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How do green finance, digital technology, trade openness, and climate change interact to shape food production in sub-Saharan Africa?

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Electronic supplementary material (ESM)

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Table S1. Summary of relevant empirical literature reviewed in the study

Authors	Country/region	Study period	Methodology (model used)	Findings
Lee and Song (2024)	China	2009–2020	difference-in-differences (DID)	Green finance reduces food production, primarily due to non-agricultural factors and financial exclusion, and this effect is confirmed by robustness tests.
Yuan et al. (2024)	China	2007–2021	two-way fixed effects mode	Green finance promotes high-quality agricultural development in China, especially in advanced eastern regions, with technology acting as a key mediator. Its effects are non-linear and extend to neighbouring areas through spatial spillovers.
Zhou and Li (2022)	China	1986–2019	autoregressive distributed lag (ARDL)	Green finance and renewable energy are positively linked to sustainable development and negatively associated with carbon emissions in China.
Bah et al. (2025)	sub-Saharan Africa	2001–2022	method of moment quantile regression (MMQR)	Digital technology adoption significantly enhances cereal production over the long term by improving efficiency, optimising resource use, and supporting informed decision-making in agricultural practices.
Abdullahi et al. (2024)	sub-Saharan Africa		panel quantile autoregression distributed lag (PQARDL)	In the long run, climate factors and CO_2 emissions boost agricultural production and trade, while the ecological footprint and ICT have mixed effects. In the short run, ICT and the ecological footprint support agriculture, whereas temperature and CO_2 emissions have negative impacts.
Addai et al. (2024)	sub-Saharan Africa	2003–2018	panel corrected standard error (PCSE) estimator	Mitigated green finance, internet and mobile phone use, and sustainable energy utilisation each have a positive impact on agriculture, forestry, and fishing value added, both individually and collectively.
Shamshiri et al. (2024)	Africa (multiple)		literature synthesis + policy analysis	Despite the numerous benefits of digitalisation, several challenges remain, including high costs, limited reliability, and scalability issues. Many existing systems are custom-built for specific applications and remain too costly for widespread commercial adoption. Others are still in the early stages of development, lacking the reliability and scalability required for broad acceptance and use by farmers.
Dithmer and Abdulai (2017)	sub-Saharan Africa	1980–2007	system generalised method of moments (GMM) approach	Trade openness and economic growth have positive and significant effects on dietary energy consumption and also contribute to greater dietary diversity.
IPCC (2021)	global		intergovernmental report using climate models and scenario projections	Climate change adversely impacts crop yields and water resources, especially in rainfed systems, requiring adaptation strategies.
Thornton et al. (2022)	global		integrated assessment models (IAM) & climate-impact modelling	Climate variability affects livestock and fisheries through heat stress and habitat changes, requiring systemic adaptation responses.

Source: Authors' own construction

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Table S2. List of sub-Saharan Africa countries in our sample

No.	Countries	Regions
1.	Angola	Middle Africa
2.	Benin	Western Africa
3.	Botswana	Southern Africa
4	Burkina Faso	Western Africa
5.	Burundi	Eastern Africa
6.	Cameroon	Middle Africa
7.	Central Africa Republic	Middle Africa
8.	Chad	Middle Africa
9.	Comoros	Eastern Africa
10.	Congo Democratic Republic	Middle Africa
11.	Congo Republic	Middle Africa
12.	Cote d'Ivoire	Western Africa
13.	Djibouti	Eastern Africa
14.	Eritrea	Eastern Africa
15.	Eswatini	Southern Africa
16.	Ethiopia	Eastern Africa
17.	Equatorial Guinea	Middle Africa
18.	Gabon	Middle Africa
19.	Gambia	Western Africa
20.	Ghana	Western Africa
21.	Guinea	Western Africa
22.	Guinea Bissau	Western Africa
23.	Kenya	Eastern Africa
24.	Lesotho	Southern Africa
25.	Liberia	Western Africa
26.	Madagascar	Eastern Africa
27.	Malawi	Eastern Africa
28.	Mali	Western Africa
29.	Mauritania	Western Africa
30.	Mauritius	Eastern Africa
31.	Mozambique	Eastern Africa
32.	Namibia	Southern Africa
33.	Niger	Western Africa
34.	Nigeria	Western Africa
35.	Rwanda	Eastern Africa
36.	São Tomé and Príncipe	Middle Africa
37.	Senegal	Western Africa
38.	Seychelles	Eastern Africa
39.	Sierra Leone	Western Africa
40.	Somalia	Eastern Africa
41.	South Africa	Southern Africa
42.	Tanzania	Eastern Africa
43.	Togo	Western Africa
44.	Uganda	Eastern Africa
45.	Zambia	Eastern Africa
46.	Zimbabwe	Eastern Africa

Source: Authors' own estimation

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Table S3. Shapiro–Wilk test for normal distribution

Variables	Observations	Coefficient	*P*-value
Food production	1 058	0.942***	0.000
Green finance	1 058	0.693***	0.000
Agricultural innovation	1 058	0.633***	0.000
Digital technologies	1 058	0.779***	0.000
Climate change	1 058	0.959***	0.000
Rural population	1 058	0.955***	0.000
Urban population	1 058	0.989***	0.000
Research and development	1 058	0.928***	0.000
Agricultural credit	1 058	0.966***	0.000
Education	986	0.967***	0.000
Foreign direct investment	1 058	0.919***	0.000

***significance at 0.01 level
Source: Authors' own estimation

Table S4. Cross-sectional dependency test result

Variables	CD-test	*P*-value	Corr	Abs(corr)
Food production (kg)	79.91	0.000	0.518	0.671
Green finance	67.14	0.000	0.435	0.591
Agricultural innovation	43.69	0.000	0.283	0.580
Digital technology	147.15	0.000	0.954	0.954
Trade openness	12.44	0.000	0.081	0.402
Natural disaster	16.41	0.000	0.106	0.211
Rural population	87.42	0.000	0.567	0.939
Urban population	147.66	0.000	0.957	0.957

***significance at 0.01 level
CD –
Source: Authors' own estimation

Table S5. Slope heterogeneity test result

Static model	Coefficient	*P*-values
$\hat{\Delta} Statistics$	8.287***	0.000
$\tilde{\Delta}_{adjusted}$	13.220***	0.000
HAC model for autocorrelation		
$\hat{\Delta} Statistics$	11.460***	0.000
$\tilde{\Delta}_{adjusted}$	18.282***	0.000

***significance at 0.01 level
Source: Authors' own estimation

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Table S6. 2^{nd} generation panel unit root test

Variables	Level		1st difference	
	constant	constant & trend	constant	constant & trend
CIPS				
Food production (kg)	–2.676*	–3.088	–5.190***	–5.354***
Green finance	–2.214*	–2.633**	–4.798***	–4.990***
Agricultural innovation	–2.027*	–2.353	–4.321***	–4.415
Digital technology	–1.833	–1.974	–3.656***	–3.694**
Trade openness	–1.746	–2.504*	–4.518***	–4.618***
Natural disaster	–4.080***	–4.186***	–5.761***	–5.783***
Rural population	–1.637***	–1.657*	–1.842**	–2.129***
Urban population	–1.511***	–1.689	–1.779*	–2.439*
CADF				
Food production (kg)	–1.977*	-2.250	–3.563***	–3.876***
Green finance	–1.982*	–2.566**	–3.578***	–3.846***
Agricultural innovation	–1.969*	–2.250	–3.231***	–3.308***
Digital technology	–1.596	–1.969	–2.383***	–2.239**
Trade openness	–1.689	–2.495*	–3.377***	–3.553***
Natural disaster	–3.503***	–3.498***	–4.447***	–4.400***
Rural population	–2.340***	–2.494*	–2.030**	–2.209***
Urban population	–2.096***	–2.353	–1.992*	–2.487*

***, ** and *significance at 1%, 5% and 10% levels, respectively

CIPS –; CADF–

Source: Authors' own estimation

Table S7. Cointegration tests

Kao	Statistic	*P*-value
Modified Dickey–Fuller t	–37.8571	0.000
Dickey–Fuller t	–33.2851	0.000
Augmented Dickey–Fuller t	–18.8848	0.000
Unadjusted modified Dickey–Fuller t	–45.4769	0.000
Unadjusted Dickey–Fuller t	–33.7669	0.000
Pedroni		
Modified Phillips–Perron t	6.6216	0.000
Phillips–Perron t	–32.8395	0.000
Augmented Dickey–Fuller t	–26.6899	0.000
Westerlund		
Variance ratio	–3.0778	0.001

Source: Authors' own estimation