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Original Research Article

Digital Readiness and Agricultural Productivity in ASEAN: A Fertilizer-Intensity Threshold Analysis

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Abstract: Digital readiness is widely expected to improve agricultural productivity, yet its benefits may differ across agricultural systems with varying input-use conditions. This study examines whether the productivity relevance of national-level digital readiness in ASEAN changes across fertilizer-intensity regimes. Evidence from ten ASEAN economies over 2011–2023, based on a fixed-effects threshold design, indicates a non-linear pattern. Below the estimated fertilizer-intensity threshold of 44.17 kg/ha, digital readiness is not significantly associated with agricultural productivity; above the threshold, the association becomes positive and statistically significant (coefficient = 0.210). The findings suggest that digital connectivity alone does not automatically translate into productivity gains; its value appears stronger where agricultural systems provide greater scope to adjust inputs and act on information. Fertilizer intensity is therefore interpreted as an observable indicator of input-use conditions rather than a direct measure of commercialisation, management quality, or precision agriculture adoption. The study contributes to the digital-agriculture literature by showing that the productivity relevance of digital readiness is conditional rather than uniform across ASEAN. The results support policies that combine digital infrastructure with extension services, input access, rural finance, and farmers' capacity to use digital information. The estimated threshold should nevertheless be understood as a sample-specific statistical boundary rather than an agronomic recommendation or commercialisation benchmark.

Keywords: Digital readiness; Agricultural productivity; ASEAN; Fertilizer intensity; Threshold analysis

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1. Introduction

Digital technologies can improve access to market prices, weather information, production advice, and input-related knowledge, thereby reducing information and communication costs in agriculture (Aker, 2011). Recent evidence also links digitalisation with improved agricultural performance in ASEAN, although the gains vary across countries and production systems (Thann *et al.*, 2025). Information alone may not alter production outcomes when farmers face constraints in finance, inputs, infrastructure, or extension support (Feder *et al.*, 1985; Fabregas *et al.*, 2019). The productivity relevance of digital readiness may therefore depend on whether agricultural systems allow information to be translated into production decisions.

This issue is particularly important in ASEAN, where agricultural productivity, input use, rural structure, and digital infrastructure differ substantially across member countries. Digital-agriculture adoption remains uneven because affordability, institutional coordination, farmer capability, and supporting services vary across national and local settings (Montesclaros & Teng, 2023). Regional policy increasingly recognises digital technologies as part of agricultural and food-system development, but similar improvements in digital infrastructure may still generate different productivity outcomes across the region (Kozono *et al.*, 2024).

A distinction is therefore required between national digital readiness and farm-level technology adoption. In this study, digital readiness refers to the national information and communication technology environment represented by internet users, mobile cellular subscriptions, fixed broadband subscriptions, and secure internet servers. The index captures the wider enabling environment in which farmers, service providers, and public agencies operate. It does not measure the direct use of digital advisory applications or precision-agriculture technologies. Digital agriculture involves interactions among technologies, institutions, services, and users rather than infrastructure alone (Klerkx *et al.*, 2019).

Existing research generally supports the contribution of ICT to agricultural development, but cross-country evidence remains limited on whether its productivity relevance changes across agricultural input-use conditions. Agricultural technology adoption is shaped by liquidity, risk, complementary inputs, and farmers' ability to adjust production practices (Feder *et al.*, 1985). Similar constraints affect the use of digital extension services among smallholders in Southeast Asia (Sen *et al.*, 2024). Average-effect estimates may therefore conceal differences between lower- and higher-input production systems.

Fertilizer intensity provides an observable indicator for examining this heterogeneity. It measures fertilizer nutrient use per hectare and may reflect the extent to which production involves adjustable decisions concerning input quantity, timing, and allocation. However, it is not a direct measure of commercialization, production maturity, management quality, or precision-agriculture adoption. Fertilizer use may also vary because of crop composition, soil conditions, prices, subsidies, climate variability, or inefficient application. It is therefore treated as an indicator of input-use intensity rather than as a normative measure of agricultural development.

The objective of this study is to examine whether the association between national digital readiness and agricultural productivity varies across fertilizer-intensity conditions in ASEAN. The following research questions are addressed:

RQ1: Is national-level digital readiness associated with agricultural productivity in ASEAN after country-specific characteristics and common regional shocks are taken into account?

RQ2: Does the association between national-level digital readiness and agricultural productivity differ across fertilizer-intensity levels?

Using a balanced panel of ten ASEAN economies over 2011–2023, the study applies a fixed-effects threshold design. It contributes to the digital-agriculture literature by distinguishing the national ICT enabling environment from farm-level technology adoption and by testing whether the productivity relevance of digital readiness differs across input-use regimes.

2. Literature Review

2.1. Digital Readiness and Agricultural Productivity

Digital technologies may support agricultural productivity by reducing information frictions and improving access to market prices, weather forecasts, extension advice, and input-related knowledge (Aker, 2011). Digital services can extend agricultural information beyond conventional advisory systems, although information provision alone does not ensure changes in farm practices or production outcomes (Fabregas *et al.*, 2019).

National digital readiness reflects the broader ICT environment in which farmers, service providers, and public institutions operate. Farm-level digitalisation additionally depends on affordability, skills, institutional arrangements, and the relevance of available services (Klerkx *et al.*, 2019; Wolfert *et al.*, 2017). Improved connectivity therefore cannot be treated as direct evidence of technology adoption.

This distinction is visible in ASEAN. Regional evidence associates technological advancement and digitalisation with stronger agricultural performance (Chandio *et al.*, 2023; Thann *et al.*, 2025). However, the adoption and continued use of digital agricultural services remain uneven because farmer capability, service quality, institutional coordination, and local production constraints differ across countries and communities (Montesclaros & Teng, 2023; Sen *et al.*, 2024). Digital readiness may consequently have different productivity implications across agricultural environments.

2.2. Complementary Assets and Agricultural Input-Use Conditions

Agricultural technologies rarely produce comparable outcomes across production systems. Adoption decisions are shaped by liquidity, risk, expected returns, input access, and farmers' ability to modify established practices (Feder *et al.*, 1985; Foster & Rosenzweig, 2010). Evidence from developing agriculture similarly shows that technology effects depend on local constraints, complementary resources, and institutional support rather than technical availability alone (Ruzzante *et al.*, 2021; Takahashi *et al.*, 2020).

These conditions also affect the value of digital information. Advice concerning fertilizer application, irrigation, pest control, or planting schedules may have limited operational value when farmers lack the finance, input, or flexibility required to implement it (Fabregas *et al.*, 2019; Takahashi *et al.*, 2020). Digital readiness is therefore better understood as an enabling condition whose productivity relevance may vary with the capacity to act on information.

Precision agriculture technologies illustrate this complementarity because they are intended to improve the timing, quantity, and spatial allocation of inputs rather than simply increase their use (Bongiovanni & Lowenberg-DeBoer, 2004; Gebbers & Adamchuk, 2010). Their effectiveness also depends on usability, decision context, and implementation capacity (Rose *et al.*, 2016). The present study does not measure precision agriculture adoption. Instead, it examines whether the productivity association of national digital readiness differs across observable agricultural input-use conditions.

2.3. Fertilizer Intensity as a Conditioning Indicator

Fertilizer intensity, measured as nutrient use per hectare, provides an observable indicator of agricultural input use. It captures differences in the quantity of purchased nutrients entering production and may reflect the scope of decisions concerning input quantity, timing, and allocation. However, agricultural commercialisation involves broader changes in markets, capital use, labour allocation, and production organisation; fertilizer use alone cannot represent this process (Pingali, 2012).

Higher fertilizer intensity also does not necessarily indicate greater efficiency, stronger management, or a more advanced production system. Nitrogen, a major component of fertilizer use, displays substantial cross-country variation because technological and socioeconomic conditions influence both nutrient application and use efficiency (Zhang *et al.*, 2015). Climate conditions, farm structure, crop composition, soil characteristics, and policy incentives may also affect fertilizer use, efficiency, and nutrient losses (Ren *et al.*, 2023; Zhang *et al.*, 2015).

Despite these limitations, fertilizer intensity remains an internationally comparable and continuously measured indicator of input use. It is therefore suitable for testing whether the productivity relevance of digital readiness varies across agricultural input-use conditions at the country level. The variable is used as a conditioning indicator rather than a direct measure of commercialisation, production maturity, management quality, or technological adoption.

The threshold analysis tests whether the association between digital readiness and agricultural productivity differs across lower- and higher-input regimes. Any estimated threshold is interpreted as a sample-specific statistical boundary, not as an agronomic target, a commercialisation standard, or a minimum requirement for precision-agriculture adoption.

3. Data and Methodology

3.1. Sample and Data Integration

The study uses a balanced panel of ten Association of Southeast Asian Nations (ASEAN) economies from 2011 to 2023: Brunei Darussalam, Cambodia, Indonesia, Lao PDR, Malaysia, Myanmar, the Philippines, Singapore, Thailand, and Viet Nam. This period provides a consistent common data window for the variables included in the analysis, while data from 2010 are used to construct the one-year lagged explanatory variables. The balanced design maintains consistent country and year coverage across the sample.

Agricultural productivity, digital-readiness indicators, and control variables are obtained from the World Bank's World Development Indicators, while fertilizer-use data are drawn from FAOSTAT (Food and Agriculture Organization of the United Nations, 2024; World Bank, 2024). The datasets are merged at the country-year level. All explanatory variables enter the models with a one-year lag to establish temporal ordering between the explanatory variables and agricultural productivity.

The data-processing workflow was implemented in Python. The ICT indicators were standardised before aggregation, while nitrogen, phosphate, and potash nutrients were combined to measure total fertilizer use per hectare. The final balanced panel contains 130-year observations. Table 1 reports the descriptive statistics.

Table 1. Descriptive statistics

Variable	N	Mean	SD	Min	Median	Max
Agricultural productivity, ln	130	8.363	1.3	6.939	7.966	10.94
Digital readiness	130	−0.051	0.776	−1.639	−0.135	2.696
Fertilizer intensity, ln	130	4.412	0.84	2.492	4.691	5.624
Fertilizer intensity, kg/ha, lagged	130	109.258	74.899	11.080	107.960	276.099
Digital × fertilizer	130	0.152	3.305	−4.75	−0.526	12.832
GDP per capita, ln	130	8.525	1.224	6.822	8.11	11.114
Agricultural employment share	130	31.42	21.865	0.098	31.726	77.432
Rural population share	130	46.663	22.331	0.0	49.954	77.01

Note. The table reports descriptive statistics for the model-ready ASEAN panel, 2011–2023. All explanatory variables are lagged by one year. Fertilizer intensity in kg/ha is reported for interpretation; regression models use the logarithmic measure.

3.2. Variable Construction

Agricultural productivity is measured as the natural logarithm of agriculture, forestry, and fishing value added per worker in constant 2015 US dollars (World Bank, 2024). Digital readiness is represented by a composite index constructed from four WDI indicators: internet users, mobile cellular subscriptions, fixed broadband subscriptions, and secure internet servers. Each component is standardised before aggregation to ensure comparability across different measurement units (OECD & European Commission, 2008). A country-year observation is retained when at least two ICT components are available. The resulting index represents the national ICT enabling environment rather than the direct adoption of digital technologies at the farm level.

Fertilizer intensity is measured as the natural logarithm of total fertilizer nutrient use per hectare plus one, expressed as $\ln(kg/ha + 1)$. It is used as an observable and internationally comparable indicator of agricultural input-use intensity. The measure may reflect the extent to which production involves decisions concerning nutrient quantity, timing, and allocation, but it does not directly represent commercialisation, production maturity, management quality, fertilizer-use efficiency, or precision-agriculture adoption. Fertilizer use may also vary with crop composition, soil conditions, climate, prices, subsidies, and application efficiency. Its role in the analysis is therefore limited to testing whether the productivity association of digital readiness varies across input-use conditions.

The control variables include the natural logarithm of GDP per capita, agricultural employment as a share of total employment, rural population share, arable land share, and agriculture value added as a share of GDP. Table 2 presents the variable definitions and data sources.

Table 2. Variable definitions and data sources

Variable	Definition / construction	Source
Agricultural productivity	ln (agricultural value added per worker, constant 2015 US$).	World Bank WDI
Digital readiness	Lagged composite index from standardised ICT indicators.	World Bank WDI
Fertilizer intensity	Lagged ln (total fertilizer nutrient use per hectare + 1).	FAOSTAT
Digital readiness × fertilizer intensity	Interaction between mean-centred digital readiness and fertilizer intensity.	Author calculation
Below-threshold digital readiness	Digital readiness interacted with the below-threshold regime indicator.	Author calculation
Above-threshold digital readiness	Digital readiness interacted with the above-threshold regime indicator.	Author calculation
GDP per capita	Lagged ln (GDP per capita, constant prices).	World Bank WDI
Agricultural employment share	Lagged agricultural employment as a share of total employment.	World Bank WDI
Rural population share	Lagged rural population as a share of total population.	World Bank WDI
Arable land share	Lagged arable land as a share of land area.	World Bank WDI
Agriculture value-added share	Lagged agriculture, forestry and fishing value added as a share of GDP.	World Bank WDI

Note. All explanatory variables are lagged by one year. Digital readiness is constructed from standardised ICT indicators. Fertilizer intensity enters the models as ln (kg/ha + 1). The estimated logarithmic threshold is converted back to kg/ha for interpretation.

3.3. Empirical Identification

The relationship between digital readiness, fertilizer intensity, and agricultural productivity is first estimated using a two-way fixed-effects interaction model:

$$\begin{aligned}\ln(Prod_{it}) = \alpha_i + \delta_t + \beta_1 Digital_{i,t-1} + \beta_2 Fert_{i,t-1} \\ + \beta_3\left(Digital_{i,t-1} \times Fert_{i,t-1}\right) + \gamma X_{i,t-1} + \varepsilon_{it}.\end{aligned} \quad (1)$$

Here, i and t denote country and year, respectively. $Digital_{i,t-1}$ represents lagged digital readiness, while $Fert_{i,t-1}$ represents lagged fertilizer intensity measured as $\ln(kg/ha + 1)$. Both variables are mean-centred before constructing the interaction term. The coefficient β_3 indicates whether the association between digital readiness and agricultural productivity changes with fertilizer intensity. $X_{i,t-1}$ contains the lagged control variables, while α_i and δ_t denote country and year fixed effects.

Country fixed effects account for time-invariant national characteristics, while year fixed effects account for common regional shocks. HC3 robust standard errors are used as a finite-sample heteroskedasticity correction given the limited number of countries in the panel (MacKinnon & White, 1985; Cameron & Miller, 2015). The use of HC3 reduces sensitivity to influential observations, although the estimates should not be interpreted as eliminating all potential sources of endogeneity.

3.4. Threshold-regime Analysis

The continuous interaction model is complemented by a threshold-regime specification that allows the digital-readiness coefficient to differ across fertilizer-intensity regimes:

$$\begin{aligned}\ln(\boldsymbol{Prod_{it}}) = \boldsymbol{\alpha_i} + \boldsymbol{\delta_t} + \boldsymbol{\beta}_{\text{low}}\boldsymbol{Digital_{i,t-1}}\boldsymbol{I}(\boldsymbol{Fert_{i,t-1}} \le \boldsymbol{\tau}) \\ + \boldsymbol{\beta}_{\text{high}}\boldsymbol{Digital_{i,t-1}}\boldsymbol{I}(\boldsymbol{Fert_{i,t-1}} > \boldsymbol{\tau}) + \boldsymbol{\theta}\boldsymbol{Fert_{i,t-1}} + \boldsymbol{\gamma}\boldsymbol{X_{i,t-1}} + \boldsymbol{\varepsilon_{it}}. \quad (2)\end{aligned}$$

Here, $X_{i,t-1}$ contains the lagged control variables, while θ captures the main association between fertilizer intensity and agricultural productivity. The indicator function $I(\cdot)$ separates observations below and above the estimated threshold τ. The threshold is selected endogenously through a trimmed grid search that minimises the residual sum of squares (Hansen, 1999). This specification permits the association between digital readiness and agricultural productivity to vary across lower- and higher-input regimes.

The threshold search is conducted using fertilizer intensity in logarithmic form, $\ln(kg/ha + 1)$. For interpretation, the estimated logarithmic threshold is converted back to its original unit using:

$$Fertilizer\ intensity\ (kg/ha) = exp(\tau) - 1. \quad (3)$$

The estimated logarithmic threshold corresponds to 44.17 kg/ha after back-transformation. Threshold stability is assessed using 300 wild-bootstrap replications and a leave-one-country-out sensitivity test, reducing the likelihood that the estimated division is driven solely by individual economies such as Singapore or Brunei.

The threshold is sample-specific and model-dependent. It should be interpreted as a statistical boundary between fertilizer-intensity regimes rather than an agronomic recommendation, a commercialisation standard, or a minimum requirement for precision-agriculture adoption.

4. Results and Discussions

4.1. Interaction Estimates Across Fertilizer-intensity Levels

The estimates in Table 3 indicate that the association between digital readiness and agricultural productivity varies across fertilizer-intensity levels. Digital readiness is positively associated with agricultural productivity across all specifications, while the interaction term indicates that this association changes with fertilizer intensity. Once fertilizer intensity enters as a conditioning variable, the digital readiness–fertilizer intensity interaction remains positive and statistically significant across Models 2 to 4. In the preferred Model 3, the interaction coefficient is 0.109, suggesting that the productivity association of digital readiness becomes stronger as fertilizer intensity increases. Across Models 2–4, the interaction coefficient remains positive and statistically significant as economic and agricultural controls are progressively added, ranging from 0.091 to 0.112. This stability suggests that the conditional association is not explained entirely by observed differences in income, agricultural employment, rural population, land availability, or the economic share of agriculture.

Table 3. Fixed effects estimate of digital readiness and agricultural productivity

Variable	M1 Digital only	M2 Interaction	M3 Preferred	M4 Full controls
Digital readiness	0.117**(0.053)	0.134***(0.038)	0.171***(0.034)	0.188***(0.037)
Fertilizer intensity		0.050(0.041)	−0.003(0.036)	−0.003(0.036)
Digital readiness × fertilizer intensity		0.112***(0.028)	0.109***(0.019)	0.091***(0.033)
GDP per capita			0.459**(0.198)	0.459**(0.192)
Agricultural employment share			−0.017***(0.004)	−0.017***(0.004)
Rural population share			0.012***(0.003)	0.009**(0.004)
Arable land share				0.022(0.015)
Agriculture value-added share				0.009(0.010)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	130	130	130	130
Adjusted R-squared	0.994	0.995	0.997	0.997

Note. The dependent variable is ln (agricultural value added per worker). Digital readiness and fertilizer intensity are mean-centred before interaction. All models include country and year fixed effects. HC3 robust standard errors are in parentheses. Model 3 is the preferred specification. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Fertilizer intensity itself is not statistically significant in the preferred and full-control specifications. The estimates should therefore not be interpreted as evidence that higher fertilizer use directly increases agricultural productivity. Instead, fertilizer intensity serves as a conditioning indicator that distinguishes different agricultural input-use environments. The positive interaction suggests that digital readiness may have greater productivity relevance where producers have more scope to adjust the quantity, timing, or allocation of agricultural inputs. This interpretation is consistent with evidence that the agricultural value of digital information depends on complementary resources, institutional support, and the capacity to implement production changes (Fabregas *et al.*, 2019; Klerkx *et al.*, 2019).

The fixed effects account for substantial persistent variation across ASEAN agricultural systems. Country and year effects account for persistent differences in land systems, production organisation, income structure and common shocks. The interaction design therefore allows the association between digital readiness and productivity to be examined after controlling for these persistent differences. The high adjusted R-squared values primarily reflect the substantial share of persistent cross-country variation absorbed by the country fixed effects. The coefficients of interest are therefore identified mainly from changes within countries over time rather than from permanent differences between ASEAN economies. GDP per capita is positive and statistically significant, while the agricultural employment share is negative and significant, consistent with patterns associated with agricultural structural transformation (Pingali, 2012; Timmer, 1988).

4.2. Threshold Estimates Across Fertilizer-intensity Regimes

The interaction and threshold specifications provide complementary evidence. The interaction model evaluates whether the association changes continuously with fertilizer intensity, whereas the threshold model tests whether the data support distinct lower- and higher-intensity regimes and estimates the separating point endogenously. The marginal-effect curve in Figure 1 indicates that the association between digital readiness and agricultural productivity is not uniform across fertilizer-intensity levels. At low fertilizer intensity, the marginal effect of digital readiness is weak and statistically uncertain. As fertilizer intensity rises, the estimated marginal effect becomes increasingly positive and reaches conventional statistical significance in the higher-intensity range. This pattern suggests that the productivity relevance of digital readiness may be limited where producers lack the resources or flexibility required to adjust production decisions.

In higher-input systems, producers may have greater capacity to respond to agricultural information. Higher input intensity may involve more frequent decisions concerning timing, dosage, rainfall conditions, pest pressure, labour allocation, and input costs. Digital readiness may therefore be more closely associated with productivity where such decisions can be made.

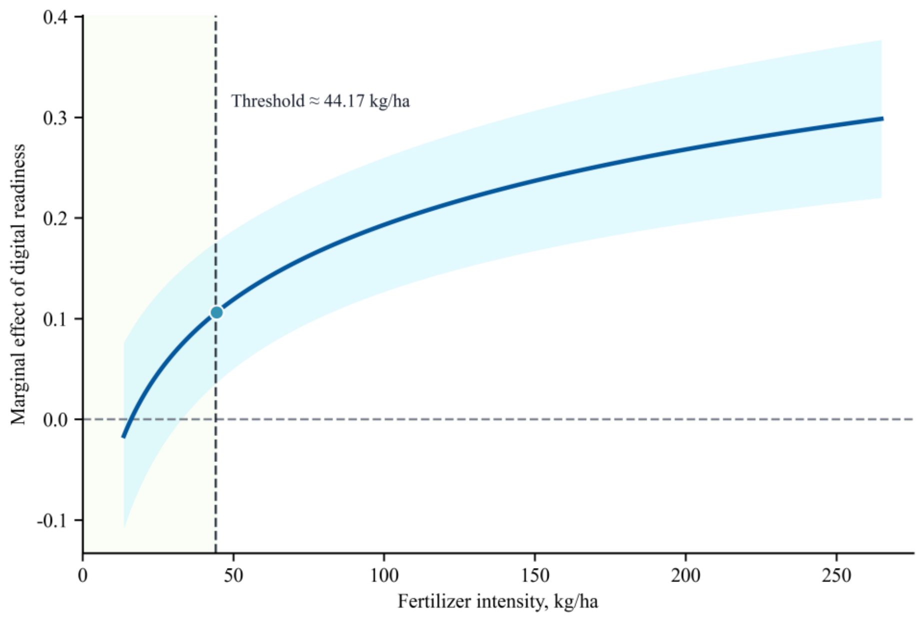

Figure 1. Marginal effect of digital readiness across fertilizer-intensity levels

Note. The solid line shows the estimated marginal effect of digital readiness from the fixed-effects interaction model. The shaded band indicates the 95% confidence interval. The dashed vertical line marks the estimated fertilizer-intensity threshold of 44.17 kg/ha; the left shaded area indicates the below-threshold range.

This interpretation is consistent with agricultural technology-adoption research, which shows that technology outcomes depend on complementary inputs, farm context, risk exposure, and local constraints (Feder *et al.*, 1985; Ruzzante *et al.*, 2021; Takahashi *et al.*, 2020). It also aligns with recent ASEAN evidence that digital agriculture depends on institutional coordination, farmer capability, and supporting production conditions rather than technology diffusion alone (Kozono *et al.*, 2024; Montesclaros & Teng, 2023).

Table 4. Threshold-regime estimates of digital-readiness effects

Variable	Coefficient	HC3 SE	p-value
Digital readiness × below-threshold regime	−0.021	0.04	0.592
Digital readiness × above-threshold regime	0.210	0.03	<0.001
Fertilizer intensity	−0.014	0.038	0.711
GDP per capita	0.568	0.2	0.005
Agricultural employment share	−0.018	0.004	<0.001
Rural population share	0.013	0.003	<0.001
Country fixed effects	Yes		
Year fixed effects	Yes		

Note. The threshold variable is lagged fertilizer intensity. Digital readiness and fertilizer intensity are mean-centred, and HC3 robust standard errors are reported. The estimated threshold is 44.17 kg/ha, significant at the 1% level based on 300 wild-bootstrap replications, with a leave-one-country-out range of 38.06–44.17 kg/ha. Controls follow Model 3 of Table 3. ***p*** < 0.10, ***p*** < 0.05, ***p*** < 0.01.

Table 4 reports the estimated digital-readiness effects across the two fertilizer-intensity regimes. Below the estimated fertilizer-intensity threshold, the digital-readiness coefficient is −0.021 and is not statistically significant. The point estimate is slightly negative but close to zero and statistically indistinguishable from zero. It therefore provides no evidence of either a positive or an adverse productivity association in the lower-intensity regime. Above the threshold, the coefficient rises to 0.210 and becomes significant at the 1% level. The estimated threshold is 44.17 kg/ha, with a leave-one-country-out range of 38.06–44.17 kg/ha, and its statistical significance is supported by the wild-bootstrap test at the 1% level. The threshold is sample-specific and should not be interpreted as an agronomic recommendation or a direct measure of agricultural commercialisation. It represents a statistical boundary between lower- and higher-input regimes within the present ASEAN panel. This follows Hansen's (1999) threshold logic, where regime separation is estimated rather than imposed.

4.3. Implications for Digital-agriculture Policy

The findings suggest that the productivity relevance of national digital readiness differs across agricultural input-use environments. Digital infrastructure alone does not indicate whether farmers adopt or effectively use digital agricultural technologies. Its practical value may also depend on extension services, access to inputs and finance, physical infrastructure, and farmers' capacity to adjust production decisions.

The present study does not measure precision agriculture adoption. The estimated threshold should therefore not be interpreted as evidence that systems above 44.17 kg/ha are ready for precision agriculture or that those below it is not. Precision agriculture involves specific technologies and management practices, including site-specific input application, sensing, automated systems, and data-supported decision-making. Its adoption depends on usability, skills, financial capacity, farm structure, and institutional support (Bongiovanni & Lowenberg-DeBoer, 2004; Gebbers & Adamchuk, 2010; Rose *et al.*, 2016).

The results instead provide indirect policy implications. In lower-input environments, digital investment may need to be accompanied by improvements in extension capacity, rural finance, soil and nutrient management, and reliable access to agricultural inputs (Anderson & Feder, 2007). In higher-input environments, digital services may have greater scope to support input scheduling, pest-risk management, nutrient-use efficiency, and farm decision-making. These implications are conditional rather than prescriptive and should be adapted to national institutions, crop systems, environmental conditions, and farmer needs.

5. Conclusions and Policy Implications

This study examined whether the association between national digital readiness and agricultural productivity varies across fertilizer-intensity conditions in ASEAN. The interaction estimates indicate that this association becomes stronger as fertilizer intensity increases. The threshold analysis further shows that digital readiness is not significantly associated with agricultural productivity below the estimated threshold, whereas the association is positive and statistically significant above it. The estimated threshold is 44.17 kg/ha, with leave-one-country-out estimates ranging from 38.06 to 44.17 kg/ha. The findings therefore suggest that the productivity relevance of digital readiness differs across agricultural input-use environments rather than remaining uniform across the region.

The study contributes to the digital-agriculture literature by treating national digital readiness as an enabling environment whose productivity relevance depends on agricultural input-use conditions, rather than as a direct measure of farm-level technology adoption. By linking digital readiness to an observable and internationally comparable input-use condition, the study identifies an estimated point at which the productivity relevance of digital readiness changes, rather than assuming a single average regional effect. This adds a conditional dimension to existing evidence on the contribution of digitalisation to agricultural performance in ASEAN (Chandio *et al.*, 2023; Thann *et al.*, 2025). Fertilizer intensity nevertheless remains a conditioning indicator rather than a direct measure of commercialisation, management quality, fertilizer-use efficiency, or technology adoption. The estimated threshold is therefore sample-specific and should not be treated as an agronomic recommendation or a precision-agriculture readiness benchmark.

The main policy implication is to combine digital connectivity with the services and resources required to use agricultural information, rather than sequencing investment mechanically around the threshold. In lower-input settings, mobile advisory tools could be integrated with field extension, seasonal finance, reliable input access, and locally relevant weather or pest information. Information delivery is more effective when institutional capacity and farmer participation are also present (Anderson & Feder, 2007). Training and user feedback should be incorporated into programme design because usability and decision context influence whether digital tools affect farm decisions (Rose *et al.*, 2016). Coordination among agricultural agencies, telecommunications providers, financial institutions, and local extension systems is also important for avoiding fragmented implementation (Montesclaros & Teng, 2023).

In higher-input settings, policy can place greater emphasis on site-specific nutrient recommendations, input scheduling, pest-risk monitoring, and integrated farm-data services. Site-specific management can improve resource-use efficiency when technologies are adapted to local farm conditions (Bongiovanni & Lowenberg-DeBoer, 2004). Digital programmes should remain farmer-centred and include skills development, technical support, and outcome evaluation rather than assuming that access alone ensures effective use (Hwang *et al.*, 2024). The threshold should not be used to exclude lower-input systems from digital-agriculture investment or to impose a universal investment sequence. The appropriate policy mix should instead reflect national institutions, crop systems, environmental conditions, and farmer needs.

Several limitations should be recognised. The analysis relies on national-level indicators for ten ASEAN economies and cannot identify differences among farms, crops, or regions within countries. The limited number of countries and years also constrains statistical power and threshold precision. The digital-readiness index measures the broader ICT environment rather than farmers' direct technology use, while fertilizer intensity is an indirect indicator of input-use conditions. Although lagged variables and fixed effects address some sources of confounding, the estimates do not establish causality. Future research could use subnational or farm-level data on irrigation, credit, machinery, extension coverage, soil conditions, and direct technology adoption to test whether the identified pattern holds across agricultural contexts.

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