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IMPACT OF AGRICULTURAL PRACTICES ON GREENHOUSE GAS EMISSIONS: A DATA-DRIVEN ANALYSIS AND POLICY IMPLICATIONS

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Abstract
The agricultural sector produces substantial greenhouse gas (GHG) emissions that stem mostly from carbon dioxide (CO_2) emissions together with methane (CH_4) and nitrous oxide (N_2O). This research investigates the primary factors which produce agricultural emissions through fertilizer use and crop yields and animal husbandry practices and agricultural output value. Econometric models enabled researchers to study agricultural activity relationships with CO_2 emissions in both the short-run and the long-run. The excessive application of fertilizer stands as the main driver of emissions based on research assessments yet sustainable livestock management techniques and ecological agricultural practices result in decreased environmental impacts. Climate-smart agricultural policies and precise farming techniques combined with renewable energy systems emerge as key solutions to lower emissions according to this study. Future research needs to evaluate methane and nitrous oxide emissions in combination with ways to analyse various countries and policy structures which promote low-carbon farming systems. Measurable outcomes from this study present crucial findings that help policy-making authorities along with agricultural researchers and stakeholders to achieve sustainability between food production and environmental preservation.

INTRODUCTION
The Earth's atmosphere is becoming a heat trap, with greenhouse gases acting like an invisible blanket that fuels global warming and intensifies extreme weather events—from scorching heat waves and relentless droughts to devastating wildfires and storms (Kikstra,2022). The three principal greenhouse gas compounds stemming from agricultural practices are carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O). The warming potentials over 100 years of CH_4 and N_2O exceed CO_2 by 28 times and 265 times although these gases exist at lower concentrations. During the period from 1990 to 2024 atmospheric CO_2, CH_4, and N_2O measurements rose by 9% and 19% and 13% until reaching their historical peaks at 423 ppm, 1932 ppb, and 338 ppb (Lan, Thoning, & Dlugokencky, 2024). The agricultural sector is **a** significant contributor to GHG emissions, particularly in South Asian Association for Regional Cooperation (SAARC) countries, where agriculture forms the backbone of economic activity. Agriculture-driven CO_2 emissions (ACO_2) are largely influenced by fertilizer consumption (FC), crop production (CP), livestock production (LSP), and agriculture's share of GDP (AGDP). The main sources of emissions in agriculture include livestock production combined with manure

processing and nitrogen fertilizer use as well as crop residue management and irrigation and forest clearing for farming land (IPCC, 2014).

The paradox shows that modern agriculture could reduce emissions through improved efficiency practices but more research is needed to validate this hypothesis. Agricultural procedures produce complex GHG reactions because they affect emissions levels through their double role of managing aboveground plant biomass and belowground soil organic carbon (SOC). The combination of drainage techniques and biomass burning during agricultural deforestation activities causes SOC depletion that enhances CO_2 emissions significantly according to Lan et al. (2024). The combination of afforestation and reforestation presents a promising answer since it boosts both soil carbon sequestration and reduces greenhouse gas outputs according to Psistaki et al.(2024) and Ménard et al. (2025). Augmented livestock farming speed combined with rising nitrogen fertilizer use has made these sources vital contributors of methane and nitrous oxide pollution which demonstrates an urgent necessity to implement smart agricultural solutions for climate control(Singh et al.,2024)

Through its farming practices, the global economy achieves food security and generates billions of livelihoods(Sila et al.,2025). Agriculture production methods stand as major GHG sources, making them essential elements of climate change(Bhatti et al.,2024). Environmental emissions mostly stem from actions like forest clearance and raising animals, applying fertilizers and transforming land through different processes(Küfeoğlu et al.,2024). Global warming originates from three main agricultural GHGs including carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O)(Sahu et al.,2024). All efforts to mitigate greenhouse gas emissions must start with an in-depth analysis of agricultural emission sources because this knowledge will help develop sustainable farming methods(Kamyab et al.,2024).

Research into agricultural emissions remains insufficient for determining climate change effects at both global and regional levels despite improving understanding of agricultural contribution to climate change. Most current research fails to analyze agricultural practices as a complete system for emission generation.

1. Key Drivers of Agricultural Greenhouse Gas Emissions

Earth's agricultural sector produces notable greenhouse gas amounts worldwide because farmers transform land practices and adopt intensive agricultural methods and chemical-based farming systems. The agricultural sector produces emissions from four main sources such as fertilizer practices and crop farming operations and livestock management as well as its economic operations. These separate elements shape agricultural environmental outcomes because they determine the release of three main greenhouse gases including carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O).

1.1 Fertilizer Consumption and Nitrous Oxide Emissions

Agricultural production receives essential boosts and food security protection comes from the use of fertilizers(Rehman et al.,2024). The nitrogen-bearing fertilizers along with other fertilizers serve as significant sources of nitrous oxide (N_2O) production which has a global warming effect 300 times more damaging than carbon dioxide (CO_2). Soil fertility receives improvement when farmers use synthetic fertilizers like urea and ammonium nitrate, yet these chemicals increase emissions because microbial actions like nitrification and denitrification occur (amin et al.,2024). Organic fertilizers, including manure and compost, together produce emissions because of microbial decomposition processes that take place in the soil(Khan et al.,2024).

Both N_2O emission intensification and nutrient runoff impairments occur because farmers apply excessive amounts of fertilizers, causing negative environmental effects on soils and water quality(Rathore et al.,2024). Farmers across multiple developing countries improperly use fertilizers because they apply excessive amounts above guidelines to enhance their crop output. Excessive fertilizer usage generates substantial environmental concerns while resulting in decline of agricultural ecosystems in the long run(Ma et al.,2024).

Hypothesis 1: There is a positive correlation between increased fertilizer consumption (FC) and nitrous oxide (N_2O) emissions, positioning it as a significant factor in agricultural greenhouse gas emissions.

1.2 Crop Production and CO_2 Emissions

Crop production holds essential importance within agricultural systems, yet its expansion leads to important negative environmental consequences(Li et al.,2024). Crop cultivation remains a significant CO_2 emissions source because it stems from three main factors, which include deforestation, together with soil degradation and agricultural practices that need lots of energy(Bambi et al.,2024). Many parts of Earth experience degraded CO_2 absorption capabilities as forests and grasslands get transformed into farming areas(Khachoo et al.,2024).

Soil organic matter oxidation becomes worsened by land conversion and agricultural tillage operations thus producing additional CO_2 emissions(Brandao et al.,2024, Ghosh et al.,2024). Plowing soil as a standard farming practice and disturbing land surfaces promotes both quick degradation of soil and decreases its natural ability to capture carbon(Rathi et al.,2024).The use of tractors along with irrigation systems and harvested goods transportation under modern agricultural mechanical operations leads to increased carbon emissions because these functions depend on fossil fuels(Kamyab et al.,2024).

Hypothesis 2: There is a positive correlation between increased crop production (CP) and CO_2 emissions, driven by deforestation, soil degradation, and energy-intensive agricultural practices.

1.3 Livestock Production and Methane Emissions

Greenhouse gas emissions from livestock agriculture stem mainly from CH_4 methane byproducts of enteric fermentation processes and manure management practices in the agricultural realm(Sahu et al.,2024). Three major ruminant groups which include cattle, sheep and goats naturally produce methane through their digestive system functions(Khan et al.,2024). The released methane functions as a major factor in global warming since it acts as a powerfully effective trap for atmospheric heat(Omemen et al.,2025)

The emission control system of manure from livestock creates an important environmental impact(Searchinger et al.,2019). The improper management of manure allows it to decompose under anaerobic conditions releasing methane together with nitrous oxide (N_2O)(Symeon et al.,2025). Rearing livestock systems require massive production of feed crops including corn and soybeans leading to environmental problems with deforestation along with escalated CO_2 emissions resulting from land use alterations(Nejad et al.,2024).

Hypothesis 3: An increase in livestock production (LSP) correlates with elevated methane (CH_4) emissions, establishing it as a primary source of greenhouse gases in agriculture.

1.4 Agricultural GDP Share and Greenhouse Gas Emissions

National economies depend on agriculture to different degrees because some nations establish this sector as their primary means for economic development(Saleem et al.,2024). Many developing nations generate substantial net domestic product through agriculture thus creating essential drivers for both land utilization transformations and environmental emissions changes(Liu et al.,2024). Modern agricultural development produces major environmental problems because farmers intensify production methods and cut forests and enhance their machinery usage(Padhiary,2025).

Hypothesis 4: A high level of agricultural contribution to GDP (AGDP) results in higher CO_2 emission levels because mechanized farming and land use adjustments along with energy-intensive agricultural methods.

2. Predictive Model for Agricultural CO_2 Emissions

This research analysis investigates greenhouse gas emission impacts of major agricultural practices by studying the relationships between fertilizer use along with crop production and livestock output in addition to agricultural segment size within GDP. The model structure arranges its sections as follows:

$ACO_2 = f(FC, CP, LSP, AGDP)$ (1)

The linear econometric model bases its structure on findings from Balsalobre-Lorente et al. (2018) and Rahman & Kashem (2017) research.

$ACO_{2t} = \propto_0 + \propto_1 FC_t + \propto_2 CP_t + \propto_3 LSP_t + \propto_4 AGDP_t + \varepsilon_t$ (2)

The intercept in the previously stated equation is denoted ∝0 and all explanatory variable coefficients appear as ∝1, ∝2, ∝3, ∝4. The error term ε uses subscript t to indicate the particular time period during analysis. A transformation of the original equation occurs upon computing the natural logarithm of all its variables.

$lnACO_{2t} = \propto_0 + \propto_1 lnFC_t + \propto_2 lnCP_t + \propto_3 lnLSP_t + \propto_4 lnAGDP_t + \varepsilon_t$

(3) MATERIALS AND MEHODS

The research implements regression analysis to study the relationships between agricultural emissions of CO_2 along with essential agricultural elements in Pakistan. The five independent variables within this analysis include agricultural GDP (lnGDP), irrigated land (lnIL), livestock population (lnLS), fertilizer consumption (lnFC) and climate variability (lnCV) expressed through natural logarithms. This research analyzes annual statistical data spanning from 1996 to 2022 which it gathers from World Development Indicators (WDI) along with Our World in Data (OWD) and Notre Dame Global Adaptation Initiative (NDGAI).

The assessment unfolds through the application of an adjusted Autoregressive Distributed Lag (ARDL) method according to Jordan and Phillips (2018) to explore long-term and short-term variations of these variables on CO_2 emissions. ARDL provides optimal analysis for time series data containing mixed stationarity elements because it enables examination of variables which are stationary at I(0) level or I(1) first difference without including I(2) variables. The specified procedure helps prevent scientists from discovering invalid results because of irregular data behavior.

Before running the ARDL estimation the study performs a diagnostic analysis which checks the stationary characteristics and variance properties of the data series. The analysis depends on demonstrating stationarity between variables because non-stationary regressions produce invalid results. The tests for unit root determine the degree of integration for variables at both the standard form and the first-differences version. A variable with level-unit root becomes stationary when differenced once so it qualifies as I(1).

The study conducts stationarity detection through both the Phillips-Perron (PP) test and the Dickey-Fuller (DF) test, as described by Dickey & Fuller (1979). The tests identify between dataset items that are difference-stationary processes and items that exhibit stochastic trends. The tests help strengthen the analysis by confirming whether roots exist at all.

ARDL Bound test

Numerous methodologies have been established over the years to assess both short- and long-term relationships among variables and evaluate co-integration. This research will employ the ARDL Bounds Testing approach, which presents several advantages compared to traditional co-integration methods. Among these advantages are: Using VECM has several advantages, including: (a) better results if the data are cointegrated of I(0) or I(1); (b) ease of use when working with a single equation; (c) handling small samples; (d) using different lag order for the variables; and (e) objective estimation of long-run co-movement and short-run relationships. The system will return to the long-run equilibrium position following the application of the ARDL technique and the ECM analysis. It is possible to determine the maximum lag lengths of up to 1, 2, and 3 by applying information criteria such as AIC, SC, and HQ. Pesaran (2001) provided important F-statistic data related to the limits testing methodology. They accomplished this by using this process to determine the highest and lowest values for important variables in various circumstances. There is no cointegration between the variables when the computed F-statistic is smaller than the lower bound. This demonstrates their independence from each other. Conversely, a long-term connection is suggested if the value is over the upper threshold. The test's results are unclear if it lies in the middle of these two ranges.

$$\Delta lnACO2_t = \propto_0 + \sum_{i=1}^{p} \propto_1 \Delta lnACO2_{t-i} + \sum_{i=1}^{p} \propto_2 \Delta lnFC_{t-i} + \sum_{i=1}^{p} \propto_3 \Delta lnCP_{t-i} + \sum_{i=1}^{p} \propto_4 \Delta lnLSP_{t-i} + \sum_{i=1}^{p} \propto_5 \Delta lnAGDP_{t-i} + \beta_1 lnACO2_{t-i} + \beta_2 lnFC_{t-i} + \beta_3 lnCP_{t-i} + \beta_4 lnLSP_{t-i} + \beta_5 lnAGDP_{t-i} + \varepsilon_t \quad (4)$$

Symbols containing ∑ represent the short-term dynamics of error correction, while those with β signify the long-term relationships among the variables (Queirós et al., 2017; Rahman & Kashem, 2017). The optimal lag selection is denoted by t-i, whereas the ideal lag lengths ρ, ρ1, ρ2, ρ3, and ρ4 are determined using the Akaike Information Criterion (AIC). Pesaran (2001) established the critical values for the F-statistic within the bounds testing approach, providing both lower and upper bound thresholds for different cases. These values indicate that if the calculated F-statistic falls below the lower bound, the variables are not cointegrated. Conversely, if the F-statistic exceeds the upper bound, it confirms the presence of a long-term relationship.

Diagnostic analysis

This study aims to analyse the model by applying best practices. Homoscedasticity remains the essential base for the ARDL Bounds testing method because it requires errors to be distributed equally without any bias. The research utilized Breusch-Godfrey Serial Correlation LM test to examine serial correlation then the Jarque-Bera test determined the error model normality (Rois et al., 2012). The Breusch-Pagan-Godfrey (BPG) test together with the ARCH test was conducted to examine heteroscedasticity throughout the model.

Stability test

Autoregressive models require stable metrics since their operations heavily depend on model stability. The model reliability will be determined using recursive CUSUM and CUSUM of squares tests that require appropriate adjustments. The evaluation protocol follows Pesaran (2001) framework and develops upon Brown et al. (1975)'s methodological approach.

The study variables are displayed in Table 1 and their symbols together with measurement units and data sources appear inside the table.

Table 1: Study variables and their explanations

Variable	Symbol	Units	Source
CO_2 emissions (share of agriculture)	ACO_2	Annual %	WDI
Fertilizer Consumption	FC	Total fertilizer consumption mt	OWD
Crop Production	CP	Index	WDI
Livestock Production	LSP	Index	WDI
Gross Domestic Product (share of agriculture)	AGDP	% of GDP	WDI

The research dependent variable will measure CO_2 emissions (share of agriculture) levels. Climate variability, fertilizer consumption, irrigated land, livestock population, and gross domestic product (share of agriculture) will each play the role of an explanatory variable.

Findings and conversation

The descriptive data for the six variables included in the correlation analysis—CO_2 greenhouse gas emissions, climate variability, fertilizer use, irrigated land, livestock population, and gross domestic product—are shown in the upper portion of Table 2. Climate variability has a negative association with CO_2 emissions, whereas fertilizer usage and livestock population have a substantial positive link with CO_2 emissions (proportion of agriculture), according to the Pearson correlation grid at the bottom of Table 2. Additionally, there is a moderately

negative correlation between CO2 emissions and gross domestic product, which is the proportion of agriculture. Correlation analysis aids in detecting possible multicollinearity, which may skew regression predictions if correlation coefficients between independent variables are higher than 0.95 (Hamsal, 2015). All Pearson correlation coefficients, however, are below 0.95, as shown in Table 2, corroborating

Table 2: Correlation matrix as well as descriptive statistics

Variables	$lnACO_2$	lnCP	lnFC	lnLSP	lnAGDP
Mean	1.4700	4.4892	15.2822	4.3249	3.1195
Median	1.4957	4.5322	15.2989	4.3660	3.1207
Maximum	1.8086	4.7310	15.6515	4.8307	3.2342
Minimum	1.1009	4.2294	14.8475	3.7905	2.9926
SD	0.2065	0.1480	0.2322	0.3355	0.0654
Correlation Matrix					
$lnACO_2$	1				
lnCP	0.9297	1			
lnFC	0.9797	0.9438	1		
lnLSP	0.9112	0.9508	0.9487	1	
lnAGDP	-0.5202	-0.3759	-0.4893	-0.3456	1

Unit Root

It is essential to make sure that no sequence is I(2) before using the ARDL technique because doing so would render the results invalid. Each series was put through the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests to confirm this. No one of the data series are stable at I(2), according to the results. The results of these unit root tests thereby validate that the dynamic ARDL model is suitable for the specified series.

Table 3: Unit Roots Outcome

VARIABLE	AUGMENTED DICKEY-FULLER (ADF)		DECISION	PHILLIPS PERRON (PP)		DECISION
	Level	**1st Difference**		**Level**	**1st Difference**	
$LNACO_2$	-0.9262 (0.7626)	-8.6359* (0.0000)	I(1)	-1.0689 (0.7123)	-14.7786* (0.0000)	I(1)
LNFC	-1.2220*** (0.6491)	-5.7118* (0.0000)	I(1)	-1.1073 (0.6972)	-18.0747* (0.0000)	I(1)
LNCP	-1.4147 (0.5966)	-4.7925** (0.0009)	I(1)	-1.6102 (0.4633)	-7.6409** (0.0000)	I(1)
LNLSP	-0.5412 (0.8674)	-5.2791* (0.0000)	I(1)	-0.5523 (0.8650)	-5.2790* (0.0000)	I(1)
LNAGDP	-2.7013*** (0.0878)		I(0)	-2.311*** (0.0759)		I(0)

*Note: *p < 0.01; **p < 0.05; ***p < 0.1*

It is possible to specify distinct lag orders for independent and dependent variables in the autoregressive distributed lag model. Table 4 displays the outcomes of several tests of the lag selection criteria. The best lag length for variables in econometric models is frequently found using the AIC, SC, and HQ. The AIC criteria indicates that a lag of two best fits the

model based on the lag selection because its value of -26.2848 is less than the AIC values for the other lag lengths. The AIC is the main criterion employed here, demonstrating that lag 2 is the best option for this study even though the SC and HQ criteria suggest a preference for lag 1. Table 5 below displays the findings:

Table 5: Lag Length Criteria

Lag	AIC	SC	HQ
0	-20.2002	-19.9077	-20.1191
1	-26.0724	-24.0247	-25.5044*
2	-26.2848*	-22.4819*	-25.2301

Model Diagnostic Test

Table 6 presents the key analytical metrics utilized to assess the model's fit. The results of the Breusch-Godfrey LM test confirm that serial correlation is not an issue in the model. Additionally, the findings from the ARCH and Breusch-Pagan-Godfrey tests indicate the absence of heteroscedasticity. The Jarque-Bera test further confirms that the model's residuals follow a normal distribution. Moreover, the R-squared value demonstrates that the model provides an excellent fit to the data.

Table 6: Statistics for diagnosis

Diagnostic test	F-Stat (Prob)	Decision
Breusch-Godfrey LM Test	0.3466	No problem with serial correlations
Breusch-Pagan-Godfrey	0.1051	No heteroscedasticity problem
ARCH	0.1194	No heteroscedasticity problem
Jarque-Bera test	0.6796	Estimated residuals are normal
R^2	0.9522	The model fit is very good

The F-statistics revealed in Table 7 show the results of cointegration evaluation. The model variables show evidence of prolonged relationship in both 10% and 5% significance zones since F-statistics surpass the corresponding critical boundaries. The results lead to rejecting the null hypothesis about the absence of relationship (Bilal et al., 2024; Zubair et al., 2020).

Table 7: Cointegration bound test

T-Stat	Value	K
F-statistics	3.8377	4
Critical values		
Significance	**Lower Bound**	**Upper Bound**
10%	2.2	3.09
5%	2.56	3.49

Table 8: Both short-term and long-term ARDL estimates

The short-term and long-term variable relationships for Pakistan were analyzed using an ARDL (1,0,2,2,1) model.

Dependent Variable: $lnACO_2$				
Variable	**Coefficient**	**Std. error**	**t-stat**	**p-value**
Long-run estimates				
lnCP	0.1573	0.2277	0.6908	0.5010
lnFC	1.0064	0.2525	3.9843**	0.0014
lnLSP	-0.2843	0.1000	-2.8430**	0.0042
lnAGDP	-0.3538	0.1211	-2.9215**	0.0035

Short-run estimates				
D(lnFC)	0.9937	0.0703	-2.9860**	0.0098
D(lnLSP)	0.1780	0.1512	1.1777	0.2585
D(lnLSP(-1))	0.6037	0.1603	3.7656**	0.0021
D(lnAGDP)	0.2041	0.1478	1.3805	0.1891
ECM(-1)	-0.8392	0.1501	-5.5902**	0.0001

*Note: *p < 0.01; **p < 0.05; ***p < 0.1*

ACO_2 and its four primary factors crop production (CP), fertilizer consumption (FC), livestock population (LSP), and agricultural contribution to GDP (AGDP) display their long-term relationship in Table 8.

The long-term data shows fertilizers (LnFC) cause meaningful positive effects on ACO_2 because each 1% increase in fertilizer use leads to 1.01% more emissions from nitrous oxide emissions. The data shows that livestock population (lnLSP) has a negative correlation because a one percent increase in LSP results in a 0.28 percent decrease in emissions because livestock management practices have improved. The data reveals that agricultural developments and sustainable farming practices reduce ACO_2 emissions by 0.35% whenever AGDP grows by 1%. However, the relationship between lnCP and ACO_2 is positive but statistically insignificant, indicating that consumer price fluctuations do not significantly impact emissions in the long term. The short-run ARDL results confirm a strong positive effect of fertilizer use on emissions, where a 1% increase in FC raises ACO_2 by 0.99%, reinforcing the immediate impact of fertilizer applications. Additionally, the error correction coefficient (-0.8392, p = 0.0001) is statistically significant, indicating a rapid adjustment toward equilibrium, with 83.92% of the previous period's disequilibrium corrected in the current period. The robustness of the model further strengthens the understanding of how agricultural activities in Pakistan influence CO_2 emissions over time.

Stability test

Following Pesaran's (2001) recommendations, the CUSUM and CUSUMSQ tests were conducted on the model parameters to validate the short-term findings for Saudi Arabia and evaluate the structural stability of the long-term dynamics. The outcomes are illustrated in Figures 1 and 2. Based on existing research, when the CUSUM and CUSUMSQ boundaries remain within the 5% threshold, it signifies the stability of the model parameters. The graphical display shows that CUSUM and CUSUMSQ metrics remain below set 5% significance thresholds and thus prove both plots follow their designated limits.

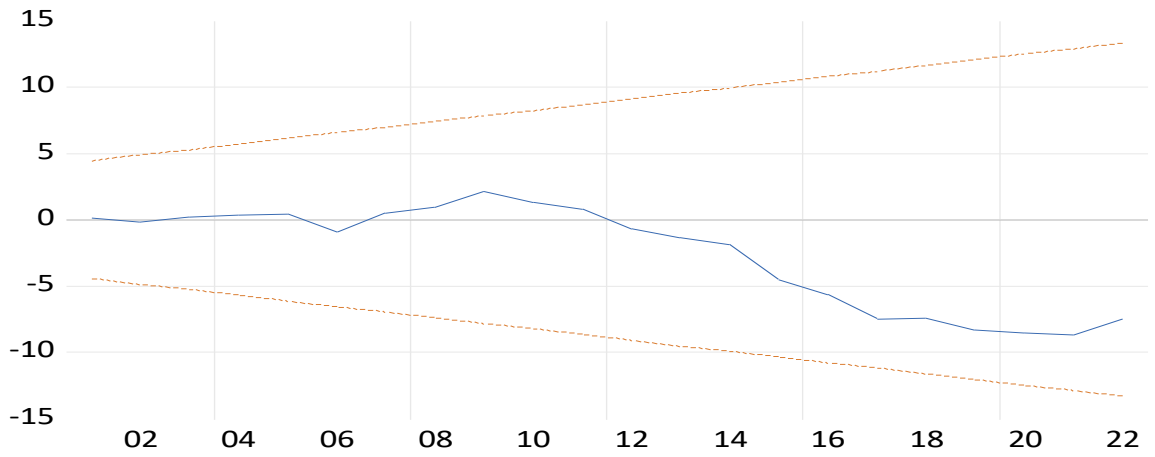


Figure 1: Illustrates the CUSUM test at a 5% significance level

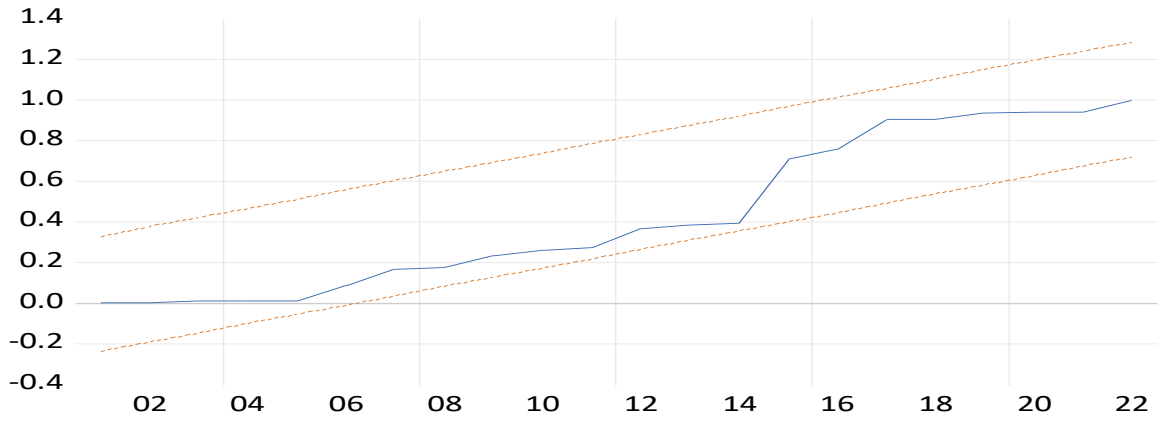


Figure 2: Illustrates the CUSUM of Square test at a 5% significance level

Discussion

The impact of biochar emissions depends on the specific application strategy and soil type together with climatic conditions (Yang et al., 2022). Biochar demonstrates increased CO2 emissions in subtropical areas to present complex behavioral patterns yet shows effective CH4 emission reduction in tropical regions raising potential environmental applications in hot climates (Jia et al., 2023). The influence of biochar on greenhouse gas emissions reacts significantly to soil texture because coarse-textured soils show prominent reductions of nitrogen oxides and CH4 emissions. Biochar exhibits different emission effects because it establishes distinct microbial areas and creates better soil ventilation between soil types. Research conducted by Wang et al. (2025) supports the current study results about the relationships between fertilizer use and GDP and livestock production on CO2 emissions. Biochar displays superior efficacy in minimal nutrient conditions since it leads to documented carbon dioxide emission decreases in soils that contain low concentrations of soil organic carbon (SOC) and total nitrogen (TN). Biochar formulation needs to be individually optimized to achieve maximum benefits because its effect on soil depends on its specific pH level (Liu et al., 2024).

MITIGATION STRATEGIES

Optimizing farm fertilizer/chemical inputs

The increased productivity of agriculture requires various chemical inputs consisting of ammonia and urea together with phosphate (P_2O_5) and potash (K_2O) alongside lime and pesticides. Greenhouse gas (GHG) emissions originate from two primary sources when it comes to fertilizers: their production in manufacturing plants and their on-ground agricultural usage.

Synthetic nitrogen fertilizers applied to agricultural areas cause microbial soil processes that produce nitrous oxide (N_2O) as a major GHG emission. The nitrogen applied during farming results in N_2O formation through microbial nitrification and denitrification before atoms escape to air. Environmental damage expands through two channels of indirect N_2O emissions which include nitrate leaching as well as the breakdown of nitrogen fertilizers.

The high Global Warming Potential value of 265 for N_2O means that its emissions during fertilizer production while also used in production significantly affect the total GHG impact across a product's life cycle. The prevention of such emissions stands as a top priority for achieving environmental targets in agricultural fields.

The adoption of precision agriculture with its variable rate technology component shows potential to enhance fertilizer efficiency while cutting down on emissions. The application of VRT for maize cultivation in the Midwest area of the United States rose drastically from 8% to 35% during the period of 2010 to 2016 as reported by Baranski et al. (2018). The use of nitrification inhibitors represents a promising N_2O emission reduction strategy because these treatment agents suppress nitrifier activity resulting in decreased N_2O production levels of up to 33–44% compared to standard fertilizer use (Thapa et al., 2016).

The outcomes of enhanced efficiency fertilizers (EEFs) show diverse results which depend heavily on agricultural products, nutrient compounds along with local soil contents and farming standards. Soil-specific conditions determine the success of mitigation measures and growers should examine site characteristics with management practices prior to selecting an appropriate emission-reduction technique (Thapa et al., 2016).

Through precision agriculture systems and specific fertilizer planning, the agricultural sector could achieve simultaneous GHG emission reductions and sustainability goals.

Producing low-carbon chemicals and fertilizers

In addition to the previously described strategies for lowering greenhouse gas emissions from on-field operations, advancements are also taking place upstream, in the stages of fertilizer and chemical manufacture, by employing more renewable energy sources as energy and raw materials. Further reductions in agricultural GHG emissions and lessening the agriculture sector's reliance on fossil fuels are possible outcomes of these "greener" routes. For instance, water, air, and renewable electricity from solar or wind power can be used to manufacture ammonia, the starting point for all other nitrogen fertilizers (Liu, Elgowainy, et al., 2020). The so-called environmentally conscious ammonia, which is produced from N2 by the cryogenic distillation process and H2 by temperatures below freezing oxidation using renewable electricity, can reduce ammonia GHG emissions by 91% when compared to the conventional ammonia production method, which uses steam methane for the reforming of natural gas. Corn grown in the United States can have its greenhouse gas emissions cut by 18% from the seed to the farm.

Decreasing the amount of fuel and energy used in farming

On-farm energy use gets periodically evaluated through the USDA's Agricultural Resource Management Survey (ARMS) since the early 1990s. The Economic Research Service through Hitaj & Suttles (2016) identified three principal methods to diminish agricultural greenhouse gas emissions through conservation tillage together with farming electrical power generation and anaerobic digesters as biogas production facilities.

Soil carbon sequestration increases while fuel consumption decreases and emissions decrease when using no-till farming as part of conservation tillage practices. The implementation of this approach results in higher costs for fertilizers and pesticides for corn and wheat producers according to Hitaj & Suttles (2016).

A transition from fossil fuel energy to renewable power sources represents an effective solution. The use of biodiesel manufactured from animal fats and vegetable oils coupled with anaerobic digestion produces biogas as a bioprocessing method which stops emission of methane in animal manure (Wang et al., 2020).

The application of renewable energy with sustainable farming methods allows agriculture to boost energy efficiency while reducing GHG emissions and contributing to climate change mitigation without losing production levels.

System of Cropping

The nitrogen production process from chickpeas generates N2O but legume crop cycling stands out as an effective GHG emission reduction technique by reducing nitrogen imports. Researchers in Illinois conducted extended field tests which demonstrated that swapping between grain and soybeans leads to higher yields and reduced GHG outputs than ongoing soybean production or extended corn farming. Agricultural techniques using fewer inputs result in decreased emissions since they apply fewer herbicides and other substances while emitting fewer greenhouse gases. Gul, A. (2023).

Increasing soil carbon stocks

There is a chance that soil carbon can be stored in crops and through the conversion of agricultural residues into organic carbon, even though some land-use changes, like switching from native grassland or woodland to agriculture, would release soil carbon as CO2 (EEA, 2021). By either reducing carbon outflows from soils or boosting carbon inputs to lands, conservation techniques are typically taken into consideration to increase soil carbon storage (Paustian et al., 2019). When combined with

crop rotations that include fallow-season and off-season cover crops, conservation tillage has been shown to enhance soil carbon retention in specific areas (Jian et al., 2020). Carbon can be sequestered in the soil by applying livestock manures. However, when determining the net decrease in greenhouse emissions from manure application, it is important to consider the fuels used to transport waste from feed processing plants to farms for application on the land (Qin et al., 2018). New methods are also being developed to increase the amount of carbon stored in the root biomass, such as growing crop varieties with deep roots (Paustian et al., 2019).

Management of nutrients

Concern has long been raised about the excessive, incorrect, and inconsistent application of nitrogen and fertilizer in the field. Improving crop N consumption efficiency may help reduce N2O emissions by reducing the possibility of significant residual NO3 in the soil profile. When compared to urea, fertilizers such as ammonium sulfate decreased CH4 emissions; however, they also significantly increased nitrogen dioxide emissions, which can be decreased by using nitrification inhibitors.

Approaches to Reduce Ag-GHG Emissions

Programs for Cost-Sharing and Technical Support in Ag-GHG Reduction

The Title 2 programs offer established programs that let farmers access shared costs alongside technical support to lower their agricultural greenhouse gas (ag-GHG) emissions. These initiatives help solve technical and financial problems, which make the adoption process easier to accomplish. The successful implementation of these programs needs USDA professionals to join forces with ranchers and farmers to establish suitable practical solutions (McCann & Claassen, 2016). The experts use environmental impact assessments to guide farmers through picking recommended mitigation strategies from an updated selection that includes both regional cost information and behavioral constraints. Department grants provide funds according to the chosen activity along with cost index formulas but also make provision for additional funding when selecting high-cost mitigation options. The relationship between funding and policy implementation creates reduced performance risks for farmers, although their GHG reduction achievements are not part of the funding criteria. The system enables participation, yet it deteriorates motivational factors to pick up advanced greenhouse gas reduction methods. The implementation of the latest technology for lowering costs may restrict possible reductions in expenses, thereby decreasing farmer motivation. Fresh practices which incorporate cover cropping alongside nitrogen reductions face identification as yield risks which lead farmers to avoid adoption (Sawadgo and Plastina 2022).

Programs for Climate-Smart Agricultural Commodities

Through their Partnerships for Climate-Smart Commodities, the program enhances measurement along with verification of reduced greenhouse gas emissions from agricultural low-GHG products. This initiative implements similar principles to environmental product certification schemes like wood sustainability standards and sustainable energy standards, which market their services to consumer segments focused on purchasing eco-friendly products at premium prices.

Two important questions emerge about how to establish carbon intensity thresholds and whether buyers will purchase climate-friendly products at elevated prices. Market research on eco-friendly product demand, especially focused on certified green wood, will reveal how much money consumers will invest in the sustainability initiative.

Mechanisms for Reducing Ag-GHG Emissions Credits

The effectiveness of ag-GHG mitigation credits solely depends on verifying their ecological soundness for regulatory purposes. Poor or biased GHG reduction assessments diminish public trust as they reduce the effectiveness of regulatory goals (Wongpiyabovorn et al., 2022; SchulteMoore & Jordahl, 2022). Quality credit-generating activities need to prove genuine GHG decrease detection while stopping the problem of "hot air" credits from developing.

Government-funded conservation and climate-smart programs should produce less

environmental benefit than emission credits do in order to fulfill their purpose. When unrestrained credit offsetting happens through the usage of reductions that would take place naturally, this eliminates any possible environmental advantages of these programs. Establishing a definite threshold for additional carbon reductions in credit systems becomes complicated because we cannot accurately predict the total GHG reductions from government-funded programs.

Strengthened oversight with precise measurement enables these mechanisms to promote agricultural emissions reduction and preserve market trust together with environmental reliability.

Policy implications

Prioritizing Disease Control for Economic and Environmental Benefits

The selection of livestock diseases that need control or eradication requires analysis of three main factors which comprise economic impact alongside biological efficiency and existing control strategies. Johne's disease causes major productivity loss and enables greenhouse gas (GHG) emission reductions (Takahashi et al.,2024). The control of diseases faces obstacles from three main factors: there is no cure available and no vaccine exists and no reliable diagnostic tests exist and the pathogen continues to exist within wildlife species and environmental reservoirs.

Several countries have successfully eliminated Infectious Bovine Rhinotracheitis (IBR) because they possess both effective vaccines and strategic control approaches. The involvement of farmers proves essential for reaching desired outcomes in this scenario. The Dutch national IBR eradication program stopped its operations when infected vaccines resulted in new outbreaks reducing farmer trust and turning their participation into voluntary status. The projected analysis suggests elimination of the disease will not succeed with only voluntary vaccine programs hence a national disease management policy remains crucial.

Economic factors determine the type of policymaking strategies. National disease control programs become necessary whenever the expense of disease management reaches the level of its economic consequences such as with neosporosis. The successful control of diseases depends heavily on what stakeholders do because farmers actively take part and organizations in the industry offer important backing.

The control of sheep diseases depends on the combined factors of economic value and environmental effects. Parasitic gastroenteritis (PGE) demonstrated a higher economic impact than enzootic abortion (chlamydiosis) or footrot in ewes according to the assessment results. The disease control efforts can benefit from existing industry initiatives since Quality Meat Scotland started their footrot and lameness campaign in 2015 (Henry et al.,2024)

Another essential factor involves the threat of diseases reintroduction. Locally occurring diseases negatively impact business operations but authorities tend to focus on rare infections like Bluetongue and Schmallenberg and Foot and Mouth Disease which create significant economic damage. Natural immunity against endemic pathogens persists within the livestock populations because the pathogens circulate routinely. Once eradication occurs the protective effect from natural immunity also ends which heightens the possibility of destructive disease outbreaks if the disease reappears. The benefits derived from eradication programs regarding GHG reduction and productivity enhancement need to be balanced against the emergence risks of eliminated diseases.

Conclusion

Unless considerable efforts are made to reduce them, greenhouse gas emissions—which are linked to society's basic requirements for food and energy—will keep rising and warming the planet. Climate change affects and is influenced by agriculture. Despite the trend toward lowering greenhouse gas emissions from agriculture, practices in this direction shouldn't negatively affect farm productivity and profitability because doing so would limit their use.

the quantity of greenhouse gases released by various activities, such as the use of organic and inorganic amendments. Most of these gases are produced by the processes of methanogenesis, nitrification, and denitrification. GHG fluxes

from agricultural systems vary greatly in time and location due to complex interactions between physical, chemical, and biological components. Increasing agricultural efficiency might be possible with precision agriculture. Optimal management methods are being applied in farm and field settings through systematic, site-specific procedures, as opposed to advocating for general messaging or all-encompassing solutions. Calculating the Global Warming Potential (GWP), incorporating measures for mitigation (conservation tillage, cropping systems, nutrient management, etc.), and evaluating the financial feasibility of these initiatives are all steps in the process of developing more effective strategies. Notwithstanding the potential for GHG mitigation, implementation obstacles cause a discrepancy between technological potential and actual GHG mitigation such as institutional, social, educational, and financial constraints, as well as climate and non-climate policies. By increasing agricultural input usage efficiency, the government should concentrate on implementing climate-smart agriculture.

Future investigations should focus on a comprehensive analysis of greenhouse gas emissions in agriculture, specifically including methane (CH_4) and nitrous oxide (N_2O) alongside carbon dioxide (CO_2) in predictive models. A detailed examination of emissions sources—such as livestock, fertilizer use, irrigation, and deforestation—will provide better insights. Comparative studies across South Asian countries can reveal region-specific patterns and policy impacts. Expanding research to include long-term changes in agricultural practices, like mechanization and organic farming, will enhance understanding of these dynamics. Structural break analyses can also shed light on how economic and political shifts influence emissions trends. Additionally, research should address socio-economic barriers to adopting climate-smart practices and evaluate the effectiveness of current policies, including subsidies and incentives. Incorporating strategies like biochar, agroforestry, and alternative livestock feeds could lead to more actionable solutions. Finally, exploring financial mechanisms such as carbon credits and green financing could encourage farmers to adopt low-emission practices, enhancing the effectiveness of climate-smart strategies.

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