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Impact of digital economy on agricultural land use in sub-Saharan African countries

Zhaohui Qin[1], *Manana Gaddis Elia*[1*], *Mihasina Harinaivo Andrianarimanana*[2], *Tiavina Andriamahenina Nasolomampionona*[1], *Tarir Duok Gai Dhornor*[1], *Winnie Kudzai Mazheti*[1]

[1]*College of Economics and Management, China Three Gorges University, Yichang, P.R. China*
[2]*Management Science and Engineering Post-Doctoral Research Station, China Three Gorges University, Yichang, P.R. China*

**Corresponding author: mananagaddiselia@gmail.com*

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Abstract: This study investigates the effects of digital economy (DE) on agricultural land use (ALU) in seven sub-Saharan African (SSA) countries, specifically from 2006 to 2022. Using a moderating mediation model on panel data, the work explores the extent to which the DE, as proxied by fixed telephone subscriptions, internet usage, and mobile penetration, influences the degree and intensity of ALU. The results indicate that ALU is often supported by DE, as technology will lay the groundwork for improved land management and agriculture. Results show that DE has a positive influence on ALU, with a more substantial effect being observed in countries such as Kenya and South Africa, where more developed digital infrastructure and governance are in place. In contrast, Uganda and Zambia exhibit lower impacts due to lower levels of digitalisation and governance barriers. The patent applications (PAs) and water management represent the positive mediators of the efficiency of land-use improvement. The study highlights the need for government-enabling policies and digital infrastructure so that the promise of digital technologies and their uptake for agricultural production in SSA is fully fulfilled. Whenever technology is integrated with an appropriate resource management policy, SSA societies have the potential to achieve sustainable agricultural development and food security.

Keywords: government effectiveness; digitalisation; patent applications; sustainable agricultural; panel-data analysis

Digital economy (DE) is among the most transformative forces in virtually all sectors globally, especially agriculture. Within sub-Saharan Africa (SSA), where agriculture sector still plays a significant role in economic activity and growth, there is an increasing sentiment that digital technologies *(DT)* are critical for development and sustainability. As reported by the World Bank (Jung and Rogers 2024), *DT* can even boost agricultural productivity *(AP)* by providing and disseminating access to information, therefore improving market efficiency and management.

On the one hand, low land-use efficiency, a demographic pattern in which the population is growing at a faster rate than *AP*, and land degradation compounding the impact of agriculture land use *(ALU)* in SSA sustainable land management, based on agroecological principles, can help to restore land that has been eroded. However, this has limited adoption by

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smallholder farms in SSA (Cordingley et al. 2015). Equally significant, more than 80% of the farmland of SSA is rain-fed, and its productivity is falling with the needs of a growing population (Wang et al. 2023). A digital revolution is currently taking place in SSA, mobilised through various technologies such as mobile phones and the internet to enhance the efficiencies and productivity of smallholders in agriculture. There are also potential digital agriculture approaches that enable women and youth an access to sustainable employment related to agricultural value chains (FAO and ITU 2022). Despite the high ownership of mobile phones and use of the internet, there are challenges – land degradation, substandard farming methods (Nkonya et al. 2016; Kuyah et al. 2021), and climate change, among others, that threaten food safety and well-being of the farmers (Tittonell and Giller 2013).

This study examines how the DE affects *ALU* in SSA, while filling a gap in the literature that overwhelmingly assesses the role DE plays on *AP*, which is not necessarily its direct effect on the efficiency of land use. Although current research focuses on the role of *DT* in increasing *AP* (Zhigulina et al. 2021; Pelucha and Shemetev 2025), the link between these technologies and land resource management in conjunction with the future challenges of this sector remains weak. In an attempt to bridge this gap, this study looks into the role of digital tools and platforms in achieving better utilisation of agricultural land (AL), directly impacting different *ALU* outcomes. Accordingly, recent studies have shown that DE allows more efficient management of land resources through real-time data, access to markets, and precision equipment (Wen and Li 2024). Moreover, advancements in technology like precision farming and digital infrastructures have also been found to be important in improving land-use decisions (Pelucha and Shemetev 2025). Nevertheless, the relationship of DE on *ALU* still lacks detailed exploration in the SSA context and particularly in terms of mediation through innovation policy and infrastructure (Zhigulina et al. 2021). DE can improve agricultural land management and sustainable practices in SSA, and this research investigates the relationship between DE and land use policies and governance structures.

Thus, the current study seeks to fill this gap by examining the impact of DE on *ALU* in SSA countries. Panel data from 2006 to 2022 is used in this research to show to us how exactly we can understand digitisation and to what extent digital tools and digital platforms have the potential to impact land use productivity and sustainability in agriculture (FAO and ITU 2022). Moreover, this study offers novel and recent empirical insights into larger digitalisation-related consequences of *ALU* in a farming-dominated region with many inhabitants whose livelihood depends or substantially on the agri-food sectors (Lindblom et al. 2016). This paper also examines the impact of these *DT* on *ALU*, by utilising a moderated-mediation model, explore the moderating role that market access, and evaluate the effect the infrastructure and policy environment have in mediating this relationship further. Secondly, in contrast to earlier efforts, this study includes four moderators (Figure 1) and

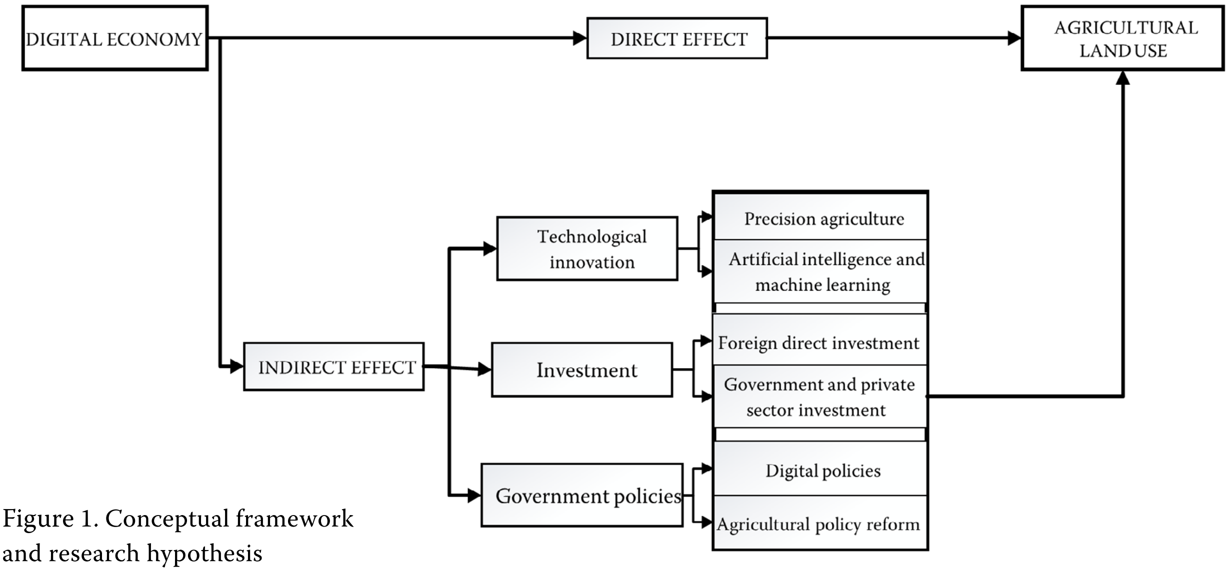

Figure 1. Conceptual framework and research hypothesis

Source: Authors' elaboration

thus delivers a more thorough view of the DE for agricultural land use. Using data from seven countries in the region, this research seeks to shed light on some possible expectations if digital advances brings transformation to agriculture sector in SSA (Mbongo and Djoumessi 2024).

Overall, the goal of this paper is to reveal ways the DE affects *ALU* as exemplified by cases from SSA. The first goal is to understand the real-world impact of digital tools on land use, and to identify technological advances as well as policy mechanisms that can help steer agricultural development towards sustainability (FAO and ITU 2022).

Literature review and hypotheses

For a decade, the expansion of DE has been ubiquitous, which has impacted the agriculture and society in general worldwide, but specifically in SSA. A digitalisation of farming as a fundamental driver that can generate productivity and sustainable growth has recently come into the spotlight. The end goal of this research is to understand the expansion and dynamics of the emergence of new *ALU* in SSA driven by DE, drawn from a literature review. DE has essentially been the driver of the digital financial service and mobile money products such as M-Pesa in Kenya that revolutionised rural economies (Jack and Suri 2011). In agriculture, for instance, DE has increased farmers' ability to perform and produce (Combary 2022) by decreasing transaction costs while allowing new business models to operate. The challenges caused by traditional agriculture limitations, such as market access, weather prediction and practice update, can be addressed with *DT* (Wang et al. 2023). Furthermore, by helping local decision-making and investment in the rural area as well as agricultural input, digital companies could contribute to eco-friendly land optimisation in the different agro-ecological zones across SSA (Ma et al. 2023).

DT has made rapid progress in recent years and has provided some hope for solutions to many of the issues that have beleaguered farming, and in particular, the ability to use land more efficiently. Indeed, the application of *ICT*s in farming is an essential process referred to as digital agriculture, allowing farmers to obtain real-time data on market trends through mobile phones. In recent years, farmers have gained access to the necessary data by using precision-farming tools (Baumüller 2017; Lwoga 2017). *DT* in agriculture has been shown to improve land use efficiency, lower input costs, and boost crop yields, thus contributing to more sustainable farming (Nakasone et al. 2014). Digital transformation in agriculture complements *ALU* through access to real-time market as well as weather information using digital tools, including *ICT* devices, and the Internet of Things, to help smallholder farmers. These technologies increase productivity and minimise the waste of land and resources (Zhong 2023). Data sharing through precision agriculture assists in better decision-making for farmers (Baskent 2021). Data-driven DE can also promote rural development and provide local resistance micro-economies by binding isolated remote areas into the global economic network (Liu et al. 2018). This demonstrates the importance of digitalisation in sustainable land management and a part that reflects changes due to application examples for each sustainable development goal towards climate-resilient agriculture (Mustashkina et al. 2020). The thermal environment is regulated by effective land-use planning and governance, which are critical for enhancing the adaptability and resilience of agricultural regions (Liu et al. 2023). Land surface temperature is becoming not only a key parameter in climate research but also an important indicator for monitoring changes in the thermal environment, both by researchers and policymakers. Such focus strives to better knowledge of the effects of land use and land cover change on thermal contexts (Liao et al. 2022; Rangel-Peraza et al. 2024).

Conceptual framework. The conceptual framework (Figure 1) demonstrated the complex effects of DE on *ALU*, highlighting both direct and indirect effects.

In the end, based on the framework, direct and combined indirect effects from DE are strong determinants of *ALU*. Better connectivity of land, with technology deployment, higher investment and favourable policies ensure that the best practices are used in implementing efficient usage of land.

The direct impact of the DE on ALU: Through connectedness and information, the DE has a positive effect on *ALU* in SSA. Farmers have better access to information such as weather forecasts, market prices, and best agricultural practices, thereby reducing information asymmetries and enhancing decision-making (Jin and Jayne 2013). Thus, scaling up access to DE will contribute to optimised resource use (energy, fertilisers, and seeds per unit harvested on land), and precision farming will reduce waste and increase productivity (Ferroni and Zhou 2012). Additionally, the DE is beneficial for spreading knowledge from other sources, as well as cutting-edge farming techniques that are genuinely feasible in the field, given the effective land use. For example, to promote ideal practices and innovative ideas for managing land in an ecologically sustainable manner, *DT* can be used to connect farmers with peer networks or agricultural experts (Bhaskara and Bawa 2021).

This has a positive impact in terms of how agricultural land is put to use, through tools and relevant data, the most DE, which helps farmers optimise their decision-making when it comes to their properties. Thus, Hypothesis 1 runs as follows:

H_1: The DE has a positive impact on *ALU* in SSA.

Mediating effect of patent applications (PA): Technological innovations are an important determinant of the adoption of *DT* in agriculture and are measured through agro-specific PA, which provide a strong proxy for innovation in SSA agro-systems. PA are the formal documentation of tech advances related to sustainable agriculture, such as PA act as a mediator between DE adoption and *ALU* outcomes. As emphasised in other research, patenting activities covering agricultural technologies are a critical aspect of diffusion in innovations, since patents indicate the likely market value and state of the art of these innovations. Research indicates that technological innovation via PA facilitates the inclusion of DE on agribusiness farms as it directly correlates with farming practices and improves land management efficiency (Yang et al. 2024). This statement also justified the findings presented by Li et al. (2024), which has been of some help by suggesting that sustainable innovations in agriculture driven by patents positively influence land-use practices through the efficient management of resources (Jiang et al. 2023; Li et al. 2023). Additionally, Kang et al. (2024) show that PA are not simply signs of technological progress but also signposts of the manner in which those innovations are making their way to improve land-use. Thus, Hypothesis 2 runs as follows:

H_2: PA acts as a mediator between the DE and *ALU* outcomes.

The moderating role of government policies: Government policies moderate the relationship between DE and *ALU.* Policies that strengthen DE's positive welfare effected by encouraging technology adoption, infrastructure building, and wider access for smallholders will increase its benefits. Examples of the policies that could enhance the adoption of technology in agriculture are those for DL and subsidies to digital tools (Chamberlin et al. 2014). In contrast, the absence of supportive policies may widen inequalities in access to digital tools and infrastructure, with disparate benefits from the DE (Chamberlin et al. 2014). This can lead to smallholdings being excluded and land concentration, counteracting the efforts of enhancing an agricultural spatial use-system in the region. As a result, government policies are needed to make the DE more beneficial for *ALU* in SSA. Thus, Hypothesis 3 runs as follows:

H_3: Government policies play a crucial moderating role in the relationship between the DE and *ALU.*

MATERIAL AND METHODS

Study area

In this study, we explored the impact of DE on *ALU* in 7 SSA countries (Ethiopia, Kenya, Madagascar, South Africa, Sudan, Uganda, and Zambia). The choice of countries is based on the availability of data, which also possess relatively well-developed technological infrastructures and numerous research institutes. Indeed, focusing on this small subset of seven countries allows for the granularity of analysis required of patenting activity and trends in innovation at universities and innovation centres (Addai et al. 2024). Figures 2 and 3 contain a map showing seven SSA countries per percentages of *ALU* and DE.

Data sources

The data used in this analysis are based on the World Bank data (Table 1). Statistical analysis was conducted using the STATA/MP 17.0 software (StatCrop, USA). Map creation was done using the Geographic Information System (QGIS v. 3.28.15).

Dependent variable. Referring to the study by Jaman et al. (2025), *ALU* is the dependent variable, an area that comprises the proportion of total land size used for agricultural activities, such as cultivated lands and pastures where crop farming and livestock are practised. *ALU* is an important variable which needs to be investigated about the principles of land resource allocation in SSA countries, mainly where agriculture contributes significantly to economic growth and food security.

Independent variables. Based on the entropy value method, the independent variables related to DE in SSA refer to the previous studies conducted by Ma and other researchers (Ma et al. 2023; Yao and Sun 2023). *FTS* (Fixed Telephone Subscriptions) is a measure of traditional telecom infrastructure, *MCS* (Mobile Cellular Subscriptions) is for mobile phone usage that gives farmers information about market conditions and weather, and *IUI* (Individuals Using the Internet) is for internet penetration that provides access to extensive data. Mobile technology is extensively used to increase farming productivity. The entropy method consolidates some such factors into a DE index, which provides an objective algorithmic approach to assess

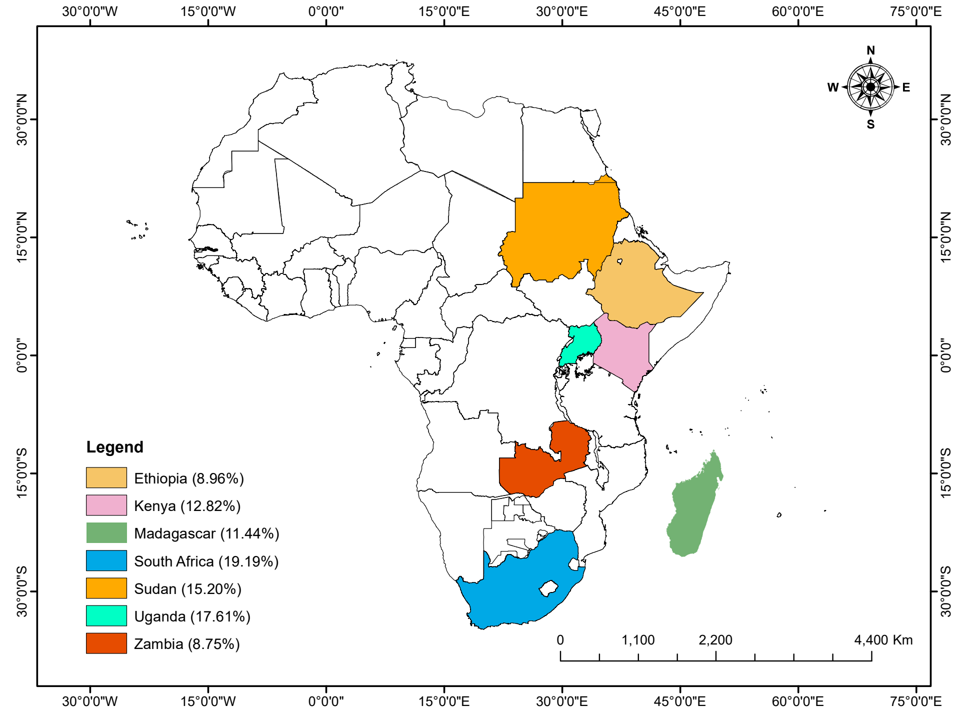

Figure 2. Seven African countries in terms of agriculture land use *(ALU)* percentages

Source: Authors' calculation

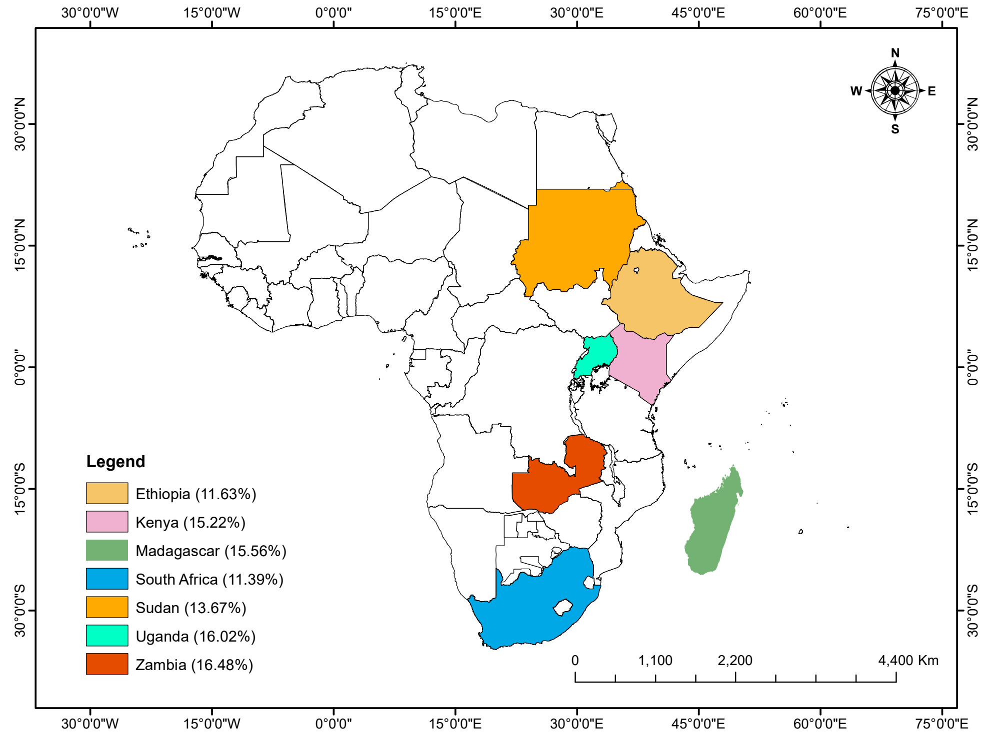

Figure 3. Seven African countries in terms of percentages of digital economy (DE)

Source: Authors' calculation

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Table 1. Variables used in the study

Type	Variables	Notation	Definition
Dependent variables	agricultural land use	*ALU*	the agricultural land variable represents the percentage of land area dedicated to agriculture (% of land area)
Independent variables	digital economy (*DE*)	*FTS*	fixed telephone subscriptions (per 100 people)
		MCS	mobile cellular subscriptions (per 100 people)
		IUI	individuals using the Internet (% of the population)
Mediation variables	technology	*PA*	patent applications, residents, patent applications filed through the Patent Cooperation Treaty procedure or with a national patent office
Moderation variable	government effectiveness	*GE*	government effectiveness: estimate
	water productivity	*WP*	water productivity is calculated as GDP in constant prices divided by annual total water withdrawal
Control variables	investment	*FDI*	foreign direct investment, net inflows (% of GDP)
		EDU	government expenditure on education, total (% of GDP)
	forest area	*FA*	forest area is land under natural or planted stands of trees (% of land area)
	GDP *per capita*	*GDP*	gross domestic product is the total income earned through the production of goods and services in an economic territory during an accounting period
	food production	*FP*	food production index (2014–2016 = 100)

ALU – agricultural land use; *EDU* – education; *FA* – forest area; *FDI* – foreign direct investment; *FP* – food production; *FTS* – fixed telephone subscriptions; *GDP* – gross domestic product *per capita*; *GE* – government effectiveness; *IUI* – individuals using the Internet; *MCS* – Mobile Cellular Subscriptions; *PA* – patent applications; *WP* – water productivity

the conditions of digital activity and its driving forces on farming practices.

Mediation variable. Referring to Zhang et al. (2023), this study's mediation variable is *PA*, which measures innovation in SSA using agriculture as a case scenario. The level of technological development indicates the extent to which farmers have adopted new technologies over time, equivalent to their adoption rate for short-run and long-run outputs such as land upgrading. The intellectual property index reflects the region's innovation potential, which is necessary to harness benefits in the DE and correct agricultural practices.

Moderating variables. Based on the findings presented by Gomes et al. (2022), we tested the interaction effects of *GE* (Government Effectiveness) and DE in SSA. It pointed to the need for quality public services and proper policies. Good governance has been found to enable the uptake of digital agriculture services, as it ensures access to the right infrastructure and support. Water productivity (*WP*) was confirmed as a moderator of water-use efficiency and *ALU*, especially in arid areas.

Control variables. Five control variables are selected based on previous studies (Wang et al. 2023; Xing et al. 2024). *FDI* (Foreign Direct Investment), which boosts economic productivity, may lead to land conversion for agriculture. *EDU* (government Expenditure on Education), as measured by government investment in education, influences human capital formation and *AP* (Nguyen and Nguyen 2023). *GDP per capita* also represents economic status, which may affect the land use type. *FP* (Food production) gives an overview of how much land is used for producing food (Kibria et al. 2023). These factors present an overview related to DE's influence on land use change.

Econometric models

We apply a fixed-effects panel data model to account for unobserved country-specific heterogeneity that is likely to impact the relationship in existence between the DE and *ALU*. In the current study, fixed-effects model controls for country-specific heterogeneity; the so-called time-invariant variables at the country level do not affect the result, as we are only looking at the within-country variation over time. Removing the bias stemming from unobserved country-specific characteristics provides a better estimation of the relationship between DE and *ALU*.

The study investigates the relationship in-between DE, PA, and *GE* (Government Effectiveness). The first step in specifying econometric models, based on the theory analysis conducted by Baron and Kenny (Cerin et al. 2006; Du et al. 2024), are written as follows:

$$ALU_{it} = \beta_0 + \beta_1 DE_{it} + \beta_i X_{it} + \lambda_i + \varepsilon_{it} \tag{1}$$

where: ALU_{it} – agricultural land use variable represents the percentage of land area dedicated to agriculture at time t for country i; DE_{it} – the digital economy at time t for country i; vector X_{it} – other control variables affecting green agriculture development; λ_i – the time fix effect at year t; ε_{it} – a random disturbance term; β_0 – the model intercept term; β_1 – the coefficient of the *DE* variables.

We construct a moderated mediation model with interaction terms to account for potential endogeneity and the robustness [Equations (3 and 4)]. More specifically, we investigate the interaction between *DE* and *GE*, where *GE* is moderator 1, to examine how governance moderates the impact of *DE* on *ALU*. Furthermore, we consider using *PA* as a mediator, with the aim of reflecting the extent to which the impact of *DE* on *ALU* occurs indirectly through technological innovation. We also include *WP* as moderator 2 to examine the interaction effect of *DE* and *PA*, and find out whether *WP* can accelerate *ALU*. These models are written as follows:

$$ALU_{it} = \beta_0 + \beta_1 DE_{it} + \beta_2 Control_{it} + \lambda_i + \varepsilon_{it} \tag{2}$$

$$\begin{aligned} PA_{it} = {} & \propto_0 + \propto_1 DE_{it} + \propto_2 GE_{it} + \propto_3 DE_{it} \times \\ & \times GE_{it} + Control_{it} + \lambda_i + \varepsilon_{it} \end{aligned} \tag{3}$$

$$\begin{aligned} ALU_{it} = {} & \varphi_0 + \varphi_1 DE_{it} + \varphi_2 GE_{it} + \varphi_3 DE_{it} \times \\ & \times GE_{it} + \varphi_4 PA_{it} + \varphi_5 WP_{it} + \varphi_6 PA_{it} \times \\ & \times WP_{it} + \varphi_7 Control_{it} + \lambda_i + \varepsilon_{it} \end{aligned} \tag{4}$$

where: GE_{it} – government effectiveness at time t for country i; $DE_{it} \times GE_{it}$ – the interaction relationship between the *DE* and *GE*: estimate at time t for country i; PA_{it} – patent applications at time t for country i; WP_{it} – water productivity at time t for country i; $\phi_6 PA_{it} \times WP_{it}$ – the interaction relationship between *PA* and *WP* at time t for country i; $\propto_0$ and ϕ_0 – constant individual fixed effects of countries i; $\propto_1$ to $\propto_3$ and ϕ_1 and ϕ_6 – the coefficient of variables.

Equation (2) estimates the direct effect of *DE* on *ALU*, controlling for other variables. Equation (3) brings in *PA* and its interaction with *DE* × *GE*, for which *PA* is an intermediary between *DE* and *ALU*, while independent *GE* predictors are identified. Equation (4) introduces *WP* and its interaction with *PA* × *WP* as additional explanatory variables for their individual effects on *ALU*. In this context, these models seek to examine how *PA* mediates the impact of *DE* on *ALU* by using interaction terms such as *DE* and *PA* × *WP* to reflect potential moderators in the DE–agriculture relationship.

Construction of the DE index

The entropy method provides a systematic method of weighing; it can be used as an index of the complexity and diversity among different countries in an inclusion-level comprehensive index for some years, directly measured from the DE (Arce et al. 2015; Gao and An 2022). Here are the steps for the calculation:

Step 1: Normalisation of the arrays of the decision matrix

$$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{5}$$

Step 2: Computation of the entropy measure of project outcomes using the following equation:

$$E_j = -K \sum_{i=1}^{m} P_{ij} \ln P_{ij} \tag{6}$$

In which:

$$K = 1/\ln(m) \tag{7}$$

Step 3: Defining the objective weight based on the entropy concept:

$$D_j = 1 - E_j \tag{8}$$

$$W_j = \frac{1 - E_j}{\sum_{i=1}^{m} (1 - E_j)} \tag{9}$$

where: m – represents the number of alternatives in the years of evaluation; P_{ij} – the value after standardisation (normalised criteria/sub-criteria rate); x_{ij} – the actual value of evaluation index (criteria/sub-criteria rate); K – entropy constant; E_j – entropy; D_j – diversity; W_j – objective weight of each criteria/sub-criteria.

RESULTS AND DISCUSSION

Statistic description. Table 2 provides descriptive statistics for the variables used in examining the impact of *DE* on *ALU* of 119 observations from SSA countries. The *ALU* has a mean of 56.13 and a range of 30.32 to 80.05, signifying a moderate variation across the levels of land utilisation. The *DE* has a mean of 0.143, relatively low with a small spread (0.0718; –0.211), which indicates that there is room for differences in digital adoption. *PA*, filed by residents, which is diverse (1 to 1 804) and of high standard deviation (325.4), indicates some important differences in innovation intensity between countries. The *GE* averages –0.676, show the structural governance challenges observed in large parts of the region. There is high heterogeneity in *WP* with a mean of 15.54 and *GDP per capita* with a minimum to maximum range between 191.8 to 8 737, demonstrating large economic inequalities. The *FDI* mean is also highly variable (mean = 3.15), but this ranges from slight inflows to 13.45. Finally, we find that *EDU* has a moderate mean of 3.737, and *FA* concentration is limited (mean = 0.081 3). *FP* averaged 98.87, with crop output capacity varying by the type of agricultural output.

Benchmark model. We have tested the relationship between different independent variables, *DE*, *GE*, *PA*, *WP*, *GDP per capita*, *FDI*, and *EDU*, against *ALU* three models 1, 2, and 3 (Table 3).

Model (1) indicates that the *DE* has a positive and significant influence on *ALU* at the 1% significance level. This finding confirms H_1, which proposed that the expansion of DE has a favourable effect on *ALU* in SSA. The positive sign implies that higher levels of digital tools and platforms adoption open new access channels for farmers to the market, climate, and farming information, which results in increasing land productivity. This is consistent with Lio and Liu (2006), that information asymmetry in the use of *ICT* declined, leading to an increase in *AP*. Additionally, Wang et al. (2023) and Schmidt et al. (2023) found that *DT* were *AP* tools. The results were also in accordance with that of Nakasone et al. (2014) who found that *DT* could work in the direction of lowering transaction costs and supporting agricultural value chain governance. In sum, the model suggests that *DE* enhances *ALU* through the increased access to critical resources and information.

In terms of country-specific impacts, the results also indicate that a selection of countries are more sensitive to the *DE*'s influence on *ALU* than others, for instance Kenya (0.058), Madagascar (0.124), and South Africa (0.156) have the highest positive effects of digitalisation on *ALU*, indicating that digital tools significantly contribute positively to land use in these regions. Accordingly, more developed digital infrastructure, stronger governance, as well as better

Table 2. Descriptive statistics

Variable	Observation	Mean	SD	Minimum	Maximum
ALU	119	56.13	17.80	30.32	80.05
DE	119	0.143	0.024 7	0.071 8	0.211
PA	119	181.2	325.4	1	1 804
GE	119	–0.676	0.484	–1.705	0.332
WP	119	15.54	16.02	0.677	64.00
GDP	119	1 873	2 143	191.8	8 737
FDI	119	3.152	2.496	–0.223	13.45
EDU	119	3.737	1.514	1.100	7.050
FA	119	0.081 3	0.060 3	0.026 9	0.226
FP	119	98.87	16.06	55.14	151.8

ALU – agricultural land use; *DE* – digital economy; *EDU* – education; *FA* – forest area; *FDI* – foreign direct investment; *FP* – food production; *GDP* – gross domestic product *per capita* current; *GE* – government effectiveness; *PA* – patent applications; *WP* – water productivity; for the detailed variables explanations and units see Table 1

Source: Authors' calculation

Table 3. Benchmark regression results of the impact of digital economy (*DE*) on agricultural land use (*ALU*)

Variable	Model (1)	Model (2)	Model (3)
DE	0.034*** (0.011)	0.609*** (0.170)	0.067*** (0.014)
GE	–	1.551*** (0.469)	0.161*** (0.038)
DE×*GE*	–	–9.982*** (3.305)	–1.042*** (0.270)
PA	–	–	–0.042*** (0.010)
WP	–	–	–0.062*** (0.017)
PA×*WP*	–	–	1.954*** (0.486)
GDP	0.010 (0.022)	0.394 (0.262)	0.004 (0.020)
FDI	0.022 (0.031)	1.603*** (0.386)	0.063** (0.032)
EDU	–0.030*** (0.005)	0.061 (0.059)	–0.030*** (0.004)
FA	–0.029*** (0.008)	0.020 (0.143)	–0.025** (0.012)
FP	0.021***(0.007)	–0.092 (0.085)	0.016** (0.007)
Kenya	0.058*** (0.001)	0.021** (0.011)	0.057*** (0.001)
Madagascar	0.124*** (0.001)	–0.022 (0.015)	0.123*** (0.001)
South Africa	0.156*** (0.003)	0.130*** (0.032)	0.158*** (0.003)
Sudan	0.090*** (0.001)	0.048*** (0.013)	0.088*** (0.001)
Uganda	0.127*** (0.001)	–0.010 (0.012)	0.127*** (0.001)
Zambia	–0.007*** (0.001)	–0.024** (0.012)	–0.008*** (0.001)
Constant	0.212*** (0.003)	–0.197*** (0.042)	0.206***(0.004)
Observations	119	119	119
R^2	0.714	0.340	0.794
Number of country ID	7	7	7
Year *FE*	yes	yes	yes

*** and **significance at a 1% and 5% levels, respectively; standard errors in parentheses

EDU – education; *FA* – forest area; *FDI* – foreign direct investment; *FE* – fixed-effects; *FP* – food production; *GDP* – gross domestic product *per capita* current; *GE* – government effectiveness; *PA* – patent applications; *WP* – water productivity

Note: Country fixed effects are included using dummies. Reported omitted reference category is Ethiopia. The reported coefficients for other countries are the estimated differences in ALU (as compared to Ethiopia), net of all the other variables described above. The estimation sample includes all 7 countries.

Source: Authors' calculation

adoption of technological innovations in these countries enhance the potential of *DE* to boost *AP*. In contrast, countries such as Zambia (–0.007) and Uganda (0.127) demonstrate weaker effects of *DE* on *ALU*. This shows less maturity in terms of digital infrastructure and governance; thus, the impact of *DE* is limited in these areas. A negative coefficient, like that of Zambia, could be interpreted as digital tools being underutilised, not yet optimised towards *ALU* improvement, or not adequately supported by infrastructure or policy frameworks in place.

Model (2) shows that the interaction terms of *DE* and *GE* negatively and significantly affect *ALU*. This indicates that although the *DE* can promote *ALU*, its effect is limited by *GE*. In particular, the advantages of digital tools are muted in contexts where government incentives and policies may not be optimal for technology adoption. This is in accordance with H_3, which reaffirms the need for such government policies to fully capture maximum gains from the digital transformation in the agriculture sector. The important interaction term suggests that *GE* highly increases the adoption of the digitisation power of *AP*. On the other hand, poor or sluggish government policies can also curtail the positive effects of *DE*. During this period, supportive policy frameworks play an important role in overcoming the barriers to agricultural digitalisation. In contrast, the negative interaction of *DE* and *GE* in Model (2) indicates that *DT* can work to its full potential with the good government policy. Investment in DE can help realise productivity gains, but if accompanied by bad policy, contribute to a smaller share of those gains in remuneration. Governance is important to facilitate digital uptake (Banga and te Velde (2018)). Government acts allowing for DL, infrastructure development, and access to technology are also crucial in achieving optimal land utilisation in the agricultural economy.

As shown in Table 3, at the 1% level, the interaction term for *PA* and *WP* is positive and significant, which indicates the complementarity between technological advancement and effective water resource management over the impact of *DE* on *ALU*. These findings provide support for H_2: technological innovation is a mediator between *DE* and *ALU* outcomes. Sowers found that using better technology and modern agriculture tools, coupled with active management of water, would improve land use. These results are in agreement with Zhang et al. (2023). The results show that greater adoption of technology and enhanced *WP* can emerge as key target strategies for AL resources. Thus, H_2 is confirmed. The interaction of *PA* with *WP* is positive, emphasising the need for technological innovation in conjunction with sustainable resource management. The results imply that positive *ALU* responses to *DE* can be enhanced by patent investment and the efficiency of water. This research outcome is in agreement with that of Finger (2023), who highlighted sustainable farming methods with the intervention of technologies to ensure sustainable productivity and land over a prolonged period of time.

Indeed, the findings provide further evidence that the *DE* can reshape *ALU* in SSA when combined with changes in government policies and technological innovations. Policymakers can harness these advantages by developing a more robust digital infrastructure, investing in the innovation of new technologies, and exercising better governance.

Figure 4 presents the predictive margins with 95% confidence intervals for the impact of *GE* and *WP* on *ALU* in SSA, as influenced by *DE* variables such as *DE* and *PA*.

The graphs show how the interaction of *DE*, *GE*, and *WP* affects *ALU*. In the left-side graph, increasing levels of *GE* (*GE* = 2, *GE* = 3) positively influence *ALU* at low *DE* levels, indicating that strong governance enhances the impact of a nascent *DE*. However, the available predictive margins continue to converge as *DE*

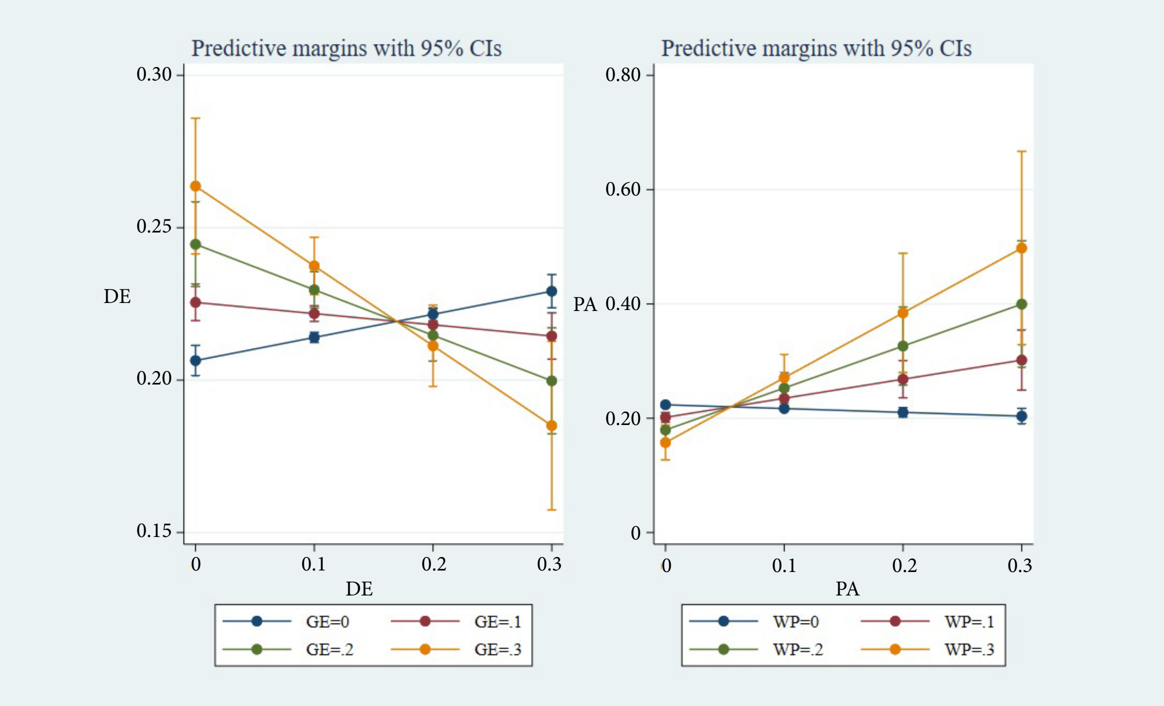

Figure 4. *GE* and *WP* in ALU

ALU – agricultural land use; *DE* – digital economy; *GE* – government effectiveness; *PA* – patent applications; *WP* – water productivity

Source: Authors' calculation

unfolds, signifying diminishing returns; accordingly, governance cannot indefinitely drive *ALU* improvements at advanced stages of *DE*. This may signal a need for dynamic governance models fitting mature *DE*.

Figure 4, in the right-side, highlights the importance of WP in optimising *ALU*. Higher *WP* levels ($WP = 2$, $WP = 3$) correspond with quadratic increases in *PA*, significantly leading to increases in *ALU*, indicating the synergy effect between technological innovation and efficient water management. The phenomenon underlines how innovation can lead to a more efficient use of resources. Taken together, these findings suggest the need for integrated policies that would combine governance, technology and resource management for sustainable, productive agriculture in SSA.

Heterogeneity analysis. This analysis examines the heterogeneity of the *DE*'s impact on *ALU* across different regions, specifically Eastern Africa and Southern Africa.

Comparing Model (3) in Table 3 with the heterogeneity localisation results in Table 4 suggests that the effects of *DE* on *ALU* for Eastern and Southern Africa are positive and significant at 1% and at least at 5% levels, respectively. This validates the positive effect of the development expenses on land-use efficiency and sustains the literature on *DT* in agriculture. DE, in the form of DE, helps farmers to obtain vital data like weather forecasts and the most efficient farming practices that lead to better decision-making and promote higher land productivity (Jack and Suri 2011; Wang et al. 2023). DE also minimises inefficiencies in farm operations and transaction costs while it also generates data-based information on effective deployment of resources (Zhang et al. 2023). However, DE and GE have a significant negative interaction at 5% for the two regions, which is consistent with decreasing returns to scale from integration, which means policies combination between the two must be tailored ones to work as well as their separate outputs (Baumüller 2017). Initial findings for the influence of *DE* on *ALU* are that there is a positive relationship, and this beneficial effect is stronger in smaller markets in Eastern Africa, suggesting the importance of government support to facilitate an uptake of DE.

These findings are consistent with the growing body of literature highlighting the role of *DT* in improving land use efficiency in SSA. DE favours more sustainable production practices by minimising information asymmetries and enhancing access to markets

Table 4. Regression results of heterogeneity localisation.

Variable	Eastern Africa	Southern Africa
DE	0.076*** (0.021)	0.065** (0.025)
GE	0.179** (0.078)	0.136*** (0.045)
DE×*GE*	–1.292** (0.519)	–1.019*** (0.355)
PA	0.033 (0.079)	0.007 (0.022)
WP	–0.086*** (0.031)	0.118** (0.055)
PA×*WP*	–5.939 (5.980)	–0.340 (1.011)
GDP	0.199** (0.086)	–0.005 (0.030)
FDI	0.048 (0.039)	–0.049 (0.057)
EDU	–0.017** (0.007)	–0.010 (0.014)
FA	–0.004 (0.012)	–
FP	–	0.030**(0.013)
Constant	0.202*** (0.006)	0.210*** (0.006)
Observations	68	51
R^2	0.919	0.846
Number of Country ID	4	3
Country FE	yes	yes
Year FE	yes	yes

*** and **significance at a 1% and 5% levels, respectively; standard errors in parentheses

DE – digital economy; *EDU* – education; *FA* – forest area; *FDI* – foreign direct investment; FE – fixed-effects; *FP* – food production; *GDP* – gross domestic product *per capita* current; *GE* – government effectiveness; *PA* – patent applications; *WP* – water productivity

Source: Authors' calculation

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and technologies suited for agriculture (Jin and Jayne 2013). However, the antagonistic role of DE and GE implies that policy measures are required to reinforce the interaction between factors towards synergy. Such policies increase the DL and technology adoption for smallholder farmers to address barriers to digital integration for the benefits of DE in sustainable land use practices (Chamberlin et al. 2014).

Robustness test. Each model includes various independent variables to explain the dependent variable related to *ALU*. The study years are replaced from 2006 to 2015 to ensure the robustness of the empirical results.

Table 5 indicates that *DE* has a positive effect across SSA on *ALU* at 1%, suggesting that an increase in *DE* induces a statistically significant improvement in land use efficiency. The result is consistent with earlier research that has identified the role of DE in the agricultural transformation, mainly using precision farming technologies (Ferroni and Zhou 2012; Nakasone et al. 2014). This research points out that DE reduces information asymmetries, facilitating decision-making with access to market prices, weather and agriculture practices (Jin and Jayne 2013). *DE* is moderated by *GE*, which strengthens the positive effect of *DE* on *ALU*, supporting H_3 that good governance is important for the successful adoption of *DT*. The *PA* variable, however, has a negative relationship to some extent, which shows that innovation itself does not directly serve in increasing land use efficiency. *WP* also has a negative effect on *ALU*, indicating that infrastructure and resource management are important (Liu et al. 2018). However, the *FDI* has a gross positive relation with *AL* that is positively used as *AL*, with the introduction of technology and infrastructure growth.

Table 5. Regression results of the robustness test

Variable	Model (1)	Model (2)	Model (3)
DE	0.038*** (0.014)	0.397*** (0.101)	0.076*** (0.018)
GE	–	0.878*** (0.271)	0.191*** (0.044)
DE×*GE*	–	–4.612** (1.975)	–1.126*** (0.307)
PA	–	–	–0.066** (0.027)
WP	–	–	–0.220*** (0.056)
PA×*WP*	–	–	4.001*** (1.161)
GDP	0.027 (0.047)	–0.327 (0.263)	0.067 (0.040)
FDI	0.050 (0.055)	0.681** (0.304)	0.101** (0.046)
EDU	–0.019*** (0.007)	0.036 (0.039)	–0.026*** (0.006)
FP	0.010 (0.012)	–0.086 (0.066)	0.018* (0.010)
Kenya	0.060*** (0.001)	0.026*** (0.008)	0.050*** (0.003)
Madagascar	0.128*** (0.002)	–0.007 (0.011)	0.119*** (0.003)
South Africa	0.157*** (0.006)	0.208*** (0.033)	0.145*** (0.007)
Sudan	0.092*** (0.002)	0.064*** (0.012)	0.081*** (0.003)
Uganda	0.130*** (0.002)	0.006 (0.010)	0.126*** (0.002)
Zambia	–0.006*** (0.002)	–0.008 (0.012)	–0.018*** (0.003)
Constant	0.207*** (0.005)	–0.078** (0.030)	0.202*** (0.005)
Observations	70	70	70
R^2	0.622	0.486	0.793
Number of Country ID	7	7	7
Year FE	yes	yes	yes

*** and **significance at 1% and 5% levels, respectively; standard errors in parentheses

DE – digital economy; *EDU* – education; *FA* – forest area; *FDI* – foreign direct investment; FE – fixed-effects; *FP* – food production; *GDP* – gross domestic product *per capita* current; *GE* – government effectiveness; *PA* – patent applications; *WP* – water productivity

Source: Authors' calculation

CONCLUSION

This study aims to analyse the role of the DE on *ALU* in SSA with close attention to how *DT* can promote land use efficiency among the various countries in the region. Using panel data from seven SSA countries for the period 2006 to 2022, a moderated-mediation model to assess the direct, mediating, and moderating effects of technology adoption, *GE*, *WP*, and *PA* was applied. The purpose of the study was to offer new empirical grounding to the systemic influence of DE on *ALU* and also encourage critical discussion about regional differentials and policy at higher levels of governance.

The research proves that DE has a positive impact on *ALU*, which is consistent with previous literature about the contribution of *DT* in increasing *AP*. *GE* substantially moderates the effect of *DE* on *ALU*, and where governance systems are stronger, more land-use efficiency improvements can be observed. Kenya and South Africa experienced the most favourable results, with strengthened infrastructure, digital platforms and governance features. Uganda and Zambia, by contrast, revealed smaller impacts driven in part by infrastructure and governance constraints. Finally, the relationship between *DE* and *PA* also symbolises that our *ALU* cannot simply increase by merely bearing innovation; policy is necessary. The results call for a scale of digital infrastructure, enhancement in developable DL, and the incorporation of technological innovations into the policy framework to maximise land utilisation and sustainable agriculture for SSA.

This study does, however, have several limitations. Observed heterogeneity in agricultural practices across SSA means that findings may not be fully representative of all contexts, particularly in rural places where access to *DT* is limited. Also, the data limitations in terms of socio-economic factors like access to credit, education, and land tenure were not explored (as these factors may also impact the adoption of *DT*). Future research can explore the dynamics within these constraints and their effect on technology uptake, especially in more heterogeneous rural contexts. Additionally, long-term studies that would look at long-duration impacts of groundwater digitalisation and DL on *ALU* would contribute to understanding the sustainable impacts of these interventions.

The study is illuminating but has limitations. Agricultural practices and production systems in SSA are, for example, so diverse that available empirical data may not be representative of such diversity. *DT* effectiveness is context-dependent, which may be determined by climate, infrastructure and governance, among other factors. Furthermore, dataset biases, e.g. as a consequence of stale land use information or incomplete technology coverage, hamper analysis. No socio-economic factors, such as available credit or education, are taken into account, but will be explored in future studies of digital innovations. Future research directions: long-term impacts of groundwater digitalisation on sustainability; the relationship between DL and technology acceptance; and comparative studies by regions. It is important to study how digital tools improve transparency, market access and land use efficiency for smallholder farmers.

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REFERENCES

Addai K., Yufenyuy M., Kifem F.L. (2024): Do green finance and digital technology matter for sustainable agricultural development? Insights from sub-Saharan Africa. Discover Agriculture, 2: 29.

Banga K., te Velde D.W. (2018): Digitalisation and the Future of Manufacturing in Africa. London, ODI. Available at https://set.odi.org/digitalisation-manufacturing/

Baskent E.Z. (2021): Assessment and improvement strategies of sustainable land management (SLM) planning initiative in Turkey. Science of the Total Environment, 797: 149183.

Baumüller H. (2017): The little we know: An exploratory literature review on the utility of mobile phone-enabled services for smallholder farmers. Journal of International Development, 30: 134–154.

Bhaskara S., Bawa K.S. (2021): Societal digital platforms for sustainability: Agriculture. Sustainability, 13: 5048.

Cerin E., Taylor L.M., Leslie E., Owen N. (2006): Small-scale randomized controlled trials need more powerful methods of mediational analysis than the Baron-Kenny method. Journal of Clinical Epidemiology, 59: 457–464.

Chamberlin J., Jayne T.S., Headey D. (2014): Scarcity amidst abundance? Reassessing the potential for cropland expansion in Africa. Food Policy, 48: 51–65.

Combary O.S. (2022): Farm productivity under financial constraints in developing countries: Evidence from maize smallholder farmers in Burkina Faso. Agricultural and Resource Economics Review, 51: 380–390.

Cordingley J.E., Snyder K.A., Rosendahl J., Kizito F., Bossio D. (2015): Thinking outside the plot: Addressing low adoption of sustainable land management in sub-Saharan Africa. Current Opinion in Environmental Sustainability, 15: 35–40.

Du Y., Liu Q., Kim P.H., Meuer J. (2024): Studying complex causal processes in technological innovation and entrepreneurship with set-theoretic mediation models. Technovation, 134: 103015.

Elena Arce M., Saavedra Á., Míguez J.L., Granada E. (2015): The use of grey-based methods in multi-criteria decision analysis for the evaluation of sustainable energy systems: A review. Renewable and Sustainable Energy Reviews, 47: 924–932.

Eyike Mbongo L.B., Djoumessi Y.F. (2024): Connecting the fields: How ICT improve agricultural productivity in sub-Saharan Africa. Review of Development Economics, 28: 888–903.

FAO and ITU (2022): Status of Digital Agriculture in 47 sub-Saharan African Countries. Rome, Food and Agriculture Organization and Geneva, International Telecommunication Union. Available at https://doi.org/10.4060/cb7943en

Ferroni M., Zhou Y. (2012): Achievements and challenges in agricultural extension in India. Global Journal of Emerging Market Economies, 4: 319–346.

Finger R. (2023): Digital innovations for sustainable and resilient agricultural systems. European Review of Agricultural Economics, 50: 1277–1309.

Gao X., An R. (2022): Research on the coordinated development capacity of China's hydrogen energy industry chain. Journal of Cleaner Production, 377: 134177.

Gomes S., Lopes J.M., Ferreira L. (2022): The impact of the digital economy on economic growth: The case of OECD countries. RAM: Revista de Administração Mackenzie, 23.

Jack W., Suri T. (2011): Mobile money: The economics of M-PESA. Cambridge, NBER – National Bureau of Economic Research. Available at https://doi.org/10.3386/w16721

Jaman M.H., Roy S., Chatterjee J., Das S., Mistri P., Sengupta S. (2025): Integrating agricultural land suitability and farmers' perception on crop selection in a water-stressed region of eastern India. Agricultural Systems, 222: 104171.

Jiang S., Wang L., Xiang F. (2023): The effect of agriculture insurance on agricultural carbon emissions in China: The mediation role of low-carbon technology innovation. Sustainability, 15: 4431.

Jin S., Jayne T.S. (2013): Land rental markets in Kenya: Implications for Efficiency, equity, household income, and poverty. Land Economics, 89: 246–271.

Jung S., Rogers M. (2024): Mobile phone adoption, deforestation, and agricultural land use in Uganda. World Development, 179: 106618.

Kang H., Fu M., Kang H., Li L., Dong X., Li S. (2024): The Impacts of urban population growth and shrinkage on the urban land use efficiency: A case study of the northeastern region of China. Land, 13: 1532.

Kibria M.G., Aspy N.N., Ullah E., Dewan M.F., Hasan M.A., Hossain M.A., Haseeb M., Hossain M.E. (2023): Quantifying the effect of agricultural greenhouse gas emissions, food production index, and land use on cereal production in South Asia. Journal of Cleaner Production, 432: 139764.

Kuyah S., Sileshi G.W., Nkurunziza L., Chirinda N., Ndayisaba P.C., Dimobe K., Öborn I. (2021): Innovative agronomic practices for sustainable intensification in sub-Saharan Africa. A review. Agronomy for Sustainable Development, 41: 16.

Li J., Sun Z., Zhou J., Sow Y., Cui X., Chen H., Shen Q. (2023): The impact of the digital economy on carbon emissions from cultivated land use. Land, 12: 665.

Li Y., Herzog F., Levers C., Mohr F., Verburg P.H., Bürgi M., Dossche R., Williams T.G. (2024): Agricultural technology as a driver of sustainable intensification: Insights from the diffusion and focus of patents. Agronomy for Sustainable Development, 44: 14.

Liao Y., Shen X., Zhou J., Ma J., Zhang X., Tang W., Chen Y., Ding L., Wang Z. (2022): Surface urban heat island detected by all-weather satellite land surface temperature. Science of the Total Environment, 811: 151405.

Lindblom J., Lundström C., Ljung M., Jonsson A. (2016): Promoting sustainable intensification in precision agriculture: Review of decision support systems development and strategies. Precision Agriculture, 18: 309–331.

Lio M., Liu M.C. (2006): ICT and agricultural productivity: Evidence from cross-country data. Agricultural Economics, 34: 221–228.

Liu X., Zeng S., Namaiti A., Xin R. (2023): Comparison between three convolutional neural networks for local climate zone classification using Google Earth Images: A case study of the Fujian Delta in China. Ecological Indicators, 148: 110086.

Liu Y., Li J., Yang Y. (2018): Strategic adjustment of land use policy under the economic transformation. Land Use Policy, 74: 5–14.

Lwoga E.T. (2017): Bridging the agricultural knowledge and information divide: The case of selected telecenters and rural radio in Tanzania. The Electronic Journal of Information Systems in Developing Countries, 43: 1–14.

Ma Y., Xiao Q., Lin T. (2023): A Study on the impact of digital economy on agricultural green total factor productivity — Empirical analysis based on mediating effect and threshold effect. In: Yen J., Abedin M.Z., Wan Ngah W.A.S.B.: Proceedings of the 2nd International Academic Conference on Blockchain, Information Technology and Smart

Finance (ICBIS 2023). Hangzhou, P.R. China, Feb 17–19, 2023: 548–563.

Mustashkina D.A., Karpova N.V., Makarov A.S., Khannanov M.M. (2020): Agricultural development using digital technologies. BIO Web of Conferences, 27: 00042.

Nakasone E., Torero M., Minten B. (2014): The power of information: The ICT revolution in agricultural development. Annual Review of Resource Economics, 6: 533–550.

Nguyen C.P., Nguyen B.Q. (2023): Environmental foe or friend: The influence of the shadow economy on forest land. Land Use Policy, 124: 106456.

Nkonya E., Mirzabaev A., von Braun J. (2016): Economics of Land Degradation and Improvement – A Global Assessment for Sustainable Development. Cham, Springer: 21–22.

Pelucha M., Shemetev A. (2025): Unravelling the link between land use policy and digital infrastructure: Insights from Czech rural communities. Land Use Policy, 150: 107452.

Rangel-Peraza J.G., Sanhouse-Garcia A.J., Flores-Gonzalez L.M., Monjardin-Armenta S.A., Mora-Felix Z.D., Renteria-Guevara S.A., Bustos-Terrones Y.A. (2024): Effect of land use and land cover changes on land surface warming in an intensive agricultural region. Journal of Environmental Management, 371: 123249.

Schmidt D., Butturi M.A., Sellitto M.A. (2023): Opportunities of digital transformation in post-harvest activities: A single case study of an engineering solutions provider. AgriEngineering, 5: 1226–1242.

Tittonell P., Giller K.E. (2013): When yield gaps are poverty traps: The paradigm of ecological intensification in African smallholder agriculture. Field Crops Research, 143: 76–90.

Wang J., Lin Q., Zhang X. (2023): How does digital economy promote agricultural development? Evidence from sub-Saharan Africa. Agriculture, 14: 63.

Wen R., Li H. (2024): Impact of digital economy on urban land green use efficiency: Evidence from Chinese cities. Environmental Research Communications, 6: 055008.

Xing H., Feihu Y., Yating L. (2024): Digital economy, government efficiency, and regional administrative monopolies: Evidence from China. Economic Analysis and Policy, 84: 1807–1819.

Yang C., Ji X., Cheng C., Liao S., Obuobi B., Zhang Y. (2024): Digital economy empowers sustainable agriculture: Implications for farmers' adoption of ecological agricultural technologies. Ecological Indicators, 159: 111723.

Yao W., Sun Z. (2023): The impact of the digital economy on high-quality development of agriculture: A China case study. Sustainability, 15: 5745.

Zhang Y., Ji M., Zheng X. (2023): Digital economy, agricultural technology innovation, and agricultural green total factor productivity. Sage Open, 13.

Zhigulina T.N., Luchnikova N.M., Lebedeva V. L. (2021): Transformations in agricultural land use: through changes in land functions to changes in information support for land management. IOP Conference Series: Earth and Environmental Science, 677: 042097.

Zhong X. (2023): Agricultural and rural digitalisation in regional sustainable development: A comparative study between China and the European Union. Cognitive Sustainability, 2.

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