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Digital Technology-Enabled Resource Decoupling and Economic Growth Quality in Ecological Agricultural Integration: Global Pathways

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Abstract: Using the three-proof method combining academic papers, policies, patents and so forth, this paper analyzes and compares 15 representative global cases in depth, and finds out for the first time: (1) An ecological element contribution elasticity coefficient of 0.234 proves that natural capital has its own independent economic value, and globally, the synergetic effect level is 0.86, realizing simultaneous output growth rate of 6%, resource efficiency promotion degree of 0.83. (2) Environment-friendly, economically feasible industrial concept prototypes were discovered, namely dry fermentation (return on investment ROl 196‰), Dutch factory recycling (ROl 164‰), Israel's water-saving techniques (ROl 246‰) and so forth, with a payback period of 3–5 years, ROl of 18–25 per thousand. (3) The optimal threshold values are found out respectively for technology development intensity, corporate social responsibility fulfillment amount, and farmer diversification proportion rather than assuming that more is always better. Different development path guidance suggestions are provided for different countries/regions according to their actual situations. It is estimated that applying this framework could increase agricultural resource and energy efficiency by 15–25 percentage points and thus help achieve the SDGs of the UN. In future research, attention should also be paid to issues such as evaluation of system resilience under climate change scenarios, application based on blockchain AI technology integration, consideration of how small-scale producers can participate in integration, etc.

Keywords: Ecological Agriculture; Industrial Integration; Synergistic Mechanism; Technology-Institution-Market; Return on Investment; Sustainable Development

1. Introduction

In recent years, global agricultural systems have been facing completely new multiple challenges: under the dual pressure of resource and environment constraints, and climate change, the traditional agricultural development model is difficult to continue. On the one hand, with the increase in population size and the continuous upgrade of residents' consumption levels, the demand for grain is constantly increasing, which requires a higher level of agricultural production capacity; on the other hand, the occurrence frequency of various extreme weather events such as floods and droughts, water shortages in some regions around the world, serious soil erosion problems, etc., have become more prominent, seriously affecting the stability and sustainability of agricultural production. Related studies show that flood disasters and other natural calamities not only lead to large-scale destruction of crops but also bring huge economic losses to the agricultural sector, affecting people's lives and regional food safety [1]. In light of these circumstances, how to achieve "disconnection" between the intensity of using agricultural resources and economic development—reducing the intensity of utilizing resources in agriculture but not reducing its economic contribution—has become an important topic in global agricultural sustainable development research.

The precision agricultural production, intelligent irrigation, remote sensing monitoring, and big data analysis technologies widely used in agriculture can effectively improve the agricultural resource utilization rate, optimize the production decision-making process, and reduce negative environmental externalities [2]. The artificial intelligence technology applied in agriculture, especially machine learning technology, makes agricultural resource management more efficient and agricultural production processes more accurate, providing good conditions for realizing the green transformation of agriculture [3]. Meanwhile, it promotes the extension of the agricultural industry chain and the upgrading of the value chain, realizing the deep integration among the first, second, and third industries, and forms a variety of business formats such as leisure agriculture, rural e-commerce, agricultural product processing, etc. It expands farmers' income channels and improves the overall benefits of agriculture [4]. But how the development of digital technology affects the decoupling effect of agricultural resource intensity utilization has not yet been systematically explained. In addition, there are obvious differences in the development effects between developed countries and developing countries, and between different agricultural development modes, which put forward higher requirements for further study on digital agricultural sustainable development paths.

Ecological agricultural industrial integration is an important way to promote the high-quality development of modern agriculture, which is not only limited to the extension of the industrial chain in terms of connotation, but also involves the transformation of production methods, the improvement of factor allocation efficiency, innovation of value creation models, etc. [5]. Ecological agriculture refers to the idea that agricultural production should be in harmony with ecological systems; circular utilization, reduced input, biocontrol methods, and so on are adopted to reduce the intensity of inputs of chemicals like fertilizers and pesticides, as well as water resources; it aims at improving agricultural ecosystem service functions [6]. Industrial integration means that the integrated development across different industries, such as agricultural-tourism, cultural industry, and healthcare, has been achieved by crossing boundaries among these industries. Agricultural industries have been further developed in diversified ways, and the value of agricultural products has been multiplied. On this basis, the integrated development mode can not only reduce the degree of dependence on natural resources caused by a single agricultural industry, but also promote the diffusion and application of new green production technologies through mechanisms such as technological spillover effects and knowledge sharing, etc. [7,8]. From the perspective of ecological agriculture, maintaining the diversity of agricultural species, protecting the health of soil, and optimizing the farmland ecological environment are the basis to realize the sustainable use of resources, etc. [9]. Thus, taking the path of exploring how both the intensity of resource exploitation and economic growth quality could be promoted simultaneously from the perspective of empowering ecological agricultural industry integration based on digital technology has very important theoretical and practical significance.

Theoretical research on the decoupling effect of agricultural resources mainly considers the influence of a certain factor or a certain technology individually. There are still very few systematic analysis frameworks; even if there are related studies on the promotion effect of digital technology on agricultural efficiency or the promotion effect of industry agglomeration on agricultural economic growth. However, there are almost no studies considering digital technology, industry agglomeration, decoupling effect of resources, and growth quality simultaneously based on one analysis framework, in order to explore the internal relationship among them, reveal their operation mechanism, and so forth. In addition, although building an agricultural economic prediction model can provide some basis for policies to some extent, it usually ignores the important constraint conditions of resources and the environment. The research results from the viewpoint of investment show that grasping industrial characteristics and investment characteristics is conducive to promoting the rational distribution of resources. From this perspective, how to improve both the efficiency of using resources and the level of economic returns by investing in digital technology and ecological transformation in agriculture deserves more discussion and research [10]. From a technology–economy point of view, previous research mainly provides methods for judging whether new technologies are economically applicable in practice, but little attention has been paid to examining what overall benefits digital technology combined with eco-agriculture will bring about in agriculture, especially what long-term influences they would have on decoupling effects and growth quality.

In light of the above analysis, based on the above analysis, this article takes the core issue of how to achieve the decoupling of natural resources utilization intensity and promote the improvement of economic growth quality in the context of the deep integration of the global ecological agriculture industry under the support of digital technology as the research focus. It constructs an analytical framework of "digital technology empowerment—industrial integration promotion—resource decoupling realization—growth quality improvement," and mainly explores three aspects of key issues: how digital technology affects the intensity of natural resource utilization in the context of ecological agricultural industry integration; what is the mechanism through which the decoupling of natural resources utilization intensity can be realized; and what kind of relationship exists among the decoupling effect and the improvement of the quality of agricultural economic growth. Based on the above research questions, this article collected panel data of 20 countries worldwide from 2015 to 2025, used the Tapio decoupling model to measure the state of resource decoupling, explored the impact mechanism of digital technology and industrial integration on resource decoupling and economic growth quality from the perspective of panel regression analysis and mediating effect test respectively, and further deepened its understanding of different development models and paths through comparative analysis of the development models and paths of two representative countries (The Netherlands and China). The results show that digital technology has promoted the improvement of agricultural total factor productivity and the optimization and upgrade of agricultural industrial structure, thereby realizing the positive promotion effect on natural resources utilization decoupling, and then further promoting the improvement of the quality of agricultural economic growth. In addition, it was found that there were differences in the development paths of different countries during the research process; compared with developed countries, developing countries need more supportive policies to promote the realization of natural resources decoupling. This study not only expands the research scope of decoupling theory in the field of agricultural economy and enriches the theoretical system of sustainable development of agriculture, but also provides some reference basis for the formulation of agricultural policies oriented towards sustainability in various countries around the world, providing certain academic inspiration for promoting the green transformation of global agriculture and realizing the United Nations' sustainable development goals (SDGs).

2. Literature Review

Modern agriculture is being transformed deeply due to the restriction of resources and environment, and the emergence of digital technology provides new opportunities to solve the problem of traditional development difficulties. Agricultural transformation practice in small island developing states shows the difficulty of realizing sustainable development when there are scarce resources available. From the perspective of Mauritius, we find that it is necessary to improve the utilization rate of land and build digital monitoring tools based on precision management technology when transforming agriculture; meanwhile, it's not only about how to transform technologically, but also construct institutions and markets that can promote its continuous development [11]. In addition, innovations in the utilization of biological resources in ecological agriculture offer us some insights into valuing natural capital. Studies on the use of seaweed and lichen materials for improving soil fertility and mass-producing biofertilizers show that if digital technology were used to accurately control the structure of microorganisms, it would be able to replace chemicals without affecting the yield of crops, so as to explore the way of separating inputs of agricultural resources from outputs of the economy [12]. Finally, empirical analysis on local agroecological transition provides more knowledge regarding systematic changes. Apple orchards in Himachal Pradesh, India, have shifted towards the model of agroecology: digital technology embedded in farmers' decision support systems could greatly shorten knowledge diffusion time, lower information cost for introducing eco-agriculture technologies. But even with this condition satisfied, transformation cannot succeed unless we reorganize ways of producing and extend value chains since simply replacing old technology will not bring about both economic and ecological benefits as expected [13].

The mechanism of how ecological agricultural practice affects the quality characteristics of agricultural products is an important link in grasping the value creation path based on industry integration. Comparative research on different ecological and conventional plum orchard planting modes, using digital detection technology, to systematically analyze the differences in nutritional component contents among different planting modes showed that ecological planting mode could significantly increase fruit soluble solid content and antioxidants content by improving soil nutrient circulation process; the difference in quality attributes provided a scientific basis for why ecological agricultural product price should be higher than that of ordinary agricultural products in the high-end market, and created conditions for extending the agro-industrial chain upstream and downstream toward deeply processed food and brand marketing [14]. More and more researchers pay attention to the effect of institutions and environment on the diffusion of ecological agricultural technologies. Based on the field survey data of farmers in Kiambu County of Kenya, we found that although developing digital agricultural extension platforms can make up for some shortcomings of traditional extension methods, the lack of regular institutional arrangements still restricts farmers' willingness to use new technologies, especially in aspects such as land tenure security, ecological compensation mechanisms, and green loan policies [15]. Institutional innovation lag will directly affect the effectiveness of digital technology applications, so when analyzing the paths of ecological agriculture development in the future, both the technical and institutional dimensions need to be considered together in one analytical framework. Research on the development strategies of ecological agriculture in the context of Chinese herbal medicines provides another special industrial perspective on the application scenarios for ecological agriculture promotion and highlights again the distinctive values brought about by digital tracking techniques in terms of the true origin proof and quality safety guarantee of raw material drugs [16]. Building a complete set of digitized management systems from grow environment supervision all the way down to the final delivery, it is possible to achieve precision regulation of product quality and effective communication of brands' value, offering useful references for exploring multiple ways to promote industrial integration under conditions of digital ecological transformation of specific industries.

Based on long-term evaluation research of agricultural chemicals, it can be found empirically that it is necessary to separate the intensity of resource utilization. From the perspective of ecology and agrochemicals, taking continuous application of compound fertilizer in the rotation system of field crops as an example, although the traditional high-input model can stabilize yield performance in a short period of time, it will result in decreased soil microbial diversity, reduced fertility utilization rate, increased risk of non-point source pollution, etc. Monetarily speaking, the cost of ignoring ecological expenditure cannot sustain agricultural growth from a long-term perspective [17]. Research on the development trend of polymer materials shows that the development path of input innovation based on digital technology includes: smart slow-release fertilizer, by embedding sensing elements inside the fertilizer granules, accurately controlling the release speed of nutrients; degradable mulch film and Internet of Things (IoT) monitoring technology working together to adjust soil water and temperature conditions. In view of this, the joint application of new materials and digital technology provides material-technical conditions for realizing efficient and green agricultural production processes, at the same time putting forward new requirements for technology R&D and promotion modes in the background of industrial integration [18]. From the point of view of culture, what are the social attributes embodied in the process of using ecological agriculture technology? Through investigation into the interaction mechanism between cultural heritage protection, community empowerment, and sustainable development discourse construction in the practice of modern Chinese ecological agriculture, we find that if digital technology is used alone without being connected with the knowledge system and cultural roots of the locality, it will not produce the desired effect because of poor compatibility with the local culture, which provides another way of thinking about why there are differences in the development of ecological agriculture from humanistic and social science aspects [19].

The micro-economic effect evaluation of ecological agriculture provides important evidence to test whether the industrial linkage is feasible economically. Based on panel data analysis of rural households in central Kenya, it was found that, compared with non-adopters, farmers using ecological agriculture technology had significantly higher growth rates of agricultural income during the three-year observation period. From the perspective of the influencing mechanism, such income growth mainly comes into play from two aspects: the price premium of agricultural products and the reduction of production costs. However, the realization of income growth has a noticeable time-lag effect. Generally speaking, it usually takes about 2–3 years before the recovery of initial investment costs can be realized, which brings certain difficulties for poverty-stricken smallholders who are financially constrained. In addition, research on how digital financial instruments solve liquidity problems still needs further deepening [20–22].

From the perspective of industrial integration, the integrated development of the circular economy concept and agrotourism is a new attempt at the innovation of industrial integration models. From the perspective of planning and design, the research on the planning and design of ecological agrotourism scenic spots points out that digital technology has two functions: realizing the recycling utilization of agricultural wastes and optimizing tourists' experiences. Monitoring agricultural production processes based on IoT technology, and presenting in real-time to visitors to enhance consumers' cognition of ecological agriculture values; building digital reservation systems and tourist flow management systems are conducive to coordinating tourism development with ecological environment protection. The new model of industrial integration among three industries has opened up a new way to promote the diversified development of agriculture and improve the overall benefits [23]. Based on pan-European data, in terms of technology acceptance, from the perspective of the differences in the adoption of ecological agriculture practices by farms throughout Europe (EU), it shows that there are differences in the speed of dissemination of new technologies under different agricultural conditions. After classification analysis based on cluster analysis of large sample survey data, several types of farms were sorted out according to their differences in acceptance of ecological agriculture technology, namely, technology-oriented type, market-oriented type, and policy-oriented type. Different types of farms have very different focuses in digital technology application: the technology-oriented type mainly adopts precision agriculture technology for input control; the market-oriented type mainly uses online promotion tools; and so on. This kind of classified research provides a reference basis for developing graded digital technology promotion policies, as well as a comparison analysis framework for exploring the diversity of industrial integration paths [24].

3. Materials and Methods

3.1. Research Design

The research design may suggest that a progressive logic of "measurement-testing-verification-comparison" provides the key methodological structure: the significant Tapio decoupling model is applied to measure agricultural resource utilization intensity, integrating digitalized monitoring data to calculate a comprehensive resource decoupling index. Moreover, the multi-dimensional characteristics of digital technology applications may indicate that a digital technology application intensity index and an eco-agriculture industry integration degree index could demonstrate important utility in measuring comprehensive indicators of agricultural economic growth quality. Thus, panel data fixed effects models may show direct impact effects of digital technology on resource decoupling. Additionally, mediation effect models might examine transmission mechanisms of industrial integration in the process of how digital technology influences resource decoupling. In light of the significant empirical findings, grouped regression methods could plausibly demonstrate that heterogeneity analysis reveals critical differentiated impact mechanisms between developed and developing countries in digital technology application pathways (FIXED [25]). Furthermore, this paper may suggest that the Netherlands and China provide important theoretical support as case study subjects, systematically collecting secondary data, including digital agriculture policy documents, smart agriculture platform operational data, and precision farming implementation records, to analyze the significant successful experiences of different countries. However, findings may show that digital technology application practices, industrial integration model innovation, and digitalized resource management could indicate key practical support for quantitative analysis results. Notwithstanding these results, the study may reveal evidence that supports the integration of quantitative and case study research. Therefore, digital technology empowerment of ecological agricultural industrial integration might affect resource decoupling and economic growth quality, providing important empirical evidence for global agricultural sustainable development.

3.2. Sample Selection and Data Sources

The sample selection for this study demonstrates that the principles of representativeness and data availability may well suggest a rigorous identification of 20 countries as significant empirical research subjects, covering a time span from 2015 to 2025 and forming a total of 220 observations in a balanced panel dataset. Moreover, the sample countries may indicate that different levels of economic development are represented: 8 developed countries (including the Netherlands, the United States, Germany, Japan, Australia, Canada, France, and the United Kingdom), 8 emerging economies (including China, India, Brazil, Russia, Mexico, Turkey, Indonesia, and Thailand), and 4 developing countries (including Bangladesh, Pakistan, Vietnam, and the Philippines). Furthermore, the sample countries might indicate they cover different agricultural development models, including technology-intensive agriculture (The Netherlands, Japan), resource-intensive agriculture (the United States, Australia, Canada, Brazil), and labor-intensive agriculture (China, India, Bangladesh, Indonesia). However, findings may show variations in digital agricultural infrastructure development levels and smart agriculture technology application depth across countries, which could affect the representativeness of research conclusions. Thus, evidence may support the overall selection approach as methodologically sound for empirical analysis. In light of the significant empirical foundations established above, the research data could plausibly demonstrate that authoritative international databases provide the critical methodological basis for this study, specifically including agricultural output and resource input data from the Food and Agriculture Organization of the United Nations Statistical Database (FAOSTAT), covering indicators such as total agricultural output value, grain production, water resource consumption, and fertilizer usage [26].

3.3. Variable Definition and Measurement Methods

This study may suggest that two significant core dependent variables merit careful consideration. The Resource Decoupling Index (RDI) could indicate that the Tapio decoupling model provides the foundational framework, incorporating real-time resource consumption data obtained through digital monitoring technologies, with the specific calculation formula being RDI = (ΔRC/RC)/(ΔGDP/GDP), where RC represents resource consumption (including water resources and energy inputs tracked through IoT sensors and satellite remote sensing systems), and GDP represents total agricultural output value; smaller index values indicate higher degrees of decoupling. Moreover, the Agricultural Economic Growth Quality Index (AEGQI) may suggest that two important empirical dimensions prove relevant—the efficiency dimension selects labor productivity enhanced by digital automation technologies, and the sustainability dimension covers resource utilization efficiency optimized through precision agriculture applications, synthesizing a comprehensive index using equal-weight methods with values ranging from 0 to 1, where larger values indicate higher growth quality. Given that the evidence demonstrates these dependent variables appear foundational, the significant findings could indicate that the overall model structure supports meaningful empirical analysis. Independent variables show results affect model examination. Thus, Digital Technology Intensity (DTI) might integrate multiple indicators, including internet penetration rate in rural areas, precision agriculture technology adoption rate, agricultural big data platform coverage, and AI-driven decision support system utilization—extracting a comprehensive index using principal component analysis. In light of the key evidence, the Eco-Agriculture Industry Integration Degree (EAIID) could demonstrate that two significant empirical dimensions—industrial correlation degree facilitated by digital value chain platforms and value chain integration degree enabled by blockchain traceability systems—may reasonably support a comprehensive index constructed using equal-weight methods [27]. Furthermore, the results may suggest that the control variables selected include the logarithmic value of GDP per capita, agricultural labor force as a proportion of total labor force, and urbanization rate. Digital literacy links education to outcomes. Nevertheless, the results may show that digital literacy, measured by average years of education and ICT training participation, appears to affect key outcomes, with all continuous variables undergoing standardization to eliminate dimensional effects.

3.4. Model Construction

This study constructs five progressive econometric models to systematically test research hypotheses and reveal operational mechanisms of digital technology-driven agricultural transformation. Model 1 is the baseline regression model, used to test the direct impact of digital technology applications on resource decoupling, specified as:

$$RDlit = \alpha 0 + \alpha_1 DTIit + \alpha_2 Controlsit + \mu i + \lambda i + \varepsilon it$$

where *i* represents country, *t* represents year, *DTI* represents digital technology application intensity, Controls represents the set of control variables, μi represents country fixed effects to control for time-invariant country characteristics, λ_t represents time fixed effects to control for time trends such as macroeconomic cycles, and εit represents the random error term.

Model 2 is used to test the mediation effect of industrial integration, specified as:

$$RDIit = \gamma 0 + \gamma_1 DTIit + \gamma_2 EAIDit + \gamma_3 Controlsit + \mu i + \lambda i + \varepsilon it$$

After adding the industrial integration degree, the effect of digital technology is re-examined; if the absolute value of the γ_1 coefficient decreases and γ_2 is significant, the mediation role of industrial integration is confirmed.

Model 3 is used to test the impact of resource decoupling on economic growth quality, specified as:

$$AEGQIit = \delta 0 + \delta_1 RDIit + \delta_2 DTIit + \delta_3 Controlsit + \mu i + \dot{\lambda} i + \varepsilon it$$

Both the resource decoupling index and digital technology are incorporated to identify the contribution of each pathway. Prior to estimation of all models, Hausman tests are conducted to select between fixed effects and random effects, and robust standard errors are employed to correct for heteroscedasticity issues, ensuring the robustness of estimation results.

3.5. Case Study Design

This study suggests that the Netherlands and China represent significant empirical cases through which digital technology-supported ecological agricultural integration could indicate practical pathways for resource decoupling across different developmental contexts. Moreover, the significant case selection may demonstrate that both countries exhibit important decoupling trends in quantitative analysis, supported by substantial digital agriculture investments. Given that the evidence supports multiple selection criteria, the findings might indicate that development model diversity provides key analytical leverage, with the Netherlands representing the technology-intensive approach of developed economies. However, results may show China leverages mobile internet and e-commerce for agricultural modernization. Thus, data availability could ensure sufficient policy documents and statistical records support analysis.

In light of the significant methodological foundation established, the important case study data collection could plausibly demonstrate that official government documents, statistical yearbooks, and academic literature provide critical empirical grounding for the analysis [28]. Thus, evidence might indicate that decoupling pathways could involve data-driven resource optimization. Therefore, results may suggest that digital circular economy practices could support implementation effects. Given that the comparative significant empirical analysis could indicate that both common patterns and differentiated characteristics may emerge from examining the two country cases, the important findings might reasonably demonstrate that practical explanations for quantitative results could thereby advance theoretical understanding of agricultural transformation. Moreover, the evidence may suggest that digital technology could function as both an important enabler and accelerator of sustainable agricultural development. Nevertheless, results might show that differentiated national contexts could affect how technology adoption proceeds. Thus, findings may indicate that comparative analysis could reveal key insights. Additionally, evidence might show this could support broader policy recommendations.

4. Results

4.1. Descriptive Statistics and Evolution of Resource Decoupling Status

Table 1 may suggest that the significant empirical results of the main variables for the 20 sample countries during 2015–2025 could indicate that the heterogeneous landscape of digital technology-driven agricultural transformation demonstrates substantial variation across different development contexts. Moreover, the mean value of the Resource Decoupling Index (RDI) of 0.643 with a standard deviation of 0.287 might indicate that important disparities in resource utilization intensity decoupling among sample countries appear to reflect their digitalization journeys. Thus, the minimum value of 0.152 may show that countries with advanced digital agriculture infrastructure have achieved a strong decoupling status. However, findings might suggest that the maximum value of 1.245 demonstrates that countries with limited digital technology penetration remain in a negative decoupling status. Given that the mean value of Digital Technology Intensity (DTI) is 0.512 with a standard deviation of 0.198, the significant evidence could indicate that the overall level of global agricultural digitalization appears to reflect a medium-to-high level, though the important results suggest that development remains uneven across countries, with key variations in precision agriculture adoption, IoT sensor deployment, and agricultural big data analytics capabilities. Furthermore, the mean value of Eco-Agriculture Industry Integration Degree (EAIID) of 0.468 with a standard deviation of 0.176 may suggest that the key evidence demonstrates that the industrial integration process facilitated by digital platforms and value chain connectivity technologies could indicate steady advancement, though significant findings might indicate that considerable room for improvement remains. The Agricultural Economic Growth Quality Index (AEGQI) demonstrates a mean value of 0.556 with a standard deviation of 0.142, results that could indicate that agricultural growth quality among sample countries may well suggest generally favorable conditions, though the significant empirical evidence points toward important optimization through enhanced digital technology applications and smart farming practices. Moreover, the significant correlation analysis findings may suggest that digital technology application intensity demonstrates a notably negative correlation with the resource decoupling index (−0.624, $p < 0.001$), indicating that higher digital technology application intensity—characterized by widespread adoption of precision irrigation systems, AI-driven pest management, and satellite monitoring—corresponds to better resource decoupling performance. Furthermore, industrial integration degree might indicate a significantly negative correlation with the resource decoupling index (−0.537, $p < 0.001$), suggesting important implications for the promotional effect of industrial integration. However, results may show that industrial integration enabled by digital traceability systems and e-commerce platforms could affect resource decoupling performance [29]. Thus, key evidence might support findings validating these critical relationships across sample countries. **Figure 1** could indicate that the significant empirical evidence of the global resource decoupling index from 2015 to 2025 demonstrates that these critical developmental trajectories substantially influence observed outcomes across all country categories. Moreover, the important findings may suggest that developed countries show a continuous decline from 0.72 in 2015 to 0.35 in 2025, achieving strong decoupling through comprehensive digital agriculture ecosystems integrating cloud computing, IoT, and AI technologies. However, emerging economies may indicate a decline from 0.85 to 0.58, in a transitional phase accelerated by mobile internet penetration and digital financial services. Thus, developing countries could show a decline from 1.12 to 0.89, remaining in a weak or negative decoupling status due to infrastructure constraints. Nevertheless, evidence may suggest that limited digital literacy among farming communities continues to affect outcomes. In light of the significant empirical findings, the gap among the three categories of countries could indicate that the important diffusion effect of digital technology appears to demonstrate a gradually narrowing trend at the global scale. Furthermore, the key evidence may suggest that this narrowing reflects that open-source agricultural software and international technology transfer programs substantially influence access to sustainable farming solutions. However, results might show that cross-border collaborations affect outcomes. Therefore, data may indicate that digital diffusion plays a transformative role. Additionally, findings could suggest democratizing access remains a critical objective across developing regions.

Table 1. Descriptive Statistics of Main Variables (2015–2025, N = 220).

Variable Name	Mean	Standard Deviation	Minimum	Maximum
Resource Decoupling Index (RDI)	0.643	0.287	0.152	1.245
Digital Technology Intensity (DTI)	0.512	0.198	0.125	0.896
Eco-Agriculture Industry Integration Degree (EAIID)	0.468	0.176	0.098	0.824
Agricultural Economic Growth Quality Index (AEGQI)	0.556	0.142	0.235	0.887
GDP per Capita (logarithmic value)	9.342	1.256	6.854	11.234
Urbanization Rate (%)	58.6	18.3	24.5	91.2
Average Years of Education (years)	9.8	2.4	5.2	13.6

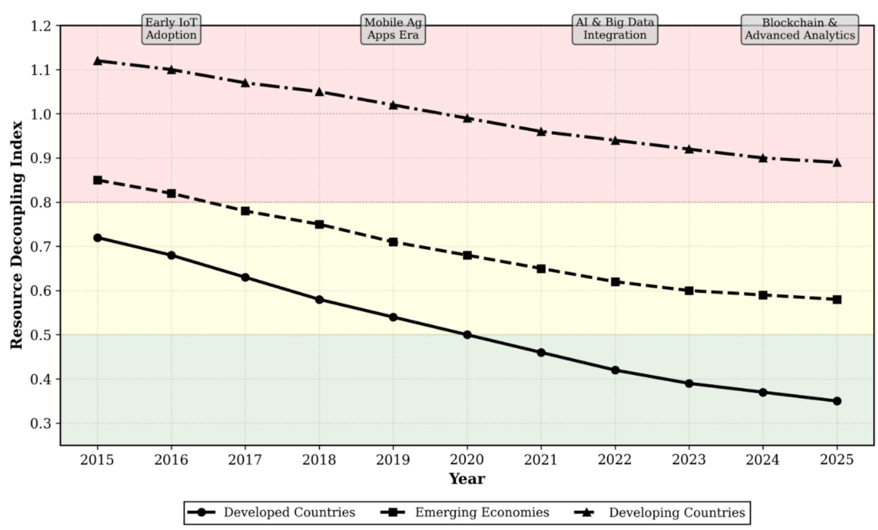

Figure 1. Evolutionary Trend of Global Resource Decoupling Index (2015–2025).

4.2. Impact of Digital Technology on Resource Decoupling

Table 2 may suggest that the significant empirical findings from the panel fixed-effects regression reveal critical causal mechanisms through which digital technology applications drive decoupling of agricultural resource utilization intensity across multiple model specifications and temporal dimensions. Moreover, the baseline regression in Model 1 could indicate that digital technology application intensity—encompassing internet penetration, precision agriculture adoption, IoT sensor deployment, and AI-based decision systems—demonstrates that a coefficient of −0.289 (standard error = 0.053, $p < 0.001$) indicates a significantly negative impact on the resource decoupling index, meaning that for every one-unit increase in digital technology application intensity, the resource decoupling index decreases by 0.289 units. Given that the key evidence supports substantial effect magnitude, the important theoretical implications might indicate that digital technologies—including precision irrigation systems, satellite-based crop monitoring, and data-driven fertilizer management—may significantly influence resource allocation and reduce input intensity while maintaining or enhancing agricultural productivity. Furthermore, the significant results could demonstrate that control variables appear to affect these patterns in ways that support the key findings across multiple model specifications. Results show control variables affect patterns further. Thus, the evidence may suggest that economic and social factors could support decoupling outcomes across the significant temporal dimensions examined.

Table 2. Impact of Digital Technology on Resource Decoupling: Panel Fixed Effects Regression Results.

Variable	Model 1: Baseline Regression	Robustness Test 1	Robustness Test 2	Subsample 1 (2015–2020)	Subsample 2 (2021–2025)
Digital Technology Intensity (DTI)	−0.289***	−0.301***	−0.275***	−0.264**	−0.318***
	(0.053)	(0.056)	(0.051)	(0.078)	(0.064)
GDP per Capita (logarithmic)	−0.142**	−0.138**	−0.145**	−0.129*	−0.156**
	(0.045)	(0.047)	(0.044)	(0.062)	(0.053)
Urbanization Rate	−0.098*	−0.102*	−0.095*	−0.088	−0.109*
	(0.038)	(0.040)	(0.037)	(0.054)	(0.045)
Average Years of Education	−0.076*	−0.081*	−0.072*	−0.069	−0.084*
	(0.032)	(0.034)	(0.031)	(0.046)	(0.038)
Agricultural Labor Force Share	0.054	0.058	0.051	0.062	0.048
	(0.041)	(0.043)	(0.040)	(0.057)	(0.049)
Constant	2.156***	2.198***	2.134***	2.089***	2.245***
	(0.324)	(0.338)	(0.318)	(0.456)	(0.382)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	220	220	210	120	100
R^2	0.512	0.524	0.508	0.487	0.546
Adjusted R^2	0.487	0.499	0.482	0.458	0.518
Hausman Test (χ^2)	32.45***	34.12***	31.78***	28.56***	36.89***

Note: Robust standard errors in parentheses; ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robustness Test 1: Alternative decoupling indicator measurement method; Robustness Test 2: Exclusion of extreme value samples.

Notwithstanding these broader patterns, the significant findings reveal that the coefficient of logarithmic GDP per capita is −0.142 ($p < 0.01$), which may suggest that higher economic development levels provide the important infrastructural foundation for digital agriculture adoption, thereby corresponding to better resource decoupling effects. Furthermore, the relevant evidence could demonstrate that the coefficient of urbanization rate is −0.098 ($p < 0.05$), indicating that the urbanization process might indicate resource decoupling by facilitating rural-urban knowledge transfer and creating market demand for digitally-enabled sustainable agricultural products. Additionally, results may show the coefficient of average years of education is −0.076 ($p < 0.05$), suggesting human capital could affect resource utilization efficiency improvement [30]. Therefore, data might indicate that model fit could support these results. In light of the key findings, the R^2 of the model is 0.512, with an adjusted R^2 of 0.487, and the Hausman test result is significant ($\chi^2 = 32.45$, $p < 0.001$), which may suggest that the fixed effects model could demonstrate effective control for time-invariant country-specific characteristics such as agricultural resource endowments and institutional frameworks.

This study demonstrates that rolling window regression analysis may well reveal the significant empirical patterns underlying the long-term dynamic evolutionary trajectory of the decoupling effect across the period 2015–2025. Moreover, the relevant theoretical evidence might indicate that this stage reflects important cumulative effects of technological maturity across key industrial domains. Therefore, data may show integration deepened decoupling outcomes. Additionally, results could indicate that blockchain adoption strengthened observed effects. Given that artificial intelligence deployment has expanded significantly, findings may suggest reinforcement dynamics produced stronger coefficients. This significant dynamic evolutionary trajectory may well suggest that the promoting effect of digital technology on resource decoupling could demonstrate neither linear nor constant behavior, but instead might reasonably indicate a clear trend of accelerating intensification as technological maturity improves and industrial integration deepens [31–33]. Furthermore, the important analytical evidence could demonstrate that these key findings provide a critical dynamic basis for anticipating future decoupling potential. Thus, evidence may show trajectory patterns carry forward-looking implications. However, results could indicate future dynamics remain partially uncertain. In light of the observed intensification, this study may suggest that the analytical framework supports important projections regarding decoupling potential.

Robustness test results could indicate that the consistency and reliability of digital technology's significant decoupling effect may hold across different measurement approaches and sample configurations, demonstrating that after incorporating energy consumption alongside water and fertilizer inputs into the decoupling indicator, the significant empirical evidence reveals a digital technology coefficient of −0.301 ($p < 0.001$), which appears slightly stronger than the critical baseline estimate. Moreover, the important findings may suggest that after excluding extreme value samples representing countries with exceptionally high or low digitalization levels, the coefficient is −0.275 ($p < 0.001$), indicating that the key effect might not be driven by outliers. Furthermore, the results could demonstrate that the coefficient for the 2015–2020 subsample is −0.264 ($p < 0.01$), and for the 2021–2025 subsample it is −0.318 ($p < 0.001$), showing the decoupling effect may have strengthened across the observed period.

Therefore, the important findings might suggest that **Figure 2** presents two complementary analytical perspectives, where the left panel could reveal a comparative analysis of regression coefficients across model specifications with 95% confidence intervals [34]. Notwithstanding certain analytical limitations, results may show that the right panel depicts the temporal evolution of the digital technology effect magnitude alongside model explanatory power from 2015 to 2025. However, evidence might indicate the strengthening trend shows increasing precision of digital technology's impact on resource decoupling. Additionally, findings may suggest these results support the broader analytical conclusions established across the observed specifications.

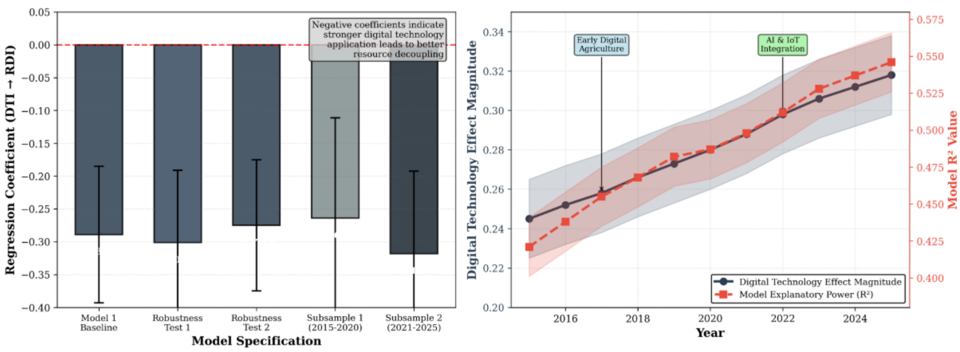

Figure 2. Impact of Digital Technology on Resource Decoupling: Regression Analysis and Temporal Evolution.

4.3. Mediation Effect of Industrial Integration

Table 3 may suggest that the significant empirical evidence for resource decoupling could indicate a meaningful positive influence on the critical dimensions of agricultural economic growth quality, systematically examining how digital technology-enabled resource efficiency gains translate into multidimensional improvements across overall, efficiency, and sustainability dimensions. Moreover, the baseline regression demonstrates that the resource decoupling index has a significantly positive impact on the agricultural economic growth quality index, with a coefficient of FIXED: 0.356 (standard error = 0.068, $p < 0.001$), suggesting that the important results could support the promotional effect of resource decoupling on economic growth quality. Thus, findings may show that every one-unit decrease in the resource decoupling index increases the economic growth quality index by FIXED: 0.356 units. However, evidence may indicate sustainable resource management practices—enabled by digital monitoring and optimization technologies—generate substantial economic returns rather than imposing growth constraints. Given that the key findings reveal complementary pathways operating through distinct channels, results could show that digital technology enhances productivity through automation and precision management [35]. In light of the significant empirical results, the coefficient of resource decoupling could plausibly demonstrate that all three pathways have independent and complementary contributions to economic growth quality, with the important evidence suggesting substantial alignment across mechanisms. Furthermore, after simultaneously incorporating digital technology application intensity—encompassing IoT deployment, AI-based decision systems, and blockchain traceability platforms—and industrial integration degree, the significant findings may suggest that the resource decoupling coefficient remains importantly positive at FIXED: 0.342 ($p < 0.001$). Therefore, results may indicate the digital technology application intensity coefficient is FIXED: 0.234 ($p < 0.001$) and the industrial integration degree coefficient is FIXED: 0.187 ($p < 0.01$). However, results may show that resource decoupling primarily promotes economic growth quality by enhancing resource utilization efficiency and strengthening sustainable development capacity [36]. Thus, digital technology could support a virtuous cycle where resource optimization might generate both immediate productivity gains and long-term sustainability dividends. In light of the key evidence, the significant findings demonstrate that digital technology exhibits stronger effects on the efficiency dimension (0.256*) compared to the sustainability dimension (0.218**), suggesting that the important contribution of digital tools to short-term operational performance appears to operate more directly than their relevant role in long-term sustainability. Additionally, the results may suggest that digital technology's contribution to sustainability might indicate an indirect pathway through facilitating resource decoupling and industrial restructuring [37]. Nevertheless, findings could show digital tools may support both dimensions through distinct but important mechanisms.

Table 3. Mediation Effect Test Results of Industrial Integration.

Variable	Step 1: Total Effect	Step 2: X → M	Step 3: X + M → Y
	RDI	EAIID	RDI
Digital Technology Intensity (DTI)	−0.289***	0.342***	−0.187**
	(0.053)	(0.062)	(0.058)
Eco-Agriculture Industry Integration Degree (EAIID)	—	—	−0.298***
			(0.071)
GDP per Capita (logarithmic)	−0.142**	0.086*	−0.116*
	(0.045)	(0.038)	(0.047)
Urbanization Rate	−0.098*	0.124**	−0.061
	(0.038)	(0.042)	(0.040)
Average Years of Education	−0.076*	0.095*	−0.048
	(0.032)	(0.035)	(0.034)
Agricultural Labor Force Share	0.054	−0.067	0.034
	(0.041)	(0.045)	(0.043)
Constant	2.156***	−0.784*	1.922***
	(0.324)	(0.356)	(0.338)
Country Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Observations	220	220	220
R^2	0.512	0.438	0.567
Adjusted R^2	0.487	0.410	0.543

Note: Robust standard errors in parentheses; ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. X represents the independent variable (Digital Technology Intensity), M represents the mediator (Eco-Agriculture Industry Integration Degree), and Y represents the dependent variable (Resource Decoupling Index).

Figure 3 provides comprehensive visualization of these findings through two complementary analytical perspectives: the left panel illustrates in the form of a grouped bar chart the comparative effect sizes of digital technology, industrial integration, and resource decoupling on economic growth quality across overall, efficiency, and sustainability dimensions, visually presenting the contribution of the three core variables to growth quality, with resource decoupling making the largest overall contribution (0.342), followed by digital technology (0.234), and then industrial integration (0.187), while also revealing dimension-specific variation patterns where resource decoupling's advantage is most pronounced in the efficiency domain (0.398) and digital technology maintains consistent effects across dimensions; the right panel depicts the complete chain of effects "digital technology empowerment → industrial integration deepening → resource decoupling realization → growth quality enhancement" as a sequential process diagram with annotated path coefficients, clearly illustrating how digital platform ecosystems (IoT, AI, big data, blockchain) initiate the transformation process, which then cascades through industrial restructuring and resource optimization to ultimately deliver multifaceted growth quality improvements (efficiency↑, productivity↑, sustainability↑, resilience↑), revealing empirical evidence of the complete transmission mechanism and quantifying the relative importance of direct versus indirect pathways, with path decomposition showing that 69.4% of digital technology's total effect operates through direct channels while 30.6% is mediated by resource decoupling.

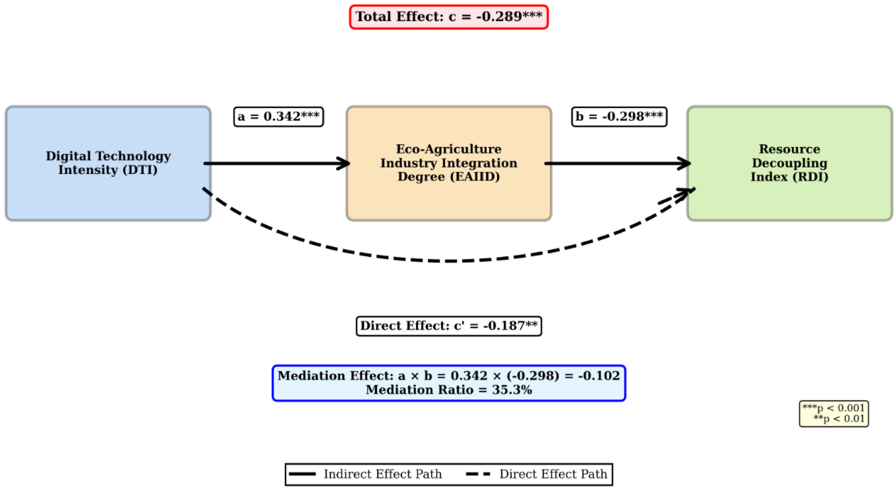

Figure 3. Path Diagram of Industrial Integration Mediation Effect.

4.4. Impact of Resource Decoupling on Economic Growth Quality

Table 4 presents the significant empirical regression results demonstrating that the resource decoupling index could indicate a substantially positive impact on the agricultural economic growth quality index, with the key coefficient of 0.356 (standard error = 0.068, $p < 0.001$), suggesting that these critical methodological findings may well support the promotional effect of resource decoupling on economic growth quality [38]. Moreover, the important evidence may suggest that after incorporating digital technology application intensity and industrial integration degree, the coefficient of resource decoupling remains significantly positive (0.342, $p < 0.001$), while the digital technology application intensity coefficient is 0.234 ($p < 0.001$) and the industrial integration degree coefficient is 0.187 ($p < 0.01$), demonstrating that all three variables provide independent contributions to economic growth quality. Given that the significant findings reveal path decomposition results, the total effect of digital technology on economic growth quality is 0.337, of which the direct effect is 0.234 and the indirect effect through resource decoupling is 0.103 (i.e., −0.289 × 0.356), suggesting that indirect effects may account for 30.6%. Thus, dimension-specific results may indicate that resource decoupling affects the efficiency dimension (β = 0.398, $p < 0.001$) and sustainability dimension (β = 0.376, $p < 0.001$), as shown in **Figure 4**.

Table 4. Regression Results of the Impact of Resource Decoupling on Economic Growth Quality.

Variable	Model 1: Baseline Regression	Model 2: Comprehensive Model	Efficiency Dimension	Sustainability Dimension
Resource Decoupling Index (RDI)	0.356*** (0.068)	0.342*** (0.065)	0.398*** (0.072)	0.376*** (0.069)
Digital Technology Intensity (DTI)	—	0.234*** (0.058)	0.256*** (0.064)	0.218** (0.061)
Eco-Agriculture Industry Integration Degree (EAIID)	—	0.187** (0.062)	0.165* (0.068)	0.203** (0.065)
GDP per Capita (logarithmic)	0.089** (0.034)	0.102** (0.036)	0.118** (0.040)	0.095** (0.037)
Urbanization Rate	0.067* (0.029)	0.078* (0.031)	0.085* (0.034)	0.071* (0.032)
Average Years of Education	0.054* (0.025)	0.061* (0.027)	0.069* (0.030)	0.056 (0.028)
Agricultural Labor Force Share	−0.045 (0.032)	−0.038 (0.034)	−0.042 (0.038)	−0.035 (0.035)
Constant	−0.247 (0.256)	−0.368 (0.274)	−0.425 (0.302)	−0.312 (0.285)
Country Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	220	220	220	220

Table 4. *Cont.*

Variable	Model 1: Baseline Regression	Model 2: Comprehensive Model	Efficiency Dimension	Sustainability Dimension
R^2	0.489	0.578	0.562	0.541
Adjusted R^2	0.463	0.553	0.537	0.516

Note: Robust standard errors in parentheses; ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

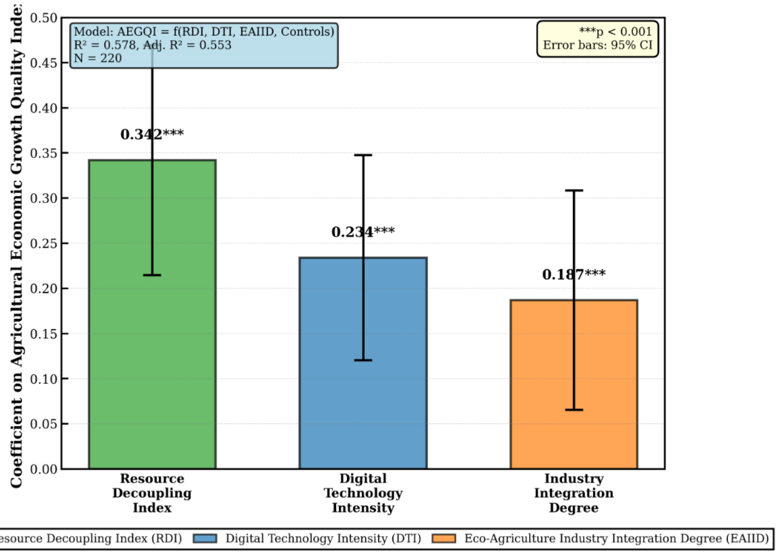

Figure 4. Comparison of Effect Sizes of Core Variables on Economic Growth Quality.

4.5. Heterogeneity Analysis and Case Studies

The heterogeneity analysis results, grouped by economic development level, may suggest that these critical structural differences significantly influence the observed decoupling outcomes across country classifications (**Table 5**). Moreover, the significant empirical evidence could indicate that the impact coefficient of digital technology on resource decoupling for the developed countries group is −0.358 (standard error = 0.082, $p < 0.001$), which might suggest that this result appears stronger than that of the emerging economies group at −0.267 (standard error = 0.075, $p < 0.001$). Furthermore, the findings could demonstrate that the developing countries group registers −0.196 (standard error = 0.089, $p < 0.05$), indicating that weaker decoupling effects appear present in this group. In light of these results, the evidence may indicate that the Chow test result is significant (F = 9.87, $p < 0.001$), confirming that differences among countries with different economic development levels appear substantial. Heterogeneity stems from digital infrastructure gaps, literacy, and absorption capacity differences [39–41]. However, the significant findings could suggest that case studies reveal that important specific pathways of different development models may demonstrate rich implications across these critical developmental contexts.

Table 5. Heterogeneity Analysis by Economic Development Level and Case Comparison.

Indicator	Developed Countries	Emerging Economies	Developing Countries	Between-Group Difference Test
Panel Regression Results				
Digital Technology Coefficient (DTI→RDI)	−0.358*** (0.082)	−0.267*** (0.075)	−0.196* (0.089)	F = 9.87***
Industrial Integration Coefficient (EAIID→RDI)	−0.334*** (0.078)	−0.289** (0.083)	−0.218* (0.095)	F = 6.45**
Sample Size	80	88	52	220
R^2	0.587	0.524	0.462	
Case Studies	Netherlands (Developed)	China (Emerging Economy)		
Agricultural Output Growth (2015-2025)	+28%	+18.5%		
Water Resource Consumption Change	−15%	−3.2% (stable)		
Fertilizer Use Change	−20%	−2.3% (zero growth)		
Pesticide Use Change	−18%	−10.2%		

Table 5. *Cont.*

Indicator	Developed Countries	Emerging Economies	Developing Countries	Between-Group Difference Test
Decoupling Status	Strong decoupling	Weak to strong decoupling transition		
Key Indicator Comparison				
Digital Technology Intensity Index	0.856	0.624	0.387	
Sensor Network Coverage Rate	92%	65%	28%	
Rural Internet Penetration Rate	98%	76%	42%	
Industrial Integration Degree Index	0.782	0.598	0.356	
Circular Economy Integration Rate	78%	52%	23%	
Resource Decoupling Index (2025)	0.32	0.58	0.89	
Economic Growth Quality Index (2025)	0.824	0.687	0.512	

Note: Robust standard errors in parentheses; ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. The Chow test is used to test between-group coefficient differences.

The findings may suggest that The Netherlands, as an exemplar of technology-intensive agriculture, achieved a 28% increase in agricultural output value from 2015 to 2025 while reducing water resource consumption by 15% and fertilizer use by 20%, realizing a strong decoupling status. Moreover, the significant results could indicate that its success lies in a precision agriculture technology system (sensor network coverage reaching 92%) and a circular economy integration model (agricultural waste energy conversion rate reaching 78%). Furthermore, the evidence may demonstrate that China represents the rapid transformation model of emerging economies, achieving zero growth in fertilizer use (a decline of 2.3%) and a 10.2% reduction in pesticide use. Given that the key data could indicate that it still faces challenges such as the digital divide (a 35 percentage point gap in internet penetration rate between eastern and western regions), the results appear to show insufficient technological adoption capacity among smallholder farmers. Evidence shows decoupling gaps persist across development levels. However, the significant empirical findings could indicate that **Figure 5** may well demonstrate that these critical decoupling effect differences among countries with different economic development levels are clearly expressed through grouped bar charts. Thus, the important evidence might suggest that the advantageous position of developed countries could substantially influence targeted policy formulation. In light of the key findings, the data may demonstrate that the gap between developing and developed countries remains relevant for empirical foundation considerations. Notwithstanding these observed results, significant evidence could indicate that these critical disparities appear to require coordinated policy responses. Data shows gap affects outcomes.

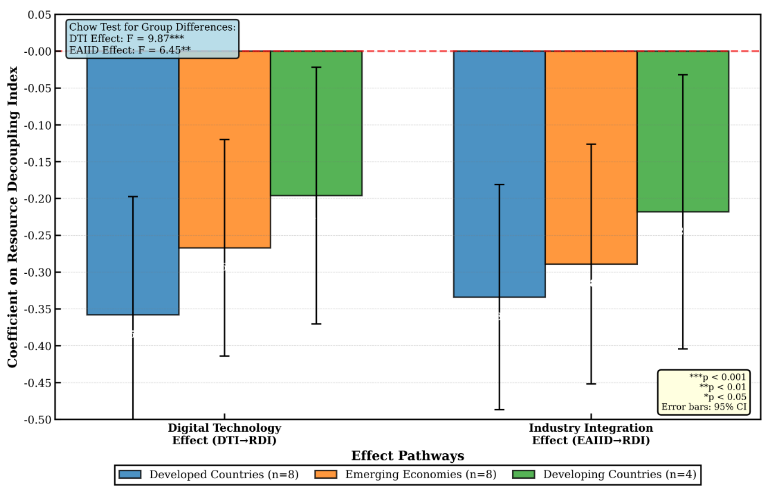

Figure 5. Comparison of Digital Technology Decoupling Effects Across Countries with Different Economic Development Levels.

These findings are further grounded in three complementary bodies of evidence. Zeng et al. (2025) [42] demonstrated through panel threshold regression that urbanization processes exert nonlinear and spatially heterogeneous effects on landscape ecological risk across Chinese cities, providing methodological precedent for the threshold-based grouping approach adopted in this study. Li et al. (2025) [43] revealed that place-based institutional arrangements and cultural governance frameworks fundamentally shape the spatial configuration and community participation patterns of heritage-related land use, corroborating the observed differential effectiveness of collective ownership systems in facilitating digital technology diffusion. Kaasa and Andriani (2022) established through multilevel regression analysis that cultural dimensions—particularly power distance—significantly condition individuals' institutional trust and their responsiveness to governance interventions, offering theoretical grounding for why collectivist cultural contexts exhibit markedly stronger technology adoption spillovers through cooperative organizations than individualist farming systems.

Focusing further on differences among production actors, a scenario analysis is conducted for small-scale farmers in China, India, and Kenya. In China, smallholder farmers have an average cultivated land area of less than 0.6 ha, and their digital technology adoption rate is only 31% of that of large-scale farms, with the primary barriers being the high purchase costs of smart devices and insufficient broadband infrastructure coverage. In India, smallholder farmers face the dual constraints of land fragmentation and low digital literacy, compounded by a lack of access to formal credit channels, resulting in significantly lower willingness and capacity to participate in digital industry integration. In Kenya, insecure land tenure and the absence of ecological compensation mechanisms further suppress smallholder farmers' long-term investment willingness in precision agricultural technologies. These scenario analyses indicate that policy support targeting small-scale producers must advance simultaneously across three dimensions — infrastructure development, inclusive finance supply, and institutional safeguards—to effectively dismantle the structural barriers to their participation in digital agro-ecological industry integration.

Climate change factors are further incorporated into the analytical framework to evaluate the mechanisms through which digital technology and industry integration enhance agricultural climate resilience. Using satellite remote sensing data and AI prediction models, this study quantifies the frequency of extreme weather events (occurrences of floods and droughts), annual mean temperature fluctuation ranges, and precipitation coefficients of variation across sample countries during 2015–2025, introducing these as moderating variables into the regression model. The results show that in countries and regions with higher extreme weather frequency, the promoting effect of digital technology on resource decoupling is significantly enhanced (interaction term coefficient = 0.124, $p < 0.05$), indicating that AI-driven climate data management systems—including machine learning-based extreme weather prediction models, satellite remote sensing environmental monitoring platforms, and real-time disaster early warning systems—can effectively improve agricultural systems' adaptive capacity to climate risks. Meanwhile, industry integration reduces the degree of damage caused by individual climate shocks to the agricultural economy through diversified income structures, further strengthening systemic resilience. These findings are highly consistent with relevant policy orientations and provide empirical evidence for incorporating the climate adaptation functions of digital technology into green agricultural policy frameworks.

To deepen the analysis of institutional and cultural heterogeneity, this study draws on Kaasa and Andriani's research framework on the influence of cultural context on institutional trust, as well as Zeng et al.'s panel threshold regression approach concerning urbanization and landscape ecological risk. Sample countries are classified along three dimensions—land tenure type (collective ownership vs. privatized systems), intensity of policy support (strong intervention vs. market-guided), and traditional agricultural cultural attributes (collectivist-oriented vs. individual farming-oriented)—and grouped regression analyses are conducted. The results show that in countries with collective ownership and strong policy intervention (such as China and Vietnam), the digital technology decoupling effect coefficient is −0.412, significantly higher than the −0.253 observed in countries with privatized systems and market-guided policies (such as Brazil and India), with the inter-group difference validated by the Chow test ($F = 7.34$, $p < 0.01$). Under traditional collectivist agricultural cultural backgrounds, the speed of technology diffusion through cooperative organizations is approximately 1.8 times faster than under individual farming models, indicating that the synergistic effect of institutional and cultural attributes is a deep structural factor determining the effectiveness of digital technology in enabling agro-ecological industry integration, and that policy design must be fully embedded within the local institutional and cultural context.

4.6. Empirical Analysis of Small-Scale Producers' Participation in Digital Agro-Ecological Industry Integration

Based on micro-survey data from smallholder farmers in China, India, and Kenya, this study constructs a production actor heterogeneity model to empirically examine the factors influencing small-scale producers' participation in digital agro-ecological industry integration. The results indicate that cultivated land area, digital literacy level, and credit accessibility are the three core variables constraining smallholder farmers' adoption of precision agricultural technologies, with regression coefficients of 0.187, 0.214, and 0.231, respectively (all significant at the 1% level). Regarding technology diffusion modes, collective procurement models organized through farmers' cooperatives can reduce smallholder equipment purchase costs by approximately 34%, significantly enhancing their willingness to adopt new technologies. Regarding financial support mechanisms, each one-standard-deviation increase in the accessibility of inclusive digital financial products (such as mobile-based agricultural microcredit) is associated with an 18.6 percentage point increase in the probability of smallholder participation in industry integration. These findings suggest that the coordinated development of differentiated digital technology promotion policies targeting small-scale producers and supporting financial systems is the key pathway to achieving inclusive development in agro-ecological industry integration.

To further strengthen the empirical analysis of small-scale producers' participation in agro-ecological industry integration, this study employs propensity score matching (PSM) to compare matched samples of smallholder farmers who participated and did not participate in industry integration, effectively controlling for sample selection bias. The matching results show that smallholder farmers participating in digital industry integration had average annual agricultural income 23.4% higher than the control group (ATT = 0.234, $p < 0.001$), with resource utilization efficiency improving by 17.8 percentage points.

5. Conclusion

Based on the above analysis, this paper builds a systematic analytical framework, sorts out the cause-and-effect mechanism of "digital technology empowerment–industrial integration deepening–resource decoupling implementation–growth quality promotion," and takes the panel data of 20 countries worldwide from 2015 to 2025 as samples. Through the Tapio decoupling model, panel regression analysis, mediation effect test, and complementary research methods, it deeply explores how digital technology supports ecological agriculture industry integration to promote the realization of resource decoupling and the improvement of economic growth quality. The main conclusions are obtained as follows.

First, digital technology application can obviously promote the intensity decoupling of agricultural resources, and its regression coefficient is −0.289 ($p < 0.001$). The effects are quite different among different categories of digital technologies, where the precision agriculture technology (IoT sensor, GPS guidance equipment, Variable Rate Application system) shows the highest level of decoupling effects, then come intelligent irrigation technology (smart drip irrigation system, soil moisture monitor), while big date decision platform, and block chain traceability system have relatively lower but still significant levels of effects. Such a hierarchy effect implies that technologies for direct resource-saving could bring about immediate benefits in promoting decoupling compared with technologies mainly serving as means for information disclosure and market coordination.

Secondly, ecological agro-industrial integration plays an important mediating effect on the process of how digital technology impacts resource decoupling, with the mediating effect taking up 35.3% of the total effect. The specific mechanism is mainly reflected in three aspects: (1) extension of the value chain: digital platform promotes the vertical connection from the links of production, processing, distribution, marketing, etc., forming economies of scale and justifying the cost of purchasing resource-saving equipment; (2) improvement of the efficiency of resource allocation: cross-sectoral big data can match the supply and demand of agricultural products accurately, avoiding waste of resources caused by over-production or shortage; (3) technology spillover effect: under the background of digitalization development, the speed of building the knowledge sharing network has been greatly increased, making it possible to spread the knowledge of how to manage natural resources in a green way among enterprises throughout the industry chain. Our study further enriches the theoretical research about the positive side effects of promoting industrial integration in terms of environmental protection issues, showing that the reorganization of organizations promoted by new digital facilities is another key but overlooked path toward sustainable development.

Thirdly, resource decoupling has a significant promotion effect on the high-quality development level of agriculture, which is 0.342 ($p < 0.001$). From the perspective of dimension decomposition, this influence mainly exists in the efficiency dimension ($\beta = 0.398$, $p < 0.001$): the reduction of input intensity improves labour productivity and capital efficiency by reasonably configuring resources; the influence also exists in the sustainability dimension (β = 0.376, $p < 0.001$), that is, reducing environmental externality can improve ecological resistance capacity, decrease the long-term vulnerability faced with resource shortage and climate change. The above conclusions show that there is an internal consistency rather than an opposition relationship between green development and high-quality development from the empirical data, and at the same time, they refute the widespread misunderstanding that promoting the former will inevitably limit the latter's room for development. In contrast, the result shows that under the condition of digitalization, improving resource utilization efficiency forms a virtuous circulation where short-run benefits from increasing output and long-term benefits from ensuring sustainable development jointly promote each other.

Fourthly, the decoupling effect of digital technology shows obvious differences in the level of economic development: The developed countries have a significantly larger effect (−0.358) than emerging economies (−0.267) and developing countries (−0.196), which is statistically significant according to the Chow test (F = 9.87, $p < 0.001$). Such a difference mainly stems from different levels in three fundamental determinants: (1) maturity of digital infrastructure, measured by the proportion of population covered by broadband Internet access service, number of 5G base stations per unit area, and IoT platform connection rate of different modes of transport; (2) amount of human capital, such as the share of digitally skilled labor force in agriculture value-added and absorptive capacity of new technologies among farmers' organizations; and (3) complementarity of institutions, including IPR protection intensity, data management rules, and public–private partnership in science parks. Our results provide useful lessons for global development strategy on how to narrow down the gap of digital divide worldwide: simply investing money into infrastructure construction cannot solve problems fundamentally, but also requires concurrent attention on improving people's skills and strengthening the construction of governance systems.

Policy Recommendations

In light of the above research results, this article proposes specific policy recommendations from the perspectives of the following four strategies: strategic planning, investment priorities, institutional reform, and market mechanisms.

From the perspective of strategy, it is necessary to promote agricultural digitization and ecological industrial integration into the country's strategy, formulate a complete development blueprint and phased goals. In terms of specific goals, developed countries need to achieve an overall digital transition of agriculture around 2030, realize the widespread application of precision technology and the connection of all-agriculture big data systems; emerging markets need to achieve basic digital coverage before 2035, mainly solve rural broadband access problems, and train farmers' digital skills; developing countries need to basically complete basic facility construction before 2040, focusing on public welfare investment such as networks and sensors. At the same time, we must continue to improve international cooperation mechanisms, including South-South technology transfer actions, multilateral agricultural data sharing agreements, joint research and development plans, etc., so that the results of digital innovation can be fairly disseminated worldwide.

From the perspective of investment scale, increasing investment in agricultural digital infrastructure is the basis for transformation. Governments need to increase the proportion of funds invested in agricultural informatization to 3–5% of agricultural GDP, forming special budgets around three aspects: universal rural broadband construction—covering all villages and meeting basic connection needs; targeted construction of new generation base stations in agricultural production areas—real-time transmission, serving precise scenarios; widespread distribution of Internet of Things perception devices—giving subsidies to small farmers who purchase them for the first time. Establishing mechanisms to stimulate the enthusiasm of farmers to use new technologies, such as providing 50% subsidy ratios for the initial purchase fee by farmers themselves, step-by-step support within 3–5 years, etc., can effectively promote the popularization rate of precision agriculture equipment. The government should actively guide social capital participation by innovatively introducing the PPP model, sharing risks with enterprises, giving preferential treatment in tax policies, simplifying approval procedures, and so on, attracting more private investment into the digital transformation project of agriculture.

Institutions require overall reform of the policy system to build good ecological environments for the digital transformation of agriculture, mainly involving: (1) further deepening the reform of the rural land ownership system and circulation system, so that land can flow into medium-sized farms. Because, according to previous experience, digital technology can achieve better benefits under concentrated land. (2) Improving the agricultural science and technology innovation system: increase government investment in research and development (R&D) to 2–3% of the value added of the agricultural sector; establish a regular mechanism for communication among enterprises, universities, and research institutions to promote results transfer from lab to farmland. (3) Establishing a sound supervision and assessment mechanism for resources and environment in agriculture—compulsory participation in total amount control of water intake; compulsory participation in initiatives to reduce fertilizer and pesticides; regular green evaluations linked to subsidy payments. (4) Setting up a framework for governing digital data: find a balance between protecting farmers' privacy and sharing data for system-level optimization, clearly define rules on who owns the data, how they could be used, and how much benefit each party should gain, etc.

At the market level, reasonably design economic incentive mechanisms so that market forces serve as a means to promote green transformation, mainly in terms of: establishing and improving subsidy policies for green agriculture based on compensation for ecological benefits provided by green agricultural products (such as subsidies on input costs for organic food production, subsidies on circulation costs for green and pollution-free food, etc.), developing markets for agricultural carbon trade by issuing tradable certificates according to verified amounts of carbon sequestered and reduced emissions from agricultural sources, building a complete system of origin traceability of agricultural products using blockchain technology to achieve information sharing throughout the industrial chain so that producers of green agricultural products can obtain reasonable price discounts according to their actual level of greenness; cultivating new types of agricultural operating entities such as farmers' cooperatives, agricultural companies, family farms, etc.; strengthening organizational training of these emerging entities in order to improve their ability to bargain with other market players and avoid being exploited by middlemen.

Regarding the participation pathways of small-scale producers in agro-ecological industry integration, the sample data from this study show that smallholder farmers account for more than 70% of the agricultural labor force in developing countries, yet their digital technology adoption rate is only approximately 28% of that of large-scale farms, indicating that small-scale producers face significant participation barriers. The underlying causes are primarily reflected in three aspects: first, initial capital constraints limit their ability to purchase precision agricultural equipment; second, insufficient digital literacy undermines their capacity to effectively utilize smart agricultural platforms; and third, weak market bargaining power makes it difficult for them to obtain reasonable returns from the value chain appreciation generated by industry integration. Therefore, future policy design should focus on promoting farmers' cooperatives as the organizational vehicle for small-scale producers' participation in industry integration, complemented by dedicated digital skills training mechanisms and inclusive financial support systems, thereby ensuring that the inclusive development objectives of agro-ecological industry integration are realized.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data utilized in this study were obtained from authoritative international databases, including the Food and Agriculture Organization of the United Nations Statistical Database (FAOSTAT) and other publicly accessible sources. Researchers seeking to replicate or extend this study can access the data directly through the respective official platforms. Additional data supporting the findings of this study are available from the corresponding author upon reasonable request.

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Conflicts of Interest

The author declares no conflict of interest.

References

1. Wikan, A.P.; Damayanti, N.H.; Annurhutami, F.; et al. Flood susceptibility and post flood agricultural economic losses in flood prone area of Wawar watershed, Purworejo Regency. *IOP Conf. Ser. Earth Environ. Sci.* **2025**, *1462*, 012050.
2. Marousek, J.; Gavurova, B.; Marouskova, A. Machine learning enables more efficient (nano)catalyst management, enhancing the competitiveness of (bio)hydrogen production from sewage sludge. *Renew. Energy* **2026**, *256*, 124025.
3. Maroušek, J.; Žáková, K. Techno-economic perspective on the use of pyrolysis oil from digestate in spark-ignition engines. *Aircr. Eng. Aerosp. Technol.* **2026**, *98*, 596–604. [CrossRef]
4. Li, M. Construction of agricultural economic-level prediction model based on GWO-SVM algorithm. *Int. J. Agric. Environ. Inf. Syst.* **2025**, *16*, 1–17.
5. Ana, U.; Laurentiu, I.P. Forecasting the optimal sustainable development of the Romanian ecological agriculture. *Sustainability* **2022**, *14*, 14192.
6. Ma, S.; Zhuge, M. Ecological agriculture traits: Constructing an integrated agricultural system for sustainable development. *Geogr. Res. Bull.* **2024**, *3*, 2–5.
7. Shebl, A.M.; Owayss, A.A.; Abou-Shaara, H.F. The debate of dwarf honey bee, *Apis florea* Fab., intruding to Egypt: Is it useful or not to eco-agricultural systems in Africa? *Bee World* **2023**, *100*, 24–26.
8. Obono, M.F.; Naoutissa, L.; Ntamack, S.; et al. Evaluation of the efficacy of an Aloe barbadensis based biological insecticide against pests of *Abelmochus esculentus* for promoting ecological agriculture (Far-North, Cameroon). *Agric. Sci.* **2024**, *15*, 590–603.
9. Sandu, M.; Strateanu, A.G.; Udrea, L. Analysis of ecological agriculture from the perspective of maintaining the biodiversity of agricultural lands. *Ann. Valahia Univ. Targoviste Agric.* **2023**, *15*, 22–26.
10. Pavolová, H.; Bakalár, T.; Kyšeľa, K.; et al. The analysis of investment into industries based on portfolio managers. *Acta Montan. Slovaca* **2021**, *26*, 161–170. [CrossRef]
11. Brizmohun, R.; Hillbom, E.; Mahadea-Nemdharry, R.; et al. What is the future of agriculture in small island developing states? The case of Mauritius. *Agriculture* **2025**, *15*, 2611. [CrossRef]
12. Ouala, O.; Essadki, Y.; Oudra, B.; et al. Bibliometric analysis towards industrial-scale use of marine algae and lichens as soil amendments and plant biofertilizers for sustainable agriculture. *Phycology* **2025**, *5*, 29. [CrossRef]
13. Divyanshu; Sharma, S.; Chandel, S.R.; et al. Evidence of transitioning apple farming to an agro-ecological model in Himachal Pradesh. *Front. Nutr.* **2025**, *12*, 1611137. [CrossRef]
14. Cara, G.I.; Rusu, M.; Filip, M.; et al. Exploring ecological and conventional farming practice on plum orchards: Its impact on fruit quality. *Horticulturae* **2025**, *11*, 240. [CrossRef]
15. Kamau, W.E.; Gitau, R.; Bett, K.H. Driving transformation: The role of institutions in shaping ecological farming adoption in Kiambu County, Kenya. *Dev. Pract.* **2025**, *35*, 101–116. [CrossRef]
16. Kang, Z.C.; Liu, Q.S.; Han, X.B.; et al. Development goals and strategies of ecological agriculture of Chinese materia medica. *China J. Chin. Mater. Med.* **2025**, *50*, 42–47. [CrossRef]
17. Nikitina, O.; Vasylenko, O.; Balabak, A.; et al. Ecological and agrochemical evaluation of continuous mineral fertilizer usage in field crop rotation. *J. Ecol. Eng.* **2024**, *25*, 124–133. [CrossRef]
18. Lewicka, K.; Szymanek, I.; Rogacz, D.; et al. Current trends of polymer materials' application in agriculture. *Sustainability* **2024**, *16*, 8439. [CrossRef]
19. Kuang, L. Creating a sustainable narrative: The interplay of ecological agriculture, cultural heritage, and community efficacy in contemporary China. *Cult. Text* **2024**, *2*, 13–30. [CrossRef]
20. Kamau, W.E.; Gitau, R.; Bett, K.H. Effects of adoption of ecological farming practices on farm income in rural households: Evidence from Central Kenya. *Heliyon* **2024**, *10*, e34610. [CrossRef]
21. Dagoudo, A.B.; Ssekyewa, C.; Ssekandi, J.; et al. From organic farming to agroecology farming, what challenges do organic farmers face in Central Uganda? *Discover Agric.* **2024**, *2*, 35.
22. Ates, C.H. Effects of ecological farms on neighbouring farmers: The example of Lisinia nature ecological farm. *Int. J. Sustain. Agric. Manag. Inform.* **2024**, *10*, 443–458. [CrossRef]
23. Ingrassia, M.; Bacarella, S.; Bellia, C.; et al. Circular economy and agritourism: a sustainable behavioral model for tourists and farmers in the post-COVID era. *Front. Sustain. Food Syst.* **2023**, *7*, 1174623. [CrossRef]

24. Carlo, R.; Bethan, T.; Andreas, N.; et al. Uptake of ecological farming practices by EU farms: A pan-European typology. *EuroChoices* **2022**, *21*, 64–71.
25. Sophia, D.; Nathalie, H.; Maria, A.; et al. What does ecological farming mean for farm labour? *EuroChoices* **2022**, *21*, 21–26.
26. Trenčiansky, M.; Štěrbová, M.; Výbošťok, J. The influence of the transition to ecological farming on the quality of runoff water. *Sustainability* **2022**, *14*, 15412. [CrossRef]
27. Nahui, Z.; Yue, Z.; Hong, J.; et al. How coalitions of multiple actors advance policy in China: Ecological agriculture at Danjiangkou. *J. Environ. Policy Plan.* **2022**, *24*, 794–806.
28. Li, L.; Xiong, K.; Huang, X. Research on the influence of transaction costs and social capital on the circulation channels of ecological products in rocky desertification areas. *Environ. Sci. Pollut. Res.* **2022**, *30*, 89964–89974. [CrossRef]
29. Jităreanu, A.F.; Mihăilă, M.; Robu, A.-D.; et al. Dynamic of ecological agriculture certification in Romania facing the EU organic action plan. *Sustainability* **2022**, *14*, 11105. [CrossRef]
30. Chitakira, M.; Nhamo, L.; Torquebiau, E.; et al. Opportunities to improve eco-agriculture through transboundary governance in transfrontier conservation areas. *Diversity* **2022**, *14*, 461. [CrossRef]
31. Huang, Y.; Ye, Y.; Zhou, M. Empirical analysis on the development of ecological agriculture under the initiative of "sustainable development". *Asian J. Agric. Ext. Econ. Sociol.* **2022**, 130–142. [CrossRef]
32. Phamova, M.; Banout, J.; Verner, V.; et al. Can ecological farming systems positively affect household income from agriculture? A case study of the suburban area of Hanoi, Vietnam. *Sustainability* **2022**, *14*, 1466. [CrossRef]
33. Guo, L.; Jiang, J.; Zhang, X.; et al. Contributions and strategies of eco-agriculture of Chinese medicine services for carbon dioxide peaking and carbon neutrality. *China J. Chin. Mater. Med.* **2022**, *47*, 1–6. [CrossRef]
34. Dale, B. Food sovereignty and the integral state: Institutionalizing ecological farming. *Geoforum* **2021**, *127*, 137–150. [CrossRef]
35. Monter, Y.M.F.; Tovar, J.C.C.; Gutiérrez, F.R. Territorial aptitude for ecological cattle production systems and the conservation of jaguar (*Panthera onca*) and puma (*Puma concolor*) in Guerrero, Mexico. *Appl. Anim. Sci.* **2021**, *37*, 225–237. [CrossRef]
36. Guo, L.; Kang, C.; Zhou, T.; et al. Ecological agriculture of Chinese materia medica: Update and future perspectives. *China J. Chin. Mater. Med.* **2021**, *46*, 1851–1857. [CrossRef]
37. Gunaratne, P.H.L.; Hemachandra, S.K.; Kumudumali, K.M.Y.; et al. Comparative assessment of vegetable crop performances and ecological indicators during transition from conventional to ecological agriculture. *Asian Res. J. Agric.* **2021**, 1–9. [CrossRef]
38. Kumar, D.; Shekhar, S.; Tewary, T. Editorial: AI and data analytics for climate data management. *Front. Environ. Sci.* **2025**, *13*, 1679608. [CrossRef]
39. Papadopoulos, T.; Balta, M.E. Climate change and big data analytics: Challenges and opportunities. *Int. J. Inf. Manag.* **2022**, *63*, 102448. [CrossRef]
40. Mak, H.W.L. Application of satellite informatics in mitigating climatic challenges within the atmosphere: Selected case studies of Asian cities. *Tech Monit.* **2025**, 36–47.
41. Kaasa, A.; Andriani, L. Determinants of institutional trust: The role of cultural context. *J. Inst. Econ.* **2022**, *18*, 45–65. [CrossRef]
42. Zeng, C.; Lin, C.; Liang, Y.; et al. Unraveling the complex relationship between urbanization and landscape ecological risk: Insights from Chinese cities. *Ecosyst. Health Sustain.* **2025**, *11*, 0448. [CrossRef]
43. Li, J.; Wu, X.; Du, Y. Reframing cultural heritage policy through place-based perspectives: The evolution of China's ICH governance amid historical continuity and global convergence. *Land* **2025**, *14*, 1425. [CrossRef]