

## Strategies to Reduce Agrifood Systems Emissions: Balancing Food Security and Economic Development Goals in Zimbabwe

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### Abstract

Focusing on Zimbabwe, this study examined the determinants of agrifood systems emissions while considering economic growth, population growth, trade openness and energy use. Using the extended STIRPAT model, the study used the ARDL technique, which showed a long-run relationship between agrifood emissions and key economic variables, which are economic growth, population growth, trade openness and energy use. The study found out that economic growth increased agrifood emissions in the short run, while sustained economic growth was linked to reduced agrifood emissions. In addition, population growth was found to be reducing the agrifood emissions in the short-run. Furthermore, trade openness was found to be contributing to higher agrifood emissions in the short-run. The findings implied that there was a need to promote the adoption of green technologies in the agrifood sector to reduce the crop residue emissions, launch crop residue management programs through the agricultural extension, aligned trade policies with environmental goals and strengthened the institutional capacity and awareness while fostering collaboration with international organisations such as FAO and UNDP.

**Keywords:** Food Security, Carbon Footprint, Energy Use, Crop Residue, Greenhouse gas emissions

### Introduction

The global agrifood sector was tasked with the fundamental goal of ensuring food and nutrition for all (World Bank, 2024,p.1). This task was intensified with a growing world population that was expected to grow by two billion by 2050. (United Nations, 2024). According to the OPEC Fund (2023), as compared to 2009, there was a need for 70% more food in 2050. Amid the significant need for food increase, reducing carbon emissions was necessary to protect the environment that supported food production. Carbon emissions contributed to global warming, which negatively affected the environment that produced the food. Moreover, reducing carbon emissions improved the nutritional value of food. (United Nations, 2020). Van Dijk, Morley, Rau and Saghai (2021) provided that, considering climate change, the world population at risk of hunger would increase by 99% between 2010 and 2050. Thus, the world was pressured to increase food production while reducing carbon emissions. Therefore, different economic sectors responded in various ways of reducing the carbon emissions using alternative and clean energy.

Despite efforts to reduce carbon emissions, there was still a long way to go to meet the net-zero emission by 2050 target. While the world was focused on increasing food production, the agrifood sector was largely contributing to carbon emissions. (World Bank, 2024, p.3).

Paradoxically, the world was focused on reducing carbon emissions in different economic sectors, often neglecting the agrifood sector. Crippa et al. (2021) established that by 2015, the food-system emissions amounted to 34% of the total Green House Gas (GHG) emissions globally. The largest contributor to these food-system emissions was agricultural and land use activities, which contributed 71%. Similarly, Nguyen, Le, Schinckus and Su (2021) established that agriculture was a significant contributor to the GHG emissions, while agriculture value added was among the major drivers of these emissions in the long run.

Studies have shown that the current agrifood system was significantly degrading the planet through GHG emissions. (Ntinyari & Gweyi-Onyango, 2020; Nguyen et al., 2021; Dogan & Kan, 2024). Food and Agriculture Organisation of the United Nations (FAO) (2023) stated that the world's hidden cost of agrifood emissions in 2020 was 12.7 trillion purchasing power parity dollars (PPP), showing that the world no longer could afford the agrifood system that fed it. At the same time, people became over-reliant on the agrifood system more than ever as it provided food security, jobs and economic development. (World Bank, 2024).

In Zimbabwe, despite the agricultural sector providing 65% of rural communities' employment, it stood as the third largest emitter in the country, with the agriculture, forestry and other land use (AFOLU) sector contributing 54% of the total GHG emissions in Zimbabwe by 2017. (World Bank, 2017; Government of Zimbabwe, 2021). In addition, the GHG emissions from the AFOLU sector was on an upward trend for the past three decades. (Government of Zimbabwe, 2021). Critically, it appeared that the GHG emissions received inadequate attention in the national efforts to reduce GHG. This oversight was exacerbated by a notable paucity of literature on the specific drivers of GHG emissions in Zimbabwe. This knowledge gap undermined the commitment of the Nationally Determined Contribution (NDC) to reduce emissions by 33% below business-as-usual by 2030. Impediments to such policies would threaten the national food security and sustainable development.

Against this background, this study aimed to examine the determinants of Agrifood Systems Emissions in Zimbabwe using an extended STIRPAT model. The results from this study would identify the sources of the agrifood systems' GHG emissions and the magnitude of their contribution. This would assist in the efforts to reduce GHG in Zimbabwe and the development of policies towards mitigating climate change.

## Literature Review

In this study, the researchers reviewed the IPAT, STIRPAT and Environmental Kuznets Curve (EKC) theoretical frameworks. The Environmental Kuznets Curve (EKC) hypothesis was based on the work of Simon Kuznets in the 1950s and 1960s. It proposed an inverted U-shaped relationship between economic growth and environmental pollution. (Anwar et al., 2022; Jeetoo & Chinyanga, 2023). The theory posits that as the country developed, initially, environmental damage increased, emanating from an increase in industrialisation and resource extraction. (Anwar et al., 2022). However, beyond a certain income threshold, environmental degradation decreased as green and smart technologies were adopted, environmental regulations were strengthened and economic structures shifted towards less polluting sectors. (Isik et al., 2021). In the context of agrifood systems, the EKC implicitly meant early agricultural development might lead to higher emissions, but with further economic progress and technological advancements in farming, emissions declined.

The IPAT (Impact = Population x Affluence x Technology) identity was proposed by Ehrlich and Holdren (1970). The theory posited that environmental impact was a direct result of population size, per capita consumption (affluence) and the environmental impact per unit of consumption (technology). (Wang & Taghvaei, 2023). The IPAT deterministic nature limited its analytical flexibility. However, furthering from IPAT, the Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model by Dietz and Rosa (1994) offered a more flexible, stochastic reformulation, allowing for empirical estimation of the elasticities of various driving forces on environmental outcomes. (Bai, Du & Chua, 2025). Hence, the STIRPAT was used in this study to analyse non-linear relationships and incorporate additional factors beyond the core (P), (A) and (T), making it highly applicable to complex systems like agrifood emissions, where specific technologies and agricultural practices could be explicitly examined.

The theories reviewed here collectively provide a robust framework for understanding the multifaceted drivers of agrifood system emissions in Zimbabwe, considering demographic, economic and technological influences.

### **Empirical Literature**

The agricultural sector played a vital role in the economy regarding food security and nutrition, along with other economic, environmental and social impacts. (Nguyen, Le, Schinckus & Su, 2020 and Pawlak & Poczta, 2024). Agriculture in Zimbabwe is the largest employment sector, occupying over seventy per cent of the labour force (Muzorewa and Chitakira, 2022). According to Hossain and Chen (2022), the agriculture sector is accountable for both the CO<sup>2</sup> emissions brought on by the conversion of natural ecosystems, mostly forest land and natural peatlands, to agricultural land usage and the non-CO<sup>2</sup> emissions produced at the farm gate by crop and animal operations. Various studies were carried out globally on the factors contributing to agricultural systems' emissions.

Nguyen et al. (2020) panel data analysis of 89 economies study showed that in the short run, income and economic integration – proxied by trade and foreign direct investment (FDI) positively impact greenhouse gas (GHG) emissions from agriculture. In the long run, income, agricultural value added and energy consumption positively impacted greenhouse gas (GHG) emissions. In addition, trade openness and FDI inflows were found to have negative effects on GHG emissions in the long run. Noting the lack of research on the determinants of the emission intensity ratio for food production, a study by Mrówczyńska-Kamińska et al. (2021) found that determinants of the growth of emission intensity of food production systems were GDP per capita, population density, nitrogen fertiliser production, utilised agriculture area, share of animal production and energy use per capita. All these variables were found to have a positive impact. This was evidenced by the 14 countries included in the study. A study from the EU G27 countries by Dogan and Kan (2024) indicated that the agricultural sector was the root of the deterioration in the ecosystem because of the effect of intensive agriculture after the green revolution. The findings indicated that the sources of agricultural emissions included use of chemical fertilisers, livestock activities, produce residues and enteric fermentation. The studies from the panel data analysis showed that the determinants of agricultural system emissions were both macro and microeconomic activities. However, these studies were cross-country studies, which might contain heterogeneous economic structures. Country-specific studies were carried out.

A study by Rafiq, Salim and Apergis (2016) revealed that affluence, non-renewable energy consumption and energy intensity variables drive pollutant emissions in linear models, while population was a significant driver in the nonlinear model. Service sector and agricultural value-added levels reduce pollution, while industrialisation increased it. Trade liberalisation significantly affected emission reduction levels, suggesting coordination between economic development, industrialisation strategies and environmental policies. Singh and Mukherjee (2019) tested the STIRPAT model by analysing drivers of greenhouse gas emissions. The study focused on per capita GHG emissions in the United States (US). The findings of this study indicated heterogeneous slope parameters in panel data models, indicating that cattle density and affluence were major drivers of per capita GHG emissions in the continental US. Overall, it implied that economic factors such as energy use and agricultural practices drove greenhouse gas emissions in the agricultural sector.

In China, a descriptive statistics analysis was carried out by Qi et al. (2024), which found similar results to those found by Mrówczyńska-Kamińska et al. (2021). The findings were that an increase in green house emission could primarily be attributed to a combination of economic growth, consumer expenditure and a shift in dietary patterns. These findings conformed to the STIRPAT model determinants of agricultural system emissions. In the Netherlands, the study by Suto (2022) found similar results that population, household size, demand, demand structure and emission intensity contribute to GHG emissions. The study indicated that decreasing consumption intensity decreased GHG emissions. Similarly, population growth was also found to have a positive relationship with GHG emissions. Hence, demographic trends in the Netherlands played a significant role in achieving mitigation and future climate policies should address these trends to optimise GHG emission reductions. (Suto, 2022).

Patrizi et al. (2020) noted that Africa had enormous natural resources in the form of biomass from agriculture and other related processes (that is, food residues). Similarly, Ntinyari and Gweyi-Onyango (2020) pointed out that emissions were caused by a lack of crop residue management, since most of the agricultural waste on the land was publicly burnt or left for cattle grazing. Savanna and grassland fires, which were prevalent in Sub-Saharan Africa, contributed significantly to GHG emissions (Ntinyari & Gweyi-Onyango, 2020). Due to the significant contribution of GHG emissions to ecosystems, agriculture has become a key aspect of the SSA. In Zimbabwe, cattle production was heavily reliant on natural resources and had a significant environmental impact due to methane and nitrous oxide emissions from fermentation processes and manure; ammonia loss during manure managing and storage; the loss of biodiversity and deforestation when cutting down forests for grazing; and degradation linked in review to poor pasture management, overgrazing and soil erosion. (Chirinda et al., 2021). There were insufficient studies on the environmental consequences of dairy production techniques in Zimbabwe.

The subject matter of Agrifood systems emissions was so important that it must be urgently addressed because reducing agricultural emissions provided significant economic and social benefits. (Singh and Mukherjee, 2019). For example, Giannadaki et al. (2018) showed that agricultural ammonia emissions strongly contributed to fine particulate matter air pollution and had significantly adverse impacts on human health, leading to increased mortality rates. Strategies to combat this included first feeding, using additives, improving herd management and managing produce residues. (Singh and Mukherjee, 2019). Burning waste and using compost for plant nutrition can also reduce emissions. (Shumba et al., 2023). Biomass power plants could obtain low-emission energy from agricultural residues and the interaction between

waste obtained from producers and energy power plant investors can contribute to sustainable agricultural production.

The empirical research has repeatedly shown that economic activities, population trends and agricultural practices all had a major impact on global agrifood system emissions. While cross-country studies provided broad perspectives, country-specific research, particularly in Zimbabwe, was sparse. Existing Zimbabwean research identified livestock, residue management and land use as major emission sources. The urgent need to examine key factors influencing agrifood systems emissions in Zimbabwe were therefore highlighted, allowing for coming up with tailored mitigation solutions with environmental and public health advantages.

**Research Methodology**

**Theoretical Model**

The study used the extended STIRPAT model to explain key factors influencing Agrifood Systems emissions in Zimbabwe. The model is an extension of the IPAT model developed by Ehrlich and Holdren (1971). The IPAT model shows the impact of population (P), affluence (A) and technology (T) on the environment (I). It is expressed as follows:

$$I = P * A * T \dots \dots \dots$$

In the IPAT model, (I) was represented by Agrifood Systems Emissions, which represented the environmental impact of human activities. The environmental impact a multiplication function of population (P), affluence (income) and technology (T), which represents resource use efficiency. (Nguyen et al., 2020). Regarding the RHS of the (3.1) model, (P) represents population growth, (A), represents GDP growth and technology (T) is represented by energy use. However, the IPAT model is considered a heuristic model, which cannot be used for estimation (Nguyen et al., 2020). As a result, the study adopted a model established by Dietz and Rosa (1997), the STIRPAT model, which is suitable for empirical estimation. The STIRPAT model is expressed as follows:

$$I_t = \alpha_t P_t^{\beta_1} A_t^{\beta_2} T_t^{\beta_3} \varepsilon_t \dots \dots \dots (3.2)$$

Equation (3.2) can be written as follows:

$$\ln I_t = \alpha_t + \beta_1 \ln P_t + \beta_2 \ln A_t + \beta_3 \ln T_t + \varepsilon_t \dots \dots \dots (3.3)$$

Where  $\beta_1, \beta_2$  and  $\beta_3$  are elasticities on environmental impact with respect to P, A and T. It is noteworthy that agrifood emissions can be explained by other factors outside the STIRPAT model, such as trade openness. The study used an extended STIRPAT model. As a result, the study also included trade openness in the model and the extended STIRPAT model used takes the following form:

$$\ln cr_t = \alpha_t + \beta_1 \ln pop_t + \beta_2 \ln gdp_c_t + \beta_3 \ln engy_t + \beta_4 \ln topen_t + \varepsilon_t \dots \dots \dots (3.4)$$

**Empirical model specification**

Various empirical models were used in the literature, including the Vector Auto Regressive (VAR) model, Autoregressive Distributed Lag (ARDL) model and Panel Bootstrapped approach to Granger causality test, among others. This study adopted an ARDL model. In its reduced form, the ARDL model is expressed as follows:

$$Y_t = \delta + \sum_{i=0}^p \gamma_i \Delta Y_{t-i} + \sum_{i=0}^q \vartheta_i \Delta X_{t-i} + \varepsilon_t \dots \dots \dots (3.5)$$

where  $Y_t$  is the dependent variable;  $X_{t-i}$  is the lagged explanatory variable;  $Y_{t-i}$  is the lag of the dependent variable which is also an independent variable;  $\delta$  represents the intercept;  $\gamma_i$  and  $\vartheta_i$  are slope coefficients of the ARDL model; and  $\varepsilon_t$  represent the error term. This study followed a study by Nguyen et al (2020) and adopted the following empirical model:

$$\begin{aligned} \Delta \ln cr &= \alpha_0 + \sum_{i=0}^p \alpha_i \ln cr_{t-i} + \sum_{i=0}^q \beta_i \Delta \ln pop_{t-i} + \sum_{i=0}^q \delta_i \Delta \ln growth_{t-i} + \sum_{i=0}^q \vartheta_i \Delta \ln engy_{t-i} \\ &+ \sum_{i=0}^q \gamma_i \Delta \ln topen_{t-i} + \mu_1 \ln cr_{t-1} + \mu_2 \ln pop_{t-1} + \mu_3 \ln gdpc_{t-1} + \mu_4 \ln engy_{t-1} \\ &+ \mu_5 \ln topen_{t-1} + \varepsilon_t \dots \dots \dots (3.6) \end{aligned}$$

Where  $cr$  is crop residue emissions,  $pop$  is population growth,  $growth$  is GDP growth representing affluence?  $engy$  is energy use representing technology in the STIRPAT model and  $topen$  is trade openness. The intercept term is represented by  $\alpha_0$ .  $\alpha$ ,  $\delta$ ,  $\beta$ ,  $\vartheta$ , and  $\gamma$  are short run coefficient and  $\mu_1, \mu_2, \mu_3, \mu_4, \mu_5$  are long-run coefficients. In the model,  $\Delta$  is the difference operator. The error term is represented by  $\varepsilon_t$ .  $p$  and  $q$  represent the lag lengths and  $t$  represents time.

With regards to pre-estimation tests conducted, all variables were tested for unit root to ensure that all of them are either integrated to order zero I (0) or integrated to order one, that is, I (1). An Augmented Dickey Fuller (ADF) test for unit root was used to test for stationarity. The presence of perfect or near multicollinearity was tested using the correlation matrix. Akaike Information Criteria (AIC) was used to determine the optimal lags in STATA 18. The model was also tested to ensure unbiased estimates using several diagnostic tests. The Jacque-Bera (JB) test was used to test for normality of residuals. The Breusch-Godfrey Lagrange Multiplier (LM) test was used to determine the presence of autocorrelation. Ramsey RESET test was used to check for model specification. The coefficient of determination ( $R^2$ ) was used to test for the goodness of fit of the model. Cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) were used to test for the stability of the model.

## Estimation Procedure

The study used an ARDL initiated by Pesaran and Shin (2001) and later developed by Pesaran et al. (2001). The model was later modified by Narayan (2005) to suit a small sample for data ranging between 30 and 80 observations. The model had several advantages over traditional approaches to cointegration in that it applies to small samples. The ARDL model could be applied to time series regardless of order of integration, that is, whether they are I (0), I (1) or a mixture of both. After estimating equation (3.6), the long-run relationship was determined using the ARDL Bounds test for cointegration. The null hypothesis for ARDL Bounds test of no long-run equilibrium relationship was tested against the alternative hypothesis that a long-run relationship existed among variables. The F-statistic from the bounds test was compared to F-critical values at 1%, 5% and 10% level of significance for both lower and upper bounds. The presence of cointegration necessitated the estimation of both long-run and short-run models. The long-run model estimated is given as follows:

$$\Delta \ln cr = \mu_1 \ln cr_{t-1} + \mu_2 \ln pop_{t-1} + \mu_3 \ln gdp_{t-1} + \mu_4 \ln engy_{t-1} + \mu_5 \ln topen_{t-1} + \varepsilon_t \dots \dots \dots (3.7)$$

In equation (3.7),  $\mu_1 - \mu_5$  are long-run coefficients. After estimating the long-run model, an Error Correction Model (ECM) was estimated and expressed as follows:

$$\begin{aligned} \Delta \ln cr = & \alpha_0 + \sum_{i=0}^p \alpha_i \ln cr_{t-i} + \sum_{i=0}^q \beta_i \Delta \ln pop_{t-i} + \sum_{i=0}^q \delta_i \Delta \ln growth_{t-i} + \sum_{i=0}^q \vartheta_i \Delta \ln engy_{t-i} \\ & + \sum_{i=0}^q \gamma_i \Delta \ln topen_{t-i} + \aleph ECT_{t-1} + \varepsilon_t \dots \dots \dots (3.8) \end{aligned}$$

In equation (3.8),  $ECT$  is an error correction term with the coefficient  $\aleph$  measuring the speed of adjustment of variables towards a long-run equilibrium.  $\aleph$  is expected to be negative and statistically significant indicating any deviation from the long-run.  $\alpha_i, \beta_i, \delta_i, \vartheta_i$  and  $\gamma_i$ .

## Identification of variables

Crop residue emissions expressed as carbon dioxide equivalents (CO<sub>2</sub>eq) according to the Intergovernmental Panel on Climate Change's (IPCC) Fifth Assessment Report (AR5) were used as a proxy for agrifood systems emissions. The variable entered the model as a dependent variable. Crop residue emissions were sourced from the Food and Agriculture Organisation (FAO). Population growth was expressed as the annual population growth rate for t, which is the exponential rate of growth of the midyear population from year t-1 to year t. The a priori expectation for the coefficient of population growth was positive. GDP was measured in current US. GDP at purchaser's prices was the total value added by all producers, including taxes and subsidies, without deductions for depreciation or natural resource degradation. The a priori expectation of the coefficient of GDP was positive.

Energy use was used as a proxy for technology in the STIRPAT model. The a priori expectation for the coefficient of energy use was positive. Energy use was the utilisation of primary energy before transitioning to other fuels, including indigenous production, imports, stock changes, exports and fuels for international transport. (WDI, 2025). Trade openness was the sum of

exports and imports of goods and services measured as a share of gross domestic product. The a priori expectation for the trade openness coefficient was positive. Data for GDP, energy use and population growth were gathered from the World Bank Indicators.

## Results and Discussion

### Descriptive Statistics

Table 2 presents a summary of the descriptive statistics for the raw data used in the study spanning between 1990 and 2022.

**Table 2: Summary of the Descriptive Statistics**

Variables	Obs.	Mean	Std. Dev	Min	Max	Skew	Kurt
cr (kt)	33	116.136	31.193	52.9	182.7	0.257	2.513
topen (% of GDP)	33	67.143	16.812	17.225	109.522	-0.298	4.375
engy (kg oil equivalent)	33	587.76	212.028	373.557	950.927	0.786	1.77
pop (annual %)	33	1.479	0.544	0.118	2.823	0.439	4.27

Using the coefficient of variation, the variation for all variables is low. Specifically, the variation of crop residue, trade openness, energy use and population growth are 0.269, 0.25, 0.361 and 0.368, respectively. Trade openness is negatively skewed, while all other variables are positively skewed. Crop residue emissions and energy use (engy) have kurtosis values of less than 3, implying a leptokurtic distribution. Trade openness and population growth have kurtosis values of more than 2, implying platykurtic distribution. In support of the STIRPAT model, the raw data for all variables were transformed into log transformations.

**Table 3: Unit Root Test**

Variable	p-value (levels)	p-value (1 <sup>st</sup> differences)	Order of integration
Lncr	0.0012	-	I(0)
Lnpop	0.0008	-	I(0)
Lngdpc	0.5851	0.0014	I(1)
Lnengy	0.8542	0.0015	I(1)
Lntopen	0.1198	0.0000	I(1)

Using the ADF test for stationarity findings presented in Table 3 shows that crop residue emissions and population growth were integrated to order zero, that is, they were I(0). On the other hand, lngdpc, legend lntopen became stationary after first differencing, that is, they are integrated to one.

**Table 4: Multicollinearity Test**

Variables	Lnpop	lngdpc	Lnengy	Intopen
Lnpop	1.000			
Lngdpc	0.2376	1.000		
Lnengy	0.0034	-0.4987	1.000	
Intopen	-0.1645	-0.6757	0.1505	1.000

Table 4 presents multicollinearity results. Absolute values of all correlation coefficients are less than 0.8, indicating no evidence of near or perfect multicollinearity and the impact of one variable on the dependent variable can be isolated, holding other variables constant.

**Bounds test for cointegration**

Table 5 presents results for ARDL bounds test.

**Table 5: ARDL Bounds Test**

		Critical Values	
F-Statistic	Significance	Lower Bound I (0)	Upper Bound I (1)
8.584***	10 per cent	2.45	3.52
	5 per cent	2.86	4.01
	1 per cent	3.74	5.06

\*\*\* denotes rejection of  $H_0$  at 1% level

The F-statistic (8.584) is greater than the upper-bound I(1) critical values at all levels. As a result,  $H_0$  of no cointegration is rejected; hence, there is cointegration between crop residue emissions and its determinants. The presence of cointegration means that we estimate and interpret both long-run and short-run models. Specifically, an Error Correction Model (ECM) as shown in Table 6.

**Post-estimation Test results**

Table 7 and Figure 2 presents diagnostic test results.

**Table 7: Diagnostic Tests**

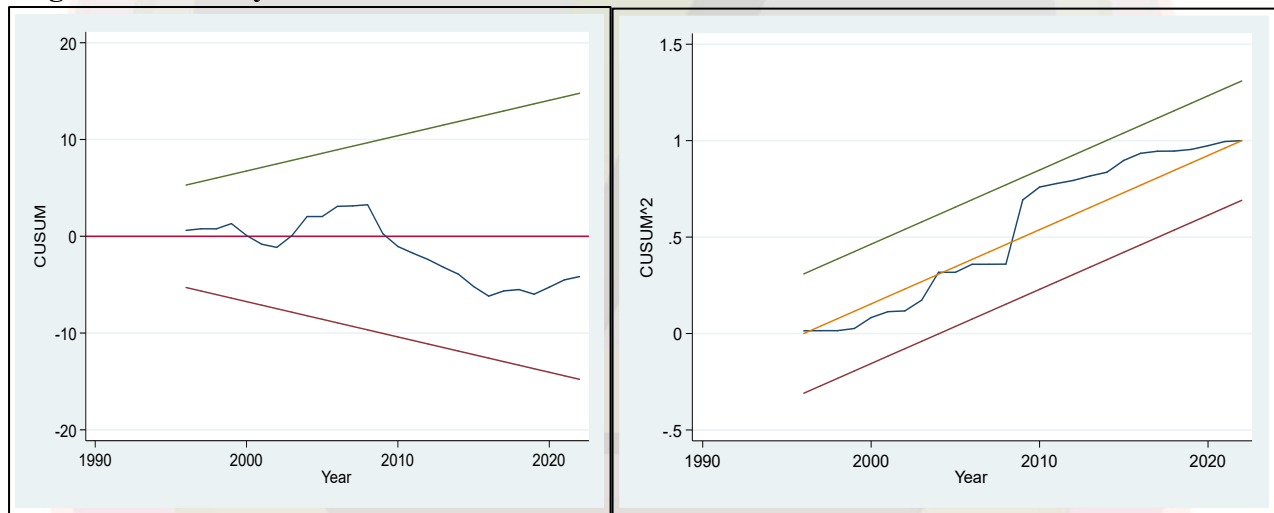
Test	p-value	Decision
Normality Test	0.7324	Normally distributed residuals
Ramsey RESET Test	0.9766	Correctly specified model

Breusch-Godfrey LM Test for autocorrelation	0.6683	No serial correlation
White Test for Heteroscedasticity	0.4140	No heteroscedasticity

Diagnostic tests showed that residuals were normally distributed as indicated by a p-value of 0.7324 from the Jarque-Bera test. The model was correctly specified as indicated by a p-value of 0.9766 from the Ramsey RESET test. There was no serial correlation given a p-value from the Breush-Godfrey LM Test for autocorrelation. In addition, the variance of the error terms as indicated by a p-value of 0.4140 from White Test for Heteroscedasticity.

Stability test results showed that there were no structural breaks as indicated in Figure 2. Both CUSUM and CUSUMSQ fell within the boundaries for the sample period, indicating that the model was stable.

**Figure 2: Stability tests**



**ARDL Model Results discussion**

Table 6 presents ARDL model results with both short run and long run coefficients.

**Table 6: Estimation Results**

<i>ARDL (1,1,1,0,3) regression</i>						
<i>Sample: 1993 - 2022</i>			<i>Number of obs</i>	=	30	
			<i>R-squared</i>	=	0.7558	
			<i>Adj R-squared</i>	=	0.6273	
<i>Log likelihood = 11.150969</i>			<i>Root MSE</i>	=	0.2097	
D.lncr	Coef.	Std.Err.	t	P>t	[95% Conf. Interval]	
<b>ADJ</b>						
lncr						
L1.	-0.716	0.187	-3.840	0.001	-1.107	-0.326

**Long Run Model**

lnpop	0.359	0.241	1.490	0.152	-0.145	0.862
lngdpc	-0.448	0.232	-1.930	0.068	-0.933	0.037
lnengy	0.281	0.226	1.240	0.230	-0.193	0.754
Intopen	-0.937	0.602	-1.560	0.136	-2.196	0.323

**Short Run Model****lnpop**

D1.	-0.221	0.084	-2.640	0.016	-0.396	-0.046
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**lngdpc**

D1.	0.617	0.303	2.030	0.056	-0.018	1.252
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**Intopen**

D1.	0.775	0.342	2.270	0.035	0.060	1.490
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LD.	0.287	0.201	1.430	0.170	-0.134	0.708
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L2D.	0.264	0.146	1.810	0.087	-0.042	0.570
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_cons	12.269	4.327	2.840	0.011	3.212	21.325
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The results from the Bounds Test for cointegration indicated the presence of cointegration. Table 6 presents ARDL findings, which is reparametrised in error correction form following Kripfganz and Shneider (2023). The reparametrised model presented both the short-run dynamic and long-run coefficients. The R-squared value of 0.7558 showed that 75.58 % of the variation in agrifood (crop residue) emissions was due to variations in the explanatory variables of the model. The findings showed that in the long run, only the coefficient of GDP was statistically significant. The coefficients of all other variables were statistically insignificant in the long run. The coefficient of ADJ was negative and statistically significant, as expected. It measured the speed of adjustment or the strength at which crop residue emissions responded to any deviations from the equilibrium relationship in one period. This showed that the long-run equilibrium adjusted by 71.6% in response to short-run shocks. The impact was relatively high, indicating that it took a short period for crop residue emissions to adjust to the long-run equilibrium when responding to shocks.

In the long-run model, the coefficient of GDP was statistically significant at the 10% level of significance. It showed that a 1 per cent increase in GDP decreases agrifood (crop residue) emissions by 44.8% in the long run. However, the short-run findings showed that a 1% increase in GDP increased agrifood (crop residue) emissions by 61.7 per cent after one year. The short-run finding was consistent with the literature in environmental economics, which posited that economic development was one major cause of environmental degradation. (Nguyen et al., 2020). The findings added new evidence regarding the increasing impact of economic development as proxied by the level of current GDP on agrifood emissions in Zimbabwe. The findings were in line with the STIRPAT theory, which claims that affluence was a major cause of emissions.

The findings about current GDP were also in line with results from other studies (Nguyen et al., 2020; Suto, 2022). Thus, economic development in Zimbabwe increased income level, which in turn increased the demand for agricultural products and hence increased agricultural activities (production). This in turn, led to increased agricultural emissions. Although the short-run result was as expected, the long-run result showed that, initially, at the early stages of economic development, GDP rises at the expense of environmental quality due to agrifood emissions. However, beyond a certain level of income, the environment was viewed as a normal good, where a country started to devise some ways to protect the environment, which could be explained by the Environmental Kuznets Curve hypothesis. Thus, in the early stages of development, farmers might resort to traditional and less environmentally friendly practices. In the long run, with sustained growth, there arose investments in technology and efficiency improvements in the agriculture sector, thereby leading to decreased agrifood emissions.

The short-run model also showed that population growth was negatively related to agrifood emissions as proxied by crop residue emissions. The coefficient of population growth was statistically significant at the 5% level. Thus, a 1% increase in population growth decreased agrifood emissions by 22.1%. The finding was contrary to the a priori expectation as well as contrary to the STIRPAT model. This showed that as the population grew in the country, it drove innovation and adoption of advanced agricultural technologies, which helped to reduce crop residues through residue management techniques such as crop rotation and the use of precision agriculture techniques. In addition, with an increase in population, there is also an increased demand for sustainable agricultural practices where farmers may be incentivised to adopt environmentally friendly methods to meet the demand for food security at the same time, minimising damage to the environment, which in turn results in a decrease in crop residue emissions. The results were contrary to the findings by Suto (2022), who found that population growth increased emissions.

The short-run model also showed a positive relationship between trade openness and crop residue emissions. The coefficients of the current period and two-period lagged trade openness were positive and statistically significant at 5% and 10 % levels, respectively. This showed that a 1% increase in trade openness increased crop residue emissions by 77.5%, Likewise, a 1% increase in trade openness after two years increased crop residue emissions by 26.4%. This showed that an increase in current trade openness had a huge impact on crop residue emissions as compared to the same increase after three years. The results conform to a priori expectations. The findings implied that in the short run, increased trade openness in the country led to intensified agricultural production to meet new international markets' demand. As a result, this resulted in higher crop residue emissions. Thus, after one year, increases in trade openness were more immediate as farmers adjusted their practices to cater for new markets, thereby leading to increased trade openness. An increase in crop residue emissions may be due to increased competitive pressure as the country opened for new markets, which pushed farmers to maximise production using practices that increase emissions. The findings were contrary to the studies by Nguyen et al. (2020), who found that trade openness negatively influenced agricultural emissions.

## Conclusion and Recommendations

Despite the valuable contribution that the agricultural sector provided to the economy of Zimbabwe, its contribution to the vulnerability of the country in terms of climate change sparked immense debate in the literature. In line with this, this study examined the determinants of agrifoods emissions in Zimbabwe, focusing on crop residue using the extended STIRPAT model through the ARDL approach. The study confirmed the existence of a long-run relationship between agrifood emissions and key economic variables, which were economic growth, population growth, trade openness and energy use.

The findings showed that economic growth increased the agrifood emissions in the short-run since the increased income encouraged agricultural expansion. However, in the long-run, the sustained economic growth was linked to reduced agrifood emissions, which could be due to improvements in technology and increased investment in sustainable agricultural practices. These findings were in line with the EKC hypothesis for the agrifood sector in Zimbabwe. In addition, population growth was found to be reducing the agrifood emissions in the short-run, suggesting that the increasing demand for food could be driving innovation and sustainable agricultural practices that improved residue management. However, this finding warranted further investigation to gain a deeper understanding of the underlying mechanisms.

Furthermore, trade openness was found to be contributing to higher agrifood emissions in the short-run since farmers were increasing production to meet the export demand. This highlights the need for complementary policies that ensure that there is no trade-off between increased market access and environmental sustainability.

The findings from this study implied that there was a need to promote the adoption of green technologies in the agrifood sector to reduce the crop residue emissions, which included precision agriculture, efficient irrigation and conservation agriculture. This would require the government of Zimbabwe to provide subsidies or tax incentives for purchasing equipment such as residue balers and zero-tillage implements. In addition, there was a need to launch crop residue management programs through the agricultural extension and this included using residue for bioenergy and converting crop residue into useful products. The trade policies would need to be aligned with environmental goals, which included the introduction of export certification schemes that rewarded low-emission and sustainably produced agrifood output. In addition, the government could support farmers to meet global standards, such as the Global GAP, which gave access to premium export markets. Another recommendation from this study was to promote climate-smart agricultural practices that simultaneously increased productivity and resilience while reducing emissions. Lastly, there was a need to strengthen the institutional capacity and awareness while fostering collaboration with international organisations such as FAO and UNDP to access technical assistance and funding.

Overall, this study established that while trade and economic growth were essential for the development of Zimbabwe, there was a need to have a coordinated approach that integrated environmental sustainability into agrifood policies and practices. Through such a balanced approach, Zimbabwe could improve food security and long-term agrifood emissions reduction.

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