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Digital agricultural transformation, green economy performance, and climate finance mobilisation in ECOWAS: Evidence from a panel data analysis

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ABSTRACT

This study examines the effects of digital agricultural technology adoption on the green economy and climate finance inflows in ECOWAS countries from 2010 to 2023. A weighted Digital Agricultural Index (DAI) was constructed from internet penetration, ICT adoption, and fertilizer utilization, with the latter serving as a complementary indicator of technology-enabled farming. The green economy was measured using CO_2 emissions per capita, while climate finance was measured by climate finance inflows. Anchored in the technology–organization–environment framework, the study used Panel Corrected Standard Errors, with Driscoll–Kraay, clustered fixed-effects, and fixed-effects instrumental-variable (FE-IV) estimations serving as robustness and endogeneity checks. Digital agricultural adoption has a positive and significant effect on climate finance inflows (coefficient = 128.719, significant at the 1% level); a 0.1 increase in the DAI is associated with approximately 12.872 additional units. Its effect on CO_2 emissions is negative but statistically insignificant. The climate finance result remains robust under the robustness and endogeneity checks. Digital agricultural adoption helps ECOWAS countries attract climate finance, but it does not, by itself, deliver a green economy transition. The study recommends strengthening digital agricultural ecosystems and integrating agricultural innovation policies with climate finance strategies to accelerate green, climate-resilient development.

Contribution/Originality: This study contributes to the body of knowledge by developing a weighted digital agricultural index and examining its effects on the green economy and climate-financing inflows across ECOWAS countries. Furthermore, the study contributes empirically by combining panel-corrected standard errors with robustness checks and instrumental-variable estimations in its analysis.

1. INTRODUCTION

Agricultural regions are challenged by climate change. Climate change is detrimental to agriculture because it negatively affects productivity through rising temperatures, land degradation, erratic rainfall, and environmental pressures. The ECOWAS region faces climate change challenges because it is dominated by agriculture. In response, economies, including those in ECOWAS, are emphasizing the transition to a green economy characterized by low carbon emissions, efficient resource utilization, environmental sustainability, and climate resilience. Thus, the green economy serves as a pathway to environmental sustainability by addressing issues associated with environmental degradation and thereby promoting economic growth. Every country strives to develop; thus, the green economy has become increasingly prominent because it enables economic development while preserving the environment. There

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are many measures of the green economy. However, in the context of environmental quality, carbon dioxide (CO_2) emissions are the best indicator because they capture environmental performance and progress toward green transformation. In their respective studies, Nwaka, Nwogu, Uma, and Ike (2020), Cosmas, Chitedze, and Mourad (2019) and Anowor, Ukpere, and Onodugo (2025) employed CO_2 emissions as an indicator of the green economy, stating that carbon emissions reduced environmental pressure, promoted greater resource efficiency, and improved sustainability outcomes.

Within the ECOWAS region, growing concerns over climate change, deforestation, desertification, and environmental degradation have stimulated efforts to promote renewable energy adoption, climate-smart agriculture, and sustainable land management practices aimed at reducing carbon intensity and improving environmental performance.

Furthermore, to ensure sustainable development in developing countries, including ECOWAS member states, climate finance is becoming a key component. Conceptually, climate finance is the mobilisation of funds from public, private, domestic, and international sources to support areas or regions affected by climate change. The effects of climate change may take the form of floods, earthquakes, and other natural disasters. Climate finance is also used for renewable energy development, climate-smart agriculture, ecosystem restoration, and sustainable infrastructure. Buchner et al. (2021) and Nhamo and Nhamo (2021) asserted that access to sustainable technologies and environmental innovation is greatly facilitated by climate finance. This implies that climate finance is needed in developing countries that are unable to implement adaptation and mitigation programmes. In ECOWAS, climate finance is needed because most countries in the region cannot afford to address climate-related issues. Therefore, climate finance is an important pathway for accelerating environmental sustainability and agricultural transformation in developing countries.

As a result of climate change, which is particularly prominent in agriculture-dependent countries, agricultural transformation requires the adoption of agricultural technologies. Digital agriculture is therefore a critical mechanism for advancing smart agriculture. To improve agricultural productivity, it is necessary to advance information and communication technologies (ICTs), precision farming, remote sensing, mobile-based extension services, climate-smart agricultural practices, and data-driven farm management systems. These technologies can help farmers make informed decisions regarding weather conditions, market intelligence, financial services, and improved production techniques. Moreover, digital agriculture can strengthen resilience to climate-related shocks and enhance agricultural sustainability. According to Feder, Just, and Zilberman (1985), Rogers (2003) and Klerkx, Jakku, and Labarthe (2019), agricultural technology adoption is very important because it reduces information asymmetries, improves decision-making, and promotes the efficient utilization of agricultural inputs.

Although previous studies acknowledge a complementary relationship between digital agricultural transformation and climate finance, the empirical evidence remains fragmented, particularly in developing regions. Existing studies largely focus on how climate finance supports agricultural innovation, while relatively few examine whether digital agricultural transformation itself enhances countries' ability to mobilize climate finance or improve environmental sustainability. Moreover, most available evidence is based on individual countries, qualitative assessments, or technical reviews, providing limited understanding of these relationships at the regional level in West Africa. Consequently, the extent to which digital agricultural transformation contributes to green economy performance and climate finance mobilisation across ECOWAS countries remains insufficiently understood.

The study addresses the following gaps: First, a weighted composite digital agriculture index was developed using fertilizer use, internet penetration, and ICT adoption. Second, the study employed several estimation techniques to ensure the consistency of the empirical findings. Lastly, all countries in the ECOWAS region were included in the study, thereby providing comprehensive regional evidence of the effects of digital agriculture on climate finance and the green economy in ECOWAS.

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ECOWAS is selected for this study because agriculture is the largest source of employment, income, and food security in the region. The region is also vulnerable to climate change, has limited access to climate finance, and faces environmental degradation. Furthermore, the ECOWAS region exhibits considerable heterogeneity in digital infrastructure, technological readiness, institutional quality, and environmental performance. These characteristics justify examining how digital agriculture influences sustainable development outcomes.

1.1. Research Objectives

The specific objectives of the study are to:

1. Examine the effect of agricultural technology adoption on green economy in ECOWAS.
2. Investigate the effect of agricultural technology adoption on climate financing in ECOWAS.

1.2. Research Hypotheses

H_{01}: Agricultural technology adoption does not have a significant effect on green economy in ECOWAS.

H_{02}: Agricultural technology adoption does not have a significant effect on climate financing in ECOWAS.

2. LITERATURE REVIEW

2.1. Theoretical Framework: Technology–Organization–Environment (TOE) Framework

This study is anchored in the Technology–Organization–Environment (TOE) framework developed by Tornatzky and Fleischer (1990). The TOE framework explains the adoption of technological innovations by considering three major dimensions that influence technology adoption decisions: technological factors, organizational capacity, and environmental conditions. Unlike individual-level technology adoption theories, the TOE framework is suitable for macro-level analysis because it explains how institutional structures, policy environments, financial capacity, and technological readiness jointly determine the adoption and diffusion of innovations. This theoretical position is consistent with the diffusion of innovations theory proposed by Rogers (2003) and with recent digital agriculture literature, which emphasizes that technological transformation requires supportive ecosystems for successful adoption and sustainable impacts (Klerkx et al., 2019; Wolfert, Ge, Verdouw, & Bogaardt, 2017).

2.2. Empirical Review

Alawode and Obunadike (2023) studied AI- driven agriculture and transparency in climate finance disbursement. The study was purely on technical evaluation and case-based study. The study found that there is a convergence between AI-driven agriculture and machine learning, and this enhances transparency in climate finance disbursement. In a similar way, Olajide et al. (2025) conducted a comparative synthesis literature review on the role of integrated finance, infrastructure, and governance reforms to ensure food security. They observed that most studies found that infrastructure development is the pathway to food security. Ogunade, Adamaagashi, and Dauda (2025) also qualitatively demonstrated how AI-enabled climate services. They found that innovation supports climate-resilient farming. Momanyi, Rasugu Riechi, and Khatete (2024) employ a structured survey of Jua Kali artisans in Nairobi, analyzing responses on digital skills and platform use to illustrate how informal workers benefit from digital platforms for marketing but struggle with digital literacy and access.

Empirically, Namara and Kaggwa (2021) studied digital inclusion and employment opportunities in Uganda. The regression analysis found that there is a significant positive effect of digital inclusion on employment opportunities. The study concluded that digital inclusion enhances employment opportunities, but its affordability and infrastructure are factors hindering its full utilization. In a similar way, Tadesse and Alemu (2023) conducted a panel regression on the effect of digital adoption on productivity across labor markets in Ethiopia. The study documented that digital adoption influences productivity. The study by Anakpo and Kollamparambil (2022) examined the effect of automation

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on unemployment in the South Africa labor market. The study employed probit regression, and it was found that automation increases unemployment risks for low-skilled workers while creating demand for high-skilled labor. The findings of this study are in agreement with the findings of Giwa and Ngepah (2024). The study of Thanyawatpornkul (2024) on AI and sustainable development in Thailand found that AI adoption in agriculture, health, and urban planning enhances resource efficiency and equity but is constrained by digital divides, privacy concerns, and algorithmic bias.

2.3. Literature Gap

After the literature above, a few gaps exist. Most studies are on AI in agriculture and climate resilience, for example, Alawode and Obunadike (2023), Olajide et al. (2025), Begho, Daubry, and Irabor (2025), Pathania, Neha, Khan, and Kumar (2025), Ogunade et al. (2025) and Mondal, Gorain, Dutta, Das, and Malakar (2026). These studies are also literature reviews, neglecting empirical examination. Some studies also concentrated on the digital labor market at micro-levels, for example, the studies of Anwar (2022), Momanyi et al. (2024), Namara and Kaggwa (2021), and Tadesse and Alemu (2023), without paying attention to the aggregate economy. Empirical studies reviewed, such as Anakpo and Kollamparambil (2022), Giwa and Ngepah (2024) and Martins-Neto, Mathew, Mohnen, and Treibich (2024), were based on automation and employment dynamics without considering climate resilience and sustainable development.

3. METHODOLOGY

3.1. Research Design and Data

The study employed an ex post facto research design and covered all ECOWAS countries, yielding a balanced panel of 225 observations. Data were sourced from the World Development Indicators (WDI), the International Telecommunication Union (ITU) database, the FAOSTAT database, and the Green Climate Fund (GCF) project database.

3.1.1. Limitation

Climate finance data were sourced from the Green Climate Fund (GCF) project database. However, the database does not capture all sources of climate finance, such as private-sector investment, bilateral donor programmes, development banks, and domestic climate expenditure. Therefore, the climate finance variable is not treated as the total volume of climate-related financial resources but rather as an indicator of formal international climate finance. This limitation is acknowledged when interpreting the empirical findings.

3.2. Measurement of Variables

A weighted composite index was created to measure agricultural technology and was called the Digital Agricultural Index (DAI). The components of this index are internet penetration, ICT adoption, and fertilizer utilization. Internet penetration was used because it captures the availability of digital connectivity needed for agricultural information. ICT adoption captures a country's technological readiness and capacity to deploy digital innovations. Consequently, fertilizer utilization serves as a proxy for technology-intensive agricultural production when interpreted alongside digital connectivity and ICT adoption, rather than as an independent measure of digitalization. Therefore, the key explanatory variable in this study is the Digital Agricultural Index (DAI).

Carbon dioxide (CO_2) emissions per capita were used as a measure of the green economy, while total climate finance inflows were used as a measure of climate financing. The control variables are renewable energy consumption (RENE), GDP per capita growth (GDPPCGR), population (POPU), and political stability (POLS).

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3.3. Construction of the Digital Agricultural Index (DAI)

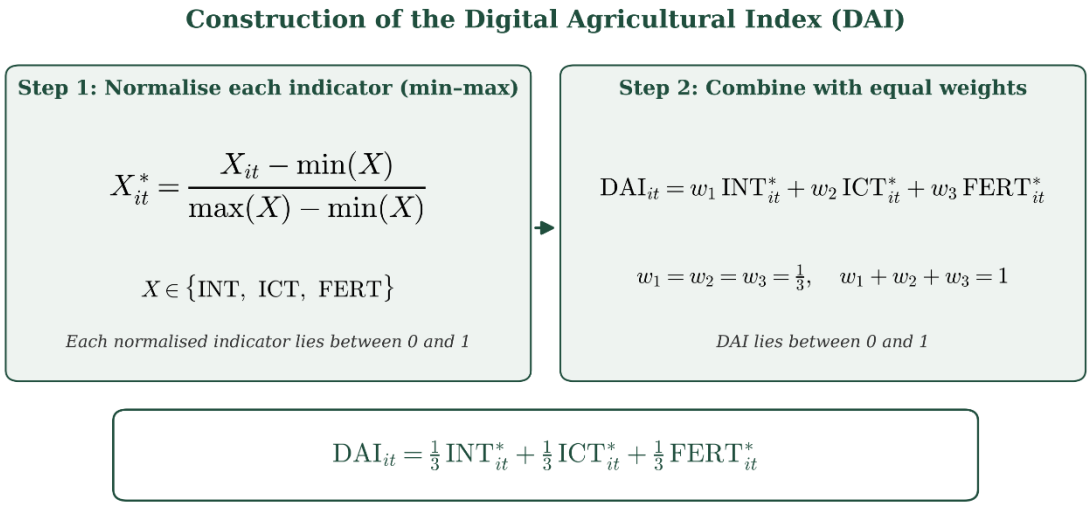

Figure 1. Construction of the Digital Agricultural Index (DAI).

Where X^{*}_{it} in Step 1 of Figure 1 denotes the normalized value of indicator X for country I in year t, and X_{it} is its raw value.

Following normalization, equal weights were assigned to each indicator because no strong theoretical or empirical basis existed for assigning different weights to the selected dimensions of agricultural technology adoption. The Digital Agricultural Index was therefore computed as shown in Step 2 of Figure 1.

Where:

(INT) = Normalized internet penetration.

(ICT) = Normalized ICT adoption index.

(FERT) = Normalized fertilizer utilization.

The resulting index ranges from 0 to 1, with higher values indicating greater agricultural technology adoption.

3.4. Estimation Strategy

The empirical analysis begins with descriptive statistics and correlation analyses to examine the distributions and relationships among variables. Multicollinearity is assessed using the variance inflation factor (VIF), while cross-sectional dependence is examined using Pesaran's cross-sectional dependence (CD) test.

Given the likelihood of heteroskedasticity and contemporaneous correlation across ECOWAS countries, the study adopted the Panel-Corrected Standard Errors (PCSE) estimator developed by Beck and Katz (1995) as the baseline estimation technique. PCSE is particularly appropriate because the dataset comprises a panel of fifteen ECOWAS countries observed over fourteen years (2010–2023), in which cross-sectional dependence, heteroskedasticity, and contemporaneous correlation are likely to arise due to regional integration, common climatic conditions, and shared economic shocks. For robustness analysis, Driscoll–Kraay standard errors and fixed-effects cluster-robust standard errors were employed. To achieve the objective of the study, a static panel model was specified because the study did not consider the long-run dynamic adjustment process.

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3.5. Endogeneity Treatment

There is a potential endogeneity problem due to reverse causality and omitted variable bias. For instance, countries that receive larger climate finance inflows may invest more in agricultural adoption than others. Given the differences in climate finance inflows, the likelihood of endogeneity in the model is high. Thus, a Fixed-Effects Instrumental Variables (FE-IV), using lagged values of the Digital Agricultural Index (DAI) and renewable energy consumption (RENE) as instruments, was employed to address this potential endogeneity.

3.6. Model Specification

Guided by the Technology–Organization–Environment (TOE) framework, agricultural technology adoption is hypothesized to influence environmental sustainability and climate finance mobilization through improvements in technological readiness, institutional capacity, and resource-use efficiency.

Model One: Agricultural Technology Adoption and Green Economy.

$$CO_{2,it} = \beta_0 + \beta_1 DAI_{it} + \beta_2 RENE_{it} + \beta_3 GDPPCGR_{it} + \beta_4 POPU_{it} + \epsilon_{it} \quad (1)$$

Model Two: Agricultural Technology Adoption and Climate Financing

$$CFI_{it} = \beta_0 + \beta_1 DAI_{it} + \beta_2 RENE_{it} + \beta_3 GDPPCGR_{it} + \beta_4 POPU_{it} + \beta_5 POLS_{it} + \epsilon_{it} \quad (2)$$

Where:

(CO_2) = Carbon dioxide emissions per capita.

(DAI) = Digital Agricultural Index.

(RENE) = Renewable energy consumption.

(GDPPCGR) = GDP per capita growth rate.

(POPU) = Population size.

(CFI) = Climate finance inflows.

(POLS) = Political stability.

Based on the TOE framework, agricultural technology is expected to negatively affect the green economy (CO_2 emissions) while having a positive effect on climate financing.

4. RESULTS AND DISCUSSION OF FINDINGS

The pre-estimation techniques employed include descriptive statistics, the correlation matrix, the variance inflation factor (VIF), and the cross-sectional dependence test. Table 1 presents the descriptive statistics for the variables based on 225 observations; the results show an absence of outliers among the variables and a wide gap between the maximum and minimum values. Table 2 presents the pairwise correlation matrix, which shows that there is no perfect correlation among the independent variables. Table 3 reports the VIF results, confirming the absence of multicollinearity, since all VIF values are far below the threshold of 10 (mean VIF = 1.190). Table 4 presents Pesaran's cross-sectional dependence (CD) test, which shows mixed results across the variables: cross-sectional dependence is present for RENE, CFI, DAI, GDPPCGR, and POPU, but not for CO_2 and POLS. Overall, the results justify adopting estimation techniques that account for cross-sectional dependence in the panel dataset to ensure valid inference.

Table 1. Descriptive statistics.

Variables	Obs.	Mean	Std. Dev.	Min.	Max.
RENE	225	1291.610	662.930	163.050	2780.390
CO_2	225	0.320	0.110	0.130	0.620
CFI	225	570.340	256.250	35.380	1226.070
DAI	225	0.480	0.260	0.010	0.990
GDPPCGR	225	2.050	3.520	-20.890	15.150
POLS	225	-0.600	0.800	-2.730	0.930
POPU	225	25.500	47.900	0.510	233.000

Note: RENE = Renewable energy consumption; CO_2 = Carbon dioxide emissions per capita; CFI = Climate finance inflows; DAI = Digital Agricultural Index; GDPPCGR = GDP per capita growth rate; POLS = Political stability; POPU = Population.

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Table 2. Correlation matrix.

Variables	RENE	CO_2	CFI	DAI	GDPPCGR	POLS	POPU
RENE	1.000						
CO_2	0.160 (0.010)	1.000					
CFI	0.250 (0.010)	0.100 (0.120)	1.000				
DAI	0.240 (0.000)	-0.040 (0.590)	0.400 (0.000)	1.000			
GDPPCGR	0.100 (0.150)	-0.020 (0.730)	0.030 (0.660)	0.010 (0.920)	1.000		
POLS	0.000 (0.950)	0.320 (0.000)	-0.050 (0.490)	-0.020 (0.800)	0.110 (0.080)	1.000	
POPU	-0.140 (0.030)	-0.180 (0.010)	-0.250 (0.002)	0.060 (0.390)	-0.110 (0.090)	-0.520 (0.000)	1.000

Note: Values are Pearson correlation coefficients. Figures in parentheses are the corresponding p-values. RENE = Renewable energy consumption; CO_2 = Carbon dioxide emissions; CFI = Climate finance inflows; DAI = Digital Agricultural Index; GDPPCGR = GDP per capita growth rate; POLS = Political stability; POPU = Population.

Table 3. Variance inflation factor (VIF).

Variables	VIF	1/VIF
POPU	1.370	0.730
POLS	1.370	0.730
GDPPCGR	1.020	0.980
DAI	1.010	0.990
Mean VIF	1.190	—

Table 4. Pesaran cross-sectional dependence (CD) test.

Variables	CD Statistic	Probability	Decision
RENE	31.450	0.000	Reject H0 (Cross-sectional dependence present)
CO_2	1.090	0.270	Fail to reject H0 (No cross-sectional dependence)
CFI	38.020	0.000	Reject H0 (Cross-sectional dependence present)
DAI	32.800	0.000	Reject H0 (Cross-sectional dependence present)
GDPPCGR	6.890	0.000	Reject H0 (Cross-sectional dependence present)
POLS	-0.300	0.770	Fail to reject H0 (No cross-sectional dependence)
POPU	39.090	0.000	Reject H0 (Cross-sectional dependence present)

Table 5. Model one: Agricultural technology adoption on green economy in ECOWAS.

Variables	FEM coefficient (Std. error)	REM coefficient (Std. error)	PCSE coefficient (Std. error)
DAI	-0.030 (0.020)	-0.030 (0.020)	-0.002 (0.021)
RENE	0.010 (0.020)	0.020 (0.002)	6.000×10^{-6} (1.000×10^{-5})
GDPPCGR	-0.020** (0.010)	-0.000 ** (0.001)	-0.001 (0.001)
POPU	0.097 (0.072)	0.018 (0.047)	-0.038** (0.013)
Constant	0.290 *** (0.040)	0.300 *** (0.040)	0.320 *** (0.030)
Observations	225	225	225
Groups (ID)	15	15	15
R^2 (Within)	0.034	0.029	0.407
R^2 (Overall)	0.015	0.007	–
F/Wald test	F(4,206) = 1.820, Prob > F = 0.125	Wald chi2(4) = 6.030, Prob > chi2 = 0.197	Wald chi2(3) = 1.550, Prob > chi2 = 0.671
Multicollinearity Test VIF Mean	1.060	1.060	1.060
Breusch-Pagan LM Test	$Chi^2(10)$ = 0.704 Prob > Chi^2 = 1.000	$Chi^2(10)$ = 0.704 Prob > Chi^2 = 1.000	$Chi^2(10)$ = 0.704 Prob > Chi^2 = 1.000
Hausman Test	$Chi^2(5)$= 1.950 Prob > Chi^2 = 0.583	Chi^2 = 1.950 Prob > Chi^2 = 0.583	Chi^2 = 1.950 Prob > Chi^2 = 0.583
Modified Wald Test for Heteroskedasticity	$Chi^2(5)$ = 2015.390 Prob > chi^2 = 0.000	$Chi^2(5)$ = 2015.390 Prob > chi^2 = 0.000	$Chi^2(5)$ = 2015.390 Prob > chi^2 = 0.000

Note: *** represents significant level at 1%, ** at 5% . The independent variable is Digital Agricultural Index (DAI). Control variables are renewable energy consumption (RENE), GDP per capita growth (GDPPCGR) and population (POPU), while the dependent variable is green economy (CO_2).

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Table 5 presents the estimates of Model One, which relates the Digital Agricultural Index (DAI) to CO_2 emissions per capita (the green economy measure) using the fixed-effects model (FEM), random-effects model (REM), and panel-corrected standard errors (PCSE) estimators. DAI has a negative and statistically insignificant coefficient under all three estimators (−0.030 under FEM and REM, and −0.002 under PCSE).

Table 6 reports the robustness check for Model One using Driscoll–Kraay standard errors and fixed-effects estimation with clustered standard errors. The DAI coefficient remains negative (−0.033) and statistically insignificant under both approaches, which is consistent with the baseline estimates in Table 5.

Table 6. Robustness check for Model One: Driscoll–Kraay and fixed-effects clustered estimates of agricultural technology adoption on green economy (CO_2) in ECOWAS.

Variable	Driscoll–Kraay Coefficient (Std. Error)	FE (Clustered) Coefficient (Std. Error)
DAI	-0.033 (0.030)	-0.033 (0.040)
RENE	1.980×10^{-5} (3.140×10^{-5})	1.980×10^{-5} (3.950×10^{-5})
GDPPCGR	-0.002 (0.001)	-0.002 ** (0.001)
POPU	0.097** (0.025)	0.097 (0.093)
Constant	0.288 (0.035)	0.288 (0.053)
Observations	225	225
Groups (ID)	15	15
R^2 (within)	0.034	0.034
R^2 (overall)	–	0.015
F/Wald Test	F(4,14) = 0.820, Prob > F = 0.533	F(4,14) = 1.850, Prob > F = 0.176

Note: ** at 5%. The independent variable is Digital Agricultural Index (DAI). Control variables are renewable energy consumption (RENE), GDP per capita growth (GDPPCGR) and population (POPU), while the dependent variable is green economy (CO_2).

Table 7. Endogeneity check for Model One: Instrumental variable (FE-IV) estimates of agricultural technology adoption on green economy (CO_2) in ECOWAS.

Variable	FE-IV Coefficient (Std. Error)	FE (Clustered) Coefficient (Std. Error)
DAI	-0.107 * (0.057)	-0.033 (0.040)
RENE	1.288×10^{-4} (8.830×10^{-5})	1.980×10^{-5} (3.950×10^{-5})
GDPPCGR	-0.002 * (0.001)	-0.002 ** (0.001)
POPU	0.144* (0.085)	0.097 (0.093)
Constant	0.170 * (0.096)	0.288 *** (0.053)
Observations	210	225
Groups (ID)	15	15
R^2 (within)	–	0.034
R^2 (overall)	0.002	0.015
F/Wald Test	Wald $\chi^2(4) = 278.770$, Prob > $\chi^2 = 0.000$	F(4,14) = 1.850, Prob > F = 0.176

Note: *** represents significant level at 1%, ** at 5% and * at 10%. The independent variable is Digital Agricultural Index (DAI). Control variables are renewable energy consumption (RENE), GDP per capita growth (GDPPCGR) and population (POPU), while the dependent variable is green economy (CO_2).

To address potential endogeneity, the study employed a fixed-effects instrumental-variable approach using lagged values of DAI and RENE as instruments. Table 7 exhibits the results: the FE-IV coefficient of DAI is −0.107 and is significant only at the 10% level, while the clustered fixed-effects estimate is −0.033 and insignificant. The IV estimate therefore retains the negative sign of the baseline estimates, and DAI does not show a significant effect on CO_2 emissions at the conventional 5% level.

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4.1. Discussion of Agricultural Technology Adoption and Green Economy (Model One)

In Table 5, it was observed that agricultural technology adoption (DAI) had a negative and insignificant effect on CO_2 emissions. This finding suggests that agricultural technology adoption has the potential to enhance green economy outcomes, but countries' capabilities and readiness are hindering factors to achieving this. Thus, if ECOWAS economies adopt agricultural technology, it will reduce agricultural waste, improve input management, and support climate-smart production systems. These findings are consistent with those of Klerkx et al. (2019), who found that digital agriculture is crucial in agriculturally dominated economies because it improves decision-making, precision farming, and resource allocation. Similarly, the Food and Agriculture Organization of the United Nations (2022) asserted that agricultural automation and digital technologies are pivotal to sustainable development because they help minimize the excessive use of land, water, and agricultural inputs. A similar study supporting this finding is Wolfert et al. (2017), who noted that data-driven agriculture enables farmers to optimize production processes, reduce inefficiencies, and improve sustainability outcomes.

The insignificant effect of digital agricultural adoption on CO_2 emissions suggests that adopting agricultural technology alone may not lead to a transition to a green economy. This implies that adopting digital agricultural technology does not automatically result in a green economy in ECOWAS economies. To achieve a green economy transition, ECOWAS countries should strengthen their infrastructure and institutional support. This finding aligns with Aker (2011) observation that digital technologies in developing countries often face implementation constraints, such as weak infrastructure, limited farmer capacity, and affordability challenges.

Table 8 presents estimates from Model Two, which relates the Digital Agricultural Index (DAI) to climate finance inflows (CFI) using the FEM, REM, and PCSE estimators. DAI has a positive and statistically significant effect at the 1% level with all three estimators (257.459 under FEM, 268.327 under REM, and 128.719 under PCSE).

Table 8. Model two: Agricultural technology adoption on climate financing in ECOWAS.

Variables	FEM coefficient (Std. error)	REM coefficient (Std. error)	PCSE coefficient (Std. error)
DAI	257.459*** (23.650)	268.327*** (22.961)	128.719*** (40.373)
RENE	0.230*** (0.032)	0.216*** (0.031)	0.066*** (0.020)
GDPPCGR	1.761 (1.132)	1.725 (1.131)	0.231 (0.920)
POPU	0.514 (0.775)	0.158 (0.678)	-1.150*** (0.309)
POLS	2.877 (11.535)	2.317 (11.435)	-2.051 (17.676)
Constant	135.696*** (38.426)	157.927** (75.640)	454.549*** (49.938)
Observations	225	225	225
Groups (ID)	15	15	15
R^2 (Within)	0.768	0.767	0.037
R^2 (Overall)	0.111	0.132	–
F/Wald Test	F(5,205) = 135.370, Prob > F = 0.000	Wald $chi^2(5)$ = 674.460, Prob > chi2 = 0.000	Wald $chi^2(5)$ = 61.010, Prob > chi2 = 0.000
Multicollinearity test VIF mean	1.200	1.200	1.200
Breusch-Pagan LM Test	$Chi^2(10)$ = 3.669 Prob > Chi^2 = 0.961	$Chi^2(10)$ = 3.669 Prob > Chi^2 = 0.961	$Chi^2(10)$ = 3.669 Prob > Chi^2 = 0.961
Hausman Test	$Chi^2(5)$= 4.410 Prob > Chi^2 = 0.353	Chi^2 = 4.410 Prob > Chi^2 = 0.353	Chi^2 = 4.410 Prob > Chi^2 = 0.353
Modified Wald Test for Heteroskedasticity	$Chi^2(5)$ = 120.890 Prob > chi^2 = 0.000	$Chi^2(5)$ = 120.890 Prob > chi^2 = 0.000	$Chi^2(5)$ = 120.890 Prob > chi^2 = 0.000

Note: *** represents significant level at 1%, ** at 5%. The independent variable is the Digital Agricultural Index (DAI). Control variables are renewable energy consumption (RENE), GDP per capita growth (GDPPCGR), population (POPU), and political stability (POLS), while the dependent variable is climate financing inflows (CFI).

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Table 9 shows the robustness check for Model Two using Driscoll–Kraay standard errors and fixed-effects estimation with clustered standard errors. The DAI coefficient (257.459) remains positive and significant at the 1% level under both approaches; the standard errors are 23.403 and 30.356, respectively.

Table 9. Robustness check for Model Two: Driscoll–Kraay and fixed-effects clustered estimates of agricultural technology adoption on climate financing in ECOWAS.

Variables	Driscoll–Kraay Coefficient (Std. Error)	FE (Clustered) Coefficient (Std. Error)
DAI	257.459 ***	257.459 ***
	(23.403)	(30.356)
RENE	0.230 ***	0.230 ***
	(0.031)	(0.044)
GDPPCGR	1.761 *	1.761 *
	(0.842)	(0.949)
POPU	0.514	0.514
	(0.432)	(0.869)
POLS	2.877	2.877
	(12.675)	(20.276)
Constant	135.696***	135.696 **
	(36.036)	(53.859)
Observations	225	225
Groups (ID)	15	15
R^2 (within)	0.768	0.768
R^2 (overall)	–	0.111
F/Wald Test	F(5,14) = 109.770, Prob > F = 0.000	F(5,14) = 51.780, Prob > F = 0.000

Note: *** represents significant level at 1%, ** at 5% and * at 10%. The independent variable is the Digital Agricultural Index (DAI). Control variables are renewable energy consumption (RENE), GDP per capita growth (GDPPCGR), population (POPU), and political stability (POLS), while the dependent variable is climate financing inflows (CFI).

Table 10. Endogeneity check for Model Two: Instrumental variable (FE-IV) estimates of agricultural technology adoption on climate financing in ECOWAS.

Variable	FE-IV Coefficient (Std. Error)	FE (Clustered) Coefficient (Std. Error)
DAI	255.305 ***	257.459 ***
	(64.585)	(30.356)
RENE	0.322 ***	0.230 ***
	(0.101)	(0.044)
GDPPCGR	1.748	1.761 *
	(1.184)	(0.949)
POPU	-0.575	0.514
	(0.947)	(0.869)
POLS	13.354	2.877
	(14.250)	(20.276)
Constant	52.207	135.696**
	(106.920)	(53.859)
Observations	210	225
Groups (ID)	15	15
R^2 (Within)	0.721	0.768
R^2 (Overall)	0.118	0.111
F/Wald Test	Wald $\chi^2(5)$ = 21353.400, Prob > χ^2 = 0.000	F(5,14) = 51.780, Prob > F = 0.000

Note: *** represents significant level at 1%, ** at 5% and * at 10%. The independent variable is the Digital Agricultural Index (DAI). Control variables are renewable energy consumption (RENE), GDP per capita growth (GDPPCGR), population (POPU), and political stability (POLS), while the dependent variable is climate financing inflows (CFI).

Table 10 displays the endogeneity check for Model Two, in which the same lagged values of DAI and RENE serve as instruments. The FE-IV coefficient for DAI is 255.305 and significant at the 1% level. This estimate is close to the clustered fixed-effects estimate of 257.459, indicating that the positive effect of DAI on climate finance inflows is not driven by endogeneity.

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4.2. Discussion of Agricultural Technology Adoption and Climate Financing (Model Two)

The results in Table 8 show that agricultural technology adoption (DAI) has a positive and statistically significant effect on climate financing inflows, with a coefficient of 128.719, significant at the 1% level. This finding indicates that improvements in digital agricultural capacity enhance the ability of ECOWAS countries to mobilize climate-related financial resources. Given that the Digital Agricultural Index is measured between 0 and 1, the coefficient implies that a 0.1-unit improvement in agricultural technology adoption is associated with an increase of approximately 12.872 units in climate financing inflows. This suggests that agricultural digitalization serves as an important pathway for climate finance mobilisation by improving climate information availability, strengthening monitoring and reporting mechanisms, and increasing the credibility of climate-related investment projects. The positive relationship between agricultural technology adoption and climate financing supports the argument that digital transformation enhances countries' readiness to access climate funds.

This result aligns with Aker (2011), who highlighted that information and communication technologies improve agricultural information access and strengthen decision-making processes among farmers and agricultural stakeholders. It is also consistent with Wolfert et al. (2017), who argued that digital agriculture and smart farming technologies enhance data availability, resource efficiency, and sustainability, which are important considerations for climate investment decisions. Furthermore, the finding agrees with Klerkx et al. (2019), who emphasized that digital agriculture supports sustainability transitions by improving innovation systems and enabling evidence-based agricultural management.

5. CONCLUSION

This study concludes that agricultural technology adoption plays an important role in promoting sustainable development outcomes in ECOWAS countries, although its effects differ across the dimensions examined. The findings reveal that digital agriculture adoption significantly enhances climate finance inflows, indicating that improved digital agricultural capacity strengthens countries' ability to attract climate-related investments through better climate information systems, greater transparency, and the effective implementation of climate-smart initiatives. However, the effect of agricultural technology adoption on the green economy is positive but statistically insignificant, suggesting that digital transformation in agriculture has not yet reached the level required to generate substantial environmental improvements across the region.

5.1. Policy Suggestion

The following suggestions are given based on the empirical findings.

i. Develop national digital agriculture strategies with clear targets and timelines.
ii. Establish climate finance coordination mechanisms that priorities agricultural innovation.
iii. Invest in rural digital infrastructure (Broadband connectivity, mobile networks).
iv. Strengthen farmer capacity building and digital literacy programs.
v. Promote public-private partnerships for agricultural technology development.
vi. Implement monitoring and evaluation systems for tracking technology adoption and environmental outcomes.

5.2. Study Limitations

The study successfully examined the effect of digital agricultural adoption on the green economy and climate financing. However, despite providing empirical evidence, it has some limitations. Climate finance data were sourced from the Green Climate Fund (GCF) project database. This database does not capture all sources of climate finance, such as private-sector investment, bilateral donor programs, development banks, and domestic climate expenditure. Therefore, the climate finance variable is not treated as the total volume of climate-related financial resources but

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rather as an indicator of formal international climate finance. In addition, the study did not consider the long-run adjustment processes associated with digital agricultural adoption, the green economy, and climate financing. Furthermore, the Digital Agricultural Index was constructed using national-level indicators and may not fully reflect differences in technology adoption among individual farmers or subnational regions. Further studies should therefore consider dynamic-panel methods and broader climate indicators.

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