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Digital Agricultural Transformation and Sustainable Development Pathways in ECOWAS: Evidence on Green Economy and Climate Financing

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Abstract

Climate change, environmental degradation, and the need for sustainable agricultural transformation have intensified interest in the role of digital technologies in promoting environmentally sustainable development across developing economies. While existing studies have separately examined agricultural technology adoption, climate finance, and environmental sustainability, limited empirical evidence exists on how agricultural technology adoption influences green economy outcomes and climate finance mobilization within a unified framework, particularly in the ECOWAS region. This study investigates the effect of agricultural technology adoption on green economy performance and climate financing in 15 ECOWAS countries over the period 2010–2023. Agricultural technology adoption is measured using a Digital Agricultural Index (DAI) constructed from internet penetration, ICT adoption, and fertilizer utilization, while green economy performance and climate financing are proxied by CO_2 emissions and climate finance inflows, respectively. Drawing on the Technology–Organization–Environment (TOE) framework, the study employs Panel Corrected Standard Errors (PCSE) as the baseline estimation technique to address heteroskedasticity and cross-sectional dependence, complemented by Driscoll–Kraay standard errors, fixed-effects clustered estimators, and instrumental variable estimations for robustness and endogeneity correction.

The findings reveal that agricultural technology adoption significantly increases climate finance inflows, suggesting that digital agricultural transformation enhances institutional readiness, project credibility, and countries' capacity to attract climate-related investments. In contrast, agricultural technology adoption exhibits a negative but statistically insignificant effect on CO_2 emissions, indicating that although digital agricultural innovations have the potential to support environmental sustainability and green economic transformation, their environmental benefits remain constrained by structural and institutional limitations within the region. The robustness and endogeneity analyses confirm the stability of these results across alternative estimation techniques. The study contributes to the emerging literature on digital agriculture and sustainable development by providing regional evidence that agricultural technology adoption serves as a critical channel for climate finance mobilization, while its environmental impact depends on complementary investments in renewable energy, digital infrastructure, institutional capacity, and climate governance. The study recommends strengthening digital agricultural ecosystems and integrating agricultural innovation policies with climate finance strategies to accelerate green and climate-resilient development across ECOWAS countries.

1. Introduction

Climate change has emerged as one of the most significant challenges confronting developing economies, particularly in regions where agriculture remains highly dependent on natural climatic conditions. Rising temperatures, erratic rainfall patterns, land degradation, and increasing environmental pressures threaten agricultural productivity, food security, and sustainable economic development across Sub-Saharan Africa. In response, policymakers and development institutions have increasingly emphasized the transition toward a green economy characterized by low-carbon production systems,

efficient resource utilization, environmental sustainability, and climate resilience. Within this transition, agriculture occupies a strategic position because it simultaneously contributes to economic growth, environmental outcomes, and climate adaptation efforts. Consequently, the search for innovative approaches capable of improving agricultural productivity while reducing environmental pressures has become a major policy priority in developing regions.

Agricultural technology adoption has increasingly been recognized as a critical mechanism for achieving sustainable agricultural transformation. Advances in digital agriculture, information and communication technologies (ICTs), precision farming, remote sensing, mobile-based extension services, climate-smart agricultural practices, and data-driven farm management systems have created new opportunities for improving productivity and resource efficiency. These technologies enable farmers to access weather information, market intelligence, financial services, and improved production techniques, thereby strengthening resilience to climate-related shocks and enhancing agricultural sustainability. Studies by Feder et al. (1985), Rogers (2003), and Klerkx et al. (2019) argue that technology adoption reduces information asymmetries, improves decision-making, and promotes efficient utilization of agricultural inputs. As a result, agricultural technology adoption has become increasingly important within broader discussions on environmental sustainability, climate adaptation, and green economic transformation.

The concept of the green economy has gained prominence as countries seek to reconcile economic growth with environmental sustainability. Since environmental quality represents a fundamental pillar of green economic development, carbon dioxide (CO_2) emissions are frequently employed as an indicator of environmental performance and progress toward green transformation. Lower CO_2 emissions generally reflect reduced environmental pressure, greater resource efficiency, and improved sustainability outcomes. Empirical studies such as Bekun et al. (2020), Nathaniel (2019), and Anowor et al. (2025) have utilized CO_2 emissions as a proxy for environmental sustainability and green development in African economies. 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.

Climate financing has also become an increasingly important component of sustainable development strategies. Climate finance refers to financial resources mobilized from public, private, domestic, and international sources to support climate mitigation and adaptation activities, including renewable energy development, climate-smart agriculture, ecosystem restoration, and sustainable infrastructure. The Paris Agreement and subsequent global climate commitments have strengthened the role of climate finance in enabling developing countries to pursue low-carbon and climate-resilient development pathways. Existing evidence suggests that climate finance facilitates access to sustainable technologies, supports environmental innovation, and strengthens countries' capacity to implement climate adaptation and mitigation programmes (Buchner et al., 2021; Nhamo & Nhamo, 2021). Consequently, climate finance represents a critical channel through which developing economies can accelerate environmental sustainability and agricultural transformation.

The ECOWAS region presents a particularly relevant context for examining the nexus between agricultural technology adoption, climate finance, and green economic transformation. Agriculture remains a major contributor to livelihoods and economic activity across member states, yet the sector faces severe challenges arising from climate variability, low productivity, inadequate infrastructure, and limited technological capacity. At the same time, the region has witnessed increasing investments in digital agriculture and growing access to climate finance. Improvements in internet penetration, ICT adoption, and agricultural modernization initiatives have expanded opportunities for digital transformation within the agricultural sector. However, substantial differences remain across ECOWAS countries regarding technological readiness, institutional capacity, environmental performance, and climate finance accessibility.

The relationship between agricultural technology adoption and climate financing is potentially bidirectional and mutually reinforcing. On the one hand, climate finance can facilitate the adoption of digital and climate-smart agricultural technologies by reducing financial constraints and supporting innovation investments. On the other hand, agricultural digitalization may improve countries' ability to attract climate finance by strengthening data systems, project monitoring, transparency, and climate-risk management capabilities. Through these channels, agricultural technology adoption and climate finance may jointly contribute to environmental sustainability and green economic transformation. Nevertheless, the extent to which agricultural technology adoption influences climate finance mobilization and environmental outcomes remains insufficiently understood in the ECOWAS context.

Despite the growing literature on digital agriculture, climate finance, and environmental sustainability, important gaps remain. Existing studies have largely examined agricultural technology adoption as a determinant of agricultural productivity, climate finance as a mechanism for adaptation and mitigation, or environmental sustainability as a separate development outcome. Relatively little empirical attention has been given to the integrated relationship between agricultural technology adoption, climate financing, and green economy performance, particularly at the regional level within ECOWAS. Furthermore, much of the existing evidence is based on single-country studies, qualitative assessments, or broader African analyses that do not adequately capture the heterogeneous experiences of ECOWAS member states. This study addresses these gaps by examining the effects of agricultural technology adoption on green economy performance and climate financing across 15 ECOWAS countries over the period 2010–2023. Using a Digital Agricultural Index constructed from internet penetration, ICT adoption, and fertilizer utilization, and employing Panel Corrected Standard Errors alongside multiple robustness and endogeneity tests, the study contributes new empirical evidence on the role of agricultural digitalization in promoting environmental sustainability and climate finance mobilization in West Africa.

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

Research Hypotheses:

$H_0$1: Agricultural technology adoption does not have a significant effect on green economy in ECOWAS

$H_0$2: Agricultural technology adoption does not have a significant effect on climate financing in ECOWAS

2. Literature Review

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

This study is anchored on 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. In the context of this study, agricultural technology adoption represented by the Digital Agricultural Index (DAI) reflects the technological dimension, capturing the availability and utilization of digital tools, information technologies, and modern agricultural practices. The framework suggests that the benefits of agricultural technologies depend not only on technological availability but also on enabling conditions such as infrastructure, institutional quality, investment support, and policy frameworks.

The TOE framework further provides a theoretical explanation for the relationship between agricultural technology adoption, climate financing, and green economic transformation. In ECOWAS countries, climate financing represents an environmental and institutional enabling factor that can facilitate the acquisition and implementation of digital agricultural technologies, renewable energy solutions, and climate-smart agricultural practices. When technological innovations are supported by appropriate financial resources and favourable institutional conditions, they can improve resource efficiency, enhance climate resilience, and contribute to sustainable economic outcomes. Therefore, the framework supports the argument that agricultural technology adoption alone may not automatically produce green economy outcomes; rather, its effectiveness depends on complementary environmental and organizational factors such as climate finance availability, policy coordination, and investment capacity. This theoretical position is consistent with innovation diffusion arguments by Rogers (2003) and recent digital agriculture literature, which emphasize that technological transformation requires supportive ecosystems for successful adoption and sustainable impacts (Klerkx et al., 2019; Wolfert et al., 2017).

Empirical Review

Artificial intelligence (AI) and digital technologies are increasingly positioned as transformative tools for agriculture and climate resilience in Africa and beyond. Alawode and Obunadike (2023), through technical evaluation and case-based analysis of precision farming systems, emphasize the convergence

of AI-driven agriculture with fraud-resistant green finance, showing how geospatial verification and machine learning can enhance transparency in climate finance disbursement. Olajide et al. (2025) extend this discussion by conducting a systematic literature review and comparative synthesis of peer-reviewed studies and policy frameworks, highlighting the importance of integrated finance, infrastructure, and governance reforms to ensure food security. Similarly, Begho et al. (2025) employ a scoping review methodology, mapping opportunities and challenges of AI adoption in African agriculture. Pathania et al. (2025) rely on a comprehensive technical review of AI/ML models including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and IoT integration to detail innovations that can support climate-resilient farming. Ogunade et al. (2025) adopt a qualitative multi-source synthesis, combining academic literature, institutional frameworks, and case studies such as the ENACTS program to illustrate AI-enabled climate services. Mondal et al. (2026) take a global perspective, using a systematic review of peer-reviewed studies and policy documents grounded in Institutional and Sustainable Development Theory, underscoring that equitable climate action requires systemic integration of finance, technology, and governance.

Parallel to agriculture, another cluster of studies examines how digital transformation reshapes labour markets and inequality. Anwar (2022), using a qualitative case study approach with interviews and document analysis, highlights gendered disparities in African digital labour, showing how women face wage gaps and algorithmic bias. Momanyi et al. (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. Namara and Kaggwa (2021) rely on household survey data combined with regression analysis, showing that digital inclusion in Uganda improves employment opportunities but is hindered by affordability and infrastructure deficits. Tadesse and Alemu (2023) apply econometric modeling using panel data and regression techniques to national labour market datasets in Ethiopia, demonstrating that digital adoption boosts productivity yet risks widening inequality without inclusive policies. Collectively, these studies reveal that while digital platforms create new opportunities, they also reproduce existing inequalities unless accompanied by targeted interventions.

A third set of papers interrogates automation, AI, and employment dynamics. Anakpo and Kollamparambil (2022) use econometric analysis with probit and regression models applied to Southern African labour market data, demonstrating that automation increases unemployment risks for low-skilled workers while creating demand for high-skilled labour. Giwa and Ngepah (2024) similarly employ econometric techniques including OLS regression and robustness checks to show that AI adoption in South Africa correlates positively with skilled employment but excludes unskilled workers. Martins Neto et al. (2023) broaden the lens by conducting a systematic review and meta-analysis of World Bank datasets, finding weaker evidence of job polarization in developing economies compared to advanced economies, and attributing this to structural labour market differences. These studies converge on the theme that automation and AI privilege skilled labour, raising concerns about exclusion of low-skilled workers.

Finally, Thanyawatpornkul (2024) situates AI within sustainable development in Thailand, adopting a systematic review methodology of peer-reviewed papers and institutional reports. The study finds 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. This aligns with African studies that stress governance, infrastructure, and ethical frameworks as prerequisites for equitable AI adoption.

Literature Gap

The reviewed scholarship demonstrates growing interest in the intersection of AI, digital technologies, agriculture, climate resilience, and labour markets. Several streams of research are evident:

1. AI in agriculture and climate resilience: Studies such as Alawode & Obunadike (2023), Olajide et al. (2025), Begho et al. (2025), Pathania et al. (2025), Ogunade et al. (2025), and Mondal et al. (2026) emphasize technical evaluations, systematic reviews, and case-based analyses of AI-driven farming systems, climate services, and governance frameworks. These works highlight opportunities but remain largely conceptual or review-based, with limited empirical testing using country-level data.
2. Digital labour markets: Research by Anwar (2022), Momanyi et al. (2024), Namara & Kaggwa (2021), and Tadesse & Alemu (2023) explores digital inclusion, gender disparities, and productivity effects. However, these studies are micro-level (household, survey, or case study) and do not connect digital labour transformations to macro-level climate resilience or green economy outcomes.
3. Automation and employment dynamics: Anakpo & Kollamparambil (2022), Giwa & Ngepah (2024), and Martins Neto et al. (2023) provide econometric evidence on automation's labour market effects, but their focus is labour polarization and inequality, not the broader systemic integration of AI into climate resilience and sustainable development.
4. Global perspectives: Thanyawatpornkul (2024) and Mondal et al. (2026) situate AI within sustainable development frameworks, but these are cross-country reviews without Africa-specific empirical modeling.

3. Methodology

3.1 Research Design and Data

This study employs a quantitative panel-data research design to examine the effects of agricultural technology adoption on green economy performance and climate financing in the Economic Community of West African States (ECOWAS). The analysis covers all fifteen ECOWAS member countries over the period 2010–2023, generating a balanced panel dataset of 225 country-year observations. The panel framework is appropriate because it captures both the cross-country heterogeneity and temporal dynamics associated with agricultural transformation, environmental sustainability, and climate finance mobilization.

Data were obtained from multiple internationally recognized sources. Information on internet penetration, renewable energy consumption, carbon dioxide (CO_2) emissions, population, GDP per capita

growth, and political stability was sourced from the World Development Indicators (WDI) database. Data on ICT adoption were obtained from the International Telecommunication Union (ITU), while fertilizer utilization data were sourced from FAOSTAT. Climate finance inflow data were obtained from the Green Climate Fund (GCF) project database and related climate finance repositories. Missing observations for selected variables were addressed using linear interpolation to maintain panel balance and minimize data loss.

3.2 Measurement of Variables

Agricultural technology adoption is measured using a composite Digital Agricultural Index (DAI), which captures the extent of technological advancement within the agricultural sector. Following the technology adoption literature, the index combines three indicators: internet penetration, ICT adoption, and fertilizer utilization. Internet penetration and ICT adoption reflect the digital dimension of agricultural modernization, while fertilizer utilization captures the application of modern agricultural inputs.

Green economy performance is proxied by carbon dioxide (CO_2) emissions per capita. Consistent with the environmental economics literature, lower CO_2 emissions indicate improved environmental quality and progress toward green economic transformation. Climate financing is measured using total climate finance inflows received by each country. Renewable energy consumption (RENE), GDP per capita growth (GDPPCGR), population (POPU), and political stability (POLS) are included as control variables because of their established influence on environmental sustainability and climate finance mobilisation.

3.3 Construction of the Digital Agricultural Index (DAI)

To construct the Digital Agricultural Index (DAI), each component indicator was first normalized using the min–max transformation method to ensure comparability across variables measured in different units:

Where X_{it} in figure step 1 denotes the normalized value of indicator (X) for country (i) in year (t).

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

where:

(INT) = normalized internet penetration;

(ICT) = normalized ICT adoption index;

(FERT) = normalized fertilizer utilization.

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

3.4 Estimation Strategy

The empirical analysis begins with descriptive statistics and correlation analysis to examine the distribution 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 adopts the Panel Corrected Standard Errors (PCSE) estimator developed by Beck and Katz (1995) as the baseline estimation technique. The PCSE estimator is particularly suitable for macro-panel datasets characterized by relatively small cross-sections and moderate time dimensions because it provides efficient standard errors in the presence of panel heteroskedasticity and cross-sectional dependence.

To ensure the robustness of the findings, two alternative estimation techniques are employed. First, Driscoll–Kraay standard errors are estimated to account for heteroskedasticity, serial correlation, and cross-sectional dependence. Second, Fixed Effects estimations with clustered standard errors are performed to correct for within-country error correlation and heteroskedasticity.

3.5 Endogeneity Treatment

Potential endogeneity may arise from reverse causality and omitted variable bias. For example, countries receiving larger climate finance inflows may subsequently invest more in agricultural technology adoption, creating simultaneity concerns. To address this issue, the study employs a Fixed Effects Instrumental Variable (FE-IV) estimator using lagged values of the Digital Agricultural Index (DAI) and renewable energy consumption (RENE) as instruments. The use of lagged instruments is based on the assumption that past values influence current agricultural technology adoption while remaining uncorrelated with contemporaneous error terms. The FE-IV estimation serves as an additional robustness test to verify whether the baseline results remain consistent after controlling for 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 mobilisation through improvements in technological readiness, institutional capacity, and resource-use efficiency.

Model One: Agricultural Technology Adoption and Green Economy

Model One: Agricultural Technology Adoption and Green Economy

$$CO2_{it} = \beta_0 + \beta_1 DAI_{it} + \beta_2 RENE_{it} + \beta_3 GDPPCGR_{it} + \beta_4 POPU_{it} + \epsilon_{it} \ldots\ldots\ldots 1$$

Model Two: Agricultural Technology Adoption and Climate Financing

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

where:

(CO2) = 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, it is expected that agricultural technology should have a negative effect on green economy ($C0_2$ emissions) while it should exhibits a positive effect on climate financing.

4. Results and Discussion of Findings

Table 1: Descriptive Statistics

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. summarize RENE C02 CFI AGEMP DAI GDPPCGR POLS POPU
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Variable	Obs	Mean	Std. Dev.	Min	Max
RENE	225	1291.612	662.9265	163.0502	2788.386
C02	225	.3186196	.1091003	.1264401	.6218341
CFI	225	570.3367	256.2496	35.3835	1226.072
AGEMP	225	4214.001	7843.866	18.58	36642.06
DAI	225	.4751422	.2567047	.01	.99
GDPPCGR	225	2.052265	3.522698	-20.89375	15.15451
POLS	225	-.5991587	.7998577	-2.729136	.9270694
POPU	225	2.55e+07	4.79e+07	509784	2.33e+08

Table 2: Correlation Matrix

	RENE	C02	CFI	AGEMP	DAI	GDPPCGR	POLS
RENE	1.0000						
C02	0.1648 0.0133	1.0000					
CFI	0.2597 0.0001	0.1041 0.1193	1.0000				
AGEMP	-0.1783 0.0073	-0.2335 0.0004	-0.2178 0.0010	1.0000			
DAI	0.2377 0.0003	-0.0361 0.5898	0.3974 0.0000	0.0328 0.6250	1.0000		
GDPPCGR	0.0964 0.1493	-0.0232 0.7297	0.0297 0.6576	-0.1135 0.0893	0.0069 0.9185	1.0000	
POLS	0.0042 0.9506	0.3155 0.0000	-0.0470 0.4834	-0.5571 0.0000	-0.0169 0.8015	0.1141 0.0878	1.0000
POPU	-0.1424 0.0327	-0.1815 0.0063	-0.2498 0.0002	0.9867 0.0000	0.0572 0.3935	-0.1107 0.0976	-0.5156 0.0000

Table 3: Variance Inflation Factor (VIF)

Variable	VIF	1/VIF
POPU	1.37	0.7291
POLS	1.37	0.7308
GDPPCGR	1.02	0.9832
DAI	1.00	0.9964
Mean VIF	**1.19**	—

Table 4: Sectional Dependency

Variable	CD Statistic	Probability	Decision
RENE	31.488	0.0000	Reject H0 (cross-sectional dependence present)
CO2	1.098	0.2720	Fail to reject H0 (no cross-sectional dependence)
CFI	38.020	0.0000	Reject H0 (cross-sectional dependence present)
DAI	32.801	0.0000	Reject H0 (cross-sectional dependence present)
GDPPCGR	6.889	0.0000	Reject H0 (cross-sectional dependence present)
POLS	-0.297	0.7661	Fail to reject H0 (no cross-sectional dependence)
POPU	39.085	0.0000	Reject H0 (cross-sectional dependence present)

The preliminary diagnostic results indicate that the variables used in the study are suitable for econometric analysis. The descriptive statistics (Table 1) provide an overview of the distribution, central tendency, and variability of the variables across the sampled countries and years, highlighting the existence of variations in renewable energy consumption (RENE), carbon emissions (CO2), climate finance inflows (CFI), digital agricultural innovation (DAI), economic growth (GDPPCGR), political stability (POLS), and population growth (POPU). The correlation matrix (Table 2) reveals the degree and direction of association among the variables and suggests that no excessively high pairwise correlations exist, indicating the absence of serious multicollinearity concerns. This finding is further confirmed by the Variance Inflation Factor (VIF) results presented in Table 3, where all VIF values range from 1.00 to 1.37, with a mean VIF of 1.19, which is far below the conventional threshold of 10. This implies that multicollinearity is not a problem and that the explanatory variables provide distinct information in the regression model. Furthermore, the cross-sectional dependence test results (Table 4) show mixed outcomes across the variables. The null hypothesis of cross-sectional independence is rejected for RENE, CFI, DAI, GDPPCGR, and POPU, as evidenced by their statistically significant CD statistics ($p < 0.05$), indicating the presence of cross-sectional dependence among countries. This suggests that shocks or developments in one country may influence others through regional integration, trade linkages, technological diffusion, or shared environmental factors. Conversely, the null hypothesis cannot be rejected for CO2 and POLS because their probability values exceed 0.05, implying the absence of significant cross-sectional dependence for these variables. Overall, the results justify the adoption of estimation techniques that can account for cross-sectional dependence in the panel dataset to ensure

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	-0.0329768 (0.0220)	-0.0267872 (0.0198)	-0.0015196 (0.0209)
RENE	0.0000198 (0.0000295)	0.0000234 (0.0000248)	0.00000647 (0.0000151)
GDPPCGR	-0.0020652** (0.00105)	-0.0021586 ** (0.00104)	-0.0006585 (0.00058)
POPU	9.70e-10 (7.21e-10)	1.78e-10 (4.66e-10)	-3.84e-10 ** (1.25e-10)
Constant	0.2881233 *** (0.0356)	0.3009645 *** (0.0411)	0.3163996 *** (0.0268)
Observations	225	225	225
Groups (ID)	15	15	15
R^2 (within)	0.0342	0.0285	0.4073
R^2 (overall)	0.0149	0.0066	–
F/Wald Test	F(4,206) = 1.82, Prob > F = 0.1254	Wald chi2(4) = 6.03, Prob > chi2 = 0.1973	Wald chi2(3) = 1.55, Prob > chi2 = 0.6710
Multicollinearity Test VIF Mean	**1.06**	**1.06**	**1.06**
Breusch-Pagan LM Test	$Chi^2(10) = 0.704$ $Prob>Chi^2 = 0.4814$	$Chi^2(10) = 0.704$ $Prob>Chi^2 = 0.4814$	$Chi^2(10) = 0.704$ $Prob>Chi^2 = 0.4814$
Hausman Test	$Chi^2(5)= 1.95$ $Prob > Chi^2 = 0.5827$	$Chi^2 = 1.95$ $Prob > Chi^2 = 0.5827$	$Chi^2 = 1.95$ $Prob > Chi^2 = 0.5827$
Modified Wald Test for Heteroskedasticity	$Chi^2(5) = 2015.39$ $Prob > chi^2 = 0.0000$	$Chi^2(5) = 2015.39$ $Prob > chi^2 = 0.0000$	$Chi^2(5) = 2015.39$ $Prob > chi^2 = 0.0000$

Note: *** represents significant level at 1%, ** at 5% and * at 10*. The dependent variable is digital agricultural index (DIA). Control variables are renewable energy consumption (RENE), GDP per capita growth (GDPPCGR) and population (POPU), while the dependent variable is green economy (C02)

Table 6: Robustness Check

Variable	Driscoll–Kraay Coefficient (Std. Error)	FE (Clustered) Coefficient (Std. Error)
DAI	-0.0329768 (0.0302)	-0.0329768 (0.0401)
RENE	0.0000198 (0.0000314)	0.0000198 (0.0000395)
GDPPCGR	-0.0020652 (0.00133)	-0.0020652 ** (0.00084)
POPU	9.70e-10 ** (2.48e-10)	9.70e-10 (9.30e-10)
Constant	0.2881233 (0.0346)	0.2881233 (0.0525)
Observations	225	225
Groups (ID)	15	15
R^2 (within)	0.0342	0.0342
R^2 (overall)	–	0.0149
F/Wald Test	F(4,14) = 0.82, Prob > F = 0.533	F(4,14) = 1.85, Prob > F = 0.176

Note: *** represents significant level at 1%, ** at 5% and * at 10*. The dependent variable is digital agricultural index (DIA). Control variables are renewable energy consumption (RENE), GDP per capita growth (GDPPCGR) and population (POPU), while the dependent variable is green economy (C02)

Table 7: Endogeneity Check

To address potential endogeneity, the study employed a fixed-effects instrumental variable approach using lagged values of DAI and RENE as instruments. The results remained consistent with the baseline estimates."

Variable	IV (FE) Coefficient (Std. Error)	FE (Clustered) Coefficient (Std. Error)
DAI	-0.1070866 *	-0.0329768
	(0.0570)	(0.0401)
RENE	0.0001288	0.0000198
	(0.0000883)	(0.0000395)
GDPPCGR	-0.0019517 *	-0.0020652 **
	(0.00105)	(0.00084)
POPU	1.44e-09*	9.70e-10
	(8.47e-10)	(9.30e-10)
Constant	0.1702772 *	0.2881233 ***
	(0.0960)	(0.0525)
Observations	210	225
Groups (ID)	15	15
R^2 (within)	–	0.0342
R^2 (overall)	0.0015	0.0149
F/Wald Test	Wald $\chi^2(4) = 278.77$, Prob > $\chi^2 = 0.0000$	F(4,14) = 1.85, Prob > F = 0.176

Note: *** represents significant level at 1%, ** at 5% and * at 10*. The dependent variable is digital agricultural index (DIA). Control variables are renewable energy consumption (RENE), GDP per capita growth (GDPPCGR) and population (POPU), while the dependent variable is green economy (C02)

Discussion

The findings in Table 5 reveal that agricultural technology adoption (DAI) has a negative relationship with CO_2 emissions, although the effect is statistically insignificant in the PCSE estimation. This suggests that increased adoption of digital agricultural technologies has the potential to improve green economy outcomes by enhancing resource-use efficiency, reducing agricultural waste, improving input management, and supporting climate-smart production systems. The negative coefficient obtained from the PCSE model (-0.0015) and the stronger negative effect from the IV-FE model (-0.1071) are consistent with the theoretical expectation that agricultural digitalization contributes to environmental sustainability. This finding aligns with Klerkx et al. (2019), who argued that digital agriculture improves decision-making, precision farming, and efficient resource allocation, thereby supporting sustainable agricultural transformation. Similarly, FAO (2022) emphasized that agricultural automation and digital technologies can reduce environmental pressures by improving productivity while minimizing excessive use of land, water, and agricultural inputs.

The finding also agrees with studies that highlight the role of agricultural technology in climate mitigation and green growth. For instance, Wolfert et al. (2017) noted that data-driven agriculture enables farmers to optimize production processes, reduce inefficiencies, and improve sustainability outcomes. The negative coefficient of DAI after correcting for endogeneity further strengthens this argument, suggesting that the environmental benefits of agricultural technology adoption may be underestimated when potential reverse causality and omitted variable bias are ignored. In the ECOWAS context, where agriculture remains highly vulnerable to climate change and resource constraints, digital technologies such as precision farming, mobile-based advisory services, remote sensing, and smart irrigation systems can contribute to reducing carbon intensity and improving environmental performance.

However, the insignificant effect of DAI in the PCSE and robustness models in Table 6 indicates that technology adoption alone may not automatically lead to a green economy transition. This finding is consistent with Aker (2011), who observed that digital technologies in developing countries often face implementation constraints such as weak infrastructure, limited farmer capacity, affordability challenges, and inadequate institutional support. Therefore, while agricultural technology adoption has a sustainability-enhancing potential, its environmental impact depends on complementary conditions such as climate financing, renewable energy access, effective extension systems, and supportive policy frameworks. The IV-FE result in Table 7 provides further evidence that when these underlying estimation issues are addressed, agricultural technology adoption plays a more meaningful role in reducing environmental degradation.

Overall, the findings support the argument that agricultural technology adoption represents an important pathway toward achieving a green economy in ECOWAS countries. The results extend previous studies by showing that the environmental contribution of digital agriculture becomes more evident after accounting for endogeneity, suggesting that technology-driven agricultural transformation can contribute to carbon reduction and sustainable development. However, the weak short-run impact observed in the baseline models indicates that ECOWAS countries need stronger investments in digital infrastructure, climate-smart agricultural systems, and green financing mechanisms to fully realize the environmental benefits of agricultural technology adoption.

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	257.4594*** (23.6500)	268.3269*** (22.9609)	128.7185*** (40.3733)
RENE	0.2301688*** (0.0318)	0.2157903*** (0.0305)	0.0659891*** (0.0203)
GDPPCGR	1.761311 (1.1324)	1.725219 (1.1310)	0.2312403 (0.9196)
POPU	5.14e-07 (7.75e-07)	1.58e-07 (6.78e-07)	-1.15e-06*** (3.09e-07)
POLS	2.877055 (11.5350)	2.317344 (11.4351)	-2.050544 (17.6759)
Constant	135.6964*** (38.4261)	157.9267** (75.6402)	454.5491*** (49.9377)
Observations	225	225	225
Groups (ID)	15	15	15
R^2 (within)	0.7675	0.7671	0.0367
R^2 (overall)	0.1108	0.1316	–
F/Wald Test	F(5,205) = 135.37, Prob > F = 0.000	Wald chi2(5) = 674.46, Prob > chi2 = 0.000	Wald chi2(5) = 61.01, Prob > chi2 = 0.000
Multicollinearity Test VIF Mean	1.20	1.20	1.20
Breusch-Pagan LM Test	$Chi^2(10) = 3.669$ Prob>$Chi^2 = 0.0002$	$Chi^2(10) = 3.669$ Prob>$Chi^2 = 0.0002$	$Chi^2(10) = 3.669$ Prob>$Chi^2 = 0.0002$
Hausman Test	$Chi^2(5)= 4.41$ Prob > $Chi^2 = 0.3529$	$Chi^2 = 4.41$ Prob > $Chi^2 = 0.3529$	$Chi^2 = 4.41$ Prob > $Chi^2 = 0.3529$
Modified Wald Test for Heteroskedasticity	$Chi^2(5) = 120.89$ Prob > $chi^2 = 0.0000$	$Chi^2(5) = 120.89$ Prob > $chi^2 = 0.0000$	$Chi^2(5) = 120.89$ Prob > $chi^2 = 0.0000$

Note: *** represents significant level at 1%, ** at 5% and * at 10*. The independent variable is the digital agricultural index (DIA). 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 9: Robustness Check

Variable	Driscoll–Kraay Coefficient (Std. Error)	FE (Clustered) Coefficient (Std. Error)
DAI	257.4594 ***	257.4594 ***
	(23.4029)	(30.3558)
RENE	0.2301688 ***	0.2301688 ***
	(0.0306)	(0.0444)
GDPPCGR	1.761311 *	1.761311 *
	(0.8422)	(0.9486)
POPU	5.14e-07	5.14e-07
	(4.32e-07)	(8.69e-07)
POLS	2.877055	2.877055
	(12.6745)	(20.2764)
Constant	135.6964 **	135.6964 **
	(36.0360)	(53.8586)
Observations	225	225
Groups (ID)	15	15
R^2 (within)	0.7675	0.7675
R^2 (overall)	–	0.1108
F/Wald Test	F(5,14) = 109.77, Prob > F = 0.0000	F(5,14) = 51.78, Prob > F = 0.0000

Note: *** represents significant level at 1%, ** at 5% and * at 10*. The independent variable is the digital agricultural index (DIA). 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

To address potential endogeneity, the study employed a fixed-effects instrumental variable approach using lagged values of DAI and RENE as instruments. The results remained consistent with the baseline

estimates."

Variable	IV (FE) Coefficient (Std. Error)	FE (Clustered) Coefficient (Std. Error)
DAI	255.3045 ***	257.4594 ***
	(64.5850)	(30.3558)
RENE	0.3224893 ***	0.2301688 ***
	(0.1007)	(0.0444)
GDPPCGR	1.747603 (1.1843)	1.761311 *
		(0.9486)
POPU	-5.75e-07 (9.47e-07)	5.14e-07
		(8.69e-07)
POLS	13.35413 (14.2498)	2.877055
		(20.2764)
Constant	52.20732 (106.9198)	135.6964 *
		(53.8586)
Observations	210	225
Groups (ID)	15	15
R^2 (within)	0.7207	0.7675
R^2 (overall)	0.1176	0.1108
F/Wald Test	Wald $\chi^2(5) = 21353.40$, Prob > $\chi^2 = 0.0000$	$F(5,14) = 51.78$, Prob > F = 0.0000

Note: *** represents significant level at 1%, ** at 5% and * at 10*. The independent variable is the digital agricultural index (DIA). 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)

Discussion

The result in Table 8 shows that agricultural technology adoption (DAI) has a positive and statistically significant effect on climate financing inflows, with a coefficient of 128.7185 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 improvement in agricultural technology adoption is associated with an increase of approximately 12.87 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. Modern agricultural technologies such as precision agriculture, remote sensing, digital extension services, and climate information platforms enable better identification of climate risks and improve the effectiveness of adaptation and mitigation interventions. 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.

The robustness checks in Table 9 further validate the positive relationship between agricultural technology adoption and climate financing. The Driscoll–Kraay and FE clustered estimations maintain the positive and significant effect of DAI on climate finance, with the coefficient remaining statistically significant at the 1% level. This consistency indicates that the relationship is not sensitive to alternative estimation techniques and remains valid after accounting for possible cross-sectional dependence and within-panel correlation among ECOWAS countries. The robustness evidence strengthens the conclusion that digital agricultural transformation contributes to climate finance mobilisation.

The endogeneity analysis in Table 10 also confirms the reliability of the findings. After applying the fixed-effects instrumental variable approach using lagged values of DAI and renewable energy consumption as instruments, the coefficient of agricultural technology adoption remains positive and significant (255.3045*). The persistence of the effect after controlling for possible reverse causality suggests that the relationship between agricultural technology adoption and climate financing is not merely driven by the possibility that countries receiving more climate finance are those that adopt more technology. Rather, agricultural technology adoption independently contributes to improving access to climate-related financial resources.

Overall, the findings demonstrate that agricultural technology adoption plays a critical role in strengthening climate financing pathways in ECOWAS countries. The evidence suggests that digital agricultural development improves institutional capacity, climate project preparedness, and investment attractiveness, thereby facilitating greater climate finance inflows. This highlights the importance of integrating agricultural digitalization into climate finance strategies to support green economic transformation and climate-resilient agricultural development in the region.

5. Conclusion and Recommendations

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 agricultural adoption significantly enhances climate financing inflows, indicating that improved digital agricultural capacity strengthens countries' ability to attract climate-related investments through better climate information systems, transparency, and 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. Therefore, while agricultural technology adoption provides a pathway for achieving climate resilience and sustainable development, ECOWAS countries need to strengthen digital infrastructure, invest in farmer capacity building, expand access to climate finance, and implement policies that ensure agricultural technologies improve environmental sustainability.

Declarations

Author contributions

Esther Lawal: Conceptualization, literature review, data collection, and drafting of the manuscript.

Ike Okereke: Methodology design, data analysis, interpretation of results, and critical revisions.

Both authors contributed to the final version of the manuscript and approved it for submission.

Clinical trial number:

Not applicable. This study did not involve a clinical trial

Ethics approval and Consent to Participate:

Not applicable. The study relied on secondary data from publicly available sources and did not involve human participants, human tissues, or animals.

Consent for Publication:

Not applicable

Disclosure statement

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Data availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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Figures

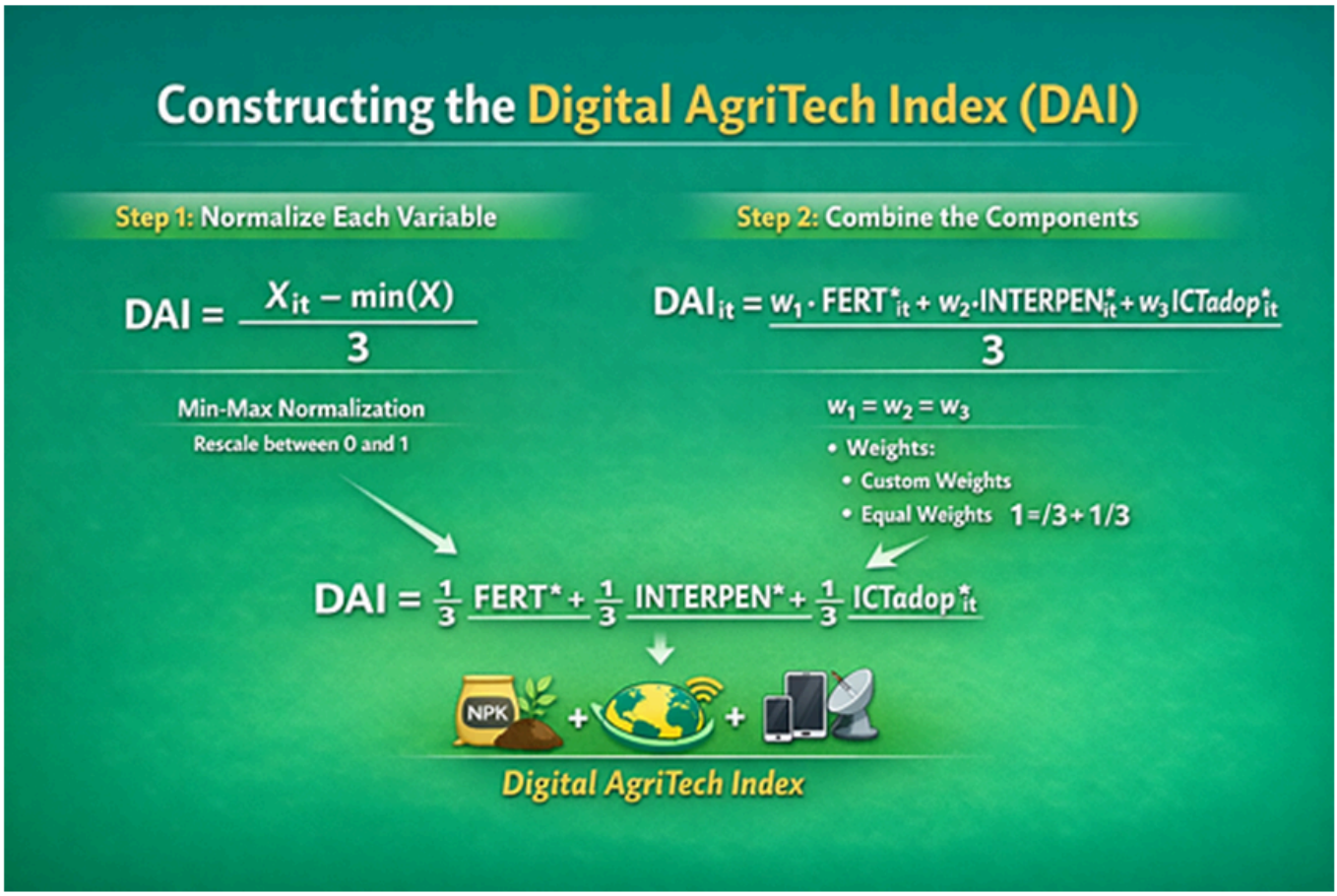


Figure 1

Digital AgriTech Index