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Agri-business transformation in Asia: The strategic role of water use, agricultural emissions, irrigation infrastructure, and digital technologies in advancing sustainable resource efficiency

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Abstract

Technology, automation, and a growing focus on sustainability are rapidly transforming agribusiness worldwide. Asia's agricultural sectors are facing significant challenges due to rising population, food insecurity, and environmental issues, highlighting the urgency of these developments. This study analyzes how technological innovation, agricultural sustainability, water efficiency, and sustainable resource management influenced the selected Asian countries, where food poverty, environmental degradation, and rapid population growth are on the rise. The study used a panel autoregressive distributed lag (ARDL) model and Dumitrescu–Hurlin panel causality test to examine the long- and short-term dynamics and causal relationships among the variables for the period 2000–2023. The results showed that water efficiency and irrigation technology increase agricultural output, whereas nitrous oxide emissions decrease it. Data-driven approaches, agro-industrial automation, and agricultural research and development boost resource efficiency and production. However, food security, environmental stress, and unequal implementation of precision agriculture reduce efficiency. New technologies may disrupt systems and raise transition costs, but also enhance resilience and sustainability over time. The Dumitrescu–Hurlin panel causality test suggests that environmental inputs and technological adoption affect resource efficiency in the short- and long-term. Overall, the study suggests several ways to boost sustainable, efficient farming in Asia, including improving water management, reducing emissions, increasing the use of digital and automated farming systems, and promoting precision agriculture.

Keywords: Agri-business transformation; Agricultural freshwater withdrawal; Agricultural nitrous oxide emissions; Irrigated agricultural land; Technology adoption; Resource efficiency; Asia

1. Introduction

Agricultural industrialization has long been the backbone of national economies. Tombe and Smuts[1] stated that this shift requires systemic reforms in the food and fiber sectors to enable new food production and consumption. In recent decades, agricultural economics and natural resources scholars have focused on agricultural modernization and sustainable development.[2] According to the United Nations (UN)'s Sustainable Development Goals (SDGs), agriculture is essential to green development. Redesigning current farming processes to be more efficient, cheaper, and environmentally friendly is called "agricultural green development."[3,4] Agricultural industrialization prioritizes environmental quality, food safety, and human well-being, according to De Alwis *et al.*[5] To upgrade the whole agricultural, animal, and food production chain, this modernization requires technological advances to make agriculture more competitive, less dependent on natural resource extraction, and promote sustainable agriculture as it expands.[6] Innovation-driven industrialization is essential for resilient agricultural systems that balance economic growth, equitable income distribution, and natural resource preservation.[7] Agriculture is still the backbone of Asian economies, providing food security, employment, and industrial raw materials. Despite an increased emphasis on industrial growth, agriculture still drives regional economic development.[8] However, the sector faces several challenges. These include climate change risks, rising environmental costs, and resource shortages. Since temperature fluctuations and severe weather raise agricultural production risks, climate-resilient and ecologically beneficial solutions are essential.[9] Cost-effective, technical innovation-driven restructuring may improve resource efficiency, reduce carbon emissions, and increase production levels.[10]

Agriculture is transforming, driven by rapid technological advances, automation, and environmental issues.[11] This study challenges the dominance of precision agriculture, data analytics, and automation in discussions of resource efficiency by emphasizing the roles of environmental inputs and sustainability in long-term agricultural performance. Resource efficiency depends on regulating agricultural freshwater withdrawal, lowering nitrous oxide emissions from agriculture, and strategically developing irrigated agricultural land.[12] Better water allocation and irrigation infrastructure can increase agricultural yields per unit of input, improve climatic resilience, and enable the adoption of modern agro-technologies consistent with input–output efficiency and infrastructure-led growth models.[13] High nitrous oxide emissions highlight the drawbacks of extensive fertilizer use, such as soil degradation and system inefficiency.[14] Combining these environmental factors with automation and technology strategies provides a broader view of agricultural resource efficiency, highlighting the dynamic relationship between ecological preservation, technological advancement, and long-term economic growth. Addressing these issues is crucial to boosting productivity, reducing environmental harm, and enhancing agribusinesses' competitiveness in fast-growing Asian countries.

Agriculture globally struggles with soil erosion, water limitations, food demand and supply imbalances, and a lack of sustainable solutions. The government, academia, companies, and agricultural communities must collaborate to promote environmentally friendly technologies to tackle these challenges.[15] Agriculture is crucial for economic growth and structural transformation in developing and middle-income nations.[16] Sustainable agricultural industrialization prioritizes soil quality and production. Farmers are using zero tillage, minimum soil disturbance, and judicious organic and inorganic fertilizer usage to boost yields and reduce degradation.[17] High-yield crops, irrigation, fertilizers, and agrochemicals saved millions of lives but caused environmental damage, groundwater depletion, and chemical dependency.[18] Recently, eco-friendly technologies that are productive and ecologically beneficial have gained attention. South Asia, a major food producer, employs over half its workers in agriculture and contributes significantly to foreign reserves.[19] Meeting the rising demand for nutritious food while safeguarding the environment requires more agro-based enterprises and environmentally aware supply chains.[20] However, inadequate resource usage and limited process acceptance make current practices and technology adoption insufficient to meet these aims. Sustainable agriculture requires current technology, resource efficiency, and ecosystems.[21]

The emergence of "smart farming", incorporating information and communication technologies (ICTs) with traditional farming methods, signals the "fourth agricultural revolution." Internet of Things (IoT), remote sensing, big data analytics, and machine learning are changing agriculture.[22,23] These technologies enable smart irrigation, crop monitoring, and input efficiency. Farmers do not know about smart agriculture technology, do not have the necessary training, do not have enough money, and institutions do not support them.[24,25] Trust is vital for sustainable technology adoption and for traditional agricultural systems to transition to modern ones.[26,27] Without institutional support, innovations may not be fully adopted, even if they are beneficial. Sustainable agricultural modernization can protect the environment, food security, and the economy for future generations.[28] Agriculture development is nested within three interrelated systems: the natural system, which provides energy and materials to all living things; the food system, which produces, harvests, processes, transports, and stores crops and livestock; and the human system, which is affected by both. Agricultural green development requires a balanced interplay between these systems and innovative, interdisciplinary research that fosters knowledge and practical solutions.[29] Green food product branding has gained popularity owing to ecologically friendly agricultural techniques. Branding, which changes consumer behavior, is crucial to agri-food industry competitiveness.[30] As markets change from real to abstract, simple to sophisticated, and quantitative to qualitative, food companies must innovate to stay competitive. Given the projected 9.7 billion global population by 2030, Liu *et al*.[31] recommended innovative agriculture technology for food security. Government and business must collaborate to implement sensor-based technologies in rural cultures. Clodoveo *et al*.[32] suggested that agricultural green development is key to alleviating hunger, boosting income, and protecting the environment. In a warming future, environmental regulations and technological usage affect productivity and resource allocation, making agricultural sustainability difficult. According to Peng *et al*.,[33] technical advances enhance resource availability and food security while reducing environmental impacts. Despite the importance of agricultural technology investments, uncertainties and dangers sometimes hinder them, particularly in low-income countries with underdeveloped insurance markets.[34] Innovative agricultural technologies, from automation to sensor-based systems, promise to save money, boost production, and improve the environment.[35] Low-income nations lack financial resources, farmer-friendly designs, and institutional support, making their implementation difficult.

This investigation is based on these research questions: First, how do irrigated land, nitrous oxide emissions, and freshwater extraction impact resource efficiency in Asian agriculture? It implies that these elements affect medium- and long-term automation, technology adoption, and environmental sustainability. Second, how much do agricultural technologies affect Asian resource efficiency? It examines how precision agriculture and other areas have decreased water, pesticides, and fertilizers while improving yields and lowering costs. Third, does smart farming that incorporates green methods boost Asian food security? This examines whether new agricultural technology can stabilize food systems and ensure sustainability by addressing supply-demand imbalances, climate challenges, and land restrictions. Finally, does modern agricultural technology reduce environmental impact? This investigates whether modern agricultural technology improves resource efficiency, emissions, and environmental impact.

The research questions determine the research goals:

- To assess the influence of irrigated agricultural land, agricultural freshwater withdrawal, and nitrous oxide emissions on resource efficiency.
- To analyze the role of technological advances in changing Asian agricultural resource utilization.
- To study sustainable agriculture, cutting-edge finance, and environmental preservation in the selected Asian economies.
- To explore the role of smart farming in improving local food security.

Technological advances have some pros and cons. Quick investments in agricultural technology may boost food production to meet population growth, but they can also raise carbon emissions if not managed carefully.[36] Sustainable development requires balancing agricultural productivity and environmental conservation. Clean and green technologies may increase agricultural productivity sustainably.[37]

Few studies have examined the interdependencies of resource-efficient farming, irrigation systems, environmental sustainability, data analytics integration, food security, agro-industrial automation, precision farming adoption, and rapidly changing agricultural systems in Asia.[38,39] Prior research treated agricultural production, environmental deterioration, and technical innovation as distinct concepts.[40,41] Given that the current literature is largely devoted to isolated agricultural indicators or country-specific analyses, there is a dearth of empirical data on the interplay among technological modernization, resource management, and environmental pressures in the broader Asian agricultural context. By developing a comprehensive agro-industrial sustainability paradigm, this research contributes to the current body of knowledge. Technological progress, irrigation efficiency, investment in agricultural research and development (R&D), automation, environmental externalities, and digital agricultural transformation are among the elements the framework aims to evaluate in relation to agricultural resource efficiency. This study examines the dynamic links and directed causal interactions across Asian economies using the panel autoregressive distributed lag (ARDL) model and Dumitrescu–Hurlin panel causality test over the period 2000–2023.

2. Literature review

Agricultural industrialization is increasingly recognized as a sustainable development tool, particularly in resource-constrained Asian economies. The sector needs technological improvement to boost production efficiency and ensure the environmental sustainability of agro-based enterprises worldwide. Asia's rapid economic expansion highlights the need for sustainable, resource-efficient, and high-production agricultural systems.

2.1. Environmental and infrastructure determinants of agricultural resource efficiency

Water is the most important resource for agriculture in Asia, where water shortages and monsoon unpredictability threaten crop productivity. Yadav *et al.*[42] revealed that water management enhances resource efficiency by increasing output per acre and minimizing waste. Initial investments in irrigation infrastructure boost productivity, though excessive water usage may lead to inefficiencies. Environmental management and technological innovation are linked, as argued by Bocean,[43] with nations that adopt better water management practices achieving higher agricultural productivity and positive spillovers into automation adoption and precision agriculture technologies. Most nitrogen oxide emissions come from overuse of nitrogen-based fertilizers, which degrade agricultural efficiency and harm the environment.[44] Nitrous oxide emissions from agriculture arise because private manufacturing fails to account for the social and environmental impacts of pollution.[45] Empirical data link high nitrous oxide levels to soil degradation, reduced nutrient-use efficiency, and long-term declines in production.[46] Paramesh *et al.*[47] showed that emission mitigation methods, including integrated nutrient management, organic fertilizers, and precision fertilization, improve resource efficiency over time. In climate-change-prone locations, irrigating more arable land makes farming more efficient and robust. Irrigation infrastructure enables high-yield agricultural cultivation, a consistent water supply, and minimal reliance on rainfall. Infrastructure-led development theory posits that productive capital investments (such as irrigation systems in this instance) improve output per unit of input.[48] Irrigated agricultural land and resource efficiency are mutually reinforcing: enhanced irrigation increases efficiency, and efficient management promotes the adoption of optimal irrigation systems.

2.2. Agriculture technology and agriculture resource efficiency

Studies are increasingly looking at how agricultural technology affects resource efficiency in diverse environments. For instance, Yao *et al.*[49] investigated the water–land–energy–food nexus in northeast China. They found that although water and energy efficiency rose from 2006 to 2019, food subsystem performance varied substantially over time and across regions. Priyadarshini and Abhilash[50] examined the Indian agri-food market and found that various states were effective in different ways. The most efficient states were Goa, Himachal, and Sikkim. Their analysis suggests investing in processing and storage facilities and in resource circularity for long-term agricultural growth. According to Cao *et al.*,[51] crop-specific water footprints are a key measure of agricultural productivity, and beans are more efficient than rice and wheat. Technological innovation has more than environmental and economic effects. Hao *et al.*[52] showed that digitalization and green innovation in China fostered green economic growth and favorable regional spillovers, demonstrating the relevance of digital infrastructure in agricultural transformation. Papadopoulou *et al.*[53] stated that economic incentives, renewable energy consumption, and technological adoption influence farmers' circular bio-economy acceptance. Kirikkaleli[54] provided global proof that agricultural modernization may reduce carbon emissions by increasing energy production and resource efficiency, meeting the SDGs. Technology addresses climate change, resource limitations, population limits, and resource productivity. Yeboah[55] recommended precision farming, advanced irrigation, remote sensing, organic farming, and agroforestry to increase agricultural sustainability in developing nations. Kucher *et al.*[56] found considerable regional disparities in Ukrainian water resource efficiency. This emphasizes the necessity for regional management solutions. However, Duque-Acevedo *et al.*[57] identified a considerable rise in agricultural waste research after 1998 in a bibliometric analysis from 1931 to 2018. This shows that global policy objectives are shifting toward trash recovery and resource efficiency.

The literature states that sustainable agricultural modernization requires technological advancement and resource management. Despite our progress, ecological indicators and agricultural output metrics are still inadequately integrated, particularly in developing nations. Empirical studies are crucial in Asia, where reforming agriculture is essential for food security, economic stability, and environmental resilience.

2.3. Agricultural greenhouse gas emissions intensity and its role in decreasing resource efficiency

Greenhouse gas reduction remains a key barrier to sustainable agricultural expansion and resource efficiency. Many studies have examined the link between emissions intensity, technology, and regional economies. For instance, Ulucak and Khan[58] found that renewable energy, resource rents, and urbanization lower ecological footprints in BRICS nations. This supports the Environmental Kuznets Curve. Their study indicates that the ecological footprint is a key indicator of unsustainable growth and environmental degradation. Trinks *et al.*[59] investigated 1,572 enterprises from 2009 to 2017 and found that carbon efficiency provides financial and environmental benefits. Carbon-efficient enterprises were more lucrative and less risky. Delmas *et al.*[60] found that investors appreciate U.S. corporations' environmental efforts even if they reduce short-term profitability, supporting Tobin's Q theory and favoring proactive environmental measures. National research contributes to the corpus of knowledge on emissions intensity and sustainability initiatives. Finland's improved raw-material production reduced greenhouse gas emissions by 70%,[61] but its gross domestic product (GDP) growth threatened environmental sustainability, underscoring the necessity for circular-economy rules. Wang *et al.*[62] found a negative association between resource richness and carbon emissions in China, supporting the idea that resource dependency inhibits emissions efficiency and low-carbon transition strategies. Goldemberg[63] found that although several European Union (EU) economies have seen a decrease in carbon intensity (CO_2/GDP) since 2000, economic growth has outpaced the drop in emissions, resulting in conflicting outcomes. Comparative investigations revealed emissions' structural drivers. Lamb *et al.*[64] examined 10global regions. They found that industrialization and agricultural expansion increased emissions in southern and eastern Asia, parts of Africa, and Latin America, while Europe and North America moderately decarbonized their energy sectors. Lamb *et al.*[65] examined 24 economies and identified three ways emissions may decrease: fast, over time, and for countries that have hit their peak. Energy, namely heat and electricity generation, is the major offender in all three scenarios. Based on these findings, climate policy measures that include regional industrial structures should target energy-intensive businesses. Country-specific examinations revealed further issues. In their examination of emissions of CO_2, methane, and nitrous oxide in Australia from 1990 to 2017, Ivanovski and Churchill[66] found diverse state-level routes toward Paris Agreement targets. Their findings suggest regionally specialized policy should target income, urbanization, and trade. Oreggioni *et al.*[67] used the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database and found that global anthropogenic emissions (excluding land use and forestry) were 50% higher in 2015 than in 1990, with industrialized countries reducing emissions by 9%.

Efficiency enhancements, renewable energy sources, and technology advances may reduce emissions, but economic growth, resource dependence, and structural rigidities typically overwhelm them. Agriculture is Asia's economic engine and a major emitter; therefore, understanding greenhouse gas intensity and resource efficiency is vital. The lack of empirical data in this area demands further research into sustainable agricultural techniques that may boost productivity while reducing emissions.

2.4. Food system and innovation literature

Food system innovation boosts resource efficiency, food security, and sustainability. Corporate assistance programs improve social and environmental innovation among Australian food and beverage managers[67] by providing financial support, time, and advisory services. Moral business ideals boost these impacts. Al-Khatib[68] found that big data analytics improves Jordan's food industry's green supply chain performance, emphasizing the relevance of digital transformation in sustainability. Technical intensity and green technology innovation influence this impact. A systemic view of innovation illuminates its implications on food security and the environment beyond business practices. Tseng *et al.*[69] suggested eco-labeling and recycling to achieve sustainable food systems in Thailand via behavior changes, improved storage and distribution, and technological monitoring. According to Gouvea *et al.*,[70] technological innovation improves food security in Organisation for Economic Co-operation and Development (OECD) economies by increasing food availability, but it has a greater price effect in impoverished countries. Urbanization reduces food security, but GDP, energy transition, and agricultural value-added improve it. Ray *et al.*[71] stated that current harvesting methods limit direct calorie intake. Due to agricultural diversification for feed, industry, and exports, sub-Saharan Africa may not be able to end hunger by 2030. Stadtbäumer *et al.*[72] found that excessive rainfall and drought reduce Zambian household welfare by 20–30%. Their study showed that climate-vulnerable regions, such as sub-Saharan Africa, require flexible food security solutions. Institutional and structural factors affect food system innovation. Aibar-Guzmán *et al.*[73] found that cross-holding companies are more likely to fund sustainable product innovation, often with debt, than family-owned enterprises in the global agri-food industry. Digital platforms greatly affect food system sustainability. Hanaysha[74] found that informational and interactive social media marketing strongly impacts United Arab Emirates food consumers' buying decisions. D'Odorico *et al.*[75] examined food disparity and human rights in Japan, the Middle East, and Africa, reflecting social challenges. Even when there is abundant food, famine persists, and unjust trade practices worsen it.

These initiatives show how innovation is affecting food systems, including supply chain management, corporate practices, and global food equity and security. Combining technological innovation with climate adaptation, governance frameworks, and social justice concerns is difficult in developing countries where food poverty and climate risk are linked. Future research should examine how innovation ecosystems enhance global and regional food systems' productivity, resilience, and equity.

2.5. Efficiency and automation in agro-industry

Terence and Purushothaman[76] found that the agriculture industry swiftly adopted digitalization despite its lengthy history of manual labor. Innovative farming approaches were categorized by whether they employed the internet, devices for monitoring and management, plant disease identification, or automatic watering. Smart farming is vital for long-term survival because sensor-driven tactics increase agricultural production, GDP growth, and export competitiveness. Zhou *et al.*[77] examined digital agriculture progress and agricultural total factor output in 30 Chinese provinces from 2011 to 2019. They found an inverted U-shaped relationship between digital agriculture and productivity growth, even while technological innovation outpaced technical efficiency. To fully achieve digital agriculture's revolutionary potential, the study stressed solid institutional processes, a uniform digital infrastructure, higher-quality agricultural goods, and improved social services. Smagulova *et al.*[78] examined Kazakhstan's energy-intensive economy from 2014 to 2021, focusing on its inefficient agro-industrial complex. Their digital adoption research was limited by older electrical and agricultural equipment. However, innovative farming technology and renewable energy integration were essential for agricultural productivity and economic growth. Su *et al.*[79] examined the complex links between digital financial technology and urban ecological efficiency in 284 Chinese cities from 2008 to 2018. Some regions had constraining effects later on, but digital money and ecological efficiency were linked early on. The study emphasized integrated digital finance and ecological activities as potential drivers of sustainable urban development. Liu *et al.*[80] evaluated how agricultural technology affects output and sustainability using panel data from 2003 to 2015. Rural financial development improved agricultural technological innovation, depending on marketization, but generally, it was favorable. Rural financing is a key driver of agricultural innovation and sustainability. Stentoft *et al.*[81] surveyed 190 manufacturing companies to evaluate Industry 4.0 adoption drivers and barriers. The findings revealed that small and medium enterprises participated in Industry 4.0, but identified more challenges than opportunities. The study suggested legislative frameworks to address adoption issues. In their examination of Spanish manufacturing businesses, Opazo-Basáez *et al.*[82] highlighted the move from digital services to technological innovation. They found, via parametric and non-parametric tests, that manufacturers with digital service integration innovated more and made better goods. Digital services and technological innovation must work together to support competitive growth.

Recent advancements in smart agriculture focus on boosting production and sustainability through energy-efficient technologies, embedded systems, cloud computing, and IoT. Today, internet-connected irrigation systems are a game-changer for modern farming, making water and resource use much more efficient. Morchid *et al.*[83] introduced a smart irrigation system that uses embedded sensors to monitor soil moisture, temperature, humidity, and water levels in real-time, leveraging IoT and cloud computing. The system uses cloud-based analytics to automate irrigation decisions, ensuring precise water control and reducing waste. Even amid concerns about water shortages and climate change, research indicates that internet-connected irrigation systems could significantly improve water efficiency and support sustainable farming practices. Morchid *et al.*[84] presented a new agricultural system that combines smart irrigation management, IoT, and cloud computing to enhance food security, indicating that automated decision-making systems and sensor technologies can improve irrigation scheduling, thereby increasing agricultural yields. The proposed framework not only enhances operational efficiency but also highlights how smart irrigation systems promote sustainability by reducing water waste and making farming practices more eco-friendly.

Digitization, automation, and financial integration are changing global agro-industrial systems. Innovative technology, digital finance, and Industry 4.0 may increase agricultural productivity, resource efficiency, and environmental impact, promoting sustainability. Based on the cited literature, this study has the following research hypotheses (H):

(i) H1: Agricultural freshwater withdrawal and irrigated agricultural land have a positive impact, while nitrous oxide emissions from agriculture hurt resource efficiency.
(ii) H2: Precision farming applications, which enhance resource efficiency using green digital technology, would help Asian nations meet the SDGs.
(iii) H3: Conventional farming practices in Asia will increase greenhouse gas emissions and diminish resource efficiency.
(iv) H4: Automation in Asian agro-based industries

will increase resource efficiency and environmental sustainability via innovative agriculture approaches.

(v) H5: Agricultural resource efficiency improvements will minimize food security challenges in this densely populated region by increasing production.

2.6. Research gaps and contribution of the study

This study addresses many literature gaps. First, automation, technological adoption, and precision agriculture have been extensively investigated, but few studies have examined how environmental inputs and infrastructure affect resource efficiency in Asian countries.[9,85] Limpamont *et al.*[86] examined environmental sustainability and technology adoption separately, without incorporating water consumption, emissions, and irrigation infrastructure into a holistic agricultural resource-efficiency model. Water use and emissions affect productivity, though few studies examine how they interact with technology and automation in the short- and long-term.[87,88] This information gap highlights the need for comprehensive research that considers environmental, infrastructural, and technological variables affecting agricultural efficiency and sustainable growth.

Second, assessments of resource optimization have concentrated on labor, production management, and bio-refinery approaches, not agricultural resource efficiency. This study, which builds on Song *et al.*,[89] Zhang *et al.*,[90] and Onyango *et al.*,[91] finds that resource efficiency is a key indicator of how technical advances enhance agricultural operations by enabling more efficient use of resources. This boosts productivity and sustainability. Third, most studies have assumed a causal relationship between macroeconomic issues and environmental degradation without conducting sector-specific analyses. To remedy this gap, our study uses agricultural greenhouse gas emissions intensity as an environmental impact surrogate. The new measure considers the environmental effect of farming by including CO_2, methane, and nitrous oxide emissions per metric ton of agricultural output, underlining the relevance of technological innovation in decreasing emissions and improving resource efficiency.

Fourth, although precision agriculture is considered innovative, there has been little study linking it to data analytics and automation to enhance resource efficiency. Combining the effects of intelligent farming data analytics, automation in agro-industrial processes, and precision agriculture on resource efficiency gives a more complete picture of agriculture technology adoption. Finally, sustainable agriculture research has focused on food security using freezing, ICT, artificial intelligence (AI), and contaminant-detection systems. The frequency of undernourishment, as a proxy for food security, has received little consideration in agricultural resource efficiency research. This indicator illuminates how technical advances and resource efficiency may address Asia's biggest food supply issue.[92,93] Our study provides a paradigm for studying sustainable agricultural development in Asia via undernourishment, automation, emissions intensity, and resource efficiency. This comprehensive strategy contributes to the research literature and gives practitioners and policymakers practical ideas to improve food security and environmental sustainability.

3. Theoretical framework

3.1. Agroecology theory

The Green Revolution increased agricultural yields and livestock productivity but caused ecological and social concerns, prompting the agroecology hypothesis. The critique of neo-classical economics led to agroecology, which emphasizes conventional farming's negative externalities. Neo-classical economics focused on product development, distribution, and consumption. Norgaard and Sikor[94] and Francis *et al.*[95] observed that herbicides, monocultures, and automated technologies initially enhanced production but degraded agro-biodiversity and sustainability. Therefore, agroecology is a comprehensive approach to long-term food security based on ecological and social considerations. This scientific discipline and set of agricultural methods aim to optimize interactions between humans, animals, plants, and the environment.[96] Agroecology has become transdisciplinary since its emphasis has expanded beyond crop management. French, German, Brazilian, and American interpretations of agroecology vary.[97] It is an agricultural and social movement in France and a scientific field in Germany. The 21st century has enhanced agricultural issues such as biodiversity loss, pollution, and climate change. New precision agroecology advancements advocate the use of technology to make food production more sustainable. Agroecology replaces synthetic inputs with cover crops and green manure to create sustainable agricultural systems and decrease environmental consequences.[98]

3.2. Social network theory

Social network theory may illuminate how participants' relationships, communication, and collaboration affect agricultural innovation and adoption. Borgatti and Halgin[99] defined social networks as groups of individuals with structured interactions based on mutual interests, information exchange, and favors. These networks provide farmers with knowledge spillovers, creative methods, and support systems to adapt to new challenges. The theory holds that social relationships impact behavior. Manski[100] listed three types of effects in such networks: exogenous, endogenous, and correlated. Exogenous effects are outside the network, while endogenous effects are within it. These mechanisms may explain farmers' adoption of no-till farming and improved seed varieties. Network structure and variation significantly impact knowledge distribution. Bouamra-Mechemache and Zago[101] stated that networks may help innovate by linking unconnected firms and giving fresh information. De Kraker[102] claimed that professional partnerships, such as family, tenancy, and community ties, are essential for these exchanges. Larger social networks help organizations, academics, and politicians collaborate with farmers and other stakeholders. Scaling up agroecological strategies and fighting resource degradation and climate change need this sort of collaboration.[103] Mutual trust is essential to this process because it fosters long-term cooperation and innovation. Once confidence is established, information flows more freely, and the project proceeds faster.[104] Agroecology and social network theory may show us how ecological principles and social interactions can make agriculture more sustainable. Figure 1 shows the conceptual framework of the study.

4. Methodology

Agricultural industrialization is necessary to sustain human life and agro-based businesses, which are vital to Asian economies. Asia, the world's most dynamic and rapidly rising continent, must increase agricultural production and maintain the environment. Modern sustainable development emphasizes complete economic growth.[105] The agricultural industry has become a complex system of ecologically friendly production, social preferences, and government laws. This study examines the relationship between agricultural modernization, sustainability standards, and resource efficiency to enhance food production without harming the environment. Technology optimizes resources and boosts agricultural productivity. The present research extends this paradigm by emphasizing technical innovation in agricultural processes that impact resource efficiency. The research investigates whether precision farming, a cutting-edge agricultural technology that enhances productivity and reduces carbon emissions, may help Asian nations. **Equation 1** is the panel-based econometric model used to validate this relationship empirically:

$$\begin{aligned} REA_{it} &= \beta_{\circ} + \beta_1 AFW_{it} + \beta_2 NOEA_{it} \\ &+ \beta_3 IAL_{it} + \beta_4 ARPAT_{it} + \beta_5 IATRD_{it} \\ &+ \beta_6 EI_{it} + \beta_7 ALAIP_{it} + \beta_8 DAI_{it} \\ &+ \beta_9 FS_{it} + e_{it} \end{aligned} \tag{1}$$

where REA is the resource efficiency in agriculture, AFW is the freshwater withdrawal, NOEA is nitrous oxide emissions from agriculture, IAL is irrigated agricultural land, ARPAT is the adoption rate of precision agriculture techniques, IATRD is the investment in agricultural technology R&D, EI is the environmental impact, ALAIP is the automation level in agro-industrial processes, DAI is the data analytics integration, and FS is food security. $\beta_{\circ}$ is the intercept, β_1 to β_6 are the coefficients, and e is the error term. Table 1 shows the list of variables and their measurement.

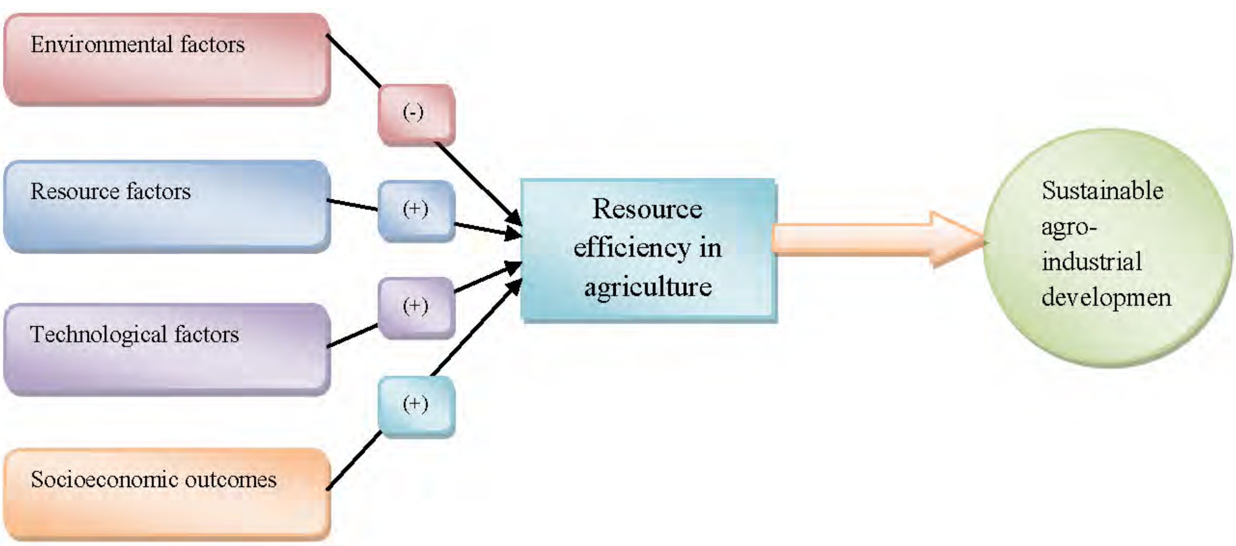

Figure 1. Conceptual framework of the study

Table 1. List of variables and their measurement

Variables	Symbols	Measurement
Resource efficiency in agriculture	REA	Fertilizer consumption per hectare of arable land, which reflects the amount of fertilizer used per unit of arable land.
Agricultural freshwater withdrawal	AFW	% of total freshwater withdrawals
Nitrous oxide emissions from agriculture	NOEA	Million tonnes of CO_2 equivalent (Mt CO_2e)
Irrigated agricultural land	IAL	% of total agricultural land
Adoption rate of precision agriculture techniques	ARPAT	$\mathrm{ARPAT} = \frac{\text{Total internet users}}{\text{Total rural population}} \times \frac{\text{Agriculture value added}}{\text{Total GDP}} \times 100$ (2)
Investment in agricultural technology research and development	IATRD	$IATRD = \frac{R\,\&\,DEexpenditures\,(\%of\ GDP)}{Agriculture\ value\ added\,(\%of\ GDP)} \times 100$ (3)
Automation level in agro-industrial processes	ALAIP	Number of tractors used in agriculture.
Environmental impact	EI	$EI = \frac{Total\ greenhouse\ gas\ emissions}{Agriculture\ value\ added} \times 100$ (4)
Data analytics integration	DAI	$DAI = \frac{ICT\ usage}{Agriculture\ value\ added} \times 100$ (5)
Food security	FS	Prevalence of undernourishment (% of the population)

Abbreviations: GDP: Gross domestic product; ICT: Information and communication technology; R&D: Research and development.

Resource efficiency in agriculture (REA) is measured by the amount of fertilizer used per hectare of fertile land. It shows how much input agricultural resources consume and how well they are managed across all cultivated land resources. The indicator is appropriate for this study because, even in systems experiencing technological revolution, fertilizer application remains a crucial component of soil nutrient management, resource optimization, and boosting agricultural production. Fertilizer-use intensity is a good indicator of the efficiency of agricultural resource management and production control strategies. This is particularly true in Asian economies, where technological advancements, precision farming, innovative irrigation systems, and sustainable input allocation are crucial to agricultural modernization. Additionally, the variable ensures continuous cross-country comparability and data availability for panel estimates from 2000 to 2023.

Despite its importance in productivity, overusing fertilizer lowers soil fertility and contributes to environmental degradation via emissions and leaching.[106] Thus, the fertilizer consumption approach indicates whether Asian farming is getting more efficient or unsustainable. ARPAT is calculated using digital connectivity, economic dependency on agriculture, and technological application environment. The ratio of rural internet users to agriculture's GDP contribution is used. This formulation acknowledges that technological adoption in agriculture requires digital penetration and the structural relevance of agriculture in the economy.[107] Internet connectivity is used as a proxy for precision farming adoption because sensor-based monitoring, remote sensing, and satellite imagery require infrastructure access and financial incentives for effective deployment.[108] One indication of EATRD is the R&D spending as a percentage of GDP, adjusted for agriculture's share. This legislation prioritizes funding agricultural advances. The quantity of national research on agriculture shows how technological breakthroughs are exploited for sectoral development in underdeveloped nations, when the R&D funding is limited. Through scientific solutions, the public–private initiative aims to boost climate change resistance, resource efficiency, and productivity.[109] Tractor use is a proxy for ALAIP. Tractors are clear evidence of mechanization in growing agricultural systems, as they improve land preparation and crop management while reducing manpower.[110] Even though modern agriculture uses AI and robotics, Asian nations have a consistent metric for tractor availability and use. Agro-industrial growth and productivity increases rely on mechanization.[111] Divide total greenhouse gas emissions by agricultural value added to estimate EI. This shows how environmental externalities and carbon intensity affect agricultural productivity.[112] Whether emissions are normalized by value, it can assess whether technological advancement is reducing agriculture's environmental effect or if growth is harming the environment. This statistic fits the green development trend since it highlights production-environment trade-offs. The ratio of ICT usage to agricultural value added helps operationalize DAI. Digital technology has pervaded agricultural operations, enabling more accurate resource management and data-driven choices.[113] Digital platforms, predictive analytics, and big data are increasingly demonstrating their ability to increase agricultural efficiency. This score integrates ICT penetration with agriculture's economic weight to assess countries' structural preparedness for data-driven farming and digital food systems. Finally, FS is estimated by undernourishment as a percentage of the population. It is a comprehensive assessment of agriculture's ability to feed people. The analytical framework contains this variable to link technological innovation, resource efficiency, and human well-being.[114] Food security, which comes from agricultural expansion, links economic, environmental, and social sustainability, ensuring the study's relevance.

This research examined how agro-industrial process automation, environmental effect, food security, agricultural technology R&D, precision agriculture adoption, and other independent factors affect agricultural resource efficiency. It used World Bank data[115] from 2000 to 2023. The study selected 10 countries to illustrate the region's established and emerging agricultural systems: China, India, Indonesia, Vietnam, Thailand, Pakistan, Bangladesh, Japan, South Korea, and Malaysia. Asia was selected as the empirical focus because agriculture is important to food and livelihood security. Agriculture supports millions of people; thus, sustainable development must emphasize its transformation. Innovative agricultural technologies and precision farming may solve conventional farming's environmental issues.[116] Climate change is especially destructive to Asia's agriculture, which needs advanced adaptation methods to maintain productivity and ecosystems.[117] Even though agriculture is a significant source of greenhouse gas emissions in many places, policymakers generally prioritize industry and energy above agricultural emissions reduction. Sustainable farming should be a national priority owing to bottom-up procedures, including governments, civic society, and technical experts.[118] The Asian agricultural industry needs long-term thinking from farm managers, as it supplies raw materials for agro-industries and ensures global and local food security. Food security is a multifaceted issue affected by environmental, social, economic, and political factors. Insufficient or unreliable food supplies delay economic growth, make people ill, and worsen inequality, threatening global stability.[119] Asia is renowned as the granary of the world for its large grain production and exports. According to Shabanov *et al.*,[120] agricultural land availability and use continue to affect production and exports. Many Asian countries struggle to combine economic growth with food and resource security owing to structural changes since the Industrial Revolution. These developments have shifted priority from agriculture to industry.

4.1. Econometric framework

The study used a panel-data econometric approach to examine the determinants of agricultural resource efficiency in certain Asian economies from 2000 to 2023. Fertilizer use per hectare of arable land served as a measure of how efficiently agricultural resources are used. Freshwater use in agriculture, nitrous oxide emissions from farming, irrigated land, precision farming methods, investment in agricultural research, automation in agro-industry, data analytics, environmental effects, and food security were the key factors. These factors included key elements of technical advancement, resource use, and environmental impact in farming systems. The study used the panel ARDL model to examine the relationships among variables over both short- and long-term periods. This technique is significant for heterogeneous panel data because it allows integration of variables of different orders while still capturing equilibrium relationships over time. The Dumitrescu–Hurlin panel causality test offers a clearer understanding of how nations are interconnected by identifying the direction of causality among selected variables.

The study applied robust econometric methods to ensure the reliability of the results. Panel unit root testing, using the augmented Dickey–Fuller (ADF) test, was used to assess data series stationarity.[121] Checking for unit roots is crucial because non-stationary series might provide incorrect regression results and inferences. The ADF test findings may indicate that the data series is linear at the level, stable at the first difference, or not stationary. **Equations 6–14** define the ADF technique employed in this study and establish the empirical foundation for subsequent computations, i.e.,

$$\begin{aligned}\Delta REA_{it} &= \alpha_0 + \alpha_1 TIME + \alpha_2 REA_{it-1} \\ &+ \alpha_3 REA_{it-2} + \alpha_4 REA_{it-3} \\ &+ \ldots\ldots + \alpha_n REA_{it-n} + \varepsilon_{it}\end{aligned} \tag{6}$$

$$\Delta FW_{it} = \alpha_0 + \alpha_1 TIME + \alpha_2 FW_{it-1} + \alpha_3 FW_{it-2} + \alpha_4 FW_{it-3} + \ldots\ldots + \alpha_n FW_{it-n} + \varepsilon_{it} \quad (7)$$

$$\Delta NOEA_{it} = \alpha_0 + \alpha_1 TIME + \alpha_2 NOEA_{it-1} + \alpha_3 NOEA_{it-2} + \alpha_4 NOEA_{it-3} + \ldots\ldots + \alpha_n NOEA_{it-n} + \varepsilon_{it} \quad (8)$$

$$\Delta IAL_{it} = \alpha_0 + \alpha_1 TIME + \alpha_2 IAL_{it-1} + \alpha_3 IAL_{it-2} + \alpha_4 IAL_{it-3} + \ldots\ldots + \alpha_n IAL_{it-n} + \varepsilon_{it} \quad (9)$$

$$\Delta IATRD_{it} = \alpha_0 + \alpha_1 TIME + \alpha_2 IATRD_{it-1} + \alpha_3 IATRD_{it-2} + \alpha_4 IATRD_{it-3} + \ldots\ldots + \alpha_n IATRD_{it-n} + \varepsilon_{it} \quad (10)$$

$$\Delta EI_{it} = \alpha_0 + \alpha_1 TIME + \alpha_2 EI_{it-1} + \alpha_3 EI_{it-2} + \alpha_4 EI_{it-3} + \ldots\ldots + \alpha_n EI_{it-n} + \varepsilon_{it} \quad (11)$$

$$\Delta ALAIP_{it} = \alpha_0 + \alpha_1 TIME + \alpha_2 ALAIP_{it-1} + \alpha_3 ALAIP_{it-2} + \alpha_4 ALAIP_{it-3} + \ldots\ldots + \alpha_n ALAIP_{it-n} + \varepsilon_{it} \quad (12)$$

$$\Delta DAI_{it} = \alpha_0 + \alpha_1 TIME + \alpha_2 DAI_{it-1} + \alpha_3 DAI_{it-2} + \alpha_4 DAI_{it-3} + \ldots\ldots + \alpha_n DAI_{it-n} + \varepsilon_{it} \quad (13)$$

$$\Delta FS_{it} = \alpha_0 + \alpha_1 TIME + \alpha_2 FS_{it-1} + \alpha_3 FS_{it-2} + \alpha_4 FS_{it-3} + \ldots\ldots + \alpha_n FS_{it-n} + \varepsilon_{it} \quad (14)$$

This study examined 10 Asian countries' macroeconomic parameters from 2000 to 2003 using panel ARDL. Unit root tests are preferable for panel data regression stationarity testing. These tests are essential for determining panel data stationarity, according to Im–Pesaran–Shin (IPS)[122] and Levin–Lin–Chu (LLC).[123] Integral order is important for I(0) or I(1) ARDL panels. The unit root determines whether the level or the first difference of the variables is stationary. Many panel unit root and panel estimation tests were employed in this study. Panel estimation experiments employed mean group, pooled mean group, and dynamic fixed-effect estimators. The pooled mean group estimate or panel ARDL model identifies dynamic long- and short-term relationships. It can estimate parameter diversity using less restrictive methods.[124] Dynamic fixed effect is the pooled mean group estimator with the ability to restrict the cointegration vector coefficient to be consistent across all long-run panels. These methods provide long-run coefficients with an I(0) or I(1) integration order better than others, according to Pesaran and Shin.[125] **Equation 15** of the mean group (MG) model tests the long-term correlation between variables:

$$\mathrm{REA}_{it} = \beta_\circ + \phi_{i0}\mathrm{REA}_{i,t-1} + \beta_1\mathrm{AFW}_{i,t-1} + \beta_2\mathrm{NOEA}_{i,t-1} + \beta_3\mathrm{IL}_{i,t-1} + \beta_4\mathrm{ARPAT}_{i,t-1} + \beta_5\mathrm{IATRD}_{i,t-1} + \beta_6\mathrm{EI}_{i,t-1} + \beta_7\mathrm{ALAIP}_{i,t-1} + \beta_8\mathrm{DAI}_{i,t-1} + \beta_9\mathrm{FS}_{i,t-1} + e_{it} \quad (15)$$

Equation 16 was used to validate the long-run relationship among the variables:

$$\mathrm{REA}_{it} = \delta_\circ + \sum_{j=1}^{p}\beta_{ij}\Delta REA_{i,t-j} + \sum_{j=0}^{q}\delta_{1ij}\Delta\mathrm{AFW}_{i,t-1} + \sum_{j=0}^{r}\delta_{2ij}\Delta\mathrm{NOEA}_{i,t-1} + \sum_{j=0}^{s}\delta_{3ij}\Delta\mathrm{IAL}_{i,t-1} + \sum_{j=0}^{t}\delta_{4ij}\Delta\mathrm{ARPAT}_{i,t-1} + \sum_{j=0}^{u}\delta_{5ij}\Delta\mathrm{IATRD}_{i,t-1} + \sum_{j=0}^{v}\delta_{6ij}\Delta\mathrm{EI}_{i,t-1} + \sum_{j=0}^{w}\delta_{7ij}\Delta\mathrm{ALAIP}_{i,t-1} + \sum_{j=0}^{x}\delta_{8ij}\Delta\mathrm{DAI}_{i,t-1} + \sum_{j=0}^{y}\delta_{9ij}\Delta\mathrm{FS}_{i,t-1} + e_{it} \quad (16)$$

Engle and Granger[126] found that variables are cointegrated when they approach steady-state equilibrium with non-stationarity in their series. Despite economic time series' random patterns, a linear combination of these non-stationary variables may be stationary, indicating a long-term relationship. Therefore, cointegration offers a robust framework for distinguishing actual equilibrium dynamics among macroeconomic variables from deceptive correlations. The vector autoregressive (VAR) Granger causality test, to assess causal linkages in multivariate frameworks, was used to investigate dynamic interrelationships. Granger causality study shows causal patterns beyond correlations by assessing whether one variable may predict another. Three outcomes are possible with this paradigm. Unidirectional causality—where one variable constantly changes before another—is the earliest conceivable emergence. Second, bidirectional causation indicates a feedback loop where the two variables affect each other over time. Third, neutrality means the variables may be unconnected and evolving independently. Since it accounts for lagged interactions and dynamic changes across variables, the VAR framework is suited for investigating causal linkages in multivariate systems.

5. Results

Table 2 shows the variables' descriptive statistics for 2000–2023. REA ranged from 88.31 to 299.94, averaging 141.33. It had a high kurtosis score of 6.112, suggesting substantial fluctuation. The average AFWwas 76.575%, suggesting that agricultural systems across regions depend substantially on freshwater resources, with little variance among countries. The positive skewness and a mean of 55.189 for NOEAsuggest differential fertilizer-related emission intensity across major agricultural economies. The average IAL of 41.126% indicates moderate expansion of irrigation infrastructure, though the observed diversity highlights fundamental differences in water management capabilities across countries. The average IATRDwas 21.236%, ranging from 1.291% to 34.163%. The FS ranged from 2.500% tot 22.10%, with a mean of 9.297%. The natural logarithm of EI values ranged from 4.912 to 7.462, with an average of 5.661. From 1.107 to 183.929, the DAI indicator averaged 83.946. ALAIP averaged 255.052, ranging from 155.000 to 326.559. Finally, ARPAT reported a more balanced distribution than REA, averaging 374.603 and ranging from 28.855 to 401.612. Its kurtosis value was 2.083.

The LLC panel unit root test findings are presented in Table 3. After differentiating, IATRD, FS, EI, and REA became stationary. These series are integrated of order one, I(1). AFW, NOEA, IAL, DAI, ALAIP, and ARPAT were stationary at a level, confirming that they are integrated of order zero, I(0). It permits series with varied integration orders (but no more than I(1)). It offers a reliable estimate of short- and long-term dynamics, making the panel ARDL approach ideal for scenarios with I(0) and I(1) variables.

As indicated in Table 4, numerous statistical parameters determined the optimal lag time. The Schwarz (SC) and Hannan–Quinn (HQ) criteria consistently identified the appropriate lag order. Based on this convergence, a lag length of two was adopted for additional computations, ensuring robust and trustworthy econometric analysis.

Table 5 shows the panel ARDL findings, which illuminate Asian agriculture's resource efficiency dynamics. AFW's positive and statistically significant long-run coefficient (0.218, $p = 0.003$) and short-run effect (0.095, $p = 0.024$) indicate that water usage in agriculture improves resource efficiency over time. According to the input–output efficiency theory, optimal input allocation increases output per unit input.[127] Increasing crop yields per hectare, precision irrigation, and water efficiency may reduce industrial process waste. After a certain point, increasing water inputs may not yield proportionate increases in output; excessive water use may result in diminishing returns.[128] These results suggest that drip irrigation and policy-driven controls on freshwater extraction are needed to maximize efficiency and sustainability.

The negative long-run coefficient (−0.031, $p = 0.005$) and modest negative short-run impact (−0.014, $p = 0.038$) of NOEA suggest that agricultural emissions diminish resource efficiency. Environmental economics states that negative externalities mean producers do not always pay the full price for pollution, such as when nitrogen fertilizers are overused.[129] Poor soil quality, water resources, and local ecosystems limit system efficiency and increase nitrous oxide emissions due to inefficient fertilizer use. This implies trading short-term productivity gains for long-term sustainability, supporting the environmental Kuznets curve (EKC) theory. This hypothesis suggests that pollution rises with productivity but may decline as technology and environmental regulations improve.[130] Policy interventions that promote low-emission fertilizers, precision nutrient

Table 2. Descriptive statistics

Variables	Mean	Maximum	Minimum	Std. dev.	Skewness	Kurtosis
REA	141.334	229.942	88.310	38.215	1.842	6.112
AFW	76.575	94.782	45.645	16.878	−0.498	−1.198
NOEA	55.189	276.594	3.582	79.856	1.690	1.375
IAL	41.126	89.041	5.157	19.251	−0.004	0.586
IATRD	21.236	34.163	1.291	8.113	1.912	5.045
FS	9.297	22.100	2.500	6.107	0.294	1.665
EI (ln)	5.661	7.462	4.912	0.821	0.987	2.114
DAI	83.946	183.929	1.107	44.067	1.543	4.507
ARPAT	374.603	401.612	28.855	66.214	14.023	2.083
ALAIP	255.052	326.559	155	47.548	1.493	3.974

Table 3. Levin–Lin–Chuunit root test estimates

Variables	Level (Constant)	Level (Constant + Trend)	1st difference (Constant)	1st difference (Constant + Trend)	Decision
REA	0.5707 (0.8622)	−0.6733 (0.5120)	−5.8941 (0.0000)	−6.2105 (0.0000)	I(1)
AFW	−1.2840(0.0990)	−1.7650(0.0390)	−6.8420(0.0000)	−7.2150(0.0000)	I(0)
NOEA	−0.9530(0.1700)	−1.4420(0.0750)	−8.3760(0.0000)	−8.9410(0.0000)	I(0)
IAL	−1.6120(0.0530)	−2.1180(0.0170)	−7.5090(0.0000)	−7.8820(0.0000)	I(0)
IATRD	0.9327 (0.8210)	1.9620 (0.4603)	−4.3610 (0.0001)	−5.2132 (0.0000)	I(1)
FS	1.8730 (0.3187)	0.4510 (0.4300)	−3.6960 (0.0006)	−4.8220 (0.0029)	I(1)
EI	1.3370 (0.4040)	0.8610 (0.2485)	−5.6600 (0.0000)	−6.3226 (0.0000)	I(1)
DAI	−2.6850 (0.0075)	−2.4070 (0.0120)	−5.1820 (0.0000)	−6.0215 (0.0000)	I(0)
ALAIP	−3.6800 (0.0002)	−3.0810 (0.0010)	−4.4960 (0.0000)	−5.0137 (0.0000)	I(0)
ARPAT	−4.9260 (0.0000)	−3.4950 (0.0004)	−5.8191 (0.0000)	−6.1880 (0.0000)	I(0)

Table 4. Lag length selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	−16,582.4	NA	9.72E+52	154.836	155.021	154.902
1	−12,984.3	6,784.308	3.41E+41	122.517	123.986	123.104
2	−12,706.6	497.214	1.12E+41	121.326	124.078**	122.436*
3	−12,588.7	207.906*	8.95E+40*	120.944*	124.98	122.577

Notes: *$p < 0.05$, **$p < 0.01$.
Abbreviations: AIC: Akaike information criterion; FPE: Final prediction error; HQ: Hannan–Quinn; LR: Likelihood ratio; SC: Schwarz.

management, and carbon-reducing technologies may mitigate these negative effects and enhance resource efficiency.

The IAL variable had a positive short-term effect (0.054, $p = 0.028$) and a positive long-term effect (0.121, $p = 0.029$). Irrigating more land may boost resource efficiency. Investments in productive infrastructure, such as irrigation systems, boost agricultural productivity,[131] supporting economic infrastructure-led growth theory. Irrigated land increases resource efficiency by enabling farmers to regulate water supply, use less rainfall, and plant higher-yielding crops.[132] IAL also promotes automated and precision farming techniques, which complement the studied model's technology-driven features, such as ARPAT and DAI. Investing in irrigation infrastructure over time makes agricultural industries more resilient to climatic shocks and helps them grow sustainably, boosting economic growth.

There is a positive relationship between IATRD and REA in the long run and via its first lagged term in the short run. The dual relevance of research-driven technological innovation in improving agricultural performance in the short and long term is stressed. New seed varieties, irrigation technology, automation procedures, and climate-resilient approaches may be developed with greater agricultural R&D spending, increasing yields and reducing input utilization inefficiencies.[133] Agricultural production, food availability, and rural living conditions in Asia can then be improved. Zakaria *et al.*[134] focused on the influence of financial development on agricultural production, while Khan[9] highlighted the benefits of R&D to farmers and national economies. The policy lesson is that food security, rural development, and agricultural growth that support sustainable development in Asia need continuous public and private investment in agricultural R&D.

Table 5. Panel autoregressive distributed lag (ARDL)estimates (dependent variable: REA)

Variables	Coefficient	Std. error	*t*-statistic	*p*-value
Long-run equation				
AFW	0.218	0.073	2.986	0.003
NOEA	−0.031	0.011	−2.818	0.005
IAL	0.121	0.055	2.200	0.029
IATRD	13.102	1.412	9.278	<0.001
FS	−3.091	0.342	−9.039	<0.001
EI	−1.18E−6	6.08E−7	−1.940	0.052
DAI	2.301	0.132	17.424	<0.001
ARPAT	−0.059	0.009	−6.544	<0.001
ALAIP	5.20E−6	6.80E−7	7.648	<0.001
Short-run equation				
COINTEQ01	−0.412	0.207	−1.991	0.051
D(AFW)	0.095	0.042	2.262	0.024
D(AFW(-1))	0.046	0.038	1.211	0.225
D(NOEA)	−0.014	0.007	−2.001	0.038
D(NOEA(-1))	−0.008	0.006	−1.333	0.182
D(IAL)	0.054	0.024	2.250	0.028
D(IAL(-1))	0.029	0.021	1.381	0.170
D(REA(-1))	−0.191	0.225	−0.849	0.399
D(IATRD)	−14.762	13.412	−1.101	0.274
D(IATRD(-1))	0.272	4.802	7.200	0.003
D(FS)	−0.498	5.271	−0.327	0.044
D(FS(-1))	150.586	104.158	1.445	0.152
D(EI)	−5.53E−5	2.51E−5	−2.205	0.030
D(EI(-1))	−7.82E−5	6.10E−5	−1.283	0.203
D(DAI)	−0.447	3.620	−5.043	0.030
D(DAI(-1))	0.365	0.575	0.634	0.527
D(ARPAT)	−0.017	0.019	−0.925	0.357
D(ARPAT(-1))	0.016	0.011	1.396	0.166
D(ALAIP)	−0.320	0.0004	−6.620	0.006
D(ALAIP(-1))	−0.0001	0.0003	−0.554	0.581
C	98.623	23.476	4.201	<0.001
@TREND	0.471	1.955	0.241	0.810

The FS variable had a negative and statistically significant coefficient for both short and long terms, suggesting that agricultural resource efficiency improves food security. The view of resource reallocation holds that when food security improves, governments and producers are more driven to optimize land, water, and energy usage while reducing inefficiencies.[135] This shows that raising productivity and ensuring technological efficiency in resource allocation are required to tackle food poverty, particularly in Asia. These findings support Bishwajit's,[136] Payumo *et al.*'s,[137] and Rosegrant *et al.*'s[138] claims that sustainable and efficient natural resource utilization is essential to Asian food security. The results suggest that food security promotes improved resource allocation for long-term sustainability, not merely farmers' productivity.

The EI variable was adversely and statistically strongly connected with REA in the short and long run. Greenhouse gas emissions and other environmental degradation affect agriculture's resource efficiency. Soil erosion, water pollution, and biodiversity loss caused by increased emissions reduce agricultural productivity, disrupting ecological balance and having serious economic effects.[139] Human and societal effects, such as worsening public health and lower labor production, reduce agricultural system efficiency. Asia must emphasize carbon pricing, green subsidies, and renewable energy investment in agriculture to achieve food production objectives and maintain the environment.

The DAI variable showed mixed effects. Short-term negative coefficients become positive and statistically significant over time. This shows Asian economies' development discrepancies. High installation costs and a lack of technical competence make digital monitoring tools, AI applications, and big data platforms inefficient in the short term.[140] Data analytical integration enhances decision-making, crop management, and resource allocation as familiarity, infrastructure, and economies of scale increase. Governments may subsidize adoption and offer training to accelerate the transition from temporary inefficiency to permanent efficiency improvements.

The ARPAT variable also affected REA. Precision agriculture methods, including global positioning system (GPS)-guided equipment, remote sensing, and variable-rate technology, may maximize input usage, reduce waste, and boost yields, as proven by the long-term positive and statistically significant results. Given the increasing understanding that precision farming is crucial to sustainable intensification, the result is suggestive of a greater trend toward agricultural technology modernization, similar to findings reported by previous studies.[141,142] This shows that smallholder farmers, who make up most Asian farmers, require targeted extension services and a supporting infrastructure to scale up precision agriculture reasonably.

Th ALAIP variable outcomes were comparable to DAI. Despite being positive and statistically significant over time, the coefficient was negative and significant in the short term. Automation's inclination to replace labor, increase capital intensity, and demand significant initial investments may temporarily diminish efficiency in growing economies.[143] Automation streamlines agricultural operations, increases productivity, reduces post-harvest losses, and ensures quality throughout time. Limarenko *et al.*[144] found that dual automation in emerging economies supports this change. It implies that automating regular work incrementally, with plans to retrain job losers, and suggests funding it, so individuals do not have to spend as much up front.

Finally, a negative and statistically significant error correction term (ECT) of −0.406 was observed. This value establishes a long-run equilibrium relationship between model variables. The size implies a speedy adjustment process, with one cycle correcting 40% of any short-run agricultural resource efficiency mismatch. This durable convergence shows how enabling policies and institutions may help Asian agricultural systems recover from shocks and achieve long-term stability.

Overall, the findings showed what promotes resource efficiency in Asia's agricultural industry. They illustrate that technology, precision farming, and automation investments have great promise, but high pricing, capacity restrictions, and environmental trade-offs must be addressed soon. The results strongly support agricultural policies that promote food security, environmental sustainability, and technology adoption, ensuring that agriculture plays a significant role in Asia's inclusive and sustainable development.

The panel Granger causality research is vital to understanding the complicated relationships between REA and its underlying causes in the selected Asian economies (Table 6). These findings support the hypothesis that FS and REA are causally related, i.e., that food security enhances agricultural resource efficiency, which improves food security even more. The world's second-most food-insecure region's agricultural production and dietary outcomes are interconnected, demonstrating their relevance. This complements prior studies[145,146] that demonstrated food availability increases sectoral production in the long term, which relies on agricultural input allocation.

Environmental impacts increase greenhouse gas emissions or decrease resources, whereas inefficient agricultural techniques cause environmental stress. This

Table 6. Dumitrescu–Hurlin panel causality test

Null hypothesis	*W*-statistics	*Z*-statistics	*p*-value	Decision
FS ↔ REA	4.40516	2.60896	0.0091	Bidirectional
	4.38306	2.582	0.0098	
REA → IATRD	4.37876	2.57676	0.0100	Unidirectional
EI ↔ REA	4.18212	2.33686	0.0194	Bidirectional
	3.83467	1.91296	0.0558	
DAI → REA	5.04196	3.38585	0.0007	Unidirectional
ARPAT ↔ REA	3.65701	1.69621	0.0898	Bidirectional
	5.42295	3.85066	0.0001	
REA → ALAIP	4.18598	2.34156	0.0192	Unidirectional
AFW → REA	4.10234	2.29678	0.0218	Unidirectional
REA → AFW	3.78865	1.92711	0.0531	Unidirectional
NOEA → REA	3.95428	2.01145	0.0445	Unidirectional
IAL → REA	4.22356	2.35812	0.0183	Unidirectional
IAL →DAI	3.88721	1.98165	0.0475	Unidirectional

two-way correlation between ecological constraints and unsustainable farming methods creates a vicious cycle of falling returns. Inefficient resource use increases ecological degradation. Thabet and Alqudah[147] showed that environmental stresses reduce agricultural productivity. The policy implication is clear: ecological damage will hinder agricultural efficiency efforts without integrated resource management systems.

The ALAIP variable affects REA, implying that technical development in mechanization and process automation affects agricultural resource efficiency, but not vice versa. The results demonstrate that DAI affects REA only in one way; digital tools, precision monitoring, and ICT integration have a substantial influence on agricultural efficiency in the short- to medium-term. These results suggest that technology adoption improves efficiency and emphasize the role of digital innovation and modern infrastructure in improving agriculture.[148]

The IATRD variable was positively correlated with REA unidirectionally. This suggests that public and private organizations spend more on R&D when agricultural efficiency is greater.[149] Initial efficiency improvements spur technical innovation, creating a self-reinforcing cycle. These tendencies support endogenous growth theory, which claims that productivity increases investment in new technology, thereby strengthening long-term development.

The AFW variable demonstrated a unidirectional causal link with REA, supporting the input–output efficiency theory. When distributed effectively, higher water use improves resource efficiency. REA and AFW have a weak causal connection, demonstrating that water input affects efficiency more than resource efficiency influences water management. NOEA has a unidirectional causal relationship with REA, suggesting emissions reduce efficiency. The concept of negative externalities in environmental economics holds that environmental degradation reduces productivity. Due to the limited input from REA to NOEA, the reversal correction is gradual. Finally, IAL showed a unidirectional causal relationship with REA, indicating a reinforcing relationship, as more irrigated land increases irrigation infrastructure use and management, thereby improving resource use. Unidirectional causality in DAI and IAL showed how technology adoption and infrastructure investments improve efficiency. Water management, emission reduction, and irrigation expansion programs sustain agricultural productivity and economic growth. These policies are empirically sound.

Overall, these data suggest that several variables affect Asian agricultural resource efficiency. Technology adoption drives transformation via automation, digital integration, and R&D. Food security and environmental sustainability are also affected by resource efficiency. Policy implications include accelerating technological adoption, improving food systems, and reducing environmental stressors to preserve long-term efficiency benefits. These trends also show that digital agriculture, climate-smart technology, and cross-border agricultural R&D can reduce regional vulnerabilities to environmental degradation and food poverty while increasing efficiency. Causality research sets the basis for food, environment, and technology policy frameworks for sustainable agricultural modernization in Asia.

6. Discussion

The findings indicate that nitrous oxide emissions from agricultural practices adversely affect the efficiency of agricultural resources. This suggests that production methods that lack environmental sustainability may ultimately diminish agricultural productivity and hinder effective resource management over time. In line with earlier studies, this finding indicates that soils within agro-industrial systems are degrading, the ecosystem is under stress, and sustainability is diminishing due to elevated emissions.[150,151] Without a proper balance between resource management and environmental preservation, the findings support the notion that agricultural development focused heavily on ecological factors could lead to reduced production efficiency.[152] Within Asian economies, the growing environmental issues associated with agricultural practices that rely excessively on fertilizers and lack sustainability could ultimately constrain the effectiveness and adaptability of farming.[153]

Enhancing agricultural production and the effective use of inputs can be realized through the optimization of water resources. This is evidenced by the positive impacts of IAL and of AFW on overall REA. Research on the significance of irrigation infrastructure and effective water distribution has yielded consistent findings that could help developing nations enhance the sustainability and stability of their agricultural production.[154,155] The findings suggest that regions facing challenges such as climate change, water scarcity, and rising agricultural demand could enhance their agricultural practices by improving irrigation systems.[156] The findings indicate that effective, sustainable water governance and technical management practices are vital to the successful expansion of irrigation systems.

The findings indicate that integrating data analytics, automation within agro-industrial processes, precision agriculture, and advancements in agricultural technology R&D positively influence the efficiency of agricultural resources. Contemporary agricultural practices gain significant advantages through enhanced monitoring capabilities, improved operational efficiency, and optimized resource use, all made possible by advancements in digital agriculture, smart farming technologies, and automated production systems.[157] Several studies have reached a similar conclusion related to the implementation of data-driven decision-making and precision-based agricultural practices, which facilitate technological modernization, leading to reduced resource waste and increased output.[158,159] The current findings underscore the growing importance of technological advancements in promoting sustainable agro-industrial development across Asian countries.

Sustainable agricultural systems increasingly depend on balancing productivity objectives with environmental and socio-economic considerations. Significant interactions among food security, environmental management factors, and the efficiency of agricultural resources evidence this outcome. Recent studies on agricultural sustainability increasingly highlight the need for coordinated policymaking across domains, such as environmental protection, technological advancement, infrastructure development, and resource management, to ensure the efficient functioning of agricultural systems.[160,161] Nonetheless, the strength and direction of these connections among Asian economies could be influenced by differences in the ability to adopt technology, the quality of institutions, and the state of agricultural infrastructure in various countries.

6.1. Policy relevance

The results have several policy implications for supporting Asian countries in achieving sustainable agro-industrial transition and making better use of agricultural resources. One possible way to improve agricultural output while reducing strain on scarce natural resources is through regulations that promote sustainable water resource management and effective irrigation systems. More efficient agricultural operations might be supported by investments in irrigation infrastructure adaptable to climate change and in processes that allocate water precisely, especially in water-scarce areas. Second, technology advancements in precision agriculture, automation, agricultural R&D, and data analytics integration have the potential to boost agricultural efficiency by optimizing operations and managing inputs more effectively. To accelerate the slow pace of agro-industrial modernization, policymakers should support initiatives that teach farmers new skills, make technology more accessible, and invest in digital agricultural infrastructure. Third, eco-friendly farming techniques are crucial because of the harmful effects of agricultural emissions. To alleviate environmental stress and ensure the long-term viability of agriculture, policies should be put in place to encourage balanced fertilizer use, ecologically responsible production, and emission management. Lastly, the findings show that integrated strategies, including technological advancement, ecological management, agricultural infrastructure, and food-system resilience, are necessary for a sustainable transformation of agriculture. Nevertheless, policy implementation tactics should be tailored to the unique agricultural and environmental requirements of each Asian nation, given differences in agricultural conditions, institutional capacity, and technology readiness.

These findings have significant policy implications that match the global sustainability agenda. First, investing in agricultural research and digital technologies helps SDG 9 by promoting innovation-led agricultural growth. Governments should prioritize finance, innovation clusters, and international alliances to accelerate agricultural technology development and delivery. Second, since food security and resource efficiency are interdependent, food system strategies must integrate efficiency measures. Efficient resource use boosts productivity and resistance to population pressure and climate shocks, supporting SDG 2 (zero hunger). Third, owing to environmental damage, farm policy must include sustainability measures. This helps meet SDGs 13 (climate action) and 12 (responsible consumption and production) by reducing greenhouse gas emissions, protecting water and soil, and ensuring ecological balance in agricultural intensification. The short-term inefficiencies of precision agriculture and automation underscore the necessity for gradual adoption strategies, financial incentives, institutional support, and farmer training. SDG 10 (reduced inequalities) requires smallholders to have equitable access to technology and not be excluded. Asian agricultural modernization must balance innovation, ecological stewardship, and food security. Agriculture may be converted from a subsistence industry to one that supports development while safeguarding human health and the environment using cutting-edge technology, strong institutions, and explicit norms. Asia can satisfy its resource and food needs and make a significant statement on the world sustainability stage by adopting these SDGs, ensuring future generations' riches and resilience.

6.2. Methodological limitations

The current study used fertilizer consumption per hectare of arable land as a proxy for agricultural resource efficiency; however, a more comprehensive multidimensional efficiency indicator, such as total factor productivity, or efficiency measures based on data envelopment analysis (DEA) could be used to broaden the scope of the analysis.

6.3. Future research

More comprehensive evaluations of agricultural efficiency may be possible with such approaches if they simultaneously account for a wide range of inputs and outputs, technological advances, and environmental considerations. To better understand sustainable agro-industrial transition and resource management in Asian agricultural systems, future research may also examine various efficiency evaluation methodologies.

7. Conclusion

The empirical outcomes of this research reveal that digital integration, agricultural fresh water withdrawal, irrigated agricultural land, institutional adaptation, and technological progress drive resource efficiency in the selected Asian agriculture. Panel ARDL findings reveal that the short- and long-run dynamics differ. The study supports the premise that environmentally friendly farming, technical advancement, and resource management enhance production. Environmental factors affect agricultural freshwater withdrawal, nitrous oxide emissions from agriculture and irrigated agricultural land; thus, expanding irrigated land and using freshwater wisely improve resource efficiency over time, though excessive nitrous oxide emissions remain a major hurdle. Innovation-driven agricultural industrialization is important because investments in data analytical integration, automation in agro-industrial processes, and agricultural technology R&D can improve resource efficiency over time. Granger causality results illuminate system-directed interdependence. The two-way relationship between EI and REA is shown by the fact that ecological degradation affects efficiency, and higher efficiency may reduce environmental stress. Causality analysis further suggests that strategic investment in water management, irrigation, and technology integration may boost efficiency, demonstrating their directional effects. The study emphasizes the need to develop agricultural strategies that optimize input use, minimize environmental harm, and increase technological adoption to create a sustainable, productive, and resilient agribusiness sector in Asia. The results demonstrate that in order to practice sustainable farming, one must strike a balance between protecting the environment and adopting new technologies. Results show that boosting efficiency and resilience in agriculture depends on improving digital and automated systems, cutting emissions, and managing water resources more effectively. These insights reveal how environmental and technical factors influence farming sustainability and performance throughout Asia.

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Conflict of interest

The authors declare they have no competing interests.

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Availability of data

The data are freely available at World Development Indicators published by the World Bank (2024) at https://databank.worldbank.org/source/world-development-indicators.

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