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# A dynamic linkage between greenhouse gas (GHG) emissions and agricultural productivity: evidence from Ethiopia

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The consequences of greenhouse gas emissions are a global problem and are felt most clearly in poor countries. Every sector in Ethiopia is affected by greenhouse gas emissions, but the productivity of the agricultural sector is particularly at risk. Although climate change is a long-term phenomenon, no in-depth macro-level studies have been conducted to guide discussion in this area. Therefore, the study fills this gap and carefully examines these impacts over time from 2019 to 2022 using the Vector Auto Regressive Model. Our results show that a 1% increase in fertilizer consumption, agricultural land, nitrous oxide (N<sub>2</sub>O) emissions, rural population, and area devoted to grain production results in a 0.28, 2.09, 15.92, 5.33, and 1.31 percent increase in agricultural yield in the long-run, respectively. A negative relationship was found between agricultural employment, agricultural methane emissions (CH<sub>4</sub>), carbon dioxide emissions (CO<sub>2</sub>), and agricultural productivity with a significance level of 5%. This means that under a black box condition, a one percent increase in agricultural employment, CH<sub>4</sub>, and CO<sub>2</sub> emissions in the country in the long run will lead to a decrease in agricultural productivity by 5.82, 17.11, and 2.75 percent respectively, as we also found that all regressors except technology adoption had an elastic relationship with agricultural productivity. The short-term error correction estimates show that the coefficient of the “speed of adjustment” term for the expected productivity equation is both statistically significant and negative. The value of the coefficient term of  $-0.744$  shows that an adjustment of 74.4% is made each year to converge the long-run equilibrium level. Therefore, Ethiopia needs to take measures that keep the economy away from sectors that produce a lot of carbon. These must be coordinated at a global level to achieve social change towards a fair and environmentally sustainable future and to increase agricultural productivity.

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## Introduction

According to climate prediction models, climate change is expected to have a significant impact on agricultural productivity in the future. Global food security is seriously threatened by the expected increase in average temperature caused by increased emissions of greenhouse gases (GHGs) into the atmosphere, as well as increasing depletion of water resources and increased climate variability (Neupane et al. 2022). Over the coming 50 years, global food demand is forecast to double. Maintaining high agricultural productivity<sup>1</sup> is a key part of food security. As opposed to that, the area of fertile and arable land needed to grow these crops has been dramatically declining. The earth is currently becoming increasingly hotter as a result of increased greenhouse gas emissions brought on by human activities. As stated in the Paris Agreement, the world is quite far from achieving a global temperature rise of <2 °C. Compared to the baseline year of 1990, some countries are polluting more, some are emitting the same amount, and others are emitting less (UNEP, 2021). Carbon dioxide, nitrous oxide, and methane are the main greenhouse gases. More than 70% of the global rise in greenhouse impacts is attributable to them (FAO, 2021). Africa is one of the continents most affected by the effects of climate change, despite having the lowest greenhouse gas emissions per capita in the world. In Africa, greenhouse gas emissions related to land use and farmgate increased by 38 percent and 20 percent, respectively, between 2000 and 2018 (FAO, 2021). When we consider all agricultural products, our food systems are responsible for about 25 to 30% of world emissions, or about one-third (Hannah et al. 2020). Harvesting plant and animal products removes carbon from the agricultural system, primarily through the use of chemical pesticides, fertilizers, and animal waste. According to FAO estimates for 2018, agriculture contributed 9.3 billion tonnes of CO<sub>2</sub> equivalent (CO<sub>2</sub>eq) to global emissions (including farm gate emissions and land use change). According to research by Parry et al. (2004) food yields, productivity and the risk of hunger would all experience different impacts from climate change, with losses of up to 30% predicted in poor countries, particularly in Africa and some regions of Asia.

Although greenhouse gas emissions can accelerate plant growth, they are also responsible for climate change, ozone layer depletion, and water and nutrient shortages. Extreme rainfall and heat can stunt plant growth and reduce yields. Warmer, wetter, and higher CO<sub>2</sub> levels promote the growth of many weeds, pests, and fungi. For example, increasing CO<sub>2</sub> emissions can impact crop yields and also reduce the nutritional value of food crops. Therefore, the relationship between greenhouse gas emissions and agricultural productivity is complex and it is uncertain how these predictors dynamically interact over time. In recent years, climate change has been one of the greatest challenges, requiring innovative strategies to address its impacts on agricultural productivity and energy supplies (Bevan and Waugh, 2007); Hendre et al. 2019; Zenda et al., 2021; Mabhaudhi et al. (2019).

The majority of Ethiopians, 80 to 85%, make a living from agriculture and pastoralism. Agriculture contributes 88.8 percent of export revenue and 36.7 percent of the country's gross domestic product (World Bank, 2022). Agriculture is the main source of greenhouse gas emissions in Ethiopia, accounting for 80% of all emissions (World Bank, 2022). It contributes <0.1 percent of global emissions but is already feeling the effects of climate change. Agriculture and deforestation are responsible for >85% of emissions, with the energy, transportation, industrial, and construction sectors each contributing 3%. The trend in greenhouse gas emissions for the country's agricultural sector is that net emissions have increased from 19,586.06 Gg CO<sub>2</sub>e in 1994 to 226,157.6 Gg CO<sub>2</sub>e in 2022. Land-based CO<sub>2</sub> emissions accounted for the majority of total emissions, with CH<sub>4</sub> produced

by enteric fermentation emissions ranking second in the livestock category. The majority of greenhouse gas emissions from the energy sector come from burning liquid and solid fuels (World Bank, 2022). Climate change is expected to have a significant impact on Ethiopia's agricultural production, with projected reductions of 5–10% compared to baseline without climate change. The impacts will vary in different agroecological zones, with small changes in temperature affecting the net yield of the crop per hectare (Deressa and Hassan, 2009; Robinson et al. 2012). Deressa (2007) discovered that Ethiopian agricultural productivity is negatively affected by both increasing temperatures and decreasing rainfall.

The various aspects of agricultural productivity of Ethiopian smallholder households have been the subject of numerous studies (Mekonnen, 2022; Dawit et al., 2020; Eshetie et al. 2020; Gebreegziabher et al. 2016; Adamu, 2022; Nuno and Baker, 2021; Tesema and Gebissa, 2022; Yao, 1996; Ademe et al., 2016; Ayele and Tamirat, 2020). However, most of these studies did not consider the impact of agricultural greenhouse gas emissions on agricultural productivity over time and were limited to a specific region and production factors at a specific point in time. However, it is current ongoing human activities that are leading to climate change. Most of these studies, largely focused on the microeconomic impacts of greenhouse gases, provided only a partial picture of how greenhouse gas emissions have affected agricultural production. Few studies have examined how greenhouse gas emissions may affect agricultural productivity in Ethiopia. This study attempts to address these gaps by assessing the impact of greenhouse gas emissions on agricultural production over time. Due to the nature of the study, it is also the first attempt to assess how differences in agricultural productivity affect fertilizer use, access to land, rural population, agricultural employment, and the allocation of total area for grain production, baseline path from 1990 to 2022. Given the issues raised above, the research question of the study is posed as follows: "If there is a relationship between agricultural greenhouse gas emissions and agricultural productivity (proxied by grain yield per hectare), is there a "long-term" "lead a positive or negative relationship?". Therefore, this study is an important initiative to understand the long-term dynamics of greenhouse gas emissions and agricultural productivity and will serve as input for subsequent discussions.

## Literature review

According to the Climate Watch report (2023), climate change is driven by greenhouse gas (GHG) emissions from human activities. Just ten nations are responsible for nearly 60% of global greenhouse gas emissions, while the 100 lowest-emitting nations each contribute <3%. Agriculture is the second largest source of emissions after the energy sector. Although developing countries have a comparatively smaller share of global greenhouse gas emissions, their emissions are increasing from time to time. Research on agricultural productivity by Zhai et al. (2009) assumes that the long-term effects of climate change will last until 2080. Edoja et al. (2016) examine the impact of climate change on agricultural productivity worldwide and show that it can increase food prices and negatively impact agricultural welfare.

Developing nations, especially those in Africa, emit fewer greenhouse gases due to human activity, but they are still very exposed to and vulnerable to climate variability and events associated with it (Sarkodie and Strezov (2019)). According to research by Parry et al. (2004), food yields, productivity, and the danger of hunger would all experience various effects of climate change, with losses of up to 30% projected in poor nations, particularly in Africa and some regions of Asia. For instance, the

Valin, H. et al. (2013) study on agricultural productivity and greenhouse gas emissions in developing countries suggests that increasing yields could slow emissions expansion. Closing yield gaps for crops and livestock could reduce emissions by 8% overall and 12% per calorie produced by 2050. Ekpenyong and Ogbuagu's (2015) study reveals a negative correlation between agricultural productivity and climate change in Nigeria, with a 100% increase in greenhouse gas emissions resulting in a 22.26% decrease in AGP. And, the Edoja et al. (2016) study in Nigeria also found a long-term association between CO2 and agricultural productivity, with a one-way causal connection between CO2 and food security. Molua's (2002) study on climate variability in southwestern Cameroon revealed that climate change reduces crop yields in agriculture-based economies, highlighting the challenges and implications for food security. Similarly, Muamba and Kraybill's (2010) study on Mt. Kilimanjaro revealed that climate change impacts agriculture-dependent economies, reducing food yields.

Ethiopia's contribution to regional and global greenhouse gas emissions is also quite small. However, greenhouse gas emissions occasionally show increasing trends with slight fluctuations. Forestry and agriculture, as well as land use and land use change, have contributed significantly to the country's greenhouse gas emissions. According to the UN FAO, agricultural emissions in Ethiopia have continuously increased from around 53 million tonnes of carbon dioxide equivalent (MtCO2eq) in 1993 to around 117 MtCO2eq in 2019 (FAOSTAT, 2021). The Ethiopian government has started implementing the 2010–2030 CRGE (Climate-Resilient Green Economy) strategy to reduce the risks associated with climate change. This plan aims to promote sustainability and development while keeping greenhouse gas emissions at or below 150 Mt CO2 emissions. In Ethiopia specifically, climate change has an impact on agricultural production by shortening the maturation period and subsequently reducing crop yield, altering the availability of feed for livestock, impacting animal health, growth, and reproduction, lowering the quality and quantity of forage crops, and altering disease distribution. For instance, Mekonnen (2022), Eshete et al. (2020), and Gebreegziabher et al. (2016) studies highlight the significant impact of Ethiopia's agriculture on climate change, with CO2 emissions negatively affecting productivity and household welfare. Additionally, their research indicates potential impacts on land productivity and the economy.

In summary, research from Ethiopia and other countries shows increased greenhouse gas emissions, changing weather conditions, and other factors affecting agricultural productivity. Most studies in Ethiopia focus on micro-level effects (cross-sectional effects), but there is a lack of sufficient studies that calculate effects over time using CRGE. Therefore, this study aims to complement the existing literature.

**Methods**

The relationship between several quantities as they change over time is captured by the statistical model known as vector autoregression (VAR). Human activities can significantly change greenhouse gas emissions, which is not always permanent. Therefore, the VAR methods would be suitable to capture the dynamics between greenhouse gases and agricultural productivity. The VAR model also includes all empirical methods applied to draw more precise conclusions from the data provided; The VAR is considered for the study period from 1990 to 2022. Therefore, the unit root or stationarity tests were applied using the Augmented-Dickey-Fuller (ADF) and Phillips-Perron (PP) testing methods. Then, the cointegration test, VECM, Granger causality test, variance decompositions, and stability test are used

after selecting the appropriate delay length based on informative criteria.

**Data sources.** The study used data from the World Bank's IBRD.IDA database to analyze the relationship between agricultural productivity and greenhouse gas emissions from 1990 to 2022.

**Proxy measurements**

*Productivity measurement.* Agricultural productivity is the ratio of agricultural output to input, measured by crop yield or seed ratio. In Ethiopia, grain production is a significant subsector, employing 60% of the rural workforce and occupying 80% of agricultural land. Grains account for 40% of household food budgets, making grain per yield the perfect measure of agricultural productivity. While agriculture includes both crop production and livestock production, crop yield is preferred as a proxy variable for this study.

*Greenhouse gas emissions.* It refers to the total amount of greenhouse gases (GHGs) released into the atmosphere, including carbon dioxide (CO2), methane (CH4), and nitrous oxide (N2O). Carbon dioxide (CO2) equivalent is a common measurement of greenhouse gas emissions. A gas's global warming potential (GWP) is multiplied by its emissions to convert its emissions into CO2 equivalents. This measure is most commonly used in the scientific literature and is adopted by the United Nations Framework Convention on Climate Change (UNFCCC).

**Model specification**

*The econometric VAR specification.* To prevent heteroskedasticity and demonstrate the elasticity of the variable, we first converted all the data of the variable into a log format. The unstructured VAR model is then defined as a VAR model:

$$\begin{aligned} \text{Log}(AGP) = & \beta_0 + \beta_{1i} \log(AGP)_{t-i} + \beta_{2i} \log(FeC)_{t-i} \\ & + \beta_{3i} \log(A\_Land)_{t-i} + \beta_{4i} \log(CO2\_emissions)_{t-i} \\ & + \beta_{5i} \log(AME)_{t-i} + \beta_{6i} \log(ANOE)_{t-i} + \beta_{7i} \log(R\_PoP)_{t-i} \\ & + \beta_{8i} \log(A\_empt)_{t-i} + \beta_{9i} \log(Land\_CP)_{t-i} + \epsilon_{1t} \end{aligned} \tag{1}$$

Were,  $\beta_i$  's are coefficients of  $1 \times k$  matrix to be estimated related to each predictor variable.  $i = 1, k$  the VAR-order;  $\epsilon_{1t}$  = the error-term; Log = Log of the variables

The constraints of the model are linear, but the variables are non-linear. Semielasticities are represented by  $\beta_i$  coefficients, while a stochastic perturbation term with known characteristics is represented by  $\epsilon_{1t}$ . The relative contributions of the respective explanatory variables, which in turn depend on how well the economic system under consideration functions, determine the sign of each coefficient.

*The vector error correction specification.* We applied a vector error correction model to study the dynamical system with properties that incorporate the deviation of the current state from its long-term relationship into its short-term dynamics. An error correction model is not a model that corrects the error in another model. According to Eq. (1), the error correction model is specified as follows:

$$\begin{aligned} \Delta \text{Log}(AGP) = & \Omega[\beta_2 \log(FeC)_{t-1} + \beta_3 \log(A\_Land)_{t-1} + \beta_4 \log(CO2\_emissions)_{t-1} \\ & + \beta_5 \log(AME)_{t-1} + \beta_6 \log(ANOE)_{t-1} + \beta_7 \log(R\_PoP)_{t-1} + \beta_8 \log(A\_empt)_{t-1} \\ & + \beta_9 \log(Land\_CP)_{t-1}] + C + \pi_1 \Delta \text{Ln}(AGP)_{t-1} + \gamma_1 \Delta \text{Log}(FeC)_{t-1} \\ & + \Phi_1 \Delta \log(A\_Land)_{t-1} + \psi_1 \Delta \text{Log}(CO2\_emissions)_{t-1} + \Theta_1 \Delta \log(AME)_{t-1} \\ & + \nu_1 \Delta \log(ANOE)_{t-1} + \sigma_1 \Delta \log(R\_PoP)_{t-1} + \zeta_1 \Delta \text{Log}(A\_empt)_{t-1} \\ & + \lambda_1 \Delta \text{Log}(Land\_CP)_{t-1} + \epsilon_{1t} \end{aligned} \tag{2}$$

**Table 1 Data sources and descriptions.**

Data description	Proxy	Sources
Agricultural productivity (AGP)	AGP is agricultural productivity measured (proxied) as Cereal Yields, kilogram per hectare	The World Bank, IBRD.IDA <a href="https://data.worldbank.org/country/ET">https://data.worldbank.org/country/ET</a>
Fertilizer Consumption (FeC)	FeC is fertilizer Consumption measured in terms of fertilizer consumption, kg/ha of arable land	The World Bank, IBRD.IDA <a href="https://data.worldbank.org/country/ET">https://data.worldbank.org/country/ET</a>
Arable land size(A_Land)	A_Land is the arable land measured in terms of hectare per person	The World Bank, IBRD.IDA <a href="https://data.worldbank.org/country/ET">https://data.worldbank.org/country/ET</a>
Carbon dioxide emissions (CO2_emissions)	CO2_emissions is CO2 emission measured in terms of kt	The World Bank, IBRD.IDA <a href="https://data.worldbank.org/country/ET">https://data.worldbank.org/country/ET</a>
Agriculture Methane emissions or CH <sub>4</sub> (AME)	AME is emissions of methane (CH <sub>4</sub> ) from agriculture (thousand metric tons, of CO <sub>2</sub> equivalent)	The World Bank, IBRD.IDA <a href="https://data.worldbank.org/country/ET">https://data.worldbank.org/country/ET</a>
Agriculture Nitrous oxide emissions or N <sub>2</sub> O (ANOE)	ANOE is emissions of nitrous oxide from agriculture (thousand metric tons of CO <sub>2</sub> equivalent)	The World Bank, IBRD.IDA <a href="https://data.worldbank.org/country/ET">https://data.worldbank.org/country/ET</a>
Rural population (R_PoP)	R_PoP is the rural total population at the time, t,	The World Bank, IBRD.IDA <a href="https://data.worldbank.org/country/ET">https://data.worldbank.org/country/ET</a>
Agricultural Employment (A_empt)	A_empt is Employment in agriculture (% of total employment)	The World Bank, IBRD.IDA <a href="https://data.worldbank.org/country/ET">https://data.worldbank.org/country/ET</a>
Total land for cereal production (Land_CP)	Land_CP is the total land allocated for cereal production in hectares	The World Bank, IBRD.IDA <a href="https://data.worldbank.org/country/ET">https://data.worldbank.org/country/ET</a>

Source(s): Authors' compilation (2023).

Were,  $\Omega$  is the coefficient of the error term or the speed-of-adjustment term.  $\pi_i$ ,  $Y_i$ ,  $\sigma_i$ ,  $\Psi_i$ ,  $\Theta_i$ ,  $v_i$ ,  $\zeta_i$ ,  $\lambda_i$ , and  $\Phi_i$  are short-run coefficients of the 1X K matrix to be calculated.  $I = 1, 2, 3, \dots$  where  $\varepsilon_t$  is a vector of external shocks and  $k$  is the lag order.

**Empirical strategy for data analysis.** According to various statistical justifications, the time series data used in VAR must be stationary. Therefore, stationarity tests are carried out. Due to the ability of the tests to account for the autocorrelation issues, the “extended” Dickey-Fuller (ADF) and Phillip-Peron (PP) tests are used in this study. Second, error correction models (ECM) and cointegration are used to examine the relationships between the regressors and the dependent variable. Therefore, the choice of the delay length is one of the most important steps after the stationary test and before carrying out the cointegration test. While the Hannan-Quin is more effective when the observations are above 120, the AIC and Final Prediction Error (FPE) are more suitable when the observations are below 60 (Liew, 2004). Therefore, we applied AIC and FPE information criteria to determine the delay order of the study. We then used the Johnson test with trace or eigenvalue to test the cointegrating equation in the examined series. Since the Johnson test allows for multiple cointegrating relationships and is more generally applicable than the Engle-Granger test, which is based on the Dickey-Fuller test (or extended test) for roots of unity in the residuals of a single (estimated) cointegrating relationship, we have used it to test the cointegration equation in the series examined. Third, an error correction model is used for this study to determine the short-term dynamic characteristics of the model. We used an error correction model to consider a dynamical system with the property that short-term dynamics are affected by the deviation of the current state from the long-term relationship. A model that fixes a problem in another model is not an error correction model. Based on the parsimonious model, we then specified the short-term model of the series. Fourth, since multicollinearity often affects the coefficients of VAR models, it is pointless to evaluate these results directly (Boschi, 2005). Therefore, the variance decomposition and impulse response techniques are used to study the dynamic behavior of the data series. Fifth, the Granger causality test is used to determine the degree of relevance of one factor in predicting the other, as well as the direction of causality (unidirectional or bidirectional) between the dependent variable

and the predictors (Granger, 1969). The results are the only evidence of linear interdependence between one component and another, not coefficients of actual dependence or evidence of true causality. Finally, we also checked the stability of the study over time (Table 1).

## Result and discussions

**Unit root test.** Table 2 and Table 3 show the results of the unity root at the level and the first difference, respectively. This can be demonstrated by comparing the observed values of the ADF and PP test statistics with the critical values of the test statistics at the 1, 5, and 10% significance levels (both in absolute numbers). Table 2 provides strong evidence of nonstationarity. Since the absolute values of the test statistics fall below the critical value according to the critical value rule of Mackinnon (1991). Except for the rural population (whose stationarity is confirmed by their *P*-value), stationary values could not be determined for all variables. As a result, the null hypothesis is accepted and it is sufficient to conclude that the variables have a unit root.

The coefficients of Table 3 (test statistics) showed that all variables were stationary at the first difference compared to critical values at the 1, 5, and 10% significance levels. This rejects the null hypothesis of non-stationarity and one can safely assume that the variables are stationary. This advocates that each variable be integrated to order one or I (1), except R\_PoP which is integrated to order zero or I (0). This means that the model's variables are cointegrated or that they have a “long-run” or equilibrium relationship if the model residual is found to be stationary at the level. In other words, the hypothetical scenario is a long-term model. The plot (Fig. 1) also confirmed the stationary behavior of the residual as it crossed the zero-grid line more than once. In other words, the VAR has a “long-term” relationship. In other words, greenhouse gas emissions have significant long-term impacts on a country's agricultural productivity and performance.

## Cointegration test result and analysis

**The VAR order selection criteria analysis.** By using AIC and FPE as given in Table 4 below, an appropriate lag length is selected using a simple VAR model.

The recommended lag length in this case is two. The lowest AIC value was determined here because all information criteria

**Table 2 PP and ADF stationary test (at levels).**

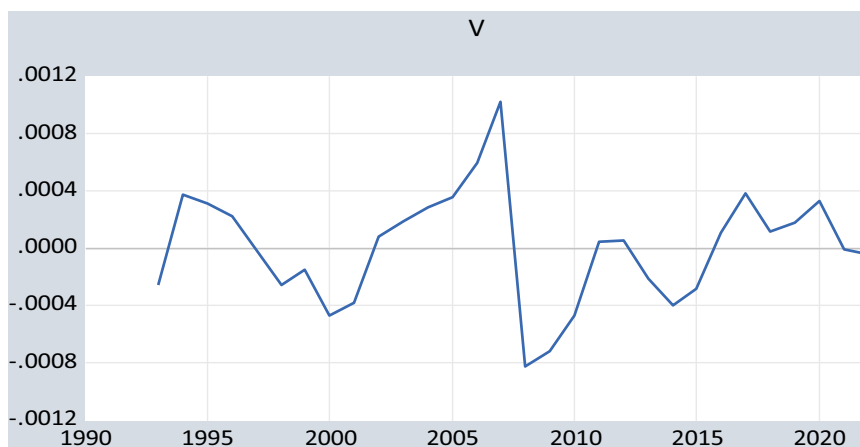
Variables	ADF (Intercept)	ADF (Trend & Intercept)	PP (Intercept)	PP (Trend & Intercept)
Log (AGP)	0.682872(-3.670170)*	-2.672438(-4.273277)	0.845484(-3.653730)*	-3.051010(-4.273277)*
Log (FeC)	-5.185613(-3.661661)*	-3.447394(-4.273277)*	-1.905916(-3.653730)*	-3.447394(-4.273277)*
Log(A_Land)	-1.711639(-3.661661)*	-2.349513(-4.284580)	-1.789907(-3.653730)*	-2.061623(-4.273277)*
Log (CO2_Emissions)	0.386750(-3.653730)*	-3.746129(-4.273277)*	0.837553(-3.653730)*	-3.743538(-4.273277)*
Log (AME)	-0.074335(-3.653730)*	-2.450443(-4.273277)*	-0.078956(-3.653730)*	-2.499049(-4.273277)*
Log (ANOE)	-0.101948(-3.653730)*	-2.665148(-4.273277)*	-0.101948(-3.653730)*	-2.665148(-4.273277)*
Log (R_PoP)	-12.81103(-3.670170)**	-2.934496(-4.296729)*	-13.66560(-3.653730)*	-4.579092(-4.273277)*
Log (Land_CP)	-1.393267(-3.711457)*	-3.466175(-4.309824)*	-15.57669(-3.653730)*	-31.19871(-4.273277)*
Log (A_Empt)	0.666734(-3.689194)*	-1.836798(-4.296729)	-1.749072(-3.653730)*	-0.858107(-4.273277)*
V	-3.491235(-2.967767)**	-3.425185(-3.221728)**	-3.198609(-2.967789)**	-3.180296(-3.221728)**

Note: Mackinnon's (1991) critical value for rejecting the unit root hypothesis was used. \* Significance at 1%, \*\* significance at 5%. Critical values are indicated by figures in parentheses. Source: Author's estimation made using EViews 13 (2023).

**Table 3 First difference, ADF and PP stationarity test.**

Variables,	ADF, (Intercept)	ADF, (Trend &, Intercept)	PP, (Intercept)	PP, (Trend &, Intercept)
Log (AGP)	-5.442758(-3.670170)*	-5.796221(-4.296729)*	-6.524712(-3.661661)*	.6524712(-3.661661)*
Log (FeC)	-10.48202(-3.661661)	-11.13399(-4.284580)	-8.948700(-3.661661)*	-9.433169(-4.284580)*
Log (A_Land)	-3.121173(-2.960411)**	-3.043001(-3.215267)**	-3.121173(-2.960411)**	-3.043001(-3.215267)**
Log (CO2_Emissions)	-5.705850(-3.661661)*	-5.734734(-4.284580)	-5.979680(-3.661661)*	-6.002109(-4.284580)*
Log (AME)	-4.059803(-3.670170)*	-4.025628(-3.568379)**	-4.989526(-3.661661)*	-4.912648(-4.284580)*
Log (ANOE)	-5.696611(-3.661661)*	-5.617268(-4.284580)*	-5.696858(-3.661661)*	-5.617332(-4.284580)*
Log (R_PoP)	-3.493137(-2.960411)**	-4.997517(-4.284580)*	-3.779139(-3.661661)*	-16.08931(-4.284580)*
Log (Land_CP)	-4.424620(-3.679322)*	-4.808460(-4.356068)*	-33.13801(-3.661661)*	-42.28315(-4.284580)
Log (A_Empt)	-1.535645(-2.625121)**	-2.885868(-3.225334)**	-1.624761(-3.661661)*	-2.298126(-3.215267)**
V	-5.897840(-3.689194)*	-5.775352(-4.323979)*	-12.689194(-3.689194)*	-12.82301(-4.323979)*

Note: Mackinnon's (1991) critical value for rejecting the unit root hypothesis was used. \* Significance at 1%, \*\* significance at 5%. Critical values are indicated by figures in parentheses. Source: Author's estimation made using EViews 13 (2023).



**Fig. 1 Stationarity of the residual both at level and first difference.** Note: The figure shows the stationary behavior of the residual at the level and first difference. since it crossed the zero-grid line more than once. Therefore, the residuals are stationary. In other words, the VAR has a “long-run” relationship. Source: Authors.

supported lag length 2. Since we are currently running the model in the first difference and not in the level, when we used VAR to determine the lag length, the lag length for cointegration is the lag length chosen above minus one. The trace and maximum eigenvalue cointegration tests of Johansen (1991) are therefore used to test the dynamic relationships between greenhouse gases and agricultural productivity.

*Johansen cointegration test result.* The result shown in Table 5 shows the maximum eigenvalue and trace statistics of greenhouse gases and agricultural productivity.

The study found a long-term dynamic relationship between greenhouse gas emissions, agricultural productivity, and other predictors, as evidenced by cointegration between independent and dependent variables at a significance level of 5%. Both tests rule out the null hypothesis that there is no cointegrating equation, which we have manipulated to reject. The degree of cointegration is between 4 and 6. Cointegration would not have proven successful in practice. Without the use of statistical theory, the parameters of linear systems cannot be tested or estimated. Therefore, the cointegration plot of the estimated VAR model was displayed to support the statistical test of the long-term impact of

**Table 4 Selection criteria for VAR lag order.**

Lag	LogL	LR	FPE	AIC	SC	HQ
0	376.4444	NA	4.10e-22	-23.70609	-23.28977	-23.57038
1	812.9627	591.4118	5.55e-32	-46.64275	-42.47956	-45.28566
2	1001.804	146.2001*	2.61e-34*	-53.60028*	-45.69023*	-51.02180*

\* Denotes the lag order chosen by the criterion.  
 LR: sequential modified LR test statistic, with each test conducted at the 5% level; Final prediction error (FPE); Akaike Information Criteria (AIC); Schwarz information Criteria (SQ); Hanna Quinn information criterion (HQ).  
 Source: Author's estimation made using EViews 13 (2023).

**Table 5 The results of the Johansen cointegration test (Trace and maximum eigenvalue).**

**Lags interval (in first differences)**

**Endogenous variables: LOG(AGP) LOG(FeC) LOG(A\_LAND) LOG(CO2\_EMISSIONS) LOG(AME) LOG(ANOE) LOG(R\_POP) LOG(LAND\_CP) LOG(A\_EMPT)**

**Deterministic assumptions: Case 3 (Johansen-Hendry-Juselius): Cointegrating**

Hypothesized- No. of CE(s)	Eigenvalue	Trace- Statistic	0.05 Critical-Value	Prob.** Critical-Value
None*	0.996135	498.9190	197.3709	0.0000
At, most 1*	0.976380	326.6870	159.5297	0.0000
At, most 2*	0.902921	210.5709	125.6154	0.0000
At, most 3*	0.793884	138.2718	95.75366	0.0000
At, most 4*	0.644743	89.31307	69.81889	0.0007
At, most 5*	0.597191	57.23077	47.85613	0.0052
At, most 6	0.437196	29.04269	29.79707	0.0609
At, most 7	0.274750	11.22314	15.49471	0.1982
At, most 8	0.039977	1.264752	3.841465	0.2608

Hypothesized No. of CE(s),	Eigen-value	Max-Eigen Statistic	0.05 Critical-Value	Prob.** Critical Value
None,*	0.996135	172.2320	58.43354	0.0000
At most, 1*	0.976380	116.1161	52.36261	0.0000
At most, 2*	0.902921	72.29909	46.23142	0.0000
At most, 3*	0.793884	48.95877	40.07757	0.0039
At most, 4	0.644743	32.08231	33.87687	0.0806
At most, 5*	0.597191	28.18808	27.58434	0.0418
At most, 6	0.437196	17.81955	21.13162	0.1367
At most, 7	0.274750	9.958390	14.26460	0.2147
At most, 8	0.039977	1.264752	3.841465	0.2608

Max-eigenvalue-test denotes 4, cointegrating equation(s) at, the 0.05, level.  
 \*Denotes, rejection of the hypothesis at the 0.05 level.  
 \*\*p-values.  
 Trace-test indicates, 6 cointegrating, equation(s), at the 0.05 level.  
 Unrestricted cointegration-Rank-Test (Max-Eigen Statistics).  
 Source: Author's estimation made using EViews 13 (2023).

greenhouse gas emissions on productivity. The graph in Fig. 2 shows a long-term relationship between the study variables. Convergence towards long-term equilibrium occurs when the grid line is crossed several times.

Similarly, the residual test (Annex 1) was conducted based on the Jarque-Bera test statistics and confirmed that the residuals do not satisfy the Jarque-Bera normality test. The residual heteroskedasticity test (Annex 2) confirmed that there was insufficient information to reject the null hypothesis. Additionally, the characteristic polynomial roots are shown below in Fig. 3.

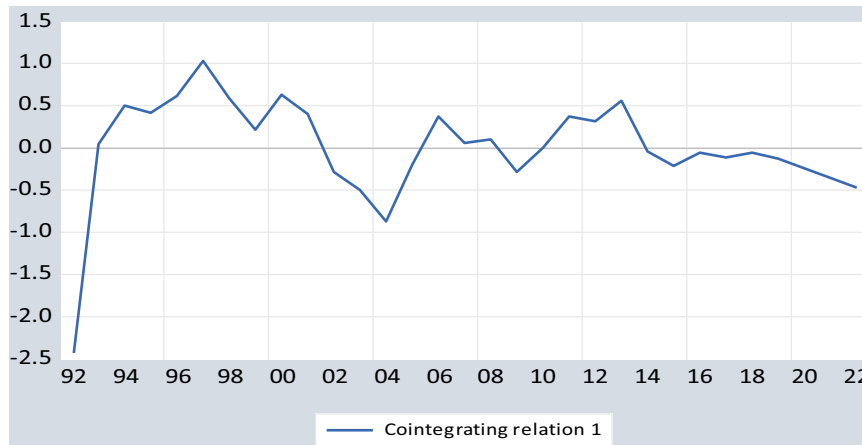
According to the inverse root of the AR characteristic polynomial, no point lies outside the circle. This shows once again that the VECM is stable and that the system contains a potentially cointegrated equation. The result showed that each error term has a normal distribution.

Similarly, to check whether the study specification suffers from autocorrelation, we used the Correlogram-Q statistics and the Breusch-Godfrey LM tests. The autocorrelation and partial

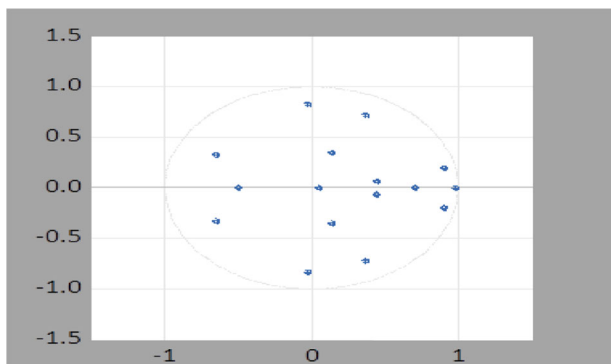
autocorrelation functions of the residuals as well as the Ljung-Box Q statistic for higher-order serial correlation are calculated to determine whether the estimates obtained using the Q statistic (Annex 4) are valid or not. All Q statistics should not be significant if there is no serial correlation. The presence of serial correlation is indicated by *p*-values <0.10. The result proved that there is no serial association as the *P*-value is >0.1. Similar to this, LM Test Statistics is used to determine whether the estimates are valid or not and it is determined that the null hypothesis of the test is that there is no serial correlation in the residuals up to the specified lag order.

*Cointegration test result.* Table 6 below shows the dynamic relationships between agricultural productivity with greenhouse gas emissions and other regressors in Ethiopia.

Therefore, the estimated long-run equation would be clearly expressed in the following general form: Thus, the stable long-run relationship is given as follows:



**Fig. 2 Cointegration graph.** Note: The co-integration graph crosses the zero-grid line more than once. It demonstrates that there is long-run relationship among the study’s variables. To put it another way, there is convergence towards long-term equilibrium. Source: Authors.



**Fig. 3 Inverse roots of AR characteristics polynomial graph.** Note: The points are inverse roots of the characteristic polynomial. According to the inverse root of the AR characteristic polynomial, no point is seen outside the circle. It demonstrates that the VECM is stable and that the system contains a potentially cointegrated equation. The outcome further reveals that each error term has a normal distribution. Source: Authors.

Substituted coefficients:

$$\begin{aligned} \text{Log}(AGP) = & 52.12487 + 0.276156\text{log}(FeC) \\ & + 2.094041\text{log}(A\_Land) - 2.748532\text{log}(CO2\_emissions) \\ & - 17.10959\text{log}(AME) + 15.91562\text{log}(ANOE) \\ & + 5.325542\text{log}(R\_PoP) + 1.314319\text{log}(Land\_CP) \\ & - 5.818187\text{log}(A\_empt) \end{aligned}$$

After identifying Table 6 above, the substituted coefficients, cointegration test output, and vector error correction estimates in the long-run coefficient model (elasticities) with “cointegration lag” shows:

**Farm size (A\_Land) and productivity.** We discover solid proof that farm size (proxied by arable farmland per hectare per person) and agricultural productivity (measured by cereal yield per hectare) are positively correlated in the long run. Let us now focus on the self-reported estimates of whether there is an inverse relationship (IR) between farm size and productivity when fertilizer use, CO2 emissions, and total area allocated to grain production are taken into account. The results in this case indicate a strong and statistically significant correlation between farm size and yield. The coefficients in the third column of row 1 in Table 6 show that increasing the size of a farm increases grain yield per

hectare by ~2.094%. These results once again underline the importance of considering fertilizer use and the main contributors to climate change (CO2 emissions) when analyzing the relationships between farm size and productivity. Here, farm size (FS) is the arable land<sup>2</sup> measured in terms of hectares per person at time t. The result showed a positive relationship between farm size and agricultural productivity with a low standard error value. Additionally, the statistical noise in the estimates is low and is statistically significant at the 1% significance level. Assuming other factors remain constant, a 1 percent increase in agricultural land in hectares per person in the economy appears to lead to a 2.094 percent increase in agricultural output in the country in the long run. Therefore, the responsiveness of the dependent variable due to a change in agricultural acreage is high and elastic. It is consistent with (Oppong et al., 2021; Paul and Wa Githinji, 2018; Diriba, 2020). In contrast to this finding, researchers found that land fragmentation in Ethiopia led to food shortages and increased the time spent traveling from one plot to another, reducing agricultural productivity (Abebe et al. 2022; Knippenberg et al. 2020).

According to a 1962 study by Amartya Sen, small farms had the highest average agricultural yields, which was a conclusion observed in many developing countries. This led to proposals for land reform and a focus on small farms in agricultural development programs. However, our results, highlighted in Table 6 above, show that the inverse relationship between farm size and yield does not hold for time series data. Large agricultural operations, on the other hand, are often considered the most productive in industrialized nations, even if these operations often have low labor productivity.

Below are the results of estimating greenhouse gas emissions using the three critical variables:

*CO2 emissions (measured in terms of kt).* Research has shown that higher atmospheric concentrations of carbon dioxide have two major effects on crops: they increase crop yields by speeding up photosynthesis, which promotes growth, and they reduce the amount of water that crops lose through transpiration. So, Table 6 above shows that carbon dioxide emissions and agricultural productivity are negatively correlated, with a low standard error value. This implies little statistical noise in the calculations and is statistically significant at the 1% level. So, holding other factors constant, a 1 percent increase in carbon dioxide emissions in the economy appears to lead to a 2.749 percent decline in Ethiopia’s agricultural output in the long run. The responsiveness of agricultural productivity is elastic as a result of the increase in CO2

**Table 6 Result of long-run cointegration relation.**

Log-Likelihood: 838.4609								
Normalized, cointegrating coefficients (standard error in parentheses)								
LOG (AGP)	LOG (FeC)	LOG (A_LAND)	LOG(CO2_EMISSIONS)	LOG(AME)	LOG(ANOE)	LOG(R_POP)	LOG(LAND_CP)	LOG(A_EMPTY)
1.000000	0.276156 (0.04348)	2.094041 (0.14240)	-2.748532 (0.08349)	-17.10959 (0.72660)	15.91562 (0.77418)	5.325542 (0.24036)	1.314319 (0.04342)	-5.818187 (0.40007)

Source: Author's estimation using EViews 13.0.

emissions. Although overall CO2 gas emissions continue to rise in Ethiopia, per capita CO2 emissions are still very low. Fossil fuel burning, deforestation, and other land use changes all contribute to carbon dioxide production in Ethiopia. We found that emissions from land use change are directly related to increasing agricultural production in Ethiopia, suggesting that crop-growing technology may be crucial in reducing atmospheric CO2 concentrations. Several micro-level empirical studies (Eshete et al. 2020) support these findings. In addition, the study refutes the positive association findings of Appiah et al., 2018.

*Agricultural methane emissions (AME).* The empirical result in Table 6 shows that a 1% increase in agricultural methane emissions would lead to a proportional decrease in agricultural productivity of 17.11 percent at the 1% significance level. The result also showed that the elasticity of agricultural productivity is highly elastic, meaning that a proportional change in agricultural methane emissions would lead to a large proportional change in agricultural productivity. Here, we didn't get any empirical evidence in Ethiopia that supplements this study. Methane (CH<sub>4</sub>)<sup>3</sup> is a strong greenhouse gas, mainly produced through agricultural activities. Methane is important when it comes to reducing emissions in the food chain and stopping catastrophic climate change. However, methane's potential to contribute to global warming is estimated to be 25–35 times greater than that of CO2 over 100 years, and since 2007, its concentration in the atmosphere has increased significantly and much faster than that of CO2. Experts believe that cutting methane emissions now could help prevent catastrophic short-term consequences while we wait for the significant long-term spending on reducing carbon emissions to pay off (Oppong et al. 2021).

*Agricultural nitrous oxide emissions (ANOE).* The result shows that a 1% increase in nitrous oxide emissions per year (carbon dioxide equivalents are used to measure) leads to a 15.916% increase in agricultural productivity. Here, the responsiveness of agricultural productivity due to these predictor variables is very elastic and positive as it is >1 with a low standard error value which implies low statistical noise in the estimates, and at a 1% significance level, it is statistically significant. Nitrous oxide (N2O), a powerful greenhouse gas, is produced primarily by agricultural practices (e.g., the use of synthetic and organic fertilizers in crop cultivation). When nitrogen (N) is added to soils, nitrogen dioxide is produced (Stehfest and Bouwman, 2006). Both nitrification and denitrification of nitrogen occur; The latter process leads to the release of N2O gas into the environment (Abebe et al. 2022). Since fertilizer application is the primary anthropogenic activity that causes N2O emissions, the increasing trend in emissions and the contribution of fertilizer application indicate the need for efficient mitigation measures. Little empirical research has been conducted in sub-Saharan Africa (SSA) to measure and understand the dynamics of soil N2O fluxes from smallholder cropping systems. There is an urgent need to summarize the sparse literature on soil N2O fluxes in Ethiopia to facilitate policy formulation activities and mitigation strategies.

*Fertilizer consumption (FeC).* From Table 6 above, it can be seen that the impact of fertilizer use on agricultural yield productivity is positive. However, the extent to which productivity value responds to a change in fertilizer use is small. Here, agricultural productivity and fertilizer consumption (kg/ha), which had low standard errors and regression coefficients, were both statistically significant at the 1% significance level. That is, putting all other things under a black box condition, a one percent increase in



fertilizer consumption in the country appears to produce a 0.276 percent increase in agricultural productivity in the long run. This is because, despite the government's efforts to provide it, Ethiopian agriculture relies heavily on fertilizers, meeting only a small percentage of farmers' needs. Compared to other emerging countries, chemical fertilizers are hardly used to increase agricultural production in Ethiopia. However, this use is currently increasing. The use of chemical fertilizers increased from 12 kg/ha in 1996 to 36.2 kg/ha in 2018. Due to this, the production of primary crops (cereals) increased from 16.5 quintals/ha in 2009 to 23.94 quintals /ha in 2018 (Abebe et al. 2022). The result also confirmed that the response to the change in agricultural productivity due to fertilizer use in Ethiopia is inelastic due to low fertilizer application in kg per hectare. This finding is consistent with (Tesema and Gebissa, 2022; Endale, 2011; Weeks et al. 2004; Alene et al. 2006; Ajao, 2012; Fuglie & Rada 2011).

*The rural population (R\_PoP).* The result in Table 6 shows that agricultural productivity is positively linked to rural populations. This result shows that a 1% increase in the growth of rural populations leads to a 5.326 percent increase in agricultural productivity, with a low standard error value implying low statistical noise in the estimates, and at the 1% level of significance, it is statistically significant. Here, agricultural productivity is highly elastic in its response. Ethiopia has seen rural development for a longer period than many other African nations. Although not to the extent anticipated, it has also benefited from rising government support over the years. According to the World Bank, Ethiopia's rural population as a percentage of the overall population was 77.83% in 2021. Variables will determine productivity increases in Ethiopia, boosting economic growth and reducing poverty, particularly among the rural population, which positively impacts agricultural productivity.

*Agricultural employment (A\_Empt).* An interesting result shows that for every 1% increase in the number of employers in the agricultural sector, agricultural productivity in Ethiopia decreases by 5.818 percent. A well-known explanation for this is the fact that Ethiopian rural households use more family labor than wage labor in their agricultural production processes. The likelihood that agricultural management activities increase agricultural productivity would therefore increase as the labor force in a household increases. This finding also showed that the number of agricultural workers hired is not efficient in increasing agricultural productivity. The result here also shows that the dependent variable is more elastic when this variable changes by 1 percent. This study is also consistent with Tessema Urgesa's (2015) findings from his research on the factors affecting agricultural production and income of rural households in Ethiopia.

*Total land allocated for cereal production in hectares (Land\_CP).* One of the important findings of this work is that when the area dedicated to grain production in Ethiopia increases by 1 percent, agricultural productivity (yield kg/ha) increases by 1.314 percent and is statistically significant at the 1 percent significance level. with a low standard error value, implying low statistical noise in the estimates. Therefore, it is crucial to promote the use of dry-season cropland farms, whether through irrigation or another type of source, to increase the productivity of rural agricultural households in Ethiopia.

*Error correction model (ECM) result.* The error correction model shown in Table 7 below provides information about the speed at which the model returns to equilibrium after an exogenous short-term shock. Engle and Granger (1987) proved that when there is a cointegrating relationship between non-stationary variables, there

is a correction plot towards equilibrium. The maximum lag length that can be included in the VECM estimation is three in level; Therefore, we propose a lag order of three to better capture the short-term movement of variables. Therefore, the agricultural productivity coefficient for the last year was negative and significant. That is, any deviation from the equilibrium point is traced back to the long-term path. Therefore, an ECM represents both the short-term and long-term behavior of a system. This means that our estimates were statistically significant at 5 percent.

Here only the statistically significant values are considered or insignificant variables are excluded to arrive at the final error correction model. The findings above yield the most parsimonious short-term model in the study:

$$\begin{aligned} \Delta(\text{LOG}(\text{AGP})) = & -0.744129 * (-0.258085 \log(\text{FeC}(-1))) \\ & - 0.1566760 \log(\text{A\_land}(-1)) \\ & - 0.082992 \log(\text{CO2\_emissions}(-1)) \\ & - 1.81031 \log(\text{AME}(-1)) + 2.420891 \log(\text{ANOE}(-1)) \\ & - 1.895112 \log(\text{R\_PoP}(-1)) + 0.130198 \log(\text{Land\_CP}(-1)) \\ & + 2.08653 \log(\text{A\_Empt}(-1)) + 8.804653 \end{aligned}$$

The estimated variables would have the following meaning in the "short term":

- The coefficients of the "speed of adjustment" or "error term" for the estimated productivity model are statistically significant and negative. This implies the convergence of the model towards long-run equilibrium in the event of an exogenous shock in the short run. The coefficient of  $-0.744$  shows that 74.4% of point adjustments occur each year to achieve long-term equilibrium. Therefore, convergence to a steady state takes  $\sim 1$  year and 4 months. This means that the variables are rapidly approaching their long-term equilibrium.
- But we got an unexpected sign: fertilizer consumption and agricultural productivity (in the first-time lag) are negatively correlated and have a statistically significant effect in the short term. All other factors being equal, a one-unit increase in the log of technological adoption (fertilizer use, kg/ha) in Ethiopia appears to result in a 0.258 percent decline in agricultural productivity. This implies that excessive fertilizer consumption is a sign that agricultural sector performance is improving slowly in the short term. This seems to bring unrealistic and nonsensical findings.
- The other predictors, including agricultural area (ha/person), CO2 emissions, agricultural methane emissions, and rural population of the country, as presented in the equation, have a negative association with agricultural productivity at the 5% significance level and an increase in it Variables by 1 percent would result in a decrease in the country's agricultural productivity by 0.157, 0.083, 1.81 and 1.89 percent, respectively. Since it is in log form, this means that rural population and agricultural methane emissions have an elastic relationship with the dependent variable ( $>1$ ), whereas agricultural land and CO2 emissions have an inelastic relationship with the country's agricultural productivity. In the short term we considered, we obtained the expected negative sign and the statistically significant coefficient, which is present in the long term and is also consistent with our previous expectation. This means that in the short run, agricultural nitrous oxide emissions, total area devoted to grain production, and agricultural employment are positively correlated with the dependent variable. All other things being equal, a one-unit increase in these factors increases the country's agricultural productivity output in the short term by 2.42, 0.13, and 2.086 percent, respectively. Thus, variable agricultural employment and

**Table 7 Estimates of vector error correction.**

Deterministic assumptions: Case 3 (Johansen-Hendry-Juselius): Cointegrating relationship includes a constant. Short-run dynamics include a constant.

	D(LOG(AGP))	D(LOG(FeC))	D(LOG(A_LAND))	D(LOG(CO2_EMISSIONS))	D(LOG(AME))	D(LOG(ANOE))	D(LOG(R_POP))	D(LOG(LAND_CP))	D(LOG(A_EMPTY))
COINTEQ1	-0.744129 (0.18975)	0.009582 (0.95136)	0.297523 (0.06257)	-0.048522 (0.19712) [-0.24616]	-0.008309 (0.11817)	0.021823 (0.12819)	0.000368 (0.00232)	0.025940 (0.29463)	0.023067 (0.00772)
D (LOG (AGP (-3)))	[-3.92157] (0.01007)	[4.75531] (0.01007)	[4.75531] (0.01007)	-0.101679 (0.13723) [-0.74094]	-0.07031 (0.08227)	[0.17025] (0.039962)	[0.15868] (2.10E-05)	[0.08804] (0.318891 (0.20512)	[2.98903] (0.002952)
D (LOG (FeC (-3)))	[-1.55418] (0.05051)	[1.38391] (0.66232)	[1.57294] (0.04356)	[-0.74094] (0.04356)	[-0.12939] (0.08227)	[0.44780] (0.08924)	[0.01303] (0.00162)	[1.55469] (0.00537)	[0.54948] (0.00537)
D (LOG (A_LAND (-3)))	[-0.07356] (0.05051)	0.248272 (0.25322)	0.064477 (0.01665)	-0.027145 (0.05247) [-0.51740]	-0.001244 (0.03145)	0.009047 (0.03412)	-2.63E-05 (0.00062)	0.140746 (0.07842)	-0.004668 (0.00205)
D (LOG (CO2_EMISSIONS (-3)))	[-0.14565] (0.090934)	[0.98048] (3.165226)	[3.87183] (0.369011)	0.015215 (0.44682) [0.03405]	[-0.03955] (0.585361)	[0.26518] (0.603937)	[-0.04262] (-0.001773)	[1.79479] (0.227954)	[-2.27283] (-0.089887)
D (LOG (LAND_CP (-3)))	[-0.21141] (0.811370)	[1.46774] (0.71586)	[2.60188] (0.071586)	[-0.85715] (-0.130557 (0.15232)	[2.18522] (0.044400)	[2.07846] (0.060064)	[-0.33691] (0.005373)	[0.34132] (0.160614)	[-5.13835] (-0.008450)
D (LOG (AME (-3)))	[1.81564] (0.869003)	[1.10371] (9.562741)	[1.48070] (2.917679)	0.286368 (1.91931) [0.149201]	[0.48623] (-1.025434)	[0.60639] (-0.551202)	[2.99544] (-0.008169)	[0.70549] (1.020503)	[-1.41695] (-0.163699)
D (LOG (ANOE (-3)))	[-0.967133] (1.77122)	[-8.072585] (8.88031)	[-2.693509] (0.58402)	-0.710972 (1.83997) [-0.38640]	[1.043691] (1.10307)	[-0.44162] (1.19653)	0.004212 (0.02167)	[-0.875427] (2.75017)	[-2.17853] (0.07204)
D (LOG (R_POP (-3)))	[-0.54603] (7.262884)	[-0.909004] (6.493814)	[-4.61204] (-7.887597)	3.274314 (7.82977) [0.41819]	[0.94617] (2.673276)	[0.49525] (3.111846)	[0.19439] (0.804274)	[-0.31832] (-6.792960)	[2.19624] (0.868467)
D (LOG (LAND_CP (-3)))	[-0.96360] (0.93951)	[0.17184] (0.19808)	[-3.17381] (0.01303)	-0.004875 (0.04104) [-0.11879]	[0.56951] (0.02460)	[0.61116] (0.02669)	[8.72319] (-0.001171)	[-0.58045] (0.135500)	[2.83314] (0.00161)
D (LOG (A_EMPTY (-3)))	2.429236 (3.21773)	-3.491506 (16.1326)	2.005217 (0.06097)	-3.505166 (3.34262) [-1.04863]	0.219365 (2.00392)	-0.334276 (2.17371)	0.058034 (0.03936)	5.995681 (4.99616) [1.20006]	0.245953 (0.13086)
C	-0.151546 (0.20055)	-0.281775 (1.00551)	0.187749 (0.06613)	0.005653 (0.20834) [0.02713]	-0.035288 (0.12490)	-0.054042 (0.13548)	0.003745 (0.00245)	0.180529 (0.31140) [0.57974]	-0.026476 (0.00816)
R-squared	0.721313	0.298634	0.724579	0.258224	0.343792	0.278164	0.964326	0.462930	0.903579

CountEq1  
1.000000  
-0.258085 (0.00365) [-70.7816]  
-1.566760 (0.01874) [-83.6113]  
-0.082992 (0.01238) [-6.70195]  
-1.810310 (0.11855) [-15.2701]  
2.420891 (0.11683) [20.7210]  
-1.895112 (0.06992) [-27.1040]  
0.130198 (0.01200) [10.8470]  
2.086530 (0.05104) [40.8835]  
8.804653

**Table 7 (continued)**

Error Correction:	D(LOG(AGP))	D(LOG(FeC))	D(LOG(A_LAND))	D(LOG(CO2_EMISSIONS))	D(LOG(AME))	D(LOG(ANOE))	D(LOG(R_POP))	D(LOG(LAND_CP))	D(LOG(A_EMPTY))
Adj. R-squared	0.566486	-0.091014	0.571567	-0.153874	-0.020769	-0.122856	0.944507	0.164558	0.850012
Sum sq. residues	0.075764	1.904481	0.008237	0.081760	0.029385	0.034576	1.13E-05	0.182658	0.000125
S.E. equation	0.064878	0.325276	0.021392	0.067396	0.040404	0.043828	0.000794	0.100736	0.002639
F-statistic	4.658852	0.766420	4.735440	0.626609	0.943031	0.693641	48.65637	1.551520	16.86812
Log-likelihood	45.08843	-1.664464	77.26371	43.98411	58.82198	56.46338	172.7944	32.32861	137.9541
Akaike AIC	-2.350926	0.873411	-4.569911	-2.274766	-3.298068	-3.135406	-11.15823	-1.470938	-8.755456
Schwarz SC	-1.832297	1.392041	-4.051282	-1.756137	-2.779438	-2.616776	-10.63960	-0.952309	-8.236827
Mean dependent	0.027565	0.053883	-0.012117	0.083295	0.028139	0.027967	0.024727	0.033770	-0.005939
S.D. dependent	0.098536	0.311413	0.032682	0.062741	0.039991	0.041361	0.003369	0.110211	0.006813
Determinant resid covariance (dof adj.)	2.23E-34								
Determinant resid covariance	3.05E-36								
Log-likelihood	815.4518								
Akaike information criterion	-48.78978								
Schwarz criterion	-43.69778								
Number of coefficients	108								

\*Significance, at 5% and \*\*significance, at 10%.  
Source: Author's estimation made use of EViews 13 (2023).

**Table 8 Variance decomposition.**

Period	S.E.	LOG(AGP)	LOG(FeC)	LOG(A_LAND)	LOG(CO2_EMISSIONS)	LOG(AME)	LOG(ANOE)	LOG(R_POP)	LOG(LAND_CP)	LOG(A_EMPTY)
Variance Decomposition of LOG(AGP):										
1	0.064878	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.085421	74.38174	16.58198	5.659815	0.001841	1.750152	0.841838	0.277396	0.504082	0.001149
3	0.101285	66.68999	21.56064	7.359148	0.002394	2.275626	1.094596	0.360682	0.655431	0.001494
4	0.109256	59.43575	24.41810	7.386548	2.869400	3.062766	1.056612	0.590036	1.179206	0.001577
5	0.124416	59.04768	22.13441	5.963507	4.483532	2.362704	4.502281	0.588804	0.915663	0.001424
Variance Decomposition of LOG(TA):										
1	0.325276	23.12096	76.87904	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.459864	23.19280	76.80715	3.24E-05	1.05E-08	1.00E-05	4.82E-06	1.59E-06	2.88E-06	6.57E-09
3	0.563167	23.21245	76.78748	3.95E-05	1.28E-08	1.22E-05	5.87E-06	1.93E-06	3.52E-06	8.01E-09
4	0.681875	26.99514	71.43462	0.116202	0.854374	0.322770	0.232358	0.004144	0.040297	9.02E-05
5	0.783381	28.57538	69.03627	0.199245	1.295595	0.467836	0.361066	0.007455	0.057012	0.000145
Variance Decomposition of LOG(A_LAND):										
1	0.021392	2.296947	20.96790	76.73516	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.037461	17.26965	46.87369	33.05010	0.001530	1.454750	0.699748	0.230575	0.490000	0.000955
3	0.047632	19.50303	51.20827	26.11539	0.001730	1.644849	0.791187	0.260705	0.473753	0.001080
4	0.058060	25.23153	47.48184	17.95723	0.015771	2.820312	2.320604	2.664300	0.800843	0.007568
5	0.064093	23.89452	51.65051	15.03385	11.41875	2.699301	1.932496	2.915551	0.719309	0.012594
Variance Decomposition of LOG(CO2_EMISSIONS):										
1	0.067396	11.20331	1.296282	0.346497	87.15391	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.096087	12.01982	1.708195	0.473828	85.78681	0.005881	0.002829	0.000932	0.001694	3.86E-06
3	0.117936	12.23704	1.855578	0.506920	85.42670	0.007136	0.003433	0.001131	0.002055	4.68E-06
4	0.138964	20.16095	1.410651	1.134435	76.04012	0.076057	0.236087	0.247177	0.007484	0.002335
5	0.156909	24.30748	1.163502	1.518120	71.03474	1.145136	0.461579	0.357573	0.008157	0.003707
Variance Decomposition of LOG(AME):										
1	0.040404	27.40143	6.565987	11.61619	0.630123	53.78627	0.000000	0.000000	0.000000	0.000000
2	0.056970	27.13308	6.857812	11.49491	0.634713	53.87903	0.00236	7.77E-05	0.000141	3.22E-07
3	0.069716	27.05914	6.937967	11.46149	0.635980	53.90486	0.00288	9.49E-05	0.000172	3.98E-07
4	0.082008	30.31593	6.646011	8.293029	1.082725	53.21230	0.419728	0.027028	0.003222	2.17E-05
5	0.096535	35.71528	4.797697	6.266011	1.216826	51.07797	0.883584	0.019561	0.022897	0.000075
Variance Decomposition of LOG(ANOE):										
1	0.043828	34.43337	12.54901	5.226313	0.472504	46.61237	0.706442	0.000000	0.000000	0.000000
2	0.062378	35.17876	11.60258	5.476128	0.464853	46.53405	0.742366	0.000447	0.000813	1.85E-06
3	0.076528	35.37930	11.34700	5.542994	0.462811	46.51438	0.751977	0.000543	0.000987	2.29E-06
4	0.092107	38.87866	10.63337	3.931821	0.964337	44.44149	1.096440	0.053051	0.000787	3.66E-05
5	0.107398	42.94944	8.368593	2.906484	1.172451	42.98087	1.555898	0.056916	0.009324	2.76E-05
Variance Decomposition of LOG(R_POP):										
1	0.000794	2.771013	0.672442	0.074682	10.56099	5.418757	31.79284	48.70928	0.000000	0.000000
2	0.001127	3.076760	0.867415	0.047722	10.47555	5.544020	31.83259	48.15523	0.000710	1.62E-06
3	0.001381	3.158685	0.918955	0.039989	10.45273	5.577961	31.84422	48.00660	0.000864	1.97E-06
4	0.002084	2.034031	0.637479	0.025212	18.76924	3.743325	33.32747	41.37332	0.087161	0.002764
5	0.002615	1.844735	0.720650	0.044278	20.90229	3.266627	34.00093	39.11444	0.102409	0.003641
Variance Decomposition of LOG(LAND_CP):										
1	0.100736	25.07898	15.51238	10.32308	5.082896	4.750898	0.197227	2.759913	36.29462	0.000000
2	0.142317	24.61478	16.02618	10.12010	5.090348	4.675896	0.185927	2.791553	36.49521	5.03E-07
3	0.174253	24.48751	16.16672	10.06444	5.092436	4.655345	0.182812	2.800242	36.55049	6.13E-07
4	0.198218	19.36091	13.07783	9.844002	7.417885	4.936188	0.155257	4.610768	40.65393	0.003235
5	0.219688	16.32609	10.86901	9.913413	8.876976	5.236511	0.137018	5.654200	42.98162	0.005162
Variance Decomposition of LOG(A_EMPTY):										
1	0.002639	10.95122	8.977742	20.08096	19.75822	0.529929	30.59231	26.18846	0.204053	0.499511
2	0.004732	17.91168	18.38917	20.91230	11.91583	0.276573	22.45403	18.05386	0.484875	0.325925
3	0.006070	18.90442	19.69762	21.07655	10.77088	0.211662	21.31273	16.89599	0.523394	0.300939
4	0.008143	14.52172	14.52178	27.94958	0.601423	0.220893	25.78122	11.65291	0.254479	0.254479
5	0.009420	14.86448	11.54890	29.48337	0.451773	0.274317	33.25174	9.472116	0.400621	0.252688

Cholesky, One S.D. (d.f. adjusted).  
 Cholesky ordering: LOG (AGP) LOG (FeC) LOG (A\_LAND) LOG (CO2\_EMISSIONS) LOG (AME) LOG (ANOE).  
 LOG (R\_POP) LOG (LAND\_CP) LOG (A\_EMPTY).  
 Source: Author's estimation using EViews 13.0 (2023).

nitrous oxide emissions in agriculture have an elastic relationship with agricultural productivity, while total grain crop area has an inelastic relationship with the country's agricultural productivity.

However, the error correction model is difficult to interpret because it sometimes gives the wrong sign for the variables under study in the short term (Engle and Granger, 1987). Therefore, analysis of the dynamic behavior of the model using the variance-decomposition and impulse-response (Annex 8) approaches is used to drive the conclusion.

*Analysis of the dynamic behavior of the model.* The variance decomposition in Table 8 quantifies the effects of exogenous shocks on variables over 5 years and captures both short- and long-term responses.

Agriculture productivity (100%) in the first year can be fully attributed to its innovation, proving its exogenous origin. However,

the following four periods show some fluctuations, and in the fifth year it is only 59.05%, fertilizer consumption (22.13%), agricultural land (5.96%), CO<sub>2</sub> emissions (4.43%), agricultural methane emissions (2.36%), agricultural nitrous oxide emissions (4.5%), rural population (0.59%), total area devoted to grain production (0.92%), and agricultural employment (0.0014%), which influence agricultural productivity. The decomposition of fertilizer consumption indicates (76.88%) the effect of its own innovation and agricultural productivity (23.12%) in the 1st year, and in the last year, it is explained, only (28.58%) by fertilizer consumption, agricultural land by (0.20%), CO<sub>2</sub> emissions by (1.30%), agricultural methane emissions by (0.48%), agricultural nitrous oxide emissions by (0.36%), rural population by (0.007%), total land for cereal production by (0.057%), and agricultural employment by (0.0001%).

If a shock is generated on agricultural land in the first period, the 76.74 percent effect of one's innovation is explained. In the fifth year: innovation in agricultural land by (15.03%), CO<sub>2</sub>

**Table 9 Testing for Pairwise Granger Causality (Lags: 3).**

Null-Hypothesis:	Obs	F Statistic	Prob
LOG(FeC), does not Granger-Cause LOG(AGP)	30	3.17372	0.0434**
LOG(AGP), does not Granger-Cause LOG(FeC)		5.51694	0.0053*
LOG(CO2_EMISSIONS) does not Granger-Cause LOG(AGP)	30	5.35651	0.0060*
LOG(AGP), does not Granger-Cause LOG(CO2_EMISSIONS)		2.83754	0.0604***
LOG(AME), does not Granger-Cause LOG(AGP)	30	6.15993	0.0031*
LOG(AGP), does not Granger-Cause LOG(AME)		2.36205	0.0976***
LOG(ANOE), does not Granger-Cause LOG(AGP)	30	5.26010	0.0065*
LOG(AGP), does not Granger-Cause LOG(ANOE)		2.05082	0.1347
LOG(R_POP), does not Granger-Cause LOG(AGP)	30	7.76616	0.0009*
LOG(AGP), does not Granger-Cause LOG(R_POP)		0.55935	0.6472
LOG(A_EMPT), does not Granger-Cause LOG(AGP)	30	0.79103	0.5113
LOG(AGP), does not Granger-Cause LOG (A_EMPT)		3.51248	0.0313**
LOG(CO2_EMISSIONS,) does not Granger-Cause LOG (FeC)	30	2.45924	0.0884***
LOG(FeC), does not Granger-Cause LOG (CO2_EMISSIONS)		0.47779	0.7008
LOG (AME), does not Granger-Cause LOG (FeC)	30	5.35985	0.0060*
LOG (FeC) does not Granger-Cause LOG (AME)		5.31043	0.0063*
LOG (ANOE) does not Granger-Cause LOG (FeC)	30	6.06867	0.0034*
LOG (FeC) does not Granger-Cause LOG (ANOE)		5.64141	0.0048*
LOG (R_POP) does not Granger-Cause LOG (FeC)	30	2.62672	0.0746***
LOG (FeC) does not Granger-Cause LOG (R_POP)		1.48465	0.2450
LOG (LAND_CP) does not Granger-Cause LOG (FeC)	30	4.22209	0.0162**
LOG (FeC) does not Granger-Cause LOG (LAND_CP)		0.72905	0.5451
LOG (AME) does not Granger-Cause LOG (A_LAND)	30	2.49523	0.0852***
LOG (A_LAND) does not Granger-Cause LOG (AME)		1.07780	0.3781
LOG (ANOE) does not Granger-Cause LOG (A_LAND)	30	2.66932	0.0714***
LOG (A_LAND) does not Granger-Cause LOG (ANOE)		0.88206	0.4650
LOG (A_EMPT) does not Granger-Cause LOG (A_LAND)	30	2.18434	0.1173
LOG (A_LAND) does not Granger-Cause LOG (A_EMPT)		3.44498	0.0334**
LOG (AME) does not Granger-Cause LOG (CO2_EMISSIONS)	30	3.04662	0.0491**
LOG (CO2_EMISSIONS) does not Granger-Cause LOG (AME)		6.02113	0.0035*
LOG (ANOE) does not Granger-Cause LOG (CO2_EMISSIONS)	30	3.29698	0.0385**
LOG (CO2_EMISSIONS) does not Granger-Cause LOG (ANOE)		5.44758	0.0056*
LOG (R_POP) does not Granger-Cause LOG (AME)	30	6.96823	0.0017*
LOG (AME) does not Granger-Cause LOG (R_POP)		1.91575	0.1552
LOG (LAND_CP) does not Granger-Cause LOG (AME)	30	7.69602	0.0010*
LOG (AME) does not Granger-Cause LOG (LAND_CP)		3.82477	0.0233**
LOG (R_POP) does not Granger-Cause LOG (ANOE)	30	6.13404	0.0032*
LOG (ANOE) does not Granger-Cause LOG (R_POP)		1.71139	0.1925
LOG (LAND_CP) does not Granger-Cause LOG (ANOE)	30	8.39432	0.0006*
LOG (ANOE) does not Granger-Cause LOG (LAND_CP)		3.64121	0.0277**
LOG (LAND_CP) does not Granger-Cause LOG (R_POP)	30	0.94495	0.4352
LOG (R_POP) does not Granger-Cause LOG (LAND_CP)		2.76560	0.0649***
LOG (A_EMPT) does not Granger-Cause LOG (R_POP)	30	3.52133	0.0310**
LOG (R_POP) does not Granger-Cause LOG (A_EMPT)		3.62678	0.0281**

\*Significance at 1 %, \*\*significance at 5%, and \*\*\*significance at 10%.  
 Source: Author's estimation made use of EViews 13 (2023).



**Fig. 4 Recursive residual stability test graph.** Note: The blue plot of the recursive residuals test shows the stability of the variables under consideration. It did not lie outside the lower and upper critical limits and also it crossed the zero-grid line many times. Hence it is stable. Source: Authors.

emissions by (1.14%), agricultural methane emissions by (2.70%), agricultural nitrous oxide emissions by (1.93%), rural population by (2.92%), total area devoted to grain production by (0.72%), and agricultural employment by (0.013%). The innovation of CO<sub>2</sub> emissions in the first period is explained by their innovation (87.15%) and (71.03%) in the 5th year. Innovations in agricultural methane emissions, agricultural nitrous oxide emissions, rural population, the total area of grain production, and agricultural employment for the first period are represented by 53.79, 0.71, 48.71, 36.29, and 0.50%, respectively explained. Similarly, the decomposition in the last period is also explained by 51.08, 1.55, 39.11, 42.98, and 0.25% respectively.

*Analysis of the Granger Causality test.* Causality does not always mean exogeneity, as the result may not make it clear whether a positive or negative relationship exists. In any case, the direction of the causal relationship between predictable variables and dependent variables is revealed by the next finding presented in Table 9 below.

Engel and Granger show that if two variables show cointegration in the long run, there must be unidirectional or bidirectional Granger causality between those variables. Our Granger causality estimate shows that there is bidirectional causality between the dependent variable log (AGP) and the three predictor variables such as log (FeC), log (CO<sub>2</sub> emissions), and log (AME). While the other predictors like log (ANOC), log (R\_PoP) and log (A\_Empt) have unidirectional causality with the dependent variable. Since pairwise Granger causality is evident at lag order three, we found statistically significant causality between the predictors and agricultural productivity at 10% significance levels. Therefore, the estimated output showed that the performance of the agricultural sector in the country is high, significant, and positive in the long run and extremely positive and significant in the short run. The estimation results showed that agricultural productivity and total land area allocated for grain production are positively correlated in the long term. However, this is not supported by the Granger causality test at lag order three. That is, there is no Granger causality from log (AGP) to log (Land\_CP). Based on the finding in Table 9, the null hypothesis that the independent variables used in the study do not influence Ethiopia's agricultural productivity is rejected and it can be safely concluded that there is a unidirectional (bi)directional and causal effect.

*Model stability tests.* The recursive residual test plot, as shown in Fig. 4, did not fall outside the lower and upper critical limits and crossed the zero-grid line many times. In addition, the Ramsey RESET test in Table 10 is used to determine whether the model is linear and whether its specifications are correct. The results of the Ramsey reset test include the test regression, the F-statistic, and the t-statistic to evaluate the statement that the model is adequately described when the coefficients of the powers of the fitted values from the regression are jointly zero. The *p*-value is >0.1. Therefore, the null cannot be rejected.

### Conclusion and policy implications

GHG emissions pose a global concern, particularly in developing countries such as Ethiopia. Agriculture is particularly at risk due to low rainfall. To address this, Ethiopia must implement climate adaptation strategies, adopt climate-smart agricultural practices, and create carbon sinks such as forests. Global coordination of these efforts is critical to the transition toward a just and environmentally responsible future. Furthermore, the study contributes to the literature on farm size and productivity in several ways. The inverse relationship between agricultural productivity and farm size has recently been discussed, particularly in the African context. The debate over whether supporting large-scale agriculture is the answer to agricultural problems or whether supporting small farms is the best way to increase productivity is one of the topics frequently discussed in the agricultural and development economics literature. This study aims to contribute to this discussion by providing the first in-depth examination of the relationship between farm size and productivity in Ethiopia. Therefore, interesting results of the cointegration study are found. These are: (1) farm size (arable land, hectare per person) has a significant positive impact on productivity over time; (2) we also found that agricultural land size has an elastic relationship with agricultural productivity over time. The above findings could have significant policy implications for agricultural policy development in Ethiopia if supported by future studies in the country. Before broad generalizations can be made about the relative productivity of small versus medium or large farms in Ethiopia, much more data is needed about the country's varying conditions. Second, the discovery that medium and large farms are more productive than small farms does not mean that policies are needed to promote their development over small farms or to support land transfers to

**Table 10 Ramsey RESET linearity test result.**

**Omitted-Variables: Squares of fitted values**

	Value	Df	Probability
t-statistic,	0.139112	23	0.8906
F-statistic,	0.019352	(1, 23)	0.8906
Likelihood ratio,	0.027754	1	0.8677

**F-test, summary:**

	Sum. of Sq.	Df	Mean-Squares
Test-SSR,	0.000107	1	0.000107
Restricted-SSR,	0.127611	24	0.005317
Unrestricted-SSR,	0.127504	23	0.005544

**LR test summary:**

	Value
Restricted LogL,	44.83705
Unrestricted LogL,	44.85093

Variable	Coefficient	Std Error	t-Statistic	Prob
C	16.50810	49.94375	0.330534	0.7440
LOG (TA)	-0.093945	0.351809	-0.267033	0.7918
LOG (A_LAND)	0.488293	1.760514	0.277358	0.7840
LOG (CO2_EMISSIONS)	-0.113384	0.460586	-0.246174	0.8077
LOG (AME)	-2.303177	8.772328	-0.262550	0.7952
LOG (ANOE)	3.189975	11.82843	0.269687	0.7898
LOG (R_POP)	1.061902	4.080185	0.260258	0.7970
LOG (LAND_CP)	-0.026997	0.104900	-0.257360	0.7992
LOG (A_EMPT)	-6.969635	26.17797	-0.266240	0.7924
FITTED^2	-0.070298	0.505336	-0.139112	0.8906
R-squared,	0.968217	Mean-dependent var	7.383585	
Adjusted R-squared,	0.955780	S.D. dependent var	0.354070	
S.E. of regression,	0.074456	Akaike-info. Criterion,	-2.112178	
Sum squared resid	0.127504	Schwarz-criterion,	-1.658690	
Log-likelihood,	44.85093	Hannan-Quinn-criteria,	-1.959593	
F-statistic,	77.85061	Durbin-Watson-stat,	2.244318	
Prob (F-statistic),	0.000000			

Unrestricted-Test Equation:  
 Dependent, Variable: LOG (AGP)  
 Method: Least-Squares  
 Source: Author's estimation using EViews 13 (2023)

medium and large farms. We are expanding farms because productivity is just one factor that matters to Ethiopian governments and societies.

To this end, the overall message of the study becomes clear in the policy-making process in Ethiopia: greenhouse gas emissions are reduced or carbon dioxide and methane sequestration are improved, while at the same time, agricultural yield is maintained or even increased. It is crucial to develop comprehensive institutional, technical, and financial innovation adaptation and mitigation strategies to reduce the impact of greenhouse gas emissions. Significant reductions in greenhouse gas emissions from agriculture are therefore essential to improve agricultural production, ensure food security, and slow climate change.

**Data availability**

Data from this research are available upon request from the corresponding author.

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**Notes**

- 1 **Agricultural Productivity:** "Productivity measures the quantity of output produced with a given quantity of inputs". It also refers to how effectively farmers use resources like land, labor, money, materials, and services to create outputs. Thus, "Agricultural productivity is the ratio of agricultural outputs to inputs".
- 2 **Agricultural arable land:** The FAO defines arable land as including land that is temporarily fallow, under temporary crops (double-cropped areas are counted once), under temporary meadows for mowing or for pasture, and under temporary market or kitchen gardens. Land that has been abandoned due to shifting cultivation is not included.
- 3 **Methane Emissions:** Enteric fermentation, manure management, rice farming, and residue burning are the main sources of methane (CH4) emissions from agriculture (FAOSTAT, 2020).

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## Author contributions

AM: conceived of the study's concept, planned it out, gathered the data, used software to analyze it, reviewed the results, and wrote the initial manuscript. Professor HM conceived of the study's concept, oversaw the research, gave direction throughout the process, and contributed critical revisions and writing assistance. All authors agreed to bear responsibility for the whole article after reading and approving the final manuscript.

## Competing interests

The authors declare no competing interests.

## Ethical approval

This study is not related to human participants performed by any of the authors.

## Informed consent

This study does not contain any study with human participants performed by any of the authors.

## Additional information

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