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Article

Farm Gate Level Analysis of Crop Production and Emissions in Africa’s Regional Trading Bloc Member States

Lathiff Sesay ^{1,2,*}, Julius Mangisoni ¹, Innocent Panga-Panga Phiri ^{1,2,3} and Assa M. Maganga ^{1,2}

¹ Department of Agricultural and Applied Economics, Bunda College, Lilongwe University of Agriculture and Natural Resources, Lilongwe, Malawi

² Africa Centre for Agricultural Policy Analysis (APA), Bunda College, Lilongwe University of Agriculture and Natural Resources, Lilongwe, Malaw

³ Centre for Agricultural Research and Development (CARD), Bunda College, Lilongwe University of Agriculture and Natural Resources, Lilongwe, Malawi

* Correspondence: lathiff33@gmail.com or 230101867@luanar.ac.mw

Abstract

An in-depth analysis of the drivers of agricultural emissions at the primary crop output and farm-gate levels is crucial to achieving net-zero emissions by 2050. This study examines the short- and long-run effects of crop production on farm-gate emissions in the regional trading bloc (RTB) member states in Africa. We proxy crop production by cereals, roots and tubers, vegetables, and fruits production, and split emissions into methane and nitrous oxide emissions. Furthermore, we collected data on these variables from 30 member states of the selected RTBs in Africa from 1990 to 2022, which we analyzed using the cross-sectional augmented autoregressive distributive lag approach that controls for endogeneity and heterogeneous slopes. We also employed the pooled mean group and sub-sample analyses as robustness checks to ensure the reliability of study findings. Our results revealed that cereal production increases farm-gate methane and nitrous oxide emissions in Africa’s RTB member states in the short- and long-run. The increase is between the range of 1.0021 to 1.0033 kilotons CO₂-eq yr⁻¹ for methane, and 1.0024 to 1.0035 kilotons CO₂-eq yr⁻¹ for nitrous oxide on average. Thus, cereal production has a more adverse effect on nitrous oxide than methane emissions. In addition, fruit production increases farm gate methane emissions in Africa’s RTB member states by 1.0023 kiloton CO₂-eq yr⁻¹ on average in the long run. We recommend promoting climate-smart agriculture, investing in agricultural emissions monitoring, surveillance, and reporting systems, and targeting cereal and fruit production systems in RTB emission control plans.

Keywords: STIRPAT; methane; nitrous oxides; cereals; fruits; vegetables; roots and tubers

1. Introduction

The global surface temperature rose by 1.1 Degree Celsius between 1850 and 1900 and between 2011 and 2020. Such a trend is expected to continue, partly with increases in greenhouse gas (GHG) emissions caused by human activities [1], posing a serious challenge in pegging warming to 1.5 degrees Celsius and achieving net zero emissions by 2050. These anthropogenic sources of GHG emissions include the Combustion of fossil fuels for energy generation, deforestation, and industrial operations [2], which contribute to climate change. Climate change causes drought, flooding, and heat stress. The combined effects of climate change, growing world population, and economic growth put significant pressure on the agricultural sector, particularly the crop subsector, to fulfill its roles [3–5].

Crops are the primary division of the agricultural sector. It can be categorized as the output from cereals, roots and tubers, vegetables, and fruits, which are geared towards increasing food security,

reducing malnutrition, and increasing trade [6,7]. The achievement of the role of crops has become critical as crop production and animal numbers will need to increase by 60% from 2006 levels to meet the food demand for the 9.7 billion people in 2050 [8]. Approximately 80% of the desired increase in the food demand in developing nations is expected to be achieved through greater cropping intensity and yields, with the remaining 20% coming from the expansion of arable land [9].

Consequently, in Africa, the regional trading bloc (RTB) member states made commitments under the Malabo Declaration (MD) to accelerate growth in the agricultural sector, achieve food security, and improve livelihoods [10]. Tracking the progress made by RTBs in fulfilling the commitments of member states under the MD in 2022 revealed that the Southern African Development Community (SADC) experienced a 2.6 percentage rise in agricultural output from 2014 to 2022, the Economic Community of West African States (ECOWAS) recorded the highest percentage change in agricultural production of 3.2 percent followed by the East African Community (EAC) with a 2.7 percent increase. The lowest annual average (1.5 percent) was registered in the Arab Maghreb Union (AMU). For individual crops, such as maize and roots and tubers produced by the EAC, ECOWAS, and SADC in 2022, cassava, with the highest average for all crops, has significant growing potential across the RTBs. Cassava is the only non-cereal crop among the top five crops, and, along with yams, represents a huge proportion of agricultural output, thus underscoring the continent's drive to attain food security [11].

The diversification of the agricultural sector in Africa extends beyond the provision of staples to trade. For instance, edible fruits and oil accounted for 21 percent of agricultural exports [11]. In addition, there is considerably higher variability in cereal production observed in RTB member states relative to the RTB level, suggesting the potential for intra-RTB trade [12]. However, the potential of the agricultural sector and trade to boost African economies is hindered by the effects of climate change.

The effect of climate change on the agricultural sector is far-reaching. The variability in climate alone is responsible for one-third of the agricultural variation [13]. The threat of climate change on traditional agrarian systems increases with the interaction of rising temperatures [14]. If adaptive measures are not taken to mitigate the effects of climate change, there is a possibility for a reduction in crop yield within the range of 7 and 23 percent and from 10 percent to 50 percent in 2030 [15]. A rise in specific methane (CH_4) and nitrous oxide (N_2O) emissions in the long run will further impact agricultural output [16]. The effects of climate change are more pronounced in Africa, where agriculture is predominantly rain-fed. Africa is susceptible to the impact of changing climates and bears disproportionate consequences, even though it contributes only 4 percent of the world's GHG emissions [17]. In Africa, maize, rice, wheat, groundnut, and vegetable yields are expected to decline by 3.4 percent, 6.9 percent, 11 percent, 9.1 percent, and 10.1 percent, respectively, in 2050 compared to the 2020 production level due to the effect of climate change [12].

Conversely, the agricultural sector is the second major contributor to GHG emissions. It contributes mainly to agricultural CH_4 and N_2O emissions [18]. The Agriculture, Forestry, and Other Land Use (AFOLU) total anthropogenic GHG emissions have grown on average from 13 percent to 21 percent between the periods 2010 and 2019. Deforestation accounts for 45 percent of agricultural emissions, partly due to land-use for agriculture, and agricultural CH_4 and N_2O emissions increased substantially from 2010 to 2019 [19]. Moreover, agriculture is a predominant emitter of farm gate emissions (FGEs) through the application of manure and nitrogen fertilizer [1], which contributes to climate change. Again, the contribution of CH_4 from rice production to GHG emissions is approximately 96 percent [20], which exceeds the agricultural emissions from N_2O [21]. This makes the agriculture sector the leading contributor to the rise in AFOLU, CH_4 , and N_2O emissions [22].

Another factor that contributes to emissions is trade [2]. The proliferation of international trade agreements in the post-World War II era, in the form of multilateral, regional, or bilateral trade agreements, led to a surge in trade and economic growth [23–25].

The increase in trade volume followed by a proportionally greater increase in GHG emissions [26–28]. This is due to the increase in the standard of living and the rise in foreign demand, resulting

in trade expansion and the extensive use of land, sea, air, and rail modes of transportation to take goods across different country borders. The movement of goods, especially to long-distance countries, involves large GHG emissions, which result in climate change [29]. The increase in world trade can deplete natural resources due to the rise in the volume of economic activities to meet the increasing foreign demand [30].

However, for countries with high population growth and biophysically less endowed, trade can be a useful means to import goods from countries with abundant water, land, and favorable climates suitable for the production of goods [31]. Trade can also play a role in cushioning the shortage of food supply due to crop failure, drought, and flooding by supplying the needed food through imports [32]. This minimizes the emissions of GHG from the importing country because there is less pressure on the environment to produce such goods [32].

The increase in trade will increase the GDP of the exporting countries. This rise in income will stimulate people's desire for better environmental quality and reduce GHG emissions [33]. Agricultural emissions can also be reduced through the technology impacts of trade and trade-related technology transfer. Among these technological spillover impacts of agrarian trade are the market competitiveness effect and the demonstration and imitation effect [34,35]. Agricultural carbon emissions can also be reduced by investing in energy-efficient technology and climate-smart agriculture, which is financed by the profit earned from the trade of farm products. This can encourage the advancement of industrial technology through technical support, technology licensing, and sales [36].

In conclusion, there is double-headed causality between crop production and emissions and between emissions and trade. Hence, these feedback effects between crop production and agricultural emissions, and trade and agricultural emissions, need to be investigated further to understand the drivers of crop-induced emissions at the RTB member states level and mitigate them. In this regard, a study from the Food and Agriculture Organization revealed that crop and livestock production are responsible for 10 to 12 percent of FGEs. In addition, 10 percent of these emissions is attributed to land use change [37].

In line with the interconnectedness of crop and livestock emissions, researchers have attempted to distinguish the contribution of crop production to emissions from livestock production, noting that carbon dioxide (CO₂), N₂O, and CH₄ emissions occur at the various stages of the food production and consumption. In parallel, disaggregating food production emissions revealed that food crops contribute to N₂O emissions. Furthermore, rice cultivation predominantly drives CH₄ emissions, whereas CO₂ emissions occur during the production of farm implements, farm operations, processing, and transportation [22].

A detailed review of the crop–emissions nexus revealed, for instance, in estimating the emission factor in China's crop production, [38] showed that the average carbon footprint from crop production was 0.01-0.11 tons of CO₂ equivalent per hectare per year. Zooming in on the various components that contribute to total emissions from crop production showed that emissions from the use of nitrogen fertilizer accounted for approximately 60 percent.

Using data on the major crops grown in China, [39] examined the direct and indirect contribution of crop production to emissions. Generally, they revealed that rice paddy contributed 0.37 kilograms of CO₂ equivalent per kilogram of paddy rice output, which is approximately three times the contribution of wheat, maize, and soybean. Furthermore, considering the ecological environment, the study revealed that for dry land, the contribution of crops to N₂O emissions (both direct and indirect) is 0.78 carbon footprint; for the lowland, direct CH₄ emissions contributed 0.69. Globally, due to conventional flooding methods that produce anaerobic soil conditions, rice farming contributes 10-12 percent of methane emissions. The methane emissions figure may be understated, as according to [40], using satellite data, showed that for most rice-producing countries, methane intensities vary between 10 to 120 kg methane per ton of rice output, with a global average of 51.

Similarly, [41] studied the key contributing grain crops to carbon footprint to inform policies on the adoption of sustainable agricultural practices. They found that the carbon footprint of rice is the

highest, followed by wheat and maize in that order. In addition, 341 grams of N₂O emissions per hectare in a season caused by rice production [42].

In contrast, [43] assessed double rice production contribution to agricultural emissions in a bid to reduce carbon and nitrogen footprints and found out that, the CO₂ equivalent emissions per kg of rice production in a year ranges from 0.83 to 0.85 for early, late, and double cropping, while N₂O emissions from double cropping (10.68) is greater than early cropping (10.47), but less than late cropping (10.89).

To identify potential influencers of agricultural emissions and provide pathways to mitigate them, [44] used the Food and Agriculture Organization database and showed that maize production contributed the most to crop emissions (11.70 percent), followed by potatoes (10.21 percent) and rice (9.25 percent). In parallel, comparing mono-cropping and intercropping, [45] found that intercropping maize and potatoes immediately after nitrogen fertilization reduced N₂O emissions by 19.0 percent–20.6 percent. Additionally, such a decrease is more noticeable in the short run.

Tracking the N₂O emissions in an agricultural production greenhouse in the root zones of hydroponic tomato and cucumber plants on gravel-wool growth sacks with drip irrigation estimation using the static chamber method [46] revealed that the average emission factors for N₂O were 0.13 percent for cucumber crop excluding drain re-use (open hydroponic method) and 0.31 percent for the cultivation of tomatoes with drain recycling (closed hydroponic technology). Furthermore, measuring and comprehending the shifting patterns of smallholder agricultural systems' soil N₂O emissions in Sub-Saharan Africa [47] revealed that, among other variables, vegetables emit 48 to 113.4 kg N₂O-N ha⁻¹ yr⁻¹.

According to [48], the production and trade of vegetables and fruits across borders negatively impact the environment. However, 16 percent of such emissions can be mitigated by optimizing nitrogen fertilizer usage [49].

We can deduce from reviewing relevant past studies that crop production contributes directly to CH₄ and N₂O emissions, though the contribution to nitrous oxide emissions is more pronounced, while contributing indirectly to CO₂ in these study areas. Again, despite the role played by the agricultural sector and trade in explaining emissions, amidst, the growing pressure on the crop subsector to achieve food security in the presence of climate change effects, a study that specifically examine the short-and long-term effects of individual crops, such as cereals, roots and tubers, vegetables, and fruits, which are most susceptible to climate change [50] at the farm-gate level on CH₄ and N₂O emissions, in the RTB member states are scarce. This study, as a novelty, investigates the short- and long-run effects of crop production on farm-gate emissions in the regional trading bloc member states in Africa. To achieve this objective, we proxy crop production by cereals, roots and tubers, vegetables, and fruits production and split emissions into CH₄ and N₂O as the dominant emissions components at the farm-gate level. Furthermore, we collected data on these variables from 30 member states of the major RTBs in Africa from 1990 to 2022, which we analyzed using the cross-sectional augmented autoregressive distributive lag approach that controls for endogeneity and heterogeneous slopes. We also employed the pooled mean group and sub-sample analyses as robustness checks to ensure the reliability of study findings.

This study makes three contributions to air quality. First, our study is perhaps among the few that focus on the primary root cause of agricultural emissions by zooming into the different sub-components of the crop sector, such as cereals, roots and tubers, and fruits, and linking them to the predominant (CH₄ and N₂O) emissions components at the farm gate level. The second contribution of our study is that it employs the panel autoregressive distributive lag (ARDL) method, which controls for cross-sectional dependency, structural breaks, slope heterogeneity, serial correlation, and endogeneity. It also accounts for the long-run effects of crop production on agricultural emissions. This enhances the robustness and reliability of our regression findings.

Thirdly, considering the role played by trade in promoting and mitigating emissions, the analysis of the crop production and emissions nexus at the RTB level member states level provides

insights into the different crops that are notorious emitters of CH₄ and N₂O emissions, and suggests pathways to mitigate them at the RTB member states and RTB levels.

Thus, with the introduction of carbon financing, the imposition of taxes on dirty goods at the international trade level, and the coordination of the activities of the RTBs in Africa, this study is important, as it exposes specific crops that are notorious emitters of GHGs. Using this information, the various blocs will be empowered to design a coordinated approach to minimizing emissions and to determine the amount of money producers of dirty goods can be charged by Environmentalists at the RTB member states' level.

2. Materials and Methods

2.1. Crop Production and Farm-Gate Level Emissions Framework

Crop production involves several processes referred to as value chains. The crop value chains comprise the assembling of inputs such as fertilizer, pesticides, and tools (Downstream production activities). Land preparation, tillage, irrigation, and other activities before the product leaves the farm (Primary production activities), and harvesting, threshing, processing, storage, and transport to market (Upstream production activities). Thus, emitting CO₂, CH₄, and N₂O in the process (Figure 1).

From panel A in Figure 1, the manufacturing of fertilizer and pesticides, the production and packaging of seeds, and the transportation of farm inputs to assemble inputs for crop production contribute mainly to CO₂ emissions [22]. Moreover, in India, crop production accounts for 87 percent of emissions from food production [22]. The carbon footprint from crop production activities, such as tillage and irrigation (panel B), is associated with CH₄ and N₂O emissions. For instance, for dry cover crop, soil deficit irrigation decreases N₂O relative to full irrigation [51]. Furthermore, no-tillage reduces N₂O relative to tillage [52]. Again, rice cultivation increases CH₄ emissions, while food crops contribute to N₂O [22]. Panel C comprises highly mechanized activities that are prone to CO₂ emissions. Upstream activities such as harvesting, threshing, processing, and transportation increase the use of fossil fuels. The further shift from small-scale to large-scale farming increases energy use, energy intensity, and dependence on fossil fuels, which promotes CO₂ emissions [53,54].

From the Figure 1 and the review of the literature, we observed that CH₄ and N₂O are the major contributors to the carbon footprint from direct crop production, occurring at the farm-gate level (panel B). Thus, an effective crop emission mitigation strategy should target emissions at the farm-gate level where crop-based emissions are predominant. Hence, this study's main focus is on CH₄ and N₂O emissions at the farm-gate level.

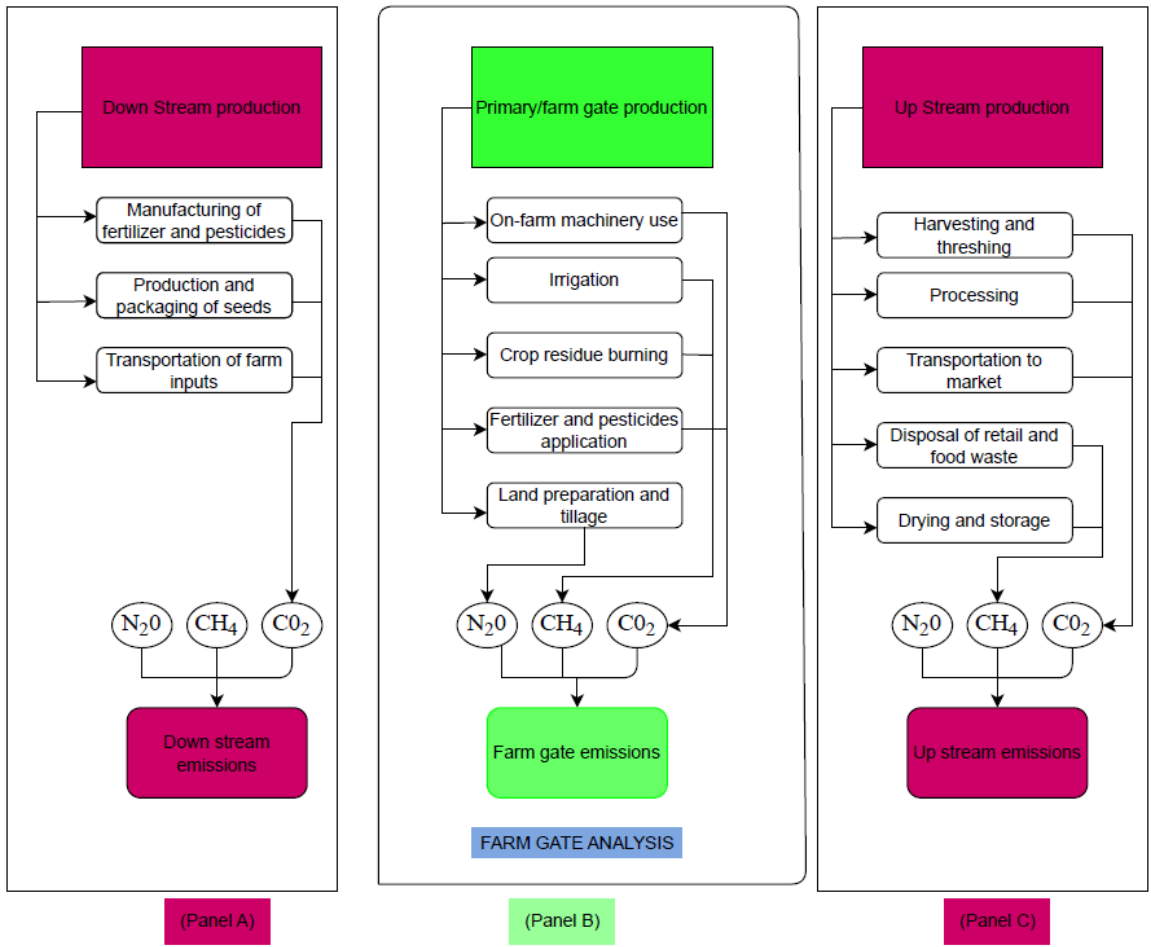


Figure 1. Farm gate level production and emissions framework. Source: Constructed by the Author.

2.2. Regression Strategy

We estimate our regression models using the strategy in Figure 2. A common mistake researchers make in panel model specification is to specify a static model instead of a dynamic model. When a model is misspecified, there is a good chance that the estimated residuals from the regression equation will exhibit some autocorrelation [55]. Thus, we specify a dynamic model because we believe that past emissions are associated with current emissions. Consequently, in our estimation strategy, we first conduct a cross-sectional dependence (CD) test using the [56] tests to examine the strength of CD, with the null hypothesis of weak CD. In the presence of CD, we conduct the second-generation unit root test because it is robust in dealing with CD [57]. We use the Pesaran cross-augmented Dickey-Fuller (Pescadf) test based on the individual Dickey-Fuller or augmented Dickey-Fuller means [58].

With large cross-section and time dimensions, we use the standardized version of Swamey's test to test for slope heterogeneity, because the incorrect imposition of slope heterogeneity will result in biased and inconsistent results [59]. Furthermore, the prevalence of policy shifts or shocks in macroeconomics warrants a structural breaks test as its omission will lead to misleading inferences. In the presence of CD, slope heterogeneity, and structural breaks, we employ the cross-sectional augmented autoregressive distributive lag (CS-ARDL) model that controls for these problems. We interpret the estimated coefficients obtained from the regressions using proportional changes. We also conduct robustness checks to validate our results, using the pooled mean group (PMG) estimation technique and sub-sample analysis. We use Stata 17 [60] to conduct all empirical estimations.

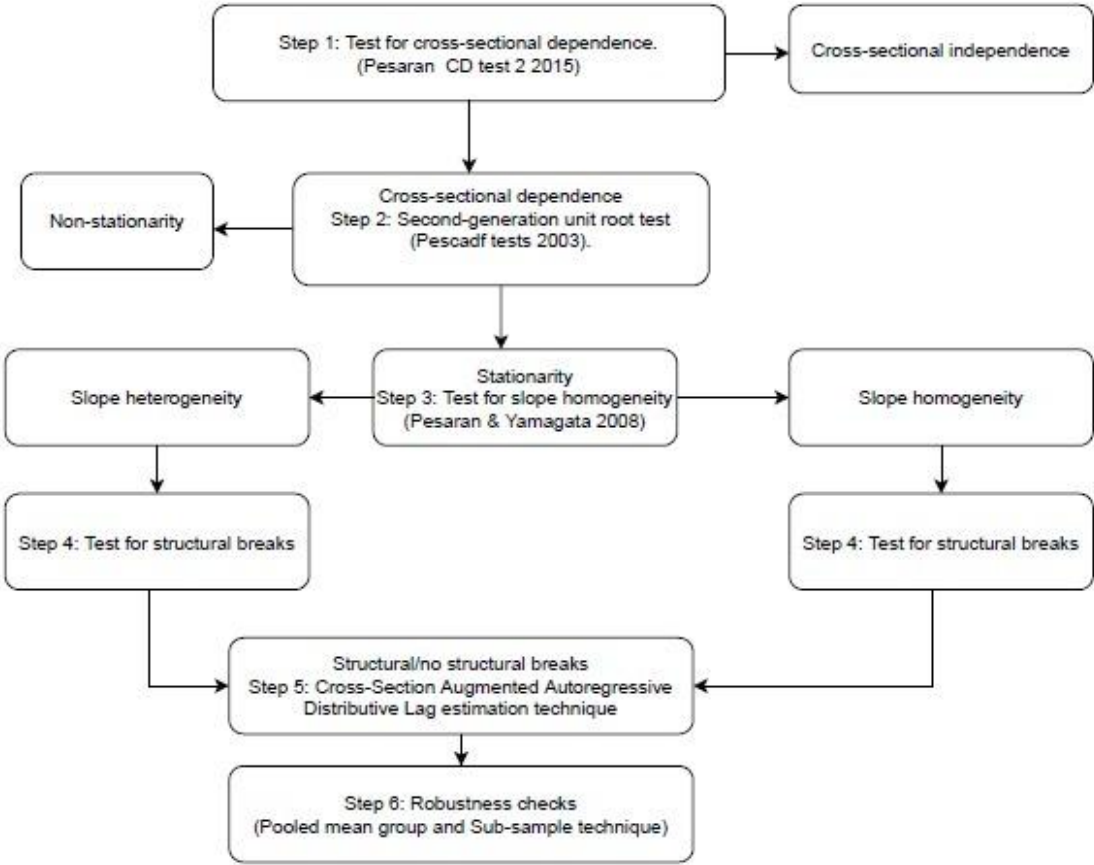


Figure 2. The regression strategy. Source: Constructed by the Author.

2.3. Theoretical Specification of the Regression Model

Researchers have developed several models of climate change human drivers. Typical of such theories is the environmental impact of population, affluence, and technology (IPAT). This theory, by [61], shows that population (P), affluence (A), and technology (T) are the drivers of environmental degradation. The IPAT provides the foundation for several other climate change theories, such as the STIRPAT. The STIRPAT, developed by [62], improves on the IPAT by incorporating a stochastic term and non-unit elasticity of the environmental impact of each driving force. Since our study examines the effects of crop production on FGEs by running a regression, we adopt the STIRPAT model to illustrate the stochastic relationship between crop production on FGEs, as shown by [63]. The theoretical specification of the STIRPAT is depicted in the following equation:

$$I = e^{\beta_0} P^{\beta_1} A^{\beta_2} T^{\beta_3} e^{\varepsilon} \tag{2.1}$$

Taking the natural logarithm throughout yields:

$$\ln I = \beta_0 + \beta_1 \ln P + \beta_2 \ln A + \beta_3 \ln T + \varepsilon \tag{2.2}$$

where β_i 's are the coefficients to be estimated, $\ln$, natural logarithm, and ε is the error term assumed to be normally distributed.

2.4. Empirical Model Specification

[64] employed the STIRPAT model to study emissions in economies at various stages of development. For instance, [65] proxied environmental degradation with CO₂ and N₂O emissions, while [66] proxied affluence with crop and livestock production indices. Several other proxies have been proposed for population and technological driving forces of emissions. Hence, we use N₂O and CH₄ emissions indicators for FGEs because they are the two most prevalent emission components in the agricultural sector [41]. Additionally, to explicitly distinguish the contribution of the crop sector's

primary output to emissions at the farm gate level, we proxy affluence into cereals, roots and tubers, vegetables, and fruit production. This is because they are the crops that are commonly grown in the member states for which data is available and they contribute significantly to the gross domestic product (GDP) of these member states.

We employ agricultural investment (Tech) and rural population (Rupop) as proxies for technology and population, respectively, and observe them as control variables. Thus, we specify a dynamic augmented STIRPAT panel model to investigate the relationship between crop production and FGEs in selected African RTB member states as follows:

$$\begin{aligned} \ln \text{Methane}_{it} = & \beta_0 + \beta_1 \ln \text{Methane}_{it-1} + \beta_2 \ln \text{Cereal}_{it} + \beta_3 \ln \text{Roots and tubers}_{it} \\ & + \beta_4 \ln \text{Vegetable}_{it} + \beta_5 \ln \text{Fruit}_{it} + \beta_6 \ln \text{Tech}_{it} + \beta_7 \ln \text{Rupop}_{it} \\ & + \varepsilon_{it} \end{aligned} \quad (2.3)$$

$$\begin{aligned} \ln \text{Nitrous oxide}_{it} = & \beta_0 + \beta_1 \ln \text{Nitrous oxide}_{it-1} + \beta_2 \ln \text{Cereal}_{it} + \beta_3 \ln \text{Roots and tubers}_{it} \\ & + \beta_4 \ln \text{Vegetable}_{it} \\ & + \beta_5 \ln \text{Fruit}_{it} + \beta_6 \ln \text{Tech}_{it} + \beta_7 \ln \text{Rupop}_{it} + \varepsilon_{it} \end{aligned} \quad (2.4)$$

where i 's represent member states, t 's, years, and $t - 1$, previous year.

2.5. Method of Estimation

2.5.1. Diagnostic Tests

2.5.1.1. Cross-Sectional Dependence Test

We are motivated to apply the CD because these RTB member states are interconnected in the sense that they share common languages, cultures, and traditions. In addition, they belong to the same blocs, hence there is the likelihood that they share similar trade policies, and with globalization, participate in regional or global value chains. Thus, to test for CD in the panel data set, we employ the [56] test for weak CD. We use this test because it can be applied to balanced [56] and unbalanced panels [67], and is more robust in detecting CD in large time and cross-sectional units [56]. The null hypothesis is weak CD.

$$CD_{Weak} = \sqrt{\frac{2}{n(n-1)}} \sum_{i=1}^{n-1} \sum_{q=i+1}^n \frac{\sqrt{Q\hat{\alpha}_{iq}}}{\sqrt{\hat{\beta}_{iq}}} \quad (2.5)$$

where $Q\hat{\alpha}_{iq}$ is the correlation between the sample residuals, $\hat{\beta}_{iq}$ is a reliable predictor of the variance.

2.5.1.2. Second-Generation Unit Root Test

With the assumption of CD, the [58] test for stationarity is used to determine the unit root of the variables because of its simplicity. The Pesaran unit root test is predicated on the statistical significance of specific cross-sectionally augmented Dickey-Fuller test statistics. Additionally, it modified the Im Pesaran Shin t-bar test statistic to test for stationarity when the residuals are correlated and CD is present. Hence, the name cross-sectional specific augmented Im Pesaran Shin (CIPS). The null hypothesis of the CIPS is that there is no unit root.

$$CIPS = \sum_{i=1}^N CADF_i N^{-1} \quad (2.6)$$

where N is the number of cross-sectional units, and i represents units.

2.5.1.3. Test for Slope Homogeneity

With the assumption of stationarity of the variables, we test for slope homogeneity across the panel units using the [59] test for homogeneous slope because it is more applicable for larger panels. Under the null hypothesis of slope homogeneity, Pesaran and Yamagata estimated two test statistics as illustrated in (2.7 and 2.8):

$$\tilde{S} = \sum_{i=1}^N (\hat{\rho}_i - \tilde{\rho}_{wfe})' \frac{X_i' M_t X_i}{\tilde{\vartheta}_i^2} (\hat{\rho}_i - \tilde{\rho}_{wfe}) \quad (2.7)$$

where $\hat{\rho}_i$ is the pooled ordinary least squares estimator of the slope coefficients, $\tilde{\rho}_{wfe}$ is the weighted fixed effect of the slope coefficients, the identity matrix is given as M_t , and the estimator of ϑ_i^2 is $\tilde{\vartheta}_i^2$. The standardize dispersion statistic ($\tilde{\Delta}$) is given as:

$$\tilde{\Delta} = \left(\frac{\tilde{S} - k}{\frac{N}{\sqrt{2k}}} \right) \sqrt{N} \quad (2.8)$$

where $\tilde{S}$ is Swamy test statistic, N is the number of cross-sectional units, and k is the degree of freedom.

2.5.1.4. Test for Structural Breaks

Structural breaks may be prevalent, particularly in macroeconomic data, due to policy shifts or shocks. These changes, whether known or unknown, may affect the interpretation of regression results and inferences. As such, [68] proposed a model to detect multiple breaks in panel data. The panel data model, consisting of a structural break k , is written as:

$$y_{i,t} = x'_{i,t} \alpha + q'_{i,t} \beta'_{k+1} + e_{i,t} \quad (2.9)$$

for $t = T_k + 1, \dots, T$,

where $y_{i,t}$ is the endogenous variable and $x_{i,t}$ and $q_{i,t}$ are exogenous variables. α and $\beta_1, \dots, \beta_{k+1}$ are vectors of coefficients. $e_{i,t}$ means error term and $T_1, \dots, T_k$ represent the structural break dates.

The error term allowed unobserved heterogeneity through the specification of an interactive fixed effects shown as:

$$e_{i,t} = f_t \delta_i + \epsilon_{i,t} \quad (2.10)$$

Where f_t is the unobserved common factor, δ_i is the factor loading, the idiosyncratic error is $\epsilon_{i,t}$, and the interactive effect is $f_t \delta_i$.

The f is likely to be correlated with the exogenous variables. To capture this, we specify the exogenous variables:

$$x_{i,t} = \tau'_{x,i} f_t + \mu_{x,i,t} \quad (2.11)$$

$$q_{i,t} = \tau'_{q,i} f_t + \mu_{q,i,t} \quad (2.12)$$

where $\tau_{x,i}$ and $\tau_{q,i}$ are factor loadings. The idiosyncratic errors are $\mu_{x,i,t}$ and $\mu_{q,i,t}$. f_t captures the correlation of the independent variables within and across cross-sections.

2.6. Cross-Sectionally Augmented Autoregressive Distributed Lag

Assuming our model is dynamic with a mixed order of integration, autocorrelation, endogeneity, long-run relationship, heterogeneous slopes, and structural breaks, we are open to three dynamic common correlation effect estimation methods: cross-sectional augmented distributed lag (CS-DL), the CS-ARDL, and the error-correction model augmented autoregressive distributed lag (ECM-ARDL) models. However, in our study, we use the CS-ARDL model to overcome the limitation of the CS-DL; it does not estimate the error correction term (ECT) that accounts for the speed of adjustment in the long-run equilibrium. Also, the CS-ARDL and the ECM-ARDL are similar long-run estimation techniques, as they account for ECT and produce numerically equivalent regression output [67]. We specify the CS-ARDL model as:

$$\Delta Y_{it} = \mathbb{V}_i + \phi_i(Y_{it-1} - \alpha_i X_{it-1} - \phi_{1i}\bar{Y}_{t-1} - \phi_{2i}\bar{X}_{t-1}) + \sum_{j=1}^{p-1} \mu_{ij}\Delta Y_{it-j} + \sum_{j=0}^{q-1} \mathfrak{z}_{ij}\Delta X_{it-j} + \mathfrak{x}_{1i}\Delta\bar{Y}_t + \mathfrak{x}_{2i}\Delta\bar{X}_t + \varepsilon_{it} \quad (2.13)$$

where Y_{it} (nitrous oxide and methane emissions) is the endogenous variable, $\mathbb{V}_i$ is the constant, ϕ_i is the speed of adjustment; which shows the speed at which the emissions converge to long run equilibrium after a short run shock such as the COVID, and the commitment to pegging emissions, α_i is the vector of the slope parameters of the exogenous variables, and lagged endogenous variables. X_{it} is a vector of the independent variables $\bar{Y}_{t-1}$ and $\bar{X}_{t-1}$ are the long-run unobserved factors $\bar{Y}_t$ and $\bar{X}_t$ are the short-run unobserved factors.

2.7. Proportional change coefficients

Since equations (2.3) and (2.4) are written in natural log, we interpret the regression coefficients using elasticity. However, our dependent variables (farm gate methane and nitrous oxide emissions) are reported yearly [30]. Hence, it is required that we convert the emissions elasticity to proportional change coefficients of emissions with the help of the preceding formula [31]:

$$\begin{aligned} \text{Proportional change in Emissions} \\ = \exp(\delta\hat{\alpha}) \end{aligned} \quad (2.14)$$

where $\exp$ represents exponent, $\delta = \ln([100 + m]/100)$, The predicted regression coefficient (α) represents the predicted rise in emissions, the change's size is denoted by m .

2.8. Data

We sampled the RTB member states because crop production plays a significant role in their growth. Figure 3 shows that RTB member states selected for our study have a greater contribution of crop production to GDP, as indicated by the closeness of crop production values to GDP on the far left end of the horizontal line. However, a few member states, like South Africa, Côte d'Ivoire, and Nigeria, have values closer to the right, probably because they have more robust extractive, industrial, or service sectors, which raise GDP above crop production. Notwithstanding, crop production still has a role to play in these RTB member states if we net out the contribution of the extractive industries, especially oil and precious minerals such as diamond and gold, as Africa generally, is characterized as an agrarian economy.

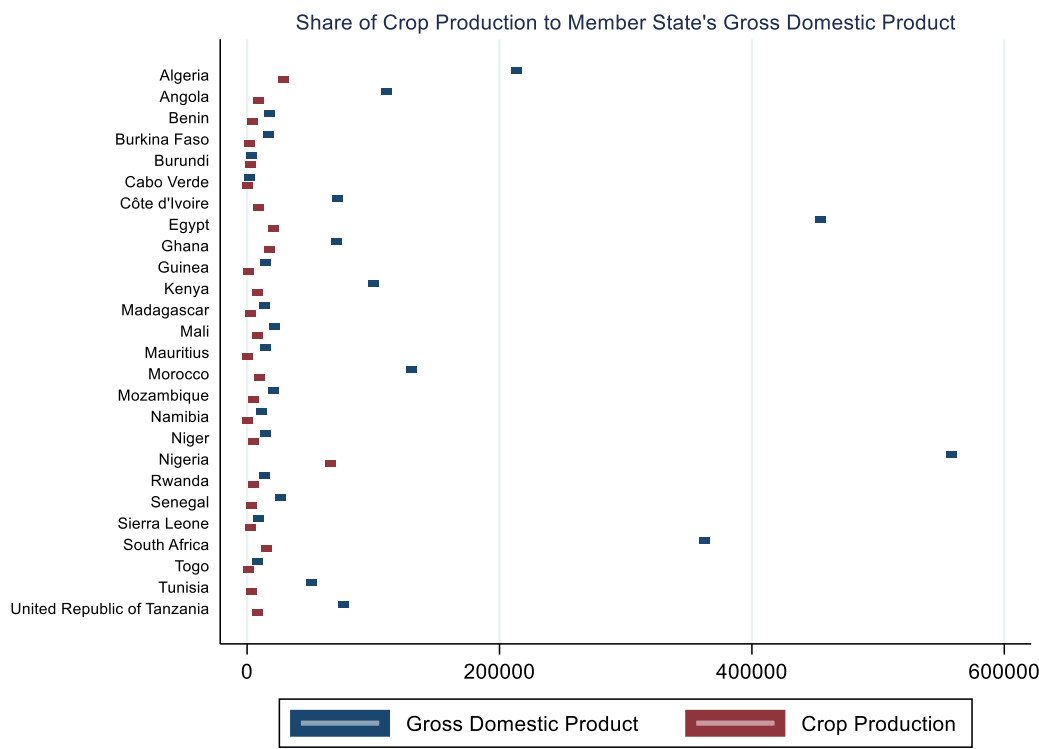


Figure 3. Showing the share of crop production to the member state’s GDP in US\$ million as of 2023. Source: Constructed by the Author.

Furthermore, some of these member states belong to more than one RTB due to overlapping membership. For instance, the United Republic of Tanzania, which belongs to RTBs such as the SADC, and EAC. In addition, there are also RTBs whose membership extends beyond regional boundaries, like the Common Market for East and Southern Africa (COMESA). Therefore, it is difficult to study these member states and RTBs. To unpack the complexity, we exclude the RTBs with a deeper cross-regional geographical scope. As such, we drop RTBs like COMESA. Thus, we select the AMU, EAC, ECOWAS, and SADC RTBs in the north, east, west, and southern regions, respectively. These four RTBs selected comprise forty-four (44) member states: five (5) from AMU, eight (8) from EAC, fifteen (15) from ECOWAS, and sixteen (16) from SADC. In addition, we exclude member states with overlapping membership to avoid duplication (Tanzania), giving us a total of forty-two (42) member states. We then exclude twelve (12) member states based on data availability on common crops produced: Cereals, vegetables, roots and tubers, and fruits, and rural population, and technology. Thus, our final sample consists of thirty (30) member states, which represent approximately 70 percent of the RTB member states (see Table 1).

Table 1. Member states of the regional trading blocs studied.

S/n	Economic Community of West African States	South African Development Community	East African Community	The Maghreb
1	Benin	Angola	Burundi	Algeria
2	Burkina Faso	Eswatini	Kenya	Egypt
3	Cabo Verde	Lesotho	Rwanda	Morocco
4	Côte d'Ivoire	Madagascar	Tanzania	Tunisia
5	Ghana	Mauritius	Uganda	
6	Guinea	Mozambique		
7	Liberia	Namibia		
8	Mali	South Africa		
9	Niger			
10	Nigeria			

11	Senegal
12	Sierra Leone
13	Togo

Source: Constructed by the Author.

2.9. Selection of key variables

Carbon dioxide equivalent emissions can broadly reflect emissions from crops, livestock, and forestry divisions. However, for a detailed analysis, we focus on the crop sub-sector’s contribution to emissions. This is because crop production faces increased pressure due to the rising world population and the attainment of food security; crop emission intensity becomes critical, as it may be associated with higher emissions. In this regard, crop emissions can result from upstream, downstream, and farm-gate levels. However, the predominant CO₂ equivalent emissions at the farm-gate level, which account for the direct contribution of crops to emissions, are methane and nitrous oxide emissions [18], as revealed by studies such as [39,40,45,49]. Thus, we employ methane and nitrous oxide emissions as our dependent variables.

Crops have faced increased pressure due to the population's growing demand for food, which requires crop intensity and yield to increase by 80 percent [8,9]. The increase in cropping intensity and yield arguably will increase agricultural emissions. The 10 major crops grown in Africa are maize, sorghum, cassava, millet, rice, groundnuts, cowpeas, wheat, beans, and vegetables. The production of these crops is expected to increase from 36.5 percent to 127.6 percent, with a corresponding increase in emissions from 0.5 to 5.2 percent from 2020 to 2050 [12]. Thus, by categorizing these crops into different food groups, such as cereals, roots and tubers, vegetables and fruits, we can quantify crop contribution to emissions as of 2022 and use the results to proffer measures to reduce emissions below the projected 5.2 percent in 2050. In addition, we include fruit production to capture its contribution to emissions to account for how the African continent’s drive to achieve nutrition security actually impacts emissions. Extant studies have examined the contribution of fruits [48,49], vegetables [46,47], roots and tubers [43,45], and cereal crops [39,42] to emissions, respectively. The control variables, such as population and technology, have also been employed by authors such as [71,72] to determine their effect on emissions. As such, we use these variables as independent variables in our study to determine their effect on CH₄ and N₂O emissions at the farm-gate level in the RTBs member states in Africa. We collected data on the variables for the sampled RTB member states from the Food and Agriculture Organization Statistical database [73] from 1990 to 2022. The description of the variable is presented in Table 2.

Table 2. Variable Description.

Variable	Description	Data source	Measurement	Reference
Methane	Emissions from agricultural activities such as burning residues and the cultivation of rice and other crops.	FAOSTAT	Kilotons	[39,40]
Nitrous oxide	Emissions from agricultural activities, like irrigation and land use change.			[45,49]
Cereal	The primary output of all cereals at the farm-gate.		Metric tons	[39,42]
Root and tuber	The total output of			[43,45]

	roots and tubers at the farm-gate.	
Vegetable	The primary output of vegetables at the farm-gate.	[46,47]
Fruit	The primary output of all fruits at the farm-gate.	[48,49]
Rural population	The total number of people that reside in the rural area per year	[71] Per thousand people.
Technology	It encompasses the government expenditure, credit, development flows, and foreign direct investment in the agricultural sector.	[72] US\$ million

Source: Computed by the Author.

2.10. Trend Analyses

From Figure 4, given that roots and tubers are comparatively stationary, member states of the AMU bloc, including Algeria, Morocco, Tunisia, and Mauritania, show stable, slight growth paths for fruits and cereals. The Mediterranean environment and irrigation-driven practices that support crop choice and yield stability in the AMU are apparent in this trend. The absence of notable shifts in root and tuber in agricultural production shows that root and tuber are not significantly impacting climate change, nor are they a priority. Focusing on the EAC, countries like Kenya, Uganda, Tanzania, Rwanda, and Burundi continue to grow a variety of crops, with cereals, vegetables, roots and tubers, and fruits demonstrating an increasing trend. This regional dependence on numerous farming techniques and the adaptability of its agricultural policies have been emphasized by this smooth, comprehensive growth [74]. The general upward trend indicates adaptable agricultural practices and efficient production; however, fluctuations in cereal and fruit production show vulnerabilities to year-to-year climatic conditions. Nigeria, Ghana, Côte d'Ivoire, Benin, Burkina Faso, Mali, and Senegal are ECOWAS member states with substantial increases in cereals, roots, and tubers. The important role crops play in ensuring household food security reflects such patterns. However, the trends show that several ECOWAS member states, notably Ghana and Nigeria, experience frequent shocks, which may be attributed to changes in input prices, significant climate variability, and shifting governmental policies [75]. Furthermore, there has not been an enormous spike in fruits and vegetables, implying that although the cultivation of vegetables is frequently done on a smaller scale, it capitalizes on controlled environments that protect against changes in the climate, such as irrigation systems [76]. South Africa, Angola, Mozambique, Namibia, Madagascar, Mauritius, and Lesotho constitute the member states that collectively make up the SADC bloc in this study. The predominant trend in this bloc is resilience, especially in terms of cereal output, which aligns with Southern Africa's greater extent of agricultural modernization and state support. Nevertheless, they lag behind cereals in growth trends. Fruits, vegetables, roots, and tubers also show a continuing positive trend, suggesting continuing progress in both the primary food and growing crop sectors. Although climate or structural shocks are undoubtedly the cause of the sporadic variability in member states like Madagascar and Lesotho, SADC member states often strive to sustain consistent trends over the years [77,78].

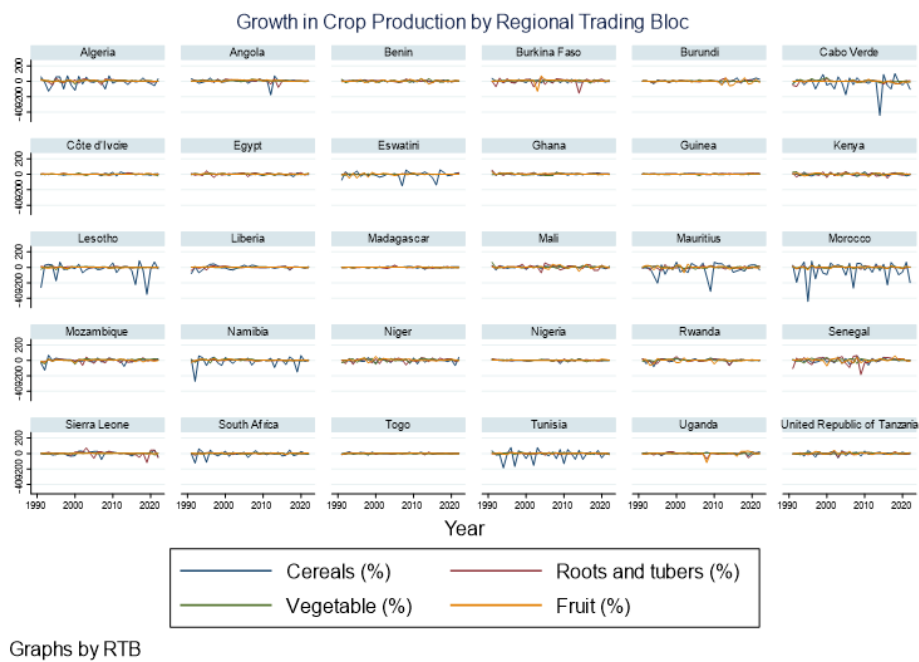
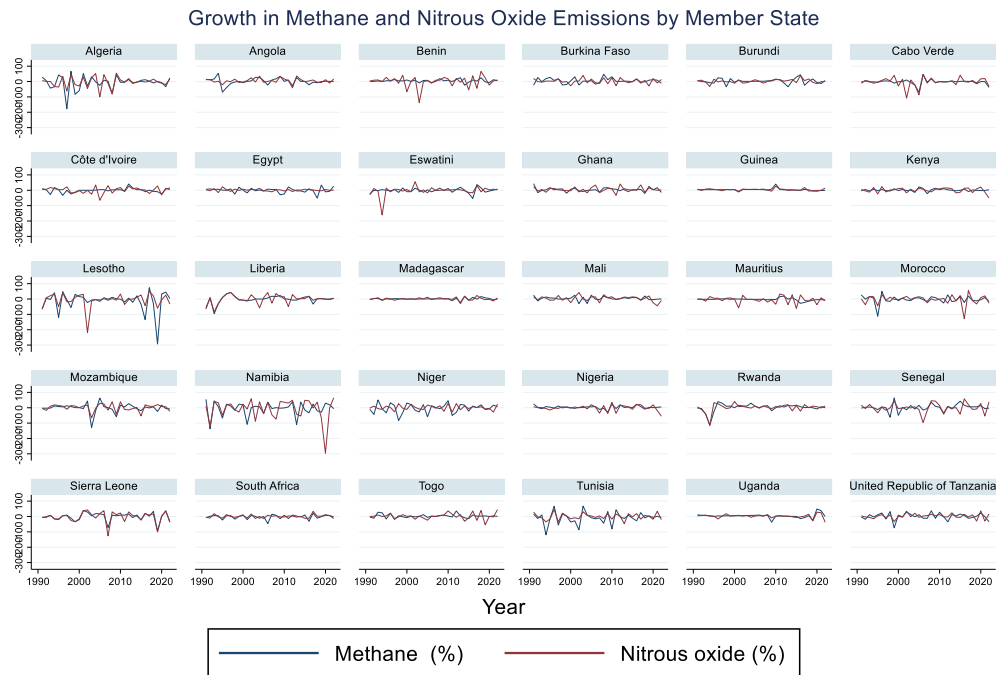


Figure 4. Shows the percentage increase in crop production in each regional trading bloc member state. Every member is displayed by a small panel that illustrates the annual percentage growth for cereals, roots and tubers, vegetables, and fruits from 1990 to 2022. Source: Constructed by the Author.

2.11. Growth in Methane and Nitrous Oxide Emissions

Over the past three decades, CH₄ and N₂O emissions have grown steadily and modestly throughout member states of the AMU, including Algeria, Morocco, and Tunisia. Large irrigation and more mechanized agriculture systems are perhaps all contributors to this resilience, with minimal variation for either GHG, the emissions patterns in AMU countries point to persistent progress in input handling and possibly more uniform implementation of environmental regulations [79]. A slightly distinct perspective is given by the EAC, which includes Kenya, Uganda, Tanzania, Rwanda, and Burundi. In this bloc, CH₄ and N₂O emission trends show slight consistent increases, especially in Kenya and Tanzania. These trends underscore the region's diverse and intensive farming methods. Importantly, weaker agricultural sectors or more reliance on small-scale farming may account for Burundi and Rwanda's reduced emission rates [80]. These patterns highlight how crucial crop management and extension services are in determining the scale and variability of GHG rise throughout EAC in the long run. The emissions narrative is more volatile in the ECOWAS. The magnitude and intensity of the agricultural sector shifted, access to agricultural inputs fluctuated, and large-scale climatic changes have contributed to the sporadic rises and falls in member states like Ghana and Nigeria. Smaller member states like Benin, Sierra Leone, and Togo, contrarily, indicate consistent but slower rises. The significant influence of environmental pollution on emission trends across ECOWAS member states shows the importance of policy coordination across crop management and climate adaptation options [81]. Notwithstanding notable differences between the region's more productive and less productive economies, the SADC bloc represents the African perspective. South Africa stands apart in that its emission trajectory is completely flat and consistent, which indicates its innovative rules and regulations and mechanized agricultural practices [82,83]. CH₄ and N₂O emissions shift marginally in other SADC member states, such as Mozambique, Namibia, Madagascar, and Lesotho. This is likely linked to fluctuations in rainfall and the interaction between subsistence and commercial farming (see Figure 5).



Graphs by RTB

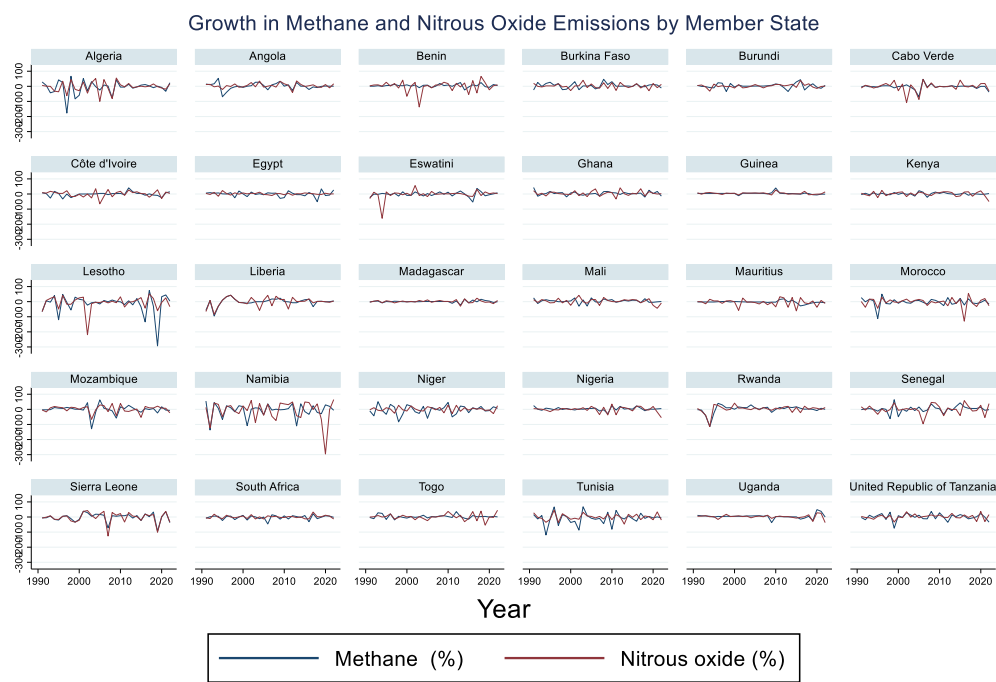
Figure 5. The growth trends in N₂O and methane CH₄ across Africa's RTB member states from 1990 to 2020 are depicted. The trajectory patterns display low to moderate variability, with notable variations in some member states of RTBs. Source: Constructed by the Author.

2.12. Crop Methane and Nitrous Oxide Intensity

Crop CH₄ and N₂O intensities across the RTBs in Africa depict several trends and patterns. Consequently, CH₄ and N₂O emission intensities remain low and stable for most member states' crops in this study. Remarkably, fruits and vegetables generally have the lowest emission intensities associated with upland and low-intensive farming practices for crop cultivation. There are occasionally notable fluctuations in emission intensity despite the general predictability; these are mostly linked to roots and tubers, and, to a lesser extent, cereals. Lesotho, Madagascar, Liberia, Mozambique, and Senegal are noteworthy examples of these unexpected rises in CH₄ and N₂O emissions per unit of output, which are mainly from member states and seasonal in source. The rises are likely triggered by several interconnected factors, such as productivity volatility, variations in farming practices, sporadic climate variations, and shifts toward more wetland or waterlogged cultivation techniques, especially for cereals [84]. In addition, CH₄ intensity appears to be more volatile than N₂O. This may be due to its greater susceptibility to aerobic conditions prevalent in waterlogged rice and tuber fields [85].

By analyzing specific crop shifts, CH₄ intensity for cereals typically remains low but often jumps drastically in member states with intermittent fluctuations in land use or farming techniques. Similarly, temporal stability is observed in N₂O intensity for cereals, with only a few minor fluctuations. This may indicate that fertilizer management is mostly efficient across a large number of member states, with exceptional inconsistencies. Roots and tubers are especially vulnerable to unexpected fluctuations in CH₄ and N₂O intensities. This phenomenon can frequently be attributed to shifts in the application of organic material, floodplain cultivation, or yield variability triggered by global warming. Fruits and vegetables, on the other hand, appear to be among the most stable and climate-resilient crops; their relatively low and predictable structures result from cultivation techniques that promote efficient nutrient utilization and reduce the creation of adverse microorganisms [86,87]. Notably, fruit crops provide low-intensity production methods with low GHG emissions. These results imply that management and policy interventions aimed at limiting

input-based emission spikes in cereals, roots, and tubers, as well as facilitating a rise in fruit and vegetable farming, can offer effective routes leading to environmentally friendly cultivation in the RTB member states in Africa [88] (see Figure 6).



Graphs by RTB

Figure 6. The intensity of methane and nitrous oxide emissions from the various crops across the RTBs in Africa is compared. The intensity is the emission per output. Source: Constructed by the Author.

3. Results

3.1. Descriptive Analyzes

Table 3 shows that, on average, the regional trading bloc member states emitted 38.62 kilotons of CH₄ and 2.81 kilotons of N₂O. The key drivers of these emissions are crop production, the size of the rural population, and expenditure on technology. However, the ECOWAS and AMU member states stood out as the major regional trading blocs whose member states are driving these emissions. That is, while the ECOWAS member states are the major emitter of CH₄ emissions (574.89 kilotons), the AMU member states are the principal emitter of N₂O (42.13 kilotons). The dominance in farm-gate emissions by the AMU and ECOWAS member states can be attributed to the ECOWAS member states engaging in large scale cereal farming with little or no emissions mitigation practices, as such, produces the highest cereals (48.1 million metric tons), and roots and tubers (123 million metric tons), and having the largest average rural population (167 million people) engaging in unfriendly environmental agricultural activities such as the burning of crop residues [18]. Furthermore, the AMU member states produce the highest vegetables (25.7 million metric tons) and fruits (32.1 million metric tons), which are high-emitting crops that drive the intensity of fertilizer usage (technology). This further explains why the AMU member states spend the most on technology (US\$201.35 billion) [89].

Moreover, an analysis of the individual indicators reveals that the lower similar differences in means between the SADC and the EAC member states in terms of fruit, and vegetable production suggest that these regional trading bloc member states share similar agro-ecological conditions, farming practices, and agricultural policies. However, there are differences in mean for cereal production across the regional trading bloc member states, with the ECOWAS member states having

the highest positive mean difference. This signifies variation in terms of the scale of farming, the type of crops cultivated, and the intensity of fertilizer usage. The ECOWAS member states are ahead of other regional trading bloc member states in terms of the scale of farming and fertilizer application, among other factors. There is also a large variation in the rural population across the regional trading bloc member states in Africa, with the ECOWAS member states noting the highest positive value. The variance of the variables symbolizes the disparity in farm-gate CH₄ and N₂O emissions and their drivers across the regional trading bloc member states.

Table 3. Summary statistics.

Variable	AMU	EAC	ECOWAS	SADC	Full sample	Means
	Mean (Standard deviation)	Mean (Standard deviation)	Mean (Standard deviation)	Mean (Standard deviation)	Mean (Standard deviation)	Highest Mean Difference (RTB)
Methane (In kilotons)	307.29 (56.90)	10.45 (3.50)	574.89 (228.59)	265.95 (31.36)	38.62 (77.89)	564.44 ⁺ * (ECOWAS)
Nitrous oxide (In kilotons)	42.13 (7.66)	3.58 (1.31)	23.12 (8.08)	15.53 (29.00)	2.81 (5.54)	38.55 ⁺ * (AMU)
Cereals (In million metric tons)	41.4 (8.88)	4.47 (1.05)	48.1 (13.2)	20.1 (4.95)	3.80 (5.81)	43.7 ⁺ * (ECOWAS)
Roots and tubers (In million metric tons)	22.4 (5.16)	7.80 (2.64)	123.0 (45.6)	20.4 (6.58)	5.79 (16.0)	115 ⁺ * (ECOWAS)
Vegetables (In million metric tons)	25.7 (7.66)	2.73 (0.88)	17.1 (6.44)	4.39 (1.48)	1.66 (3.18)	23.0 ⁺ * (AMU)
Fruits (In million metric tons)	32.1 (8.64)	7.174 (1.68)	20.9 (6.55)	9.967 (3.82)	2.34 (3.15)	24.9 ⁺ * (AMU)
Rural population (Per million people)	130.05 (22.28)	45.04 (9.44)	167.23 (26.71)	61.16 (7.68)	13.45 (17.08)	122.19 ⁺ * (ECOWAS)
Technology (In US\$ billion)	201.35 (126.10)	15.58 (15.67)	8.79 (86.12)	113.26 (92.83)	13.94 (33.77)	185.77 ⁺ * (AMU)

Source: Computed by the Author Legend: ⁽⁺⁾ positive, and ⁽⁻⁾ negative mean differences, and * represents statistical significance. NOTE: Summary statistics for individual member states are in Appendix 1.

3.2. Diagnostic Tests

First, in our regression approach, we test for the existence of CD. We employ the [56] test to determine the correlation between the RTB member states because it is suitable for unbalanced panels and more robust than the [90] CD test. The null hypothesis in this test is a weak CD between the RTB member states. From Table 4, the probability values of the variables in the CH₄ and N₂O models are statistically significant at the 1% level. Hence, we reject the null hypothesis of a weak CD and confirm the existence of a strong CD across the panels in both equations.

Table 4. Test for cross-sectional dependence.

Variable	CD test for methane	Variable	CD test for Nitrous oxide
Methane	26.349 ^a	Nitrous oxide	55.142 ^a

Cereals	34.751 ^a	Cereals	34.751 ^a
Roots and tubers	52.788 ^a	Roots and tubers	52.788 ^a
Vegetables	55.012 ^a	Vegetables	55.012 ^a
Fruits	48.092 ^a	Fruits	48.092 ^a
Rural population	61.085 ^a	Rural population	61.085 ^a
Technology	80.315 ^a	Technology	80.315 ^a

Source: Computed by the Author Legend: ^a significant at 1%, ^b significant at 5%.

Since there is a CD, we conduct a second-generation unit root test. We use the ^[58] second-generation unit root test and Z[t-bar], which is based on the average of the particular Dickey-Fuller (or Augmented Dickey-Fuller) t-statistics from each panel unit for constant term and constant term and trend in level and first difference. According to the null hypothesis, every variable is non-stationary. From Tables 5 and 6, the variables are stationary at the level for the "constant" and "constant and trend." However, roots and tubers, and technological variables are non-stationary at the level of the "constant." Similarly, technology also has a unit root at the level of the "constant and trend." Conclusively, there is mixed integration of order one and zero. However, all variables are integrated to order one for both "constant" and "constant and trend" in the CH₄ and N₂O models.

Table 5. Pescadf unit root test for the methane model.

Variables	Constant		Constant and trend	
	Level	First difference	Level	First difference
Methane	-7.095 ^a	-16.806 ^a	-5.707 ^a	-14.532 ^a
Cereals	-5.751 ^a	-17.52 ^a	-4.699 ^a	-15.825 ^a
Roots and tubers	-1.413	-15.427 ^a	-1.893 ^a	-13.645 ^a
Vegetables	-2.461 ^a	-12.72 ^a	-0.161 ^a	-7.596 ^a
Fruits	-2.675 ^a	-13.738 ^a	-1.85 ^a	-12.591 ^a
Rural population	-13.496 ^a	-7.413 ^a	-6.75 ^a	-7.037 ^a
Technology	-1.321	-14.068 ^a	1.468	-12.282 ^a

Source: Computed by the Author Legend: ^a significant at 1%, ^b significant at 5%.

Table 6. Pescadf unit root test for nitrous oxide model.

Variables	Constant		Constant and trend	
	Level	First difference	Level	First difference
Nitrous oxide	-2.991 ^a	-16.515 ^a	-2.326 ^a	-14.148 ^a
Cereals	-5.751 ^a	-17.52 ^a	-4.699 ^a	-15.825 ^a
Roots and tubers	-1.413	-15.427 ^a	-1.893 ^a	-13.645 ^a
Vegetables	-2.461 ^a	-12.72 ^a	-0.161 ^a	-7.596 ^a
Fruits	-2.675 ^a	-13.738 ^a	-1.85 ^a	-12.591 ^a
Rural population	-13.496 ^a	-7.413 ^a	-6.75 ^a	-7.037 ^a
Technology	-1.321	-14.068 ^a	1.468	-12.282 ^a

Source: Computed by the Author Legend: ^a significant at 1%, ^b significant at 5%.

Furthermore, we perform a test for slope heterogeneity. The test null hypothesis is that the slope coefficients are uniform. The coefficients are statistically significant at the 1% level, rejecting the null hypothesis and declaring the presence of heterogeneous slopes among the panels (Table 7).

Table 7. Slope heterogeneity test for methane and nitrous oxide models.

	Methane	Nitrous oxide
	Delta	Delta
	23.768 ^a	16.384 ^a
Adjusted delta	27.371 ^a	18.867 ^a

Source: Computed by the Author Legend: ^a significant at 1%, ^b significant at 5%.

For the CH₄ emissions model, Table 8 shows that for the one versus no structural breaks, two versus one structural break, and three versus two structural break hypotheses tested, the t-statistic is below the critical values at 1%, 5%, and 10% levels of statistical significance. Thus, we fail to reject the null hypotheses and conclude that there is a stable trend in the data structure. Similarly, data on the N₂O emissions for the first break [F(1/0)] does not detect any statistically significant shift in the data structure. However, the data structure strongly supports the second and third breaks over their respective lags. Thus, over time, there are significant breaks in the N₂O data in 1999, 2006, and 2015. These breaks may be associated with the credit crunch in 2007 and the commitment made by member states to reduce emissions in 2015.

Table 8. Bai & Perron test for structural breaks.

	Methane			Nitrous oxide		
	F(1/0)	F(2/1)	F(3/2)	F(1/0)	F(2/1)	F(3/2)
T – Statistic	1.71	2.26	2.39	2.62	6.97	6.62
1% Critical value	5.69	6.24	6.53	5.69	6.24	6.53
5% Critical value	4.35	4.88	5.2	4.35	4.88	5.2
10% Critical value	3.72	4.32	4.65	3.72	4.32	4.65
Detected number of breaks:	0	0	0	3	3	3

Source: Computed by the Author Three cases: cereals, roots, and tubers, and fruit are considered due to the length of the period being less than the number of variables. The lag of the cases is taken into account for the dynamism of the model. The cross-sectional means of the first difference of the lag of the cases are incorporated to account for cross-sectional dependence and the standard error ^[91] for the robustness of the result: Set trimming to 0.25 for at most 3 breaks.

From the diagnostic tests, we confirmed the presence of CD, structural/no structural breaks, and heterogeneous slope coefficients in equations (2.3) and (2.4). Hence, we use the CS-ARDL model to address these issues jointly.

3.3. Crop Production and Farm Gate Emissions: Short and Long-Run Relationships

The study examines the short-and long-run effects of crop production on farm-gate emissions in selected RTB member states in Africa. We achieve this objective by proxying crop production to mean cereals, roots and tubers, vegetable, and fruit production and separate emissions into methane and nitrous oxide emissions. We employ the CS-ARDL model, which is dynamic, controls for CD, slope heterogeneity, serial correlation, structural breaks, and endogeneity [61] to estimate our baseline model (2.13).

3.3.1. Crop Production and Methane Emissions: Short and Long Run Relationships

Table 9 shows that all crop products have a positive sign, except roots and tubers. This means that roots and tubers are the only products with the potential to reduce methane emissions at the farm gate level in the RTB member states. However, cereals and fruit products are the crop products that affect methane emissions in the short and long run. The lag of methane emissions is also significant, validating the specification of a dynamic model. Analytically, cereals have short-run proportional change coefficients of 1.0021 and 1.0033 for the long term. This means that an increase in cereal output will result in a 1.0021 and 1.0033 kilotons on CO₂ equivalent emissions increase in farm-gate methane emissions in the short and long run on average in a year, respectively. Thus, the production of cereals is a significant contributor to farm-gate emissions. Its contribution increases by 0.0012 kilotons of CO₂ equivalent emissions, yearly, in the long run. Likewise, fruit production makes a positive contribution to farm-gate methane emissions in the RTB member states in Africa, both in the short and long run. Fruit production has a short-run proportional change coefficient of 1.0019 and a long-run proportional change coefficient of 1.0023. This indicates that fruit production significantly increases farm gate methane emissions in both the short and long term. Additionally, the increase in

farm-gate methane emissions caused by fruit production is exacerbated in the long run by 0.004 kilotons of CO₂ equivalent emissions on average, yearly. This implies that fruit production is a significant contributor to farm-gate methane emissions. The lag of emissions has a co-efficient of 0.8664. The lag of the emissions coefficient shows that past emissions are correlated with present emissions, hence the estimated model is dynamic. Further-more, the negative error correction term [ECM (-1)] with a speed of adjustment of 0.866 confirms the presence of a long-run relationship, implying that approximately 87% of disequilibrium in emissions is corrected annually through policies geared towards reducing methane emissions and negative shocks. The F-statistic has a coefficient of 2.78, which means that the model is well-fitted.

Table 9. CS-ARDL Crop production and methane emissions results.

Variable	Short-run elasticity coefficient	Short-run proportional change coefficient	Long-run elasticity coefficient	Long-run proportional change coefficient
Cereals	0.4746 ^a (-0.0838)	1.0021	0.7739 ^a (-0.2882)	1.0033
Roots and tubers	-0.1425 (-0.1657)	0.9994	-0.162 (-0.1808)	0.9993
Vegetables	0.1651 (-0.1059)	1.0007	0.2923 (-0.2462)	1.0013
Fruits	0.4472 ^a (-0.1394)	1.0019	0.5403 ^a (-0.192)	1.0023
Rural population	-0.1045 (-0.4731)	0.9995	-0.3394 (-0.581)	0.9985
Technology	-0.0152 (-0.0244)	0.9999	-0.0234 (-0.0319)	0.999
Lag of emissions			0.1336 ^a (-0.05)	
Error correction term			-0.8664 ^a (0.4998)	
F-statistic			2.78 ^a	
Number of observation			949	
Number of member states			30	

Source: Computed by the Author Legend: ^a significant at 1%, ^b significant at 5%, standard error in parentheses.

3.3.2. Crop Production and Nitrous Oxide Emissions: Short and Long-Run Relationships

Cereals and the production of fruit have a positive influence on the emissions of nitrous oxide in the short term. However, cereals are the sole contributors that may account for nitrous oxide emissions in the long term (Table 10). The positive signs on the coefficients of cereals and fruits show that they are the crops that drive farm-gate nitrous oxide emissions in the member states of the regional trading blocs in Africa. Specifically, an increase in cereal production will result in a 1.0024 and 1.0035 kilotons of CO₂ equivalent emissions increase in nitrous oxide on average in a year in the short and long run, respectively. Table 10 also shows that fruit production has a proportional change coefficient of 1.0025. Thus, a move to increase fruit production by a percentage point will result in a 1.0025 kiloton of CO₂ equivalent emissions rise in nitrous oxide on average in a year in the short run. The error correction term is -0.8422. This depicts a long-run relationship and an 84.22 percent disequilibrium adjustment of nitrous oxide emissions after a shock every year. Moreover, the lag of the emissions coefficient is 0.1578 and statistically significant at 1% level. This implies that previous years’ emissions explain present emissions, hence confirming the use of a dynamic model. The F-statistic coefficient is statistically significant, representing the overall goodness of fit of the nitrous oxide regression model.

Table 10. CS-ARDL Crop production and nitrous oxide emissions results.

Variable	Short-run elasticity coefficient	Short-run proportional change coefficient	Long-run elasticity coefficient	Long-run proportional change coefficient
Cereals	0.5229 ^a (-0.1096)	1.0024	0.8115 ^a (-0.2442)	1.0035
Roots and tubers	0.2877 (-0.3431)	1.0012	0.3939 (-0.5061)	1.0017
Vegetables	0.0251 (-0.1343)	1.0001	0.1252 (-0.1647)	1.0005
Fruits	0.5784 ^b (-0.2903)	1.0025	0.6375 (-0.5519)	1.0028
Rural population	0.9891 (-1.29)	1.0043	0.6514 (-1.5189)	1.0028
Technology	0.0131 (-0.016)	1.0001	0.0089 (-0.234)	1.0000
Lag of emissions	0.1578 ^a (-0.0439)			
Error correction term	-0.8422 ^a		(-0.0439)	
F-statistic			1.44 ^a	
Observation			949	
Member states			30	

Source: Computed by the Author Legend: ^a, significant at 1%, ^b significant at 5%, standard error in parentheses.

3.4. Robustness Checks: Pooled Mean Group and Sub-Sample Analysis

We use the PMG and subsample techniques to validate our baseline model results.

3.4.1. Pooled Mean Group Results

The PMG estimator was proposed by [92]. It is a dynamic model that permits group differences in short-run coefficients and error variances while constraining long-run coefficients to be the same. This estimation technique is robust because cross-sectional units can be pooled and also averaged. Table 11 shows the results of the PMG model. The results suggest that the cereals variable has a positive sign in the short and long run for the methane and nitrous oxide emissions models. These results confirmed the findings presented in Table 9. In addition, the positive fruit production effect on methane emissions is also confirmed in the long run (Table 9). However, vegetables, the rural population, and technology also have long-run effects on methane emissions.

Table 11. PMG Crop production and methane emissions results.

Variable	Short-run elasticity coefficient	Short-run proportional change coefficient	Long-run elasticity coefficient	Long-run proportional change coefficient
Cereals	0.2971 ^a (-0.0634)	1.0013	0.3156 ^a (-0.046)	1.0014
Roots and tubers	0.0548 (-0.0675)	1.0002	-0.0524 (-0.0383)	0.9998
Vegetables	0.1134 (-0.089)	1.0005	-0.0854 ^b (-0.0405)	0.9996
Fruits	0.2068	1.0009	0.2171 ^a	1.0009

	(-0.1284)		(-0.0427)	
Rural population	-3.5268 (-5.5204)	0.9849	1.1926 ^a (-0.1126)	1.0052
Technology	-0.0025 (-0.0096)	1.0000	-0.0240 ^b (-0.0109)	0.9999
Error correction term	-0.3925 ^a (-0.0523)			
Number of observation		949		
Member states		30		

Source: Computed by the Author Legend: ^a significant at 1%, ^b significant at 5%, standard error in parentheses.

Similarly, from Table 12, the short and long run effect of cereal production is confirmed in the nitrous oxide emissions model (Table 10). However, technology is a short-run drivers of nitrous oxide emissions, while the rural population and fruit production are long-run drivers.

Table 12. PMG Crop production and nitrous oxide emissions results.

Variable	Short-run elasticity coefficient	Short-run proportional change coefficient	Long-run elasticity coefficient	Long-run proportional change coefficient
Cereals	0.2921 ^a (-0.0861)	1.0013	0.4077 ^a (-0.0438)	1.0018
Roots and tubers	0.246 (-0.2246)	1.0011	0.049 (-0.0364)	1.0002
Vegetables	0.1199 (-0.1106)	1.0005	0.0359 (-0.0392)	1.0002
Fruits	0.0376 (-0.1161)	1.0002	0.1683 ^a (-0.028)	1.0007
Rural population	4.9843 (-2.71466)	1.0218	0.7300 ^a (-0.0949)	1.0032
Technology	0.0286 ^a (-0.0103)	1.0001	0.014 (-0.0144)	1.0001
Error correction term	-0.44144 ^a (-0.0586)			
Number of observation		949		
Member states		30		

Source: Computed by the Author Legend: ^a significant at 1%, ^b significant at 5%, standard error in parentheses.

3.4.2. Sub-Sample Results

Our sample comprises member states in the four selected regional trading blocs in Africa: The AMU, the EAC, the ECOWAS, and the SADC. The largest regional trading bloc in the sample is the SADC in terms of membership. Therefore, using the same estimation technique (CS-ARDL model), we estimate the sub-sample of the SADC regional trading bloc member states. We compare the regional trading bloc member states sub-sample findings to the full sample to corroborate the CS-ARDL results for all the regional trading bloc member states in this study. The results reveal that both

the short and long-run effects of cereals on farm-gate emissions for methane and nitrous oxide, as well as the long-term effect of fruit production on farm-gate emissions for methane, are statistically significant at 1% level (Tables 13 and 14).

This confirms that cereals and fruit production are the drivers of methane and nitrous oxide emissions (Tables 9 and 10).

Conclusively, all the models confirm that cereals and fruit production are the drivers of methane and nitrous oxide emissions at different periods, and the existence of a long-run relationship between the variables, with a speed of adjustment ranging from 39% to 86% for every diversion of the emissions variable due to shocks.

Table 13. Sub-sample crop production and methane emissions results.

Variable	Short-run elasticity coefficient	Short-run proportional change coefficient	Long-run elasticity coefficient	Long-run Proportional change coefficient
Cereals	0.2773 ^a -0.0606	1.0012	0.3460 ^a -0.0746	1.0015
Roots and tubers	-0.1753 -0.2596	0.9992	-0.2123 -0.37	0.9991
Vegetables	-0.1113 -0.2973	0.9995	-0.0872 -0.376	0.9996
Fruits	0.5366 ^b -0.2485	1.0023	0.6454 ^a -0.2146	1.0028
Rural population	1.1224 -1.0674	1.0049	1.1282 -1.088	1.0049
Technology	-0.0436 -0.0369	0.9998	-0.0926 -0.0572	1.0004
Error correction term	-0.8383 ^a -0.1247			
F-statistic	2.47 ^a			
Number of observations			251	
Member states			8	

Source: Computed by the Author Legend: ^a significant at 1%, ^b significant at 5%, standard error in parentheses.

Table 14. Sub-sample crop production and nitrous oxide emissions results.

Variable	Short-run elasticity coefficient	Short-run proportional change coefficient	Long-run elasticity coefficient	Long-run proportional change coefficient
Cereals	0.2847 ^a (-0.0636)	1.0012	0.3504 ^a (-0.0755)	1.0015
Roots and tubers	1.1939 (-1.1946)	1.0052	1.359 (-1.3875)	1.0059
Vegetables	-0.5678 (-0.3646)	0.9975	-0.6273 (-0.3695)	0.9973
Fruits	0.1716 (-0.6635)	1.0007	0.2329 (-0.7807)	1.001
Rural population	3.4435 (-2.3565)	1.015	4.0475 (-2.807)	1.0176
Technology	0.0784 (-0.0677)	1.0003	0.0863 (-0.0763)	1.0004
Error correction term	-0.8568 ^a (-0.0539)			

F-statistic	1.08	
Number of observations		251
Member states		8

Source: Computed by the Author Legend: ^a significant at 1%, ^b significant at 5%, standard error in parentheses.

4. Discussion

Attaining net zero emissions by 2050 requires a reduction in the emission of greenhouse gases. However, results from the cross-sectionally augmented autoregressive distributive lag estimation technique, pooled mean group method, and the sub-sample analyses consistently show that cereal and fruit production drive farm-gate methane and nitrous oxide emissions in the regional trading bloc member states in Africa. Cereals are notorious emitters of both methane and nitrous oxide emissions in the short- and long-run. However, the effect of cereals on nitrous oxide emissions is more pronounced than on methane emissions. This result is not striking because the increase in area under cereal cultivation and application of fertilizer are strongly associated with rises in nitrous oxide emissions across the regional trading bloc's member states. On the contrary, agricultural activities such as rice cultivation or occasionally flooded crop fields cause less significant methane emissions. [93,94] supported these findings by demonstrating that agriculture-related nitrous oxide emissions are strongly driven by cereal cultivation and fertilizer use, even though methane emissions tend to be more closely linked with cereals through shifts in land use or organic management.

Specifically, from Table 9, a standard deviation increase in cereal production will result in a rise in farm-gate methane emissions of 1.0021 and 1.0033 kilotons of CO₂ equivalent year⁻¹ on average in the short- and long-run, respectively. Thus, suggesting that the continuous cultivation of cereals in waterlogged farmlands, the production of agricultural byproducts such as rice straw, incomplete combustion of burnt remnants, and the burning of crop residues may be significant contributors to methane emissions in Africa's regional trading bloc member states. The positive long-run relationship may also imply that the focus of RTB member states is to increase cereal output rather than engage in farm-gate methane emissions mitigation strategies, such as climate-smart agriculture, due to lack of training, technological challenges, and high startup costs, which leads to long-term growth in farm-gate methane emissions [95,96]. This finding aligns with [39,40], which suggested that crop production contributes directly to methane emissions through the use of conventional flooding methods. This finding is also consistent with the results of [95,97,98], which showed that increasing grain production leads to increased agricultural emissions due to the expensive coupling interruption of decoupling activities and the adoption of inefficient agricultural practices.

Similarly, cereals also drive nitrous oxide emissions in the regional trading bloc members' states. This is because of their significant positive proportional change value. Hence, a move by regional trading bloc member states to increase cereal production by a standard deviation will lead to a 1.0024 and 1.0035 kilotons of CO₂ equivalent yr⁻¹ on average rise in farm-gate nitrous oxide emissions in the short- and long-run, respectively. The increase in nitrous oxide emissions may be a result of farmers' adoption of tillage and conventional irrigation, which disturb soil structure and increase microbiological channels for generating nitrous oxide [99]. The impact of cereal on nitrous oxide emissions may also be surmountable when cereal cultivation is done on a predominantly unsustainable basis [100]. The result supports the findings of [40–42], which revealed that cereals such as rice, wheat, and maize in mixed order are significant drivers of nitrous oxide emissions in mono-cropping, intercropping, early, late, and double cropping. Furthermore, this study finding aligns with [101], who stated that differences in temperature requirements for crops grown accounted for the accumulation of more nitrous oxide emissions by cereals compared to legumes. However, [102] finding suggested that nitrous oxide emissions were reduced through the correct selection of cereal varieties and sustainable agricultural practices.

In addition to cereals, fruit production is identified as a long-run driver of methane emissions. It has a positive long-run proportional change coefficient, indicating that higher fruit output results in a 1.0023 kilotons of CO₂ equivalent increase in farm-gate methane emissions on average per year.

This is likely because fruit cultivation involves land-use changes, tillage, irrigation, mulching, or manure application, all of which can disrupt soil and raise methane emissions [103]. In addition, land use change for unsustainable agricultural production may increase the incidence of methane emissions over time [104]. [48,105] study result confirmed that fruit production can deplete water resources as a result of shifting demand for crops that require adequate water, such as avocado. In summary, cereals drive both methane and nitrous oxide emissions over time, while fruits mainly affect methane emissions. Policymakers in agriculture, climate, and trade should consider these relationships when developing strategies to increase output, promote trade, and mitigate these emissions.

5. Conclusions

The drivers of crop emissions are diverse, so limiting them to crop output will be generic and, as such, will not provide a significant contribution to the crop emissions literature, therefore, this study employs the STIRPAT model, which considers multiple drivers of emissions and is more appropriate in determining causal short- and long-run effects of crop production on farm-gate emissions in the regional trading blocs member states in Africa. This study focuses primarily on the root causes of agricultural emissions by zooming into the different sub-components of the crop sector, such as cereals, roots and tubers, and fruits, and linking them to emissions (methane and nitrous oxide) at the farm-gate level. Furthermore, we employ the CS-ARDL technique that is robust and ensures the reliability of our study findings. Our results revealed that cereal production increases farm-gate methane and nitrous oxide emissions in Africa's regional trading bloc member states in the short- and long-run. The increase is between the range of 1.0021 to 1.0033 kilotons for methane, and 1.0024 to 1.0035 kilotons for nitrous oxide emissions per year. Thus, cereal production has a more adverse effect on nitrous oxide than methane emissions. In addition, fruit production increases farm gate methane emissions in Africa's regional trading bloc member states by 1.0023 kiloton per year on average in the long run.

We offer the following policy suggestions in light of our empirical findings. First, regional agricultural policies should incentivize the uptake of climate-smart agriculture adoption technologies and practices such as low or minimum tillage, alternative wetting and drying, and the conversion of crop residues into biochar. Second, member states and regional trading blocs should invest in agricultural emissions monitoring, surveillance, and reporting systems to track and mitigate real-time farm gate-level emissions from the different primary crops. Third, we recommend the targeting of cereal and fruit production systems specifically, through the adoption of good agricultural practices such as crop residue management and improved irrigation systems. These should be included in farm-gate emissions mitigation plans.

Notwithstanding, this study has limitations. Notably, since the crop sub-sector is a fraction of the agricultural sector, other sub-sectors like livestock and forestry that also have the potential to drive farm-gate emissions should be studied for a comprehensive analysis of farm-gate emissions in the agricultural sector. However, they are excluded because the focus of this study is to provide a detailed investigation that is manageable, robust, and free from too much of complexities. Thus, this study lays the foundation for future research in the livestock and forestry sub-sectors. Again, aside from farm-gate emissions, we have pre- and post-crop production emissions, which we do not account for; hence, it also serves as a potential area for future research.

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Appendix A

Appendix A.1

Appendix 1. Showing summary statistics for member states.

RTB	Nitrous						Populatio	Technolog
	Methan	Oxide	Cereals	Roots & Tubers	Vegetable s	Fruits		
Algeria	1.905452	2.195615	3379664	2607641	3903938	3739872	12040.52	908.7052
	0.438419	0.6875611	1406411	1593811	2139947	2097809	487.5547	785.5285
	0.9479	1.0524	870017	715936	1300588	1242788	11247.75	-584.325
	2.876	3.4472	6066239	5020249	7986966	7071434	12718.63	2584.071
	33	33	33	33	33	33	33	33
Angola	7.192694	0.7512727	1218094	8470025	1008288	2349265	9078.947	28557.11
			969838.					
	3.490819	0.5161117	1	4782581	638038.5	2089799	1123.496	29812.68
	2.6818	0.2208	248500	1798899	250000	405000	7650.444	-334.5
	13.0039	1.739	3179113	1.83E+07	2016573	6120250	11168.04	106077
Benin	33	33	33	33	33	33	33	33
						348965.		
	3.604391	0.7639091	1307770	5107649	398597.7	8	4840.86	1254.186
			559093.			169602.		
	1.950024	0.5667518	4	1890488	181999.4	2	971.806	1113.204
Burkina Faso						173161.		
	1.4687	0.3029	545898	2019754	214645	4	3261.667	40.58002
						676228.		
	7.7358	2.2982	2320756	7952286	744746.3	8	6450.295	3840.753
	33	33	33	33	33	33	33	33
Burundi						537292.		
	24.57023	1.640588	3551293	130609.8	702582.7	6	11015.93	1800.319
						467407.		
	16.64094	0.6425372	1081092	72103.9	387412.5	7	2256.687	1809.728
	5.0237	0.745	1517900	37400	229116	69831	7593.826	0.466252
Burundi	58.7137	2.6971	5180702	299127	1416382	1429305	15056.71	6551.879
	33	33	33	33	33	33	33	33
			384242.					
	2.325809	0.2462879	2	2198305	348509.8	1592571	7330.446	364.0649
Burundi			278550.			312135.		
	1.223799	0.1261564	4	1070159	115611.1	2	1799.806	319.3043

					957109.			
	1.0551	0.148	224724	1262722	210000	6	5075.806	1.25543
	5.0285	0.5487	1581835	4419890	498160.5	2355697	10848.08	1493.657
	33	33	33	33	33	33	33	33
			7812.30			14251.0		
Cabo Verde	0.085012	0.0075242	3	13383.7	29258.79	7	195.4066	434.141
			7383.52			2805.70		
	0.010498	0.0023795	7	4118.413	14497.6	4	5.275204	577.4965
	0.043	0.003	4	7665	4682	6998.93	188.641	0.2526
	0.0952	0.0139	36439	21263	49973.16	19007	202.818	1619.846
	33	33	33	33	33	33	33	33
Côte d'Ivoire	18.02668	1.277182	1898790	8439046	659303.4	2317163	10262.68	3502.637
			809132.			369014.		
	5.700347	0.4033769	4	3082855	60097.09	7	1580.021	2029.808
	11.6375	0.6558	1221428	4685380	569753.7	1569720	7440.947	51.42595
	28.4025	2.1361	3308600	1.48E+07	774260.6	3155808	13017.21	8534.646
	33	33	33	33	33	33	33	33
			2.01E+0			1.11E+0		
Egypt	165.8874	27.34557	7	3760665	1.36E+07	7	45550.75	111816
	23.36905	4.536444	3288880	1745015	3373522	3181650	8533.03	71348.61
			1.30E+0					
	105.1472	18.1261	7	1600411	7459974	5977551	32450.63	735.7677
			2.41E+0			1.60E+0		
	213.8234	32.8514	7	7712031	1.88E+07	7	60691.93	237047.7
	33	33	33	33	33	33	33	33
			92247.1			125597.		
Eswatini	0.277246	0.1351758	9	61337.73	11885.88	1	891.9663	67.35088
			28131.7			24748.4		
	0.040951	0.043385	4	12613.61	941.323	4	129.0743	54.09466
			27540.6					
	0.1934	0.06	6	43917	10500	73787.1	687.362	-61.24678
						162715.		
	0.3672	0.2055	152068	94364.16	13345.9	6	1121.095	154.906
	33	33	33	33	33	33	33	33
Ghana	13.51608	1.243152	2440180	1.91E+07	628941.7	3804305	11441.48	5472.179
	5.778714	0.7866342	1063430	8996124	141073.7	1767052	1242.964	5165.18
	4.6275	0.4273	843800	4409038	376972	923900	9297.561	17.8893
	27.9498	2.8538	5136565	3.82E+07	801831.5	6397830	13250.62	12706.64
	33	33	33	33	33	33	33	33
Guinea	117.139	0.8987758	2525157	1644864	523224	1157566	6757.862	191.5825
						188701.		
	60.07551	0.4303149	1084393	904542	35209.19	8	1262.806	344.631

	48.791	0.3627	1061616	797775	440139	856803	4348.022	-101.0378
	210.1131	1.699	4745053	4313086	566956.1	1614579	9022.706	1606.981
	33	33	33	33	33	33	33	33
Kenya	6.481606	2.968221	3571863	2877909	1959503	2652795	29252.15	13663.48
			725022.			863644.		
	1.450239	1.049515	5	1035765	600950.9	3	6204.769	13785.9
	4.6951	1.6589	2539301	1437978	743080	1400923	19483.07	72.99437
	8.7265	5.5514	4881251	4734181	3359488	4468921	39817.14	54593.73
	33	33	33	33	33	33	33	33
						16010.3		
Lesotho	0.338167	0.076803	127164	96997.26	27664.9	8	1528.87	332.808
			64141.4			1412.72		
	0.102067	0.0336183	4	26693.76	5322.99	6	73.75202	329.0402
			25678.0					
	0.0889	0.0439	6	45093	18000	13000	1379.922	-0.808339
	0.5059	0.189	257418	134962.1	35000	19000	1667.714	1234.286
	33	33	33	33	33	33	33	33
Liberia			202201.			173197.		
	2.361979	0.1458152	8	524923.6	95278.76	3	1786.776	19926.22
			85830.4					
	0.942721	0.0820897	4	144054.1	19784.49	33465.9	515.1272	27234.66
	0.6364	0.0284	50000	232616.2	70996	106779	865.312	34.98093
	4.1834	0.2741	335180	769796.3	125356.5	217563	2517.04	83520.52
	33	33	33	33	33	33	33	33
Madagascar	226.4066	1.324564	3647026	3899903	394242	1031850	13197.81	368.2073
			914651.			188307.		
	27.27257	0.2881333	2	630112.1	51151.28	3	2698.242	365.3614
	181.7254	0.9841	2497184	2960139	330300	767800	8865.351	9.493062
	299.3309	1.8974	5159721	5183376	470948.3	1289990	17539.78	1349.597
	33	33	33	33	33	33	33	33
Mali	38.44375	2.425688	5033452	453662.6	1234188	1116921	8967.909	1584.893
	17.99707	1.435104	3010112	380888.9	555779	729994	1622.212	1750.402
	14.5249	0.7811	1771419	51296	296290	392951	6490.895	5.72972
			1.05E+0					
	72.7271	5.8646	7	1452527	2597052	2576204	11739.44	7679.898
	33	33	33	33	33	33	33	33
Mauritius			797.121			18964.3		
	0.119464	0.2005242	2	17387.83	70759.96	2	698.8862	1992.217
			609.113			6331.79		
	0.022647	0.050414	3	3161.57	12109.77	4	50.06979	1680.117
	0.069	0.1103	112	11654	44860.04	8370	592.342	14.77845
	0.1627	0.2829	2284	23317	93811.71	31958	756.756	4496.445

	33	33	33	33	33	33	33	33
Morocco	5.501603	6.341245	6476768	1452429	3434894	4305758	13440.26	60297.24
	0.767112	1.375903	2974395	353152.4	847129.7	1277107	264.3674	40605.3
	3.3945	3.6116	1783230	894210.1	1907077	2337928	12839.86	183.6424
			1.17E+0					
	7.2056	9.3447	7	1967534	4491362	6618471	13688.17	126623
	33	33	33	33	33	33	33	33
						565793.		
Mozambique	21.15526	1.0946	1610493	5582967	529814.5	1	15181.41	3954.453
			613783.			253428.		
	7.960271	0.5334569	8	1269572	553516.3	9	3433.196	3487.002
			244554.					
	9.8411	0.357	1	3365024	115282	280400	9935.737	23.39897
	33.6098	2.1766	2832309	7482694	2224968	1019695	21121.58	10952.81
	33	33	33	33	33	33	33	33
			114871.					
Namibia	0.078303	0.1339364	4	306863.5	39039.43	9	1244.316	4406.658
			34827.8			20785.6		
	0.019693	0.1550612	1	66667.26	22936.58	9	77.46508	3499.005
	0.0492	0.0161	31031	195000	8000	7998.06	1023.439	29.56727
			186008.			71123.6		
	0.128	0.6772	3	392075.9	67982.48	2	1299.607	13785.07
	33	33	33	33	33	33	33	33
						336543.		
Niger	2.366433	1.502612	3778998	331297.2	1250303	6	12683.56	1130.317
						243196.		
	0.592847	0.45282	1416583	278992.1	1050195	4	4475.574	1183.053
	1.4677	0.8449	1850285	118320	249554.9	43800	6781.413	40.8132
						762360.		
	3.6941	2.2857	6100262	1103733	3605640	2	21584	4599.48
	33	33	33	33	33	33	33	33
			2.40E+0					
Nigeria	306.2426	11.53765	7	8.35E+07	1.07E+07	7	85076.73	48374.03
	108.4399	3.369717	3808570	2.88E+07	3836856	2359821	10149.39	47687.52
			1.77E+0					
	147.9306	8.0291	7	3.36E+07	4168000	6382000	66993.86	1002.5
			3.03E+0			1.69E+0		
	524.1397	21.0704	7	1.36E+08	1.64E+07	7	100786.3	150428.2
	33	33	33	33	33	33	33	33
			461602.					
Rwanda	1.519518	0.3443	6	2758519	412058.7	2672650	7985.937	1548.135

			244435.					
	1.032416	0.1874906	2	1037497	216855.7	438034	1786.131	2075.845
			130072.					
	0.1871	0.0635	5	886071.8	121412.9	1549000	5344.914	7.66
			932107.					
	3.1715	0.7487	3	4485985	688418.3	3611200	11247.44	7046.425
	33	33	33	33	33	33	33	33
Senegal						586966.		
	11.22151	0.7853939	1593330	441460.1	436945	3	6801.549	3171.29
						516698.		
	7.981554	0.4486956	861180	506957.2	323109.5	2	1390.933	2647.756
	3.405	0.2624	730335	41762.52	69661	167637	4616.787	57.85107
	29.6551	1.9716	3663690	1688559	1048198	1997619	9231.74	10463.86
	33	33	33	33	33	33	33	33
Sierra Leone			831425.			214152.		
	35.25101	0.4251121	9	1703635	279722.5	9	3617.961	170.6266
			431829.			48840.2		
	14.89276	0.2197511	1	1342271	87725.94	7	680.6779	228.7765
	12.3042	0.1111	222472	224400	180000	152985	2797.796	-7.46292
						282814.		
	78.3878	0.9433	2131723	4038764	479186	1	4704.509	968.7065
South Africa								
			1.33E+0					
	10.38005	11.81278	7	1974537	2303409	5821977	19334.56	73580.81
	2.08042	1.795304	3257667	459713.8	294933.3	1346182	439.1242	59399.63
	7.2043	9.2471	5056342	1125028	1892468	3815637	18015.16	-78.45956
			1.96E+0					
	14.6091	17.0976	7	2763924	2724794	8772836	19800.02	182594.3
Togo								
			946571.			55243.6		
	2.061203	0.4702273	4	1514481	144587.5	9	3778.373	919.5698
						9354.61		
	0.761084	0.1918064	307205	390027.1	5667.2	3	696.5604	948.4203
						41660.1		
	0.9135	0.2865	464877	840495.5	130698.4	9	2704.301	22.72051
Tunisia								
						68459.4		
	3.329	1.0891	1439850	2244231	158700	6	4927.839	3053.119
	33	33	33	33	33	33	33	33
	0.799524	1.928185	1725829	337181.8	2092994	1679399	3548.361	20842.69
			592995.			442289.		
	0.232564	0.4039127	9	76908.41	729207.2	3	48.18436	10423.03

			550525.					
	0.3224	1.0384	5	199000	1096862	1049565	3462.236	101.8172
	1.3492	2.9206	2896345	465000	3219344	2530206	3622.883	43107.63
	33	33	33	33	33	33	33	33
Uganda	8.826661	0.9874939	2809803	5777216	884843.6	7835354	25121.42	2800.509
			942322.					
	4.010887	0.2932797	6	1671836	382722.5	2448102	6620.009	2786.402
	3.9167	0.5389	1576000	3501000	415500	3451798	15507.4	-5.624783
						1.18E+0		
	21.7561	1.8818	5525000	8765000	1412799	7	37099.64	8707.827
	33	33	33	33	33	33	33	33
United								
Republic	124.485	3.347121	6959240	8634589	1806026	3652592	30820.69	4679.756
	54.25941	1.67222	3043055	2112238	736986.4	1737320	6471.257	4708.991
	53.3253	1.4451	2952900	4862263	1013675	1213738	20651.76	5.606912
			1.25E+0					
	226.4278	7.1964	7	1.32E+07	3182946	5884175	42177.77	19276.83
	33	33	33	33	33	33	33	33
Total	38.61901	2.811911	3801119	5788327	1663200	2338144	13449.15	13937.07
	77.89167	5.535796	5813586	1.60E+07	3175679	3150028	17080.64	33767.77
	0.043	0.003	4	7665	4682	6998.93	188.641	-584.325
			3.03E+0			1.69E+0		
	524.1397	32.8514	7	1.36E+08	1.88E+07	7	100786.3	237047.7
	990	990	990	990	990	990	990	990

Where the mean, standard deviation, minimum, maximum, and number are in vertical order in that manner.
Source: Computed by the Author.

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