value
	coefficients	Standard Error	t-statistics	
Short run equation				
Δ(lnk)	0.025582	0.050425	0.507334	0.613
Δ(lnlbr)	−4.849210	2.66559	−1.819189[c]	0.072
Δ(lnrec)	2.262923	2.91754	0.775627	0.440
$\Delta(lnco_2)$	−0.032433	0.163689	−0.198137	0.843
Δ(lngov)	1.570614	1.029791	1.525179	0.131
Δ(lnarl)	−1.205999	0.899131	−1.341294	0.183
ect_{t-1}	−0.633963	0.180732	−3.507740[a]	0.001
Long run equation				
Lnk	0.051572	0.050089	1.029595	0.306
lnlbr	0.308794	0.123606	2.498217[b]	0.014
lnrec	1.714103	0.472375	3.628692[a]	0.000
$lnCO_2$	0.245970	0.061847	3.977093[a]	0.000
lngov	−1.589857	0.248447	−6.399185[a]	0.000
lnarl	1.120394	0.104425	10.72920[a]	0.000
constant	−8.029386	2.230327	−3.60009[a]	0.000

Note: Model selection method: Akaike info criterion (AIC); Selected Model: ARDL (1, 1, 1, 1, 1, 1, 1); Fixed regressors: Constant; Δ: is the difference operator:
[a,b,c] Denote 1 %, 5 % and 10 % statistical significance, respectively.

adjustment towards long-run equilibrium possesses a negative sign and is statistically significant at a 1% level. Therefore, any departure from long-run equilibrium is corrected each period.

In addition, the long-run analysis shows that the labour force has a substantial positive contribution to the crop production index. The study result is in line with economic theory on the key role of labour in production [46,47]. However, it disagrees with Warsame et al. [69] who find agricultural labour to have a negative effect on crop production in Somalia. We also found renewable energy consumption to have a positive effect on the crop production index. The finding is consistent with Chel and Kaushik [70] who show that the application of renewable energies has a significant contribution to sustainable agriculture. In addition, the study shows that carbon dioxide emission has a positive effect on the crop production index. This implies that the increase in the level of CO_2 emissions does not harm crop production in presence of carbon fertilization [13]. The finding is consistent with Ejemeyovwi et al. [71] in Nigeria, while it disagrees with Warsame et al. [69] who found CO_2 emissions not to have a significant effect on crop production in Somalia.

Furthermore, the study found governance to have a negative effect on the crop production index in the long run. This implies that an improvement in the quality of governance worsens the quantity of crops produced by the farmers. This is probably due to the long history of privatization of agricultural production and value chain. The regulatory framework under privatization made the smallholder farmers vulnerable to exploitation by intermediaries, and their protections under the cooperative umbrella were eroded. However, the study result is inconsistent Lio and Liu [25], who conducted a panel study among 127 countries across the world. Lio and Liu's study shows that given the same quantities of agricultural inputs, the identical amount of education, and the same climatic conditions countries with superior governance have higher agricultural output. Besides, the study found the size of arable land to have a significant effect on the crop production index. This implies that increasing land under cultivation increases the level of food produced. The finding of the study, therefore, is consistent with Warsame et al. [69] who reported that land under cereal cultivation positively and significantly affects crop production.

Table 10 reports the results of model 2 estimation using fixed effect elevated with Driscoll and Kraay standard errors [63]. Gross capital formation has a negative and insufficient effect on livestock production in EAC countries. In all the models, the gross capital formation does not affect agricultural production. This implies that existing capital investments were not directed towards agricultural mechanization, and this explains why agricultural production in EAC member countries is still dominated by peasants. The model 2 shows that labour has a positive and significant effect on the animal production index. The effect of labour on animal production is similar to that of crop production. This makes the role of labour consistent with the production theory [46,47]. Further, the study shows that renewable energy consumption has a positive effect on livestock production and is statistically significant at 1%. This implies increasing the uptake of renewable energies such as the use of solar pumps and windmills for pumping water animals, solar dryers, and solar photovoltaics for lighting by the farmers increasing the likelihood of more animal production. This study is consistent with Chel and Kaushik [70]. In addition, CO_2 emissions led to a reduction in livestock production and the result is statistically significant at 1%. The study shows that the increase in CO_2 emissions in the atmosphere affects animal production negatively. This study is contrary to Gershon and Mbajekwe [72] who found the increase in CO_2 emissions enhances livestock production in Nigeria.

Table 10
Fixed-effects regression with Driscoll-Kraay standard errors (Model2).

Variables	Coefficient	Drisc/Kraay Standard Error	t-Statistics	P-value
Capital	−0.088	0.063	−1.390	0.179
Labour	0.996	0.194	5.140[a]	0.000
Renewable energy consumption	1.098	0.438	2.510[b]	0.020
Carbon dioxide emissions	0.298	0.060	4.970[a]	0.000
Governance	1.344	0.452	2.970[a]	0.007
Arable land size	−0.255	0.160	−1.600	0.124
constant	−17.398	3.166	−5.490[a]	0.000

[a,b,c] Denote 1 %, 5 % and 10 % statistical significance, respectively.

In the second model, we found improvement in the quality of governance leads to an increase in livestock production. We expected this result since good governance provides a good institutional framework, which enables livestock production to strive. The result is consistent with a study conducted in the Netherlands, Austria and Germany revealed that agricultural production and value chain are positively influenced by governance which enables farmers to address the societal interest, vulnerability and quality of products supplied to the market [26].

Besides, the effect increase in the size of arable land as a percentage of the total land on livestock production is insignificant. In EAC countries, most of the arable land is communally owned which makes it difficult to allocate and manage livestock production in the absence of clear property rights. Coupled with the above, tropical diseases are prevalent such as foot-and-mouth disease, viral infection, and tick-borne diseases, which may undermine the increase in the size of arable land in the face of poor disease management.

4.6. *Causality test results*

Table 11 reports the Dumitrescu and Hurlin [66] causality test results. We found gross capital formation to Granger caused crop production. This implies that the increase in capital especially agricultural mechanization and other farm implements is key to in predicting crop production in EAC countries. On the other hand, the labour force is also critical in the crop production process. A bidirectional causality exists between labour and crop production index. However, renewable energy consumption does not Granger cause crop production index. This implies the use of renewable energies such as wind, solar and small-scale hydro, are not yet fully abreast by the farmers in EAC countries. The

Table 11
Causality test.

Null Hypothesis:	W-Stat.	Zbar-Stat.	Prob.	Decision
lnk ↛ lncpi	5.08321	5.68207 [a]	0.000	Reject the null hypothesis
lncpi ↛ lnk	1.73734	0.89582	0.370	Failed to reject the null hypothesis
lnlrb ↛ lncpi	5.03422	5.61199 [a]	0.000	Reject the null hypothesis
lncpi ↛ lnlbr	4.75869	5.21784 [a]	0.000	Reject the null hypothesis
lnrec ↛ lncpi	1.32770	0.30983	0.757	Failed to reject the null hypothesis
lncpi ↛ lnrec	3.12123	2.87546 [a]	0.004	Reject the null hypothesis
$lnCO_2$ ↛ lncpi	1.76843	0.94029	0.3471	Failed to reject the null hypothesis
lncpi ↛ $lnCO_2$	2.10185	1.41725	0.1564	Failed the reject null hypothesis
lngov ↛ lncpi	2.12571	1.45138	0.147	Failed to reject the null hypothesis
lncpi ↛ lngov	2.51631	2.01013 [b]	0.044	Reject the null hypothesis
lnarl ↛ lncpi	5.04354	5.62532 [a]	0.000	Reject the null hypothesis
lncpi ↛ lnarl	2.49842	1.98454 [b]	0.047	Reject the null hypothesis

Note: ↛ denotes does not Granger-cause. The lag order is 1 selected based on the information criteria. The null hypothesis shows that the regressor does not Granger cause the regressand versus the alternative hypothesis of otherwise.
[a,b,c] Denotes a 1 %, 5 % and 10 % statistical level of significance, respectively.

study shows a one-way causality running from crop production index to renewable energy consumption. Therefore, agricultural production is key in promoting the use of renewable energy systems such as solar pumps, and solar irrigation. Further, empirical evidence suggests that using renewable energy contributes to the development of pollution-free consumption, production and sustainable development [37,73].

Crop production does not Granger cause CO_2 emissions in EAC countries. This implies that crop production does not predict the future level of CO2 emissions in EAC countries. This is probably due to the use of rudimentary technologies such as pangas, hand hoes, and ox ploughs for farming. The use of heavy machines such as tractors and combine harvesters is at a very low scale. We also found crop production to Granger cause governance. The increase in crop production is a measure of wealth and therefore affluence is responsible for good governance. This is in line with a study by Lustrilanang et al. [74] for the ASEAN countries, which shows that countries with higher incomes exhibit better governance structures.

The feedback causality exists between the size of arable land and crop production index, which shows that the size of arable land in hectares predicts agricultural production to increase and at the same time the increase in agricultural production predicts the size of arable land brought under production. This is because, in EAC countries, the only sure way of increasing agricultural production is to increase the size of land. Modern crop production practices that increase productivity are still low. Most of the crop production comes from small-scale farmers who account for the bulk of marketed agricultural surpluses in the region [75]. This shades a bad future for EAC agricultural production in which agricultural land per capita is reducing due to population growth.

5. Conclusion

The study examines the effects of CO_2 emissions on agricultural production based on the standard Cobb-Douglas production function. We controlled for the effect of renewable energy consumption as an input in the production process, governance, and the size of arable land in hectares. We considered agricultural production as a vector of both crop and livestock production. To ensure that the estimations are efficient and unbiased, we tested for cross-sectional dependency, slope heterogeneity, panel unit root, and panel cointegration before estimating the PMG/ARDL and fixed effect models. The preliminary results indicate cross-sectional dependency and slope heterogeneity in all the estimated models. All the variables used in the models were at least stationary at least at the first difference and the Kao and Westerlund cointegration tests show the existence of the long-run relationship for CPI and absence for the case of LPI. We also tested for the existence of causality in some selected series in the model for CPI. The result of the study shows that in the long run, labour, renewable energy consumption, CO_2 emissions, and arable land have a positive effect on crop production. However, governance has a negative effect on crop production while gross capital formation has no significant effect on crop production. In addition, labour, renewable energy consumption, governance, and arable land have a significant effect on livestock production. Further, CO_2 has a positive effect on livestock production and the role of gross capital formation and size of arable land in EAC countries were negligible in explaining livestock production. The causality results show that gross capital formation and arable land Granger cause crop production in EAC countries. While the feedback causality exists between labour and crop production. Further, crop production Granger causes renewable energy consumption, arable land, and governance.

5.1. Policy recommendations

The study's empirical results lead to several valuable deductions that have significant policy implications for the EAC countries and other nations with comparable political and economic systems to those under consideration. Renewable energy consumption will help in decoupling agricultural production from CO_2 emissions. The study recommends that EAC countries should increase the intake of renewable energy consumption and technologies in agriculture production such as the use of solar dryers, solar pumps, and irrigation, use of wind power, and other renewable options to reduce the level of CO_2 emissions from agricultural activities. Further, EAC countries should integrate climate change in the regional sectoral plans, and more engagement by civil society organizations is required to create more awareness in the public and engage the government to be more responsive to the effect of CO_2 emissions on agricultural production. To ensure that there is effective utilization of land in EAC countries and reduced negative effects of implementing new policies, government programmes, property rights on land acquisition and land use should be carefully done so that the legal regimes do not hurt farmers without due compensation to their land. In addition, countries in the East African Community should commercialize agricultural production to meet the UN Sustainable Development Goal of zero hunger among their citizens.

Nonetheless, the study's inferences are not free from limitations. The study is based on the data provided by the World Bank, which may not be free from measurement bias. The study follows PMG/ARDL and fixed effect estimation strategies with some restricted assumptions, however, the alternate panel data approaches anchored on non-linear models with additional variables in the model estimation may generate different outcomes. We, therefore, suggest that future studies can look at the long-run effect of CO_2 emissions on livestock production in EAC countries using data on precipitation and temperature based on other panel data techniques for the robustness check and better policy formulation and intervention.

Ethical approval

We can confirm that this manuscript has not been published before and is not currently being considered by another journal. This study does not require ethical approval or informed consent.

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CRediT authorship contribution statement

Jacob Otim: Conceptualization, Data curation, Formal analysis, Writing – original draft, Writing – review & editing. **Susan Watundu:** Writing – review & editing, Supervision. **John Mutenyo:** Writing – review & editing, Supervision. **Vincent Bagire:** Writing – review & editing, Supervision. **Muyiwa S Adaramola:** Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The World Bank has data that backs up the findings of this study and it will be available upon request.

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