



Agriculture and Economic Growth in Syria: Evidence on the Dynamic Interrelationship from ARDL and Granger Causality Analysis.

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Abstract: The agricultural sector is one of Syria's vital productive sectors and is closely interconnected with national economic activity. This study examines the short-run and long-run relationship between agricultural value added (AVA), carbon dioxide emissions (CO₂), gross fixed capital formation (GCF), population (POP), the Syrian crisis (CRI), and gross domestic product (GDP) in Syria. GDP is used as the dependent variable and as a measure of aggregate economic output rather than as a direct measure of the GDP growth rate. Annual data for 1970-2021 are analyzed using the Autoregressive Distributed Lag (ARDL) approach and the Granger causality framework. The bounds test indicates a statistically significant joint long-run levels relationship among the model variables. The derived long-run coefficients are approximately 1.202 for AVA, 0.921 for POP, -1.391 for CO₂, 0.351 for GCF, and -1.398 for the crisis dummy. These coefficients are derived from the estimated levels equation and should be interpreted as conditional long-run associations; their statistical significance requires formal long-run restriction/Wald tests rather than inference from the individual levels coefficients. In the short run, AVA has a positive and statistically significant association with GDP, while GCF is positive at the 10% level. Bidirectional Granger causality is found between AVA and GDP, indicating a feedback relationship rather than a purely agriculture-led direction of causality. The strong AVA-GDP association also requires particular caution because AVA is an accounting component of GDP and both variables are measured in current US dollars. Consequently, part of the observed association may reflect national-accounting construction and common nominal valuation effects, in addition to genuine economic interdependence. The findings therefore indicate a close and mutually reinforcing relationship between agriculture and aggregate economic output in Syria, while the evidence does not justify characterizing agriculture as the sole or unambiguously leading source of economic growth.

Key words: Economic development, agriculture-GDP nexus, gross

domestic product, agricultural value added, reconstruction, Syria.

Economic development is a central objective for developing countries. Agriculture plays an important role in this process through food production, employment, income generation, rural demand, and the provision of raw materials for other sectors. Previous studies generally document a close relationship between agriculture and economic performance, although the direction and magnitude of the relationship vary across countries and development stages. In Syria, agriculture has historically been economically important and has contributed substantially to employment, food security, trade, and rural livelihoods. Before the crisis, agriculture accounted for a sizeable share of GDP, while agricultural production remained highly dependent on climatic conditions. However, the Syrian experience also illustrates why the agriculture–GDP relationship should not automatically be interpreted as evidence of agriculture-led growth. Between 2000 and 2021, GDP measured in current US dollars increased substantially, whereas agricultural value added declined over the same period. This divergence indicates that aggregate economic performance and agricultural performance can move differently and that the relationship should be examined empirically rather than inferred from the sector’s historical importance. The Syrian crisis further disrupted agricultural infrastructure, markets, inputs, labour availability, and production systems. Against this background, the present study investigates the dynamic relationship between agricultural value added and aggregate economic output, while controlling for population, investment, CO₂ emissions, and the crisis regime. The study is therefore framed around the broader agriculture–GDP nexus and reciprocal economic interdependence rather than assuming an agriculture-led growth mechanism *a priori*.

Synthesis of Previous Research

The literature has extensively examined the relationship between economic growth and the agricultural sector. In this context, Agboola *et al.* (2020) investigated the contribution of various agricultural subsectors to economic growth in Nigeria. Their findings revealed that the impact of forestry, crop production, and fisheries on economic growth is both statistically significant

and positive. Similarly, Dürr (2016) emphasized the importance of agriculture in economic development, particularly in developing countries. According to Nyamekye *et al.* (2021), the agricultural output contributed positively to the overall GDP growth of Ghana. Ceesay *et al.* (2021) analysed the Gambian economy, investigating the causal relationship between agricultural value added and economic growth. Their findings indicate that growth in fish and livestock production significantly contributes to GDP growth. In contrast, agricultural production growth negatively affects GDP growth. Similar results were reported by Jankulovski *et al.* (2021), who demonstrated a positive and statistically significant relationship between agricultural value-added and GDP growth in North Macedonia. Elalaoui *et al.* (2022) examined the dynamic relationship between agriculture and economic growth in Morocco. Their findings indicate that agricultural growth precedes economic growth, supporting the agriculture-led growth (ALG) hypothesis. This suggests that advancements in the agricultural sector can drive overall economic growth, rather than the opposite relationship. Awokuse and Xie (2014) examined the role of agriculture in fostering economic growth in developing countries. Their findings revealed a causal relationship between agricultural development and GDP growth. Additionally, they highlighted that the impact of agriculture on economic growth varies across countries. Gabriel *et al.* (2022) found that agricultural output exhibits a significantly positive long-term relationship with GDP. The study emphasized the critical role of the agricultural sector as a driver of economic growth in Nigeria and recommended enhancing its value through increased investment from both government and private stakeholders. Pervez *et al.* (2024) investigated the impact of agricultural output on economic growth in Bangladesh. Their findings provide valuable insights, indicating that agricultural output plays a more significant role in driving economic growth compared to industrial output. This suggests that for sustainable economic development, the agriculture sector cannot be overlooked. Jabuya *et al.* (2023) examined the impact of agricultural trade openness on economic growth in the East African Community. Their findings revealed that agricultural trade openness has a positive and statistically significant effect on

Table 1. Summary of literature review

Author(s)	Country(s)	Period	Method	Variables	Results
Agboola <i>et al.</i> (2020)	Nigeria	1981-2016	Vector error correction model (VECM), dynamic ordinary least squares (DOLS), fully modified ordinary least squares (FMOLS)	RGDP, FOR, CP, FIS, LSTK	Positive effect
Dürr (2016)	Guatemala	-	Combining a value chain approach with input-output-analysis	-	Positive effect
Nyamekye <i>et al.</i> (2021)	Ghana	1984-2018	Error Correction Method	Overall GDP, Agricultural GDP, Industrial GDP, Service GDP	Positive effect
Ceesay <i>et al.</i> (2021)	Gambia	1960-2017	Granger causality and ARDL	GDP, Crop, FOSEC, Pop, LiveS, Ar, CO2, FoodEX	Positive and negative effect
Elalaoui <i>et al.</i> (2022)	Morocco	1980-2019	Structural VAR model	GDP, AGR, INV, OPN	Positive effect
Awokuse and Xie (2014)	Developing Countries (Brazil, Chile, Mexico, China, Indonesia, Thailand)	1980-2011	ARDL and DAG (directed acyclic graphs) analysis	GDP, EXPT, AGR, CAP and TOT	Positive effect
Gabriel <i>et al.</i> (2022)	Nigeria	1981-2019	Vector Error Correction Model (VECM)	GDP, GCF, INT, AGO, EXCR	Positive effect
Pervez <i>et al.</i> (2024)	Bangladesh	1991-2019	VECM Approach	GDP, AGRIOUTPUT, INDOUTPUT, GCF	Positive effect
Jabuya <i>et al.</i> (2023)	East African Community (Kenya, Uganda, Tanzania, Rwanda and Burundi)	2000-2021	Panel-ARDL model	GDP, ATO, AES, AIS, REXR, GRQ, EAC, GCFA and AGR_L	Positive effect
Kamitewoko (2022)	Congo	2005-2018	ARDL	GDP, AP, GCF, and LBR	Positive effect
Le <i>et al.</i> (2024)	90 middle-income countries	1990-2020	Generalized Method of Moments	GDP, FDI, TFP, AGRI, GCF, GOV, IMP and INF	Positive effect
Sanjuán-López and Dawson (2010)	Developing countries	1970-2004	Panel Cointegration Approach	GDP, AX and NAX	Positive effect
Dawson (2005)	62 less developed countries (LDCs)	1974-1995	Fixed and random effects models	GDP, K, L, X ^A and X ^N	Positive effect
Atchadé and Nougbodé (2024)	Benin	1961-2021	ARDL and Toda-Yamamoto Granger causality framework	GDP, VA, FOOD, TP, CROP, LIVESTOCK	Positive effect
Matuka and Asafo (2021)	Albania	2000-2018	ARDL	GDP, TRANSP, INS, COMP, AGR, IND, MANU, HLTH	Positive effect
Ali <i>et al.</i> (2023)	Sub-Saharan African countries	1997-2020	two-step difference GMM (generalized method of moments)	AVA, CO2, GDP, K, L, FPI, FDI	Positive and negative effect
Katircioglu (2006)	North Cyprus	1975-2002	Simple Granger 's causality test	GDP and AGR	bidirectional causation
Ben Jebli and Ben Youssef (2019)	Brazil	1980-2013	ARDL	CRW, AVA, CO2 and GDP	Positive effect

Table 1. Cont...

Author(s)	Country(s)	Period	Method	Variables	Results
Ben Jebli and Ben Youssef (2019)	Brazil	1980–2013	ARDL	CRW, AVA, CO2 and GDP	Positive effect
Frimpong <i>et al.</i> (2024)	14 West African countries	1990 -2020	panel ARDL	GDPC, CO2, FP, AVA and PGR	Positive effect
Alharthi and Hanif (2020)	SAARC countries	1995-2018	feasible generalized least square technique	GW, L, K, AP, AFF, TRD and INF	Positive effect
Sisay <i>et al.</i> (2024)	Ethiopia	1980-2021	ARDL	RGDP, EDUEX, HEAEX, AGRIEX, DEFEX, RODEX, WATEX, CPI, FAID and TREV	Positive effect

Source: Author's compilation.

Abbreviations: RGDP, real gross domestic product; FOR, forestry production; CP, crop production; FIS, fishery production; LSTK, livestock production; FOSSEC, Food production (proxy food availability); Pop, population; LiveS, livestock; Ar, growth rate of Agriculture, CO2, CO2 emission; FoodEX, food export; AGR, agricultural GDP; INV, investment rate; OPN, trade openness; EXPT, real exports; AGR, agricultural value added; CAP, gross capital formation; TOT, terms of trade; GCF, Gross Fixed Capital Formation; INT, Interest rate; AGO, Agricultural Output; EXCR, Exchange Rate; AGRIOUTPUT, Agricultural value added per worker; INDOUTPUT, Industrial value added per worker; ATO, agricultural trade openness; AES, the ratio of agricultural exports to GDP; AIS, the ratio of agricultural imports to GDP; REXR, the real effective exchange rate; GRQ, the government regulatory quality; EAC, dummy variable for EAC membership; GCFA, the gross capital formation in agriculture; AGR_L, the agricultural labour; AP, Agricultural production; LBR, labor force; FDI, Foreign Direct Investment; TFP, Total Factor Productivity; AGRI, Agriculture; GOV, Government spending; IMP, Import; INF, Inflation; AX, agricultural exports; NAX, non-agricultural exports; VA, added value of agriculture; FOOD, food production; TP, average temperature; CROP, crop production; LIVESTOCK, livestock production; TRANSP, output for transport services; INS, insurance and financial service output; COMP, output of computer and communication related services; AGR, output of agricultural, forestry and fishing; IND, industrial output; MANU, output of manufacturing; HLTH, output of the health sector; FPI, Food price index; FDI, Foreign direct investment ;CRW, per-capita combustible renewables and waste; AVA, agricultural value added; GDPC, GDP per capita in current USD; FP, Food production index; AVA, Agriculture value added in current USD; PGR, Population growth rate; SAARC, South Asian Association for Regional Cooperation; GW, gross domestic product; L, Labour; K, Capital; FP, Total Fisheries production; AP, Aquaculture production; AFF, Agriculture, forestry and fishing; TRD, Trade; INF, Inflation; EDUEX, education expenditure; HEAEX, health expenditure; AGRIEX, agricultural expenditure; DEFEX, defence expenditure; RODEX, resource expenditure; WATEX, water expenditure; CPI, Consumer price index; FAID, Foreign aid; TREV, tax revenue.

economic growth in the long run. Similarly, Kamitewoko (2022) explored the relationship between agricultural value added and economic growth in the Congo. The study found that, in the short run, agriculture is statistically significant at the 5% level and exerts a positive influence on economic growth. However, in the long run, agricultural value added has a negative and statistically insignificant effect on economic growth. Le *et al.* (2024) identify a positive coefficient between agriculture and economic growth across 90 middle-income countries. Similarly, Sanjuán-López and Dawson (2010) highlight the significant role of agricultural exports in driving economic growth in developing countries. Their findings reveal a long-run relationship between GDP and agricultural exports. A similar study conducted by Dawson (2005) in less developed countries (LDCs) revealed significant structural differences in economic growth among low-

income, middle-income, and upper-income LDCs. The study found that investment in the agricultural export subsector had a statistically equivalent impact on economic growth compared to investment in the non-agricultural export subsector. Atchadé and Nougbodé (2024) investigated the relationship between food availability, agricultural productivity, and economic growth in Benin. Their findings indicated that both current agricultural value added and its lagged value (lag 1) have a statistically significant impact on GDP. Specifically, a 1% increase in agricultural value added was found to result in a 0.85% rise in GDP. Moreover, Matuka and Asafo (2021) found that agriculture stimulates the economy in Albania in the long run. Specifically, a 1% increase in agriculture leads to a 5.11% rise in Albanian economic growth. However, the impact of agriculture was not statistically significant in the short run. In contrast, a study by Ali

Table 2. Summary of study variables and measurement.

Variables	Variable type	Abbreviation	Units	Sources
Gross domestic product	Dependent variable	GDP	current US\$	WDI
Agricultural value added	Independent variables	AVA	current US\$	WDI
Carbon dioxide emissions		CO ₂	Metric tons per capita	WDI
Gross fixed capital formation		GCF	% of GDP	WDI
Population		POP	Total number of people	WDI
Crisis		CRI	Binary digits	Authors' computation

et al. (2023) in Sub-Saharan African countries revealed that agricultural production negatively impacts economic growth. Katircioglu (2006) analysed the importance of the agriculture sector for North Cyprus. The results indicated a bidirectional causal relationship between agricultural production and GDP. Additionally, a bidirectional causation between these variables was observed at different lag lengths. Ben Jebli and Ben Youssef (2019) inspected the dynamic short and long-run causal relationships between agriculture and economic growth in Brazil. Their findings indicated that agriculture improves economic growth. Specifically, the results demonstrated a short-run unidirectional causality from agricultural value-added to GDP, as well as a long-run bidirectional causality between the two variables.

According to Frimpong *et al.* (2024), agriculture plays a key role in promoting economic growth in West African countries. A study by Alharthi and Hanif (2020) found that agriculture, forestry and fishing in South Asian Association for Regional Cooperation (SAARC) countries are important factors that improve economic growth. Further, Sisay *et al.* (2024) emphasise the beneficial effects of agriculture on the economy of Ethiopia.

Table 1 includes a summary of the literature review of the impact of agriculture on economic growth from different countries.

Materials and Methods

Data and Methodology

Data description: This study uses annual time-series data for the period 1970-2021. The variables were selected on the basis of prior literature and include gross domestic product (GDP), used as the dependent variable and a measure of economic output; agricultural value added (AVA); CO₂ emissions per capita (CO₂); gross fixed capital formation (GCF); population (POP); and the Syrian crisis indicator (CRI). Data

were obtained from the World Development Indicators (WDI), as indicated in Table 2. All continuous variables were transformed into natural logarithms. The Syrian crisis variable was retained as a binary dummy because it represents a regime/intervention indicator and is therefore not logarithmically transformed. Table 2 summarizes the study variables, their definitions, and data sources.

Model Estimation Procedure

Examining the stationarity of variables: Before applying the ARDL bounds test, the order of integration of the time-series variables was examined. The ARDL approach can accommodate variables that are integrated of order zero, I(0), variables integrated of order one, I(1), or a combination of I(0) and I(1) variables, provided that none of the variables is integrated of order two, I(2). To assess stationarity, the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit-root tests were employed. The null hypothesis of each test is that the series contains a unit root. The null hypothesis is rejected when the reported test p-value is below the selected significance level (for example, 5%) or, equivalently, when the test statistic exceeds the appropriate critical threshold in absolute value. The integration order should be determined under the relevant deterministic specification adopted for each series, such as a constant or a constant and trend (Gebeyehu and Bedemo, 2024; Olayungbo, 2021).

Optimal lag length selection: One of the pre-estimation tests involves determining the appropriate lag length for the series using lag selection criteria. The Likelihood Ratio (LR) test statistic, Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn Information Criterion (HQ) can be employed

to identify the optimal lag order (Abdulkadr *et al.*, 2024).

Autoregressive distributed lag bounds testing approach: The baseline model for analysing the effects of AVA, CO₂, GCF, POP and CRI on GDP can be represented by the following equation (1):

$$GDP = f(AVA, CO_2, GCF, POP, CRI) \quad \dots(1)$$

After taking the natural logarithm, the model is defined as follows (equation (2):

$$\ln GDP_t = \beta_0 + \beta_1 \ln AVA_t + \beta_2 \ln CO_{2t} + \beta_3 \ln GCF_t + \beta_4 \ln POP_t + \beta_5 CRI_t + \varepsilon_t \quad \dots(2)$$

where the estimated coefficients are defined by the specified ARDL equation, $\ln GDP$, $\ln AVA$, $\ln CO_2$, $\ln GCF$, and $\ln POP$ denote the natural logarithms of gross domestic product, agricultural value added, carbon dioxide emissions, gross fixed capital formation, and population, respectively. CRI represents the Syrian crisis dummy and takes the value 1 for $t \geq 2012$ and 0 otherwise. The choice of 2012 is a modelling decision intended to represent the first full annual observation of the post-onset crisis regime. The Syrian conflict began during 2011, but the economic and institutional disruption was not confined to a single point in that calendar year. Using 2012 as the intervention date therefore avoids assigning the partially affected 2011 observation entirely to either the pre-crisis or post-crisis regime and provides a consistent annual indicator for the subsequent crisis period. This choice is also broadly consistent with the structural-break evidence in Table 7, which identifies breaks around 2011–2013, including a break in CO₂ emissions in 2012. The dummy should nevertheless be interpreted as a parsimonious intervention variable capturing the main crisis-related regime shift, not as a claim that all structural change occurred in 2012.

In order to estimate the long-term coefficients, the ARDL model that was proposed by Pesaran *et al.* (2001) (Equation (3) is expressed as:

$$\Delta \ln GDP_t = \beta_0 + \beta_1 \ln GDP_{t-1} + \beta_2 \ln AVA_{t-1} + \beta_3 \ln CO_{2,t-1} + \beta_4 \ln GCF_{t-1} + \beta_5 \ln POP_{t-1} + \beta_6 CRI_{t-1} + \sum_{i=1}^p \delta_{1i} \Delta \ln GDP_{t-i} + \sum_{i=1}^q \delta_{2i} \Delta \ln AVA_{t-i} + \sum_{i=1}^q \delta_{3i} \Delta \ln CO_{2,t-i} + \sum_{i=1}^q \delta_{4i} \Delta \ln GCF_{t-i} + \sum_{i=1}^q \delta_{5i} \Delta \ln POP_{t-i} + \varepsilon_t \quad \dots(3)$$

where: β_i and δ_i ($i = 1$ to 5) are long- and short-run coefficients, β_0 is the constant, p and q are optimal lag orders, Δ represents the first difference operator and ε_t is the error term.

To test for long-run linkages among the variables, we estimate the F-statistic. The null hypothesis (H_0) posits no long-run relationships between the variables ($H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$). The decision to reject or retain H_0 depends on whether the F-statistic exceeds the critical bounds (upper and lower). If the estimated F-statistic is below the lower bound, we fail to reject H_0 , indicating no significant long-run relationship exists. The null hypothesis of no cointegration is rejected if the F-statistic exceeds the upper-bound critical value.

Equation (4) presents the error correction version of the ARDL model to assess the short-run relationship between the variables .

$$\Delta \ln GDP_t = \delta_0 + \sum_{i=1}^p \delta_{1i} \Delta \ln GDP_{t-i} + \sum_{i=1}^q \delta_{2i} \Delta \ln AVA_{t-i} + \sum_{i=1}^q \delta_{3i} \Delta \ln CO_{2,t-i} + \sum_{i=1}^q \delta_{4i} \Delta \ln GCF_{t-i} + \sum_{i=1}^q \delta_{5i} \Delta \ln POP_{t-i} + ECT_{t-1} + \varepsilon_t \quad \dots(4)$$

The error correction method determines the speed of adjustment needed to return to long-run equilibrium following a short-run shock. Error Correction (ECT) should be negative in sign and statistically significant (Derouez *et al.*, 2024).

Stability and diagnostic tests: After estimating the ARDL model, a set of tests will be used to verify the goodness of fit and the stability of the estimated model. These tests include assessments for normality, autocorrelation, heteroskedasticity, functional form, and stability. The tests outlined in the following Table 3.

Granger causality test: Identifying causal relationships between variables is crucial, as it reveals the direction of influence and potential feedback loops (Gurbuz and Kadioglu, 2024). The test yields three possible outcomes for the relationship: unidirectional, bidirectional, or neutral (Rahman *et al.*, 2024). The null hypothesis is that the variable under consideration does not Granger-cause the other variable.

Results and Discussion

Descriptive statistics

Table 4 displays the descriptive statistics for all variables. The logarithm of GDP has an average level of 23.40 and reaches its maximum in 2011 at 24.93. AVA in logarithmic form averages 21.99 and also reaches its maximum in 2011. The Jarque–Bera probability values

Table 3. Diagnostic tests for the ARDL model

Diagnostic test	Test	Null hypothesis (H_0)
Normality	Jarque-Bera test	Normal distribution
Autocorrelation	LM test	There is no serial correlation in the residuals
Heteroskedasticity	Breusch-Pagan-Godfrey test	There is no heteroskedasticity in the residuals.
Functional Form	Ramsey's RESET test	Absence of model misspecification
Stability test	Cumulative sum of recursive residuals (CUSUM)	-
	Cumulative sum of squares of recursive residuals (CUSUMS)	-

Table 4. Descriptive statistics of the variables

Variable	Mean	StDev	CoefVar	Minimum	Maximum	Skewness	Kurtosis	Jarque-Bera	Probability
lnGDP	23.40	0.73	3.16	21.48	24.93	-0.36	0.85	1.95	0.375
lnAVA	21.99	0.76	3.46	19.98	23.35	-0.75	0.69	5.11	0.077
lnCO2	0.68	0.39	56.76	-0.18	1.15	-0.59	-1.00	5.09	0.078
lnGCF	2.90	0.39	13.59	1.92	3.58	-0.96	0.34	7.63	0.021
lnPOP	16.41	0.39	2.41	15.65	16.93	-0.41	-1.14	4.24	0.119

indicate that the reported variables do not provide strong evidence against normality at conventional significance levels. The dataset contains 52 annual observations for each continuous variable. The standard deviations describe dispersion around the sample means but should not be interpreted, by themselves, as evidence that the time series are stable or consistent over the entire period, particularly because the sample includes major structural changes and the Syrian crisis.

Figure 1 displays the evolution of gross domestic product (GDP) and agricultural value added (AVA). Both series show an upward trend over much of the pre-crisis period and a marked deterioration around the onset of the Syrian crisis. The figure is consistent with defining CRI = 1 from 2012 onward, where 2012 is treated as the first full annual observation of the post-onset crisis regime. The figure should therefore be interpreted as illustrating a major transition around 2011-2012, rather than as identifying 2012 as the precise date on which all economic effects of the crisis began.

Pearson correlation matrix: The correlation coefficient measures the strength of linear association between variables. Table 5 shows a very strong positive correlation between AVA and GDP ($r = 0.96$, $p < 0.01$), while POP is also strongly correlated with AVA and GDP ($r = 0.89$ and $r = 0.81$, respectively; $p < 0.01$). The high AVA-GDP correlation deserves special

treatment because the two variables are not conceptually independent aggregates. Under national accounting, agricultural value added contributes to the production-side measure of GDP. Moreover, both variables in this study are expressed in current US dollars, so common movements in the price level, exchange-rate valuation, and nominal economic conditions can strengthen their measured co-movement even when the underlying real quantities do not change proportionately. Thus, the correlation of 0.96 should not be interpreted as evidence that a 1% increase in agricultural value added mechanically or independently generates a 1% increase in GDP. Instead, it reflects a combination of genuine sectoral linkages, the role of agriculture within aggregate production, and the accounting and nominal valuation relationship between the two measures. This issue is particularly important for the subsequent ARDL interpretation: the estimated AVA coefficient is a conditional association within a system in which the dependent variable already incorporates agricultural production, rather than an estimate of agriculture's incremental contribution to GDP after removing the accounting identity. The very high correlation also explains why the AVA coefficient should be interpreted cautiously in conjunction with the VIF results. The reported VIF values, including 8.11 and 6.82, do not exceed the commonly used threshold of 10, but indicate potentially substantial collinearity among

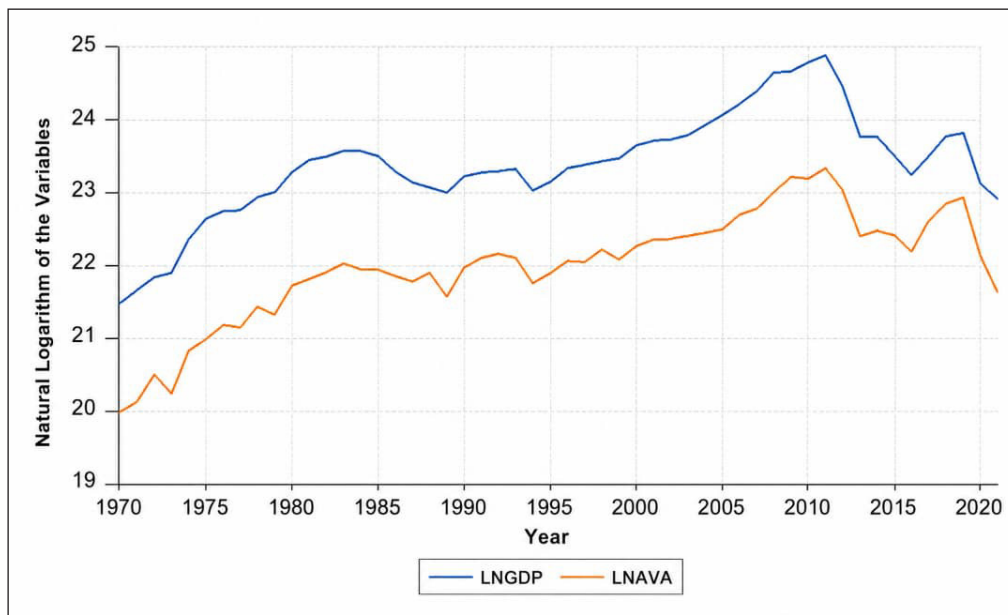


Fig. 1. GDP and AVA over time, 1970-2021.

some explanatory variables. Consequently, the empirical results are most appropriately interpreted as evidence of a close agriculture-GDP nexus rather than as a clean structural estimate of an independent causal effect of agriculture on total GDP.

Unit root test and structural breaks

Unit-root tests are essential for determining whether the time-series variables contain unit roots and for establishing their order

of integration. The present study uses the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. Because conventional tests may have low power in the presence of structural breaks, additional structural-break unit-root procedures are also considered. The results in Table 6 are interpreted variable by variable and specification by specification. The ARDL framework is appropriate provided that none of the variables is I(2) and that

Table 5. Correlation matrix and variance inflation factors

		lnGDP	lnAVA	lnCO2	lnPOP	lnGCF	VIF	1/VIF
lnGDP	Pearson Correlation	1						
	Sig. (2-tailed)							
	N	52						
lnAVA	Pearson Correlation	.961**	1				6.82	0.146
	Sig. (2-tailed)	.000						
	N	52	52					
lnCO2	Pearson Correlation	.658**	.614**	1			3.10	0.322
	Sig. (2-tailed)	.000	.000					
	N	52	52	52				
lnPOP	Pearson Correlation	.807**	.893**	.460**	1		8.11	0.123
	Sig. (2-tailed)	.000	.000	.001				
	N	52	52	52	52			
lnGCF	Pearson Correlation	-.024-	-.203-	.393**	-.443**	1	2.92	0.342
	Sig. (2-tailed)	.868	.149	.004	.001			
	N	52	52	52	52	52		
Mean VIF							5.24	-

** : Correlation is significant at the 0.01 level (2-tailed).

Table 6. Results of ADF and PP unit root tests

Variables		ADF	P-P
At Level		t-Statistic	
lnGDP	With Constant	-2.535	-2.628*
	With Constant & Trend	-1.665	-1.249
	Without Constant & Trend	0.322	0.613
lnAVA	With Constant	-2.780	-2.819*
	With Constant & Trend	-1.389	-1.199
	Without Constant & Trend	0.795	0.772
lnCO2	With Constant	0.372	-1.580
	With Constant & Trend	0.903	-0.784
	Without Constant & Trend	-0.581	-0.543
lnPOP	With Constant	-2.234	-2.230
	With Constant & Trend	2.395	-0.743
	Without Constant & Trend	2.428	3.780
lnGCF	With Constant	-0.649	-1.155
	With Constant & Trend	-2.641	-2.720
	Without Constant & Trend	-0.5874	-0.483
At First Difference		t-Statistic	
lnGDP	With Constant	-4.529***	-4.567***
	With Constant & Trend	-4.991***	-4.954***
	Without Constant & Trend	-4.560***	-4.591***
lnAVA	With Constant	-6.277***	-6.287***
	With Constant & Trend	-6.884***	-6.882***
	Without Constant & Trend	-6.277***	-6.267***
lnCO2	With Constant	-5.169***	-5.128***
	With Constant & Trend	-5.509***	-5.801***
	Without Constant & Trend	-5.211***	-5.172***
lnPOP	With Constant	-3.212**	-1.928
	With Constant & Trend	-4.036**	-2.047
	Without Constant & Trend	-1.904*	-1.650*
lnGCF	With Constant	-9.051***	-8.993***
	With Constant & Trend	-9.457***	-9.381***
	Without Constant & Trend	-9.106***	-8.922***

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

the integration orders are consistent with the bounds-testing requirements.

Structural breaks refer to sudden or persistent changes in the data-generating process that may arise from policy changes, regime shifts, external shocks, or other major events. The structural-break analysis identifies potential breaks around 2011, 2012, 2013, and 2019. These dates should not automatically be interpreted as separate intervention effects in the ARDL model. The estimated model includes the CRI dummy beginning in 2012 to capture

the main post-onset crisis regime, while the other detected breaks are retained as evidence that the data-generating process may have changed at several points. The concentration of detected breaks around 2011–2013 provides empirical support for treating the crisis period as a distinct regime, whereas the 2019 break indicates that later shocks may not be fully absorbed by the single crisis dummy.

The structural-break results therefore qualify the interpretation of the ARDL coefficients. In particular, the 2011–2013 breaks coincide

Table 7. Unit-root tests and structural breaks.

Variables		At Level		At First Difference	
		Year of break	t-Statistic	Year of break	t-Statistic
lnGDP	With Constant	1994	-2.725	2013	-5.768***
	With Constant & Trend	2019	-4.171	2013	-5.812***
lnAVA	With Constant	1973	-3.134	2019	-8.393***
	With Constant & Trend	2019	-4.287	2019	-8.615***
lnCO2	With Constant	2012	-4.944**	2013	-6.161***
	With Constant & Trend	2011	-3.827	2013	-6.433***
lnPOP	With Constant	2019	-5.089***	2012	-8.124***
	With Constant & Trend	2012	-7.122***	2011	-7.695
lnGCF	With Constant	2011	-4.479**	1977	-10.279***
	With Constant & Trend	2011	-4.724*	1988	-10.234***

(Break selection: Minimize Dickey–Fuller. Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.)

with the onset and early consolidation of the crisis regime, while the 2019 break suggests an additional structural disturbance later in the sample. The 2012 dummy is consequently a parsimonious representation of the main crisis regime rather than a complete model of all structural changes. This distinction is important because unmodelled breaks can affect coefficient magnitudes and standard errors and may contribute to the parameter instability detected by CUSUMSQ. The results should therefore be interpreted as average relationships over a structurally changing period, and the policy implications should not assume that the estimated coefficients are invariant across all subperiods.

Causality test: Table 8 presents the results of the pairwise Granger causality tests. The results indicate bidirectional Granger causality between lnAVA and lnGDP: AVA helps predict GDP and GDP also helps predict AVA within the estimated lag structure. There is also bidirectional Granger causality between lnCO2 and lnAVA. In addition, GDP Granger-causes CO2, GCF, and POP; AVA Granger-causes GCF and POP; POP Granger-causes GCF; and CO2 Granger-causes POP. The results therefore reveal a network of reciprocal and unidirectional predictive relationships. Most importantly, the two-way AVA–GDP relationship indicates feedback rather than a single direction of influence. Although the AVA → GDP direction is compatible with the agriculture-led growth hypothesis, the statistically significant GDP → AVA direction means that the evidence does not support an exclusively or unambiguously

agriculture-led interpretation. Granger causality represents predictive precedence within the specified model and should not be interpreted as proof of structural causation. The preferred interpretation is therefore that agriculture and aggregate economic output are dynamically interconnected and potentially mutually reinforcing.

Lag length selection results:

In Table 9, different lag lengths are assessed using the LR, FPE, AIC, SC, and HQ criteria. Four of the five criteria (LR, FPE, AIC, and HQ) select lag 4, whereas SC selects lag 2. Lag 4 is therefore selected as the general maximum lag length for the subsequent ARDL search. The final ARDL specification is ARDL(1, 4, 0, 4, 4, 3), which allows the lag length of each variable to differ according to the model-selection procedure. The notation ARDL (1, 4, 0, 4, 4, 3) refers to the lag orders for GDP, AVA, CO2, GCF, POP, and CRISIS, respectively, and should not be confused with the general maximum lag of four used in the preliminary lag-selection exercise.

Results of the ARDL bounds test

Table 10 presents the ARDL bounds test for cointegration. The estimated F-statistic of 6.765 exceeds the upper critical bound at the 10%, 5%, 2.5%, and 1% significance levels. Thus, the null hypothesis of no levels relationship is rejected, providing evidence of a joint long-run levels relationship among GDP and the explanatory variables. This result establishes a long-run relationship for the system as a whole; it does

Table 8. Pairwise Granger causality test

Null Hypothesis:	F-Statistic	Decision	Causality direction
lnAVA does not Granger Cause lnGDP	3.614**	Reject	AVA → GDP; GDP → AVA
lnGDP does not Granger Cause lnAVA	9.174***	Reject	
lnCO2 does not Granger Cause lnGDP	1.249	Accept	GDP → CO2
lnGDP does not Granger Cause lnCO2	2.507*	Reject	
lnGCF does not Granger Cause lnGDP	1.260	Accept	GDP → GCF
lnGDP does not Granger Cause lnGCF	5.514***	Reject	
lnPOP does not Granger Cause lnGDP	0.449	Accept	GDP → POP
lnGDP does not Granger Cause lnPOP	6.424***	Reject	
lnCO2 does not Granger Cause lnAVA	2.683*	Reject	CO2 → AVA; AVA → CO2
lnAVA does not Granger Cause lnCO2	2.573*	Reject	
lnGCF does not Granger Cause lnAVA	0.693	Accept	AVA → GCF
lnAVA does not Granger Cause lnGCF	4.359**	Reject	
lnPOP does not Granger Cause lnAVA	0.894	Accept	AVA → POP
lnAVA does not Granger Cause lnPOP	3.386**	Reject	
lnGCF does not Granger Cause lnCO2	1.636	Accept	No causality
lnCO2 does not Granger Cause lnGCF	2.190	Accept	
lnPOP does not Granger Cause lnCO2	1.927	Accept	CO2 → POP
lnCO2 does not Granger Cause lnPOP	7.734***	Reject	
lnPOP does not Granger Cause lnGCF	3.952**	Reject	POP → GCF
lnGCF does not Granger Cause lnPOP	2.154	Accept	

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

not, by itself, establish a separate pairwise cointegrating relationship between GDP and any individual explanatory variable.

ARDL Levels Equation, Derived Long-Run Effects and Short-Run Dynamics

ARDL levels equation and derived long-run estimates: Table 11 reports the estimated ARDL levels equation and the short-run error-correction representation for the selected ARDL (1, 4, 0, 4, 4, 3) model. The coefficient on lnGDP (-1) is 0.333 and is statistically significant at the 5% level. This coefficient captures persistence in GDP within the dynamic specification and is not itself a long-run explanatory coefficient. The conventional long-run coefficient for each explanatory variable is obtained from the relevant sum of levels coefficients divided by $1 - \phi$, where $\phi = 0.333$ and therefore $1 - \phi = 0.667$. Because these long-run coefficients are nonlinear functions of several estimated parameters, their statistical significance cannot be inferred from the significance of any single levels coefficient. Formal inference requires testing the corresponding long-run restrictions, preferably with a Wald test using the full estimated covariance matrix of the

ARDL parameters. The bounds-test result establishes the existence of a joint levels relationship, whereas the Wald tests are needed to determine whether each derived long-run effect is statistically distinguishable from zero.

The derived long-run coefficient for population (lnPOP) is approximately 0.921, calculated as $0.614 / (1 - 0.333)$. Thus, within the estimated multivariate model, a 1% increase in population is associated with an approximately 0.921% increase in GDP in the long run, ceteris paribus. This is a conditional long-run association and should not be interpreted as evidence that population alone causes GDP growth. Its statistical significance should be reported only after the corresponding long-run restriction has been formally tested.

For agricultural value added (lnAVA), the derived long-run coefficient is approximately 1.202, calculated as $(0.740 - 0.123 - 0.070 + 0.122 + 0.133) / (1 - 0.333)$. Within the estimated model, a 1% increase in AVA is associated with an approximately 1.202% increase in GDP in the long run, holding the other variables constant. However, this estimate requires particularly cautious interpretation because

Table 9. Lag length criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-10.943	NA	1.34e-06	0.664	0.859	0.737
1	261.468	476.719	4.49e-11	-9.644	-8.475	-9.202
2	317.380	86.197	1.28e-11	-10.93	-8.788*	-10.122
3	351.666	45.7146	9.53e-12	-11.319	-8.200	-10.140
4	387.496	40.309*	7.30e-12*	-11.770*	-7.677	-10.223*

* Indicates the lag order selected by the corresponding criterion.

AVA is an accounting component of GDP and both variables are measured in current US dollars. The coefficient should therefore not be read as an independent 1.202% causal contribution of agriculture to aggregate GDP. It is better interpreted as a model-based long-run elasticity of the measured GDP-AVA relationship, conditional on the other variables. In addition, formal inference for this derived coefficient requires a Wald/restriction test; the individual significance of the underlying levels coefficients does not establish significance of the derived long-run elasticity.

The Syrian crisis dummy has a derived long-run coefficient of approximately -1.398, calculated as $(-0.250 - 0.249 - 0.102 - 0.331)/(1 - 0.333)$. Because CRISIS is binary and $\ln GDP$ is the dependent variable, the implied difference between the crisis and non-crisis regimes is approximately $100[\exp(-1.398) - 1] = -75.3\%$, ceteris paribus. This should be interpreted as a model-implied regime difference, not as a precise estimate of the total historical GDP loss caused by the crisis, because the dummy captures a broad set of simultaneous economic, institutional, demographic, and external shocks. The statistical significance of the derived dummy effect also requires a formal long-run restriction test.

The derived long-run coefficient for CO₂ emissions is approximately -1.391, calculated as $(0.147 - 0.397 - 0.082 - 0.157 - 0.439)/(1 - 0.333)$. Within the estimated model, a 1% increase in CO₂ emissions is associated with

an approximately 1.391% decrease in GDP in the long run, ceteris paribus. The derived long-run coefficient for gross fixed capital formation is approximately 0.351, calculated as $(0.098 - 0.032 - 0.148 + 0.141 + 0.175)/(1 - 0.333)$. These values are cumulative long-run associations and cannot be inferred from the contemporaneous coefficients alone. Formal inference for both coefficients requires long-run Wald/restriction tests based on the estimated covariance matrix. Accordingly, the signs and magnitudes are discussed here without assigning significance stars that are not supported by a formal test.

Short-run model estimation

The short-run estimation results show that the contemporaneous change in agricultural value added, $D(\ln AVA)$, is positive and statistically significant at the 1% level, with a coefficient of 0.740. This means that, within the short-run error-correction specification, a 1% increase in AVA is associated with an approximately 0.740% increase in GDP in the same period, holding the other short-run terms constant. This 0.740 coefficient is a short-run response and should not be interpreted as the long-run elasticity, which is approximately 1.202 after accounting for the distributed lags in AVA and the lagged dependent variable. Kamitewoko (2022); Frimpong *et al.* (2024)

The short-run results also indicate that changes in gross fixed capital formation have a positive contemporaneous coefficient of 0.098, significant at the 10% level, followed

Table 10. Results of the ARDL bounds test for cointegration

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	6.764772	10%	2.08	3
		5%	2.39	3.38
		2.5%	2.7	3.73
K	5	1%	3.06	4.15

Table 11. ARDL levels-equation and short-run error-correction estimates for the selected model: ARDL (1, 4, 0, 4, 4, 3)

Variable	Coefficient	Std. error	t-statistic	Prob
ARDL levels equation				
lnGDP(-1)	0.333**	0.140	2.375	0.0252
lnAVA	0.740***	0.059	12.41	0.0000
lnAVA(-1)	-0.123	0.132	-0.934	0.3586
lnAVA(-2)	-0.070	0.070	-1.009	0.3222
lnAVA(-3)	0.122*	0.069	1.757	0.0906
lnAVA(-4)	0.133*	0.071	1.858	0.0745
lnPOP	0.614***	0.118	5.194	0.0000
lnCO2	0.147	0.154	0.956	0.3477
lnCO2(-1)	-0.397**	0.169	-2.346	0.0268
lnCO2(-2)	-0.082	0.179	-0.460	0.6492
lnCO2(-3)	-0.157	0.167	-0.941	0.3553
lnCO2(-4)	-0.439**	0.131	-3.354	0.0025
lnGCF	0.098	0.074	1.319	0.1985
lnGCF(-1)	-0.032	0.085	-0.375	0.7104
lnGCF(-2)	-0.148*	0.082	-1.801	0.0832
lnGCF(-3)	0.141*	0.077	1.812	0.0815
lnGCF(-4)	0.175**	0.077	2.272	0.0315
CRISIS	-0.250**	0.107	-2.325	0.0281
CRISIS(-1)	-0.249*	0.123	-2.021	0.0537
CRISIS(-2)	-0.102	0.134	-0.762	0.4524
CRISIS(-3)	-0.331**	0.110	-2.998	0.0059
C	-12.019***	1.968	-6.104	0.0000
Short- run estimation				
D(lnAVA)	0.740***	0.040	18.33	0.0000
D(lnAVA(-1))	-0.185**	0.053	-3.436	0.0020
D(lnAVA(-2))	-0.256***	0.056	-4.525	0.0001
D(lnAVA(-3))	-0.133**	0.051	-2.573	0.0161
D(lnCO2)	0.147	0.105	1.395	0.1745
D(lnCO2(-1))	0.679***	0.150	4.514	0.0001
D(lnCO2(-2))	0.597***	0.113	5.242	0.0000
D(lnCO2(-3))	0.439***	0.109	4.012	0.0005
D(lnGCF)	0.098*	0.056	1.729	0.0957
D(lnGCF(-1))	-0.167**	0.063	-2.657	0.0133
D(lnGCF(-2))	-0.316***	0.062	-5.090	0.0000
D(lnGCF(-3))	-0.175**	0.063	-2.766	0.0103
D(CRISIS)	-0.250**	0.076	-3.269	0.0030
D(CRISIS(-1))	0.433***	0.111	3.908	0.0006
D(CRISIS(-2))	0.331**	0.093	3.547	0.0015
CointEq(-1)	-0.666***	0.087	-7.634	0.000
R-squared	0.993			
Adjusted R-squared	0.987			
F-statistic	180.780			
Prob(F-statistic)	0.000			
Durbin-Watson stat	1.951			

Table 11. Derived long-run coefficient estimates for the selected ARDL model

Variable	Derived long-run coefficient	Calculation / interpretation
lnAVA	1.202	$(0.740 - 0.123 - 0.070 + 0.122 + 0.133) / 0.667$
lnPOP	0.921	$0.614 / 0.667$
lnCO2	-1.391	$(0.147 - 0.397 - 0.082 - 0.157 - 0.439) / 0.667$
lnGCF	0.351	$(0.098 - 0.032 - 0.148 + 0.141 + 0.175) / 0.667$
CRISIS	-1.398	$(-0.250 - 0.249 - 0.102 - 0.331) / 0.667$; implied dummy effect $\approx -75.3\%$

Note: Long-run coefficients are calculated as the sum of the relevant levels coefficients divided by $1 - \phi$, where $\phi = 0.333$. The coefficient on $\ln GDP(-1)$ is not itself a long-run explanatory coefficient. Because each reported long-run coefficient is a nonlinear function of several estimated parameters, its statistical significance should be evaluated using a formal long-run restriction/Wald test based on the full parameter covariance matrix. The manuscript's current coefficient table does not contain that covariance matrix; therefore, no Wald statistic, standard error, confidence interval, or p-value is fabricated here. The final submission should insert the corresponding EViews long-run-form/Wald output before making claims about statistical significance of the derived coefficients. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The long-run coefficients are derived from the levels equation as the sum of the relevant level coefficients divided by $1 - 0.333$; their statistical significance should be assessed using the appropriate long-run Wald/restriction test.

by negative and statistically significant lagged effects. This pattern indicates that the contribution of investment to GDP is dynamically distributed over time. The absence of a direct long-run inference from the individual contemporaneous coefficient should be emphasized; the long-run coefficient is the derived value of approximately 0.351 reported separately. Abdulkadr *et al.* (2024); Gabriel *et al.* (2022); Le *et al.* (2024); Mohsen and Chua (2015); Poku *et al.* (2022); Rani and Kumar (2019); Nsor-Ambala and Amewu (2023); Mohsen and Chua (2015); (Abdulkadr *et al.*, 2024; Oyedokun, 2019; Zaman *et al.*, 2021).

The contemporaneous crisis term, $D(CRISIS)$, has a negative and statistically significant coefficient of -0.250 . In the short-run log-difference specification, this coefficient corresponds to an immediate discrete change of approximately $100[\exp(-0.250) - 1] = -22.1\%$ in GDP, rather than an exact 25% decline. The subsequent positive lagged crisis terms indicate partial dynamic adjustment after the initial shock. It is therefore not appropriate to conclude that the short-run crisis effect is simply "stronger" than the long-run effect by comparing -0.250 with a long-run coefficient; the short-run coefficient and the derived long-

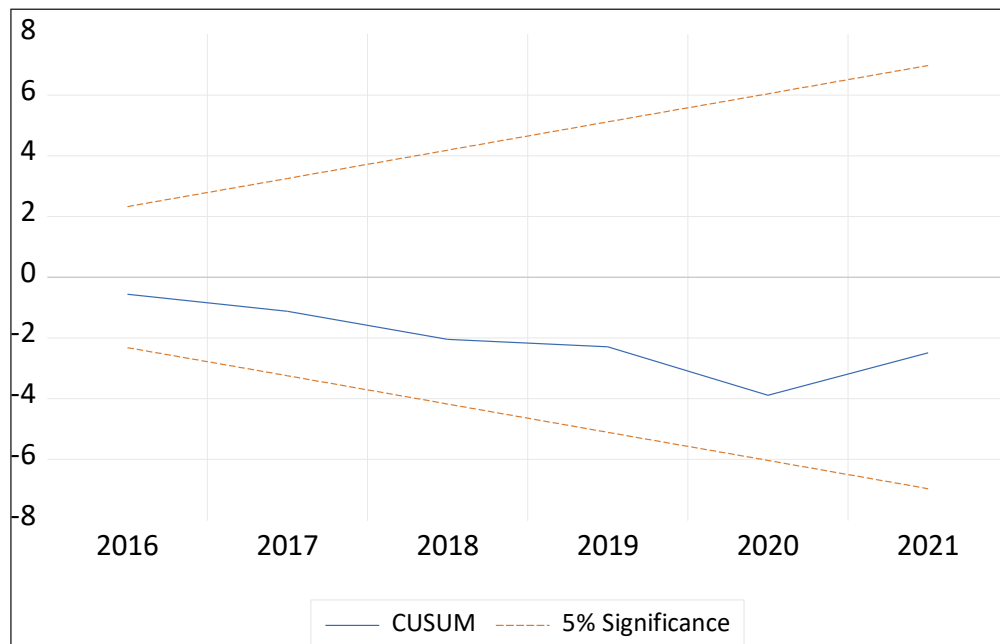


Fig. 3. Plot of the cumulative sum of recursive residuals

Table 12. Diagnostic test results of the ARDL model

Tests	F-statistic	Prob	Decision
Jarque-Bera test	0.517	0.771	Residuals are normally distributed
Breusch-Godfrey serial correlation LM test	0.076	0.926	No problem of serial correlations
Ramsey RESET test	0.193	0.664	Model is specified correctly
Heteroskedasticity test: Breusch-Pagan-Godfrey	1.180	0.340	No problem of heteroscedasticity

run dummy effect represent different dynamic quantities (Okere *et al.*, 2022).

The error-correction term, $CointEq(-1)$, is statistically significant at the 1% level and has the expected negative sign, with a coefficient of -0.666 . This indicates that approximately 66.6% of the previous period's deviation from the long-run equilibrium is corrected within one period. The magnitude therefore indicates relatively rapid adjustment toward the estimated long-run equilibrium following a short-run disturbance (Saba, 2025).

Diagnostic tests and model stability: To evaluate the adequacy of the ARDL model, the study applies tests of residual normality, serial correlation, heteroskedasticity, functional form, and parameter stability. The Jarque-Bera, Breusch-Godfrey, Ramsey RESET, and Breusch-Pagan-Godfrey tests all have p-values above 0.10; therefore, their respective null hypotheses are not rejected at the 10% level. The stability evidence is mixed and is substantively important: the CUSUM statistic remains within

the conventional 5% bounds, but the CUSUM of squares (CUSUMSQ) exceeds the 5% significance bounds. CUSUM and CUSUMSQ test different aspects of recursive stability; the former is more closely related to systematic parameter drift, whereas the latter is sensitive to changes in the variance and magnitude of recursive residuals and can signal structural instability. Thus, the model should not be described as fully parameter-stable. The CUSUMSQ result provides evidence that the relationship among the variables changed during at least part of the sample, which is consistent with the structural-break evidence around 2011-2013 and 2019. This instability is especially relevant for the Syrian case because the sample spans major conflict-related and macroeconomic disruptions. The estimated ARDL coefficients should consequently be interpreted as average conditional relationships over the sample rather than invariant structural parameters. The finding also limits the strength of policy conclusions and suggests that future work should test alternative break specifications,

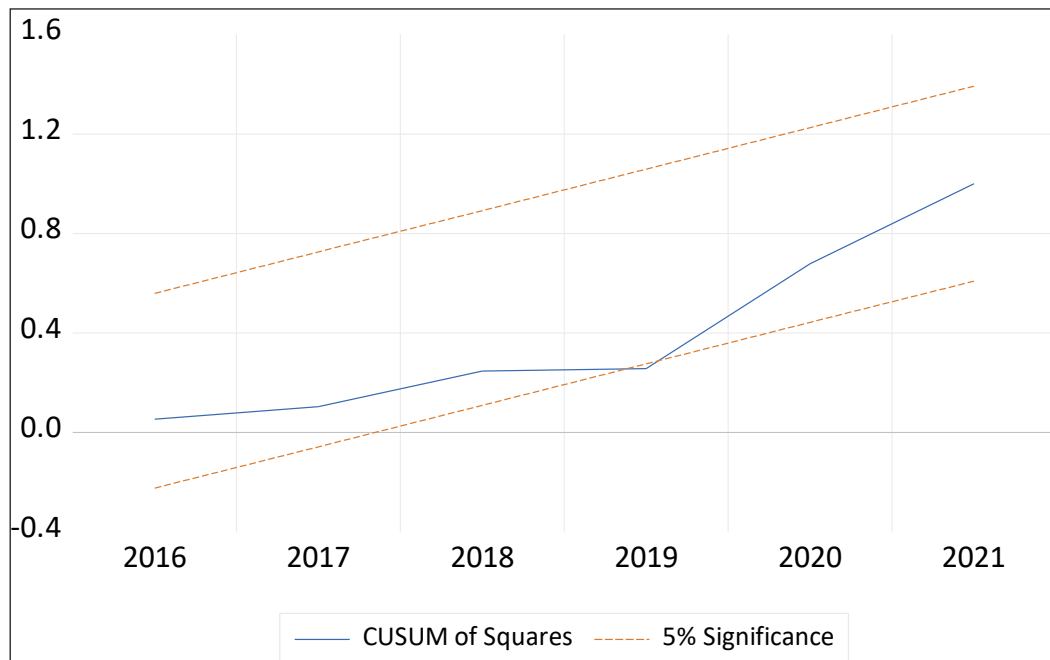


Fig. 4 Plot of the cumulative sum of squares of recursive residuals

crisis interactions, rolling or recursive estimates, and/or sub-sample models when sufficiently long samples become available.

Conclusions

This study employs the Autoregressive Distributed Lag (ARDL) approach and the Granger causality test to examine the dynamic relationship between agricultural activity and aggregate economic output in Syria over 1970-2021. GDP is the dependent variable and represents aggregate economic output. The ARDL bounds test provides evidence of a joint long-run levels relationship among the model variables. The derived long-run coefficients are approximately 1.202 for AVA, 0.921 for population, -1.391 for CO2 emissions, 0.351 for GCF, and -1.398 for the crisis dummy. These are model-derived long-run associations rather than individual contemporaneous effects, and their statistical significance requires formal long-run restriction/Wald tests based on the full covariance matrix. The AVA estimate requires particular caution because agricultural value added is an accounting component of GDP and both variables are measured in current US dollars; therefore, the strong association can reflect both genuine economic linkages and the construction and nominal valuation of the national accounts. The result should not be interpreted as a clean structural estimate of agriculture's independent contribution to total GDP.

The Granger causality results provide evidence of bidirectional predictive causality between AVA and GDP. Agriculture helps predict GDP, but GDP also helps predict agricultural value added. This feedback relationship is consistent with a mutually reinforcing agriculture-GDP nexus, but it does not establish a purely agriculture-led growth process. The policy implication is therefore not that agriculture should be treated as the sole engine of growth, but that agricultural productivity, infrastructure, investment, food systems, and rural economic activity can form part of a broader recovery strategy alongside non-agricultural sectors. The CUSUMSQ evidence of parameter instability further indicates that the magnitude of these relationships may vary across periods, so policy recommendations should be viewed as context-dependent rather than as invariant effects.

The 2012 crisis dummy should likewise be understood as a parsimonious regime indicator rather than a complete representation of all conflict-related structural changes. Overall, the evidence supports policies that strengthen agriculture as an interconnected component of economic recovery and reconstruction while recognising reciprocal feedback from aggregate economic conditions to the agricultural sector.

Consent for publication

All authors have given their consent for publication of this manuscript.

Statement

The author(s) employed ChatGPT as a resource to enhance the readability of this article. Following the use of this tool/service, the author(s) diligently reviewed and edited the content as necessary and bear full responsibility for the publication's content.

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Data availability

Data will be made available on request.

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