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EDITED BY

Chee Kong Yap,
Putra Malaysia University, Malaysia

REVIEWED BY

Ayan Paul,
Indian Institute of Technology
Kharagpur, India
Md Wali Ullah,
Westcliff University, United States

*CORRESPONDENCE

Moussa El Jarroudi
✉ mejarroudi@uliege.be

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Artificial intelligence for food security or digital inequality? Quantifying the global trade-offs between agricultural productivity, social inclusion, sustainable livelihoods, and responsible land stewardship

Moussa El Jarroudi*

SPHERES Research Unit, Department of Environmental Sciences and Management, University of Liège, Arlon, Belgium

Artificial intelligence (AI) is increasingly recognized as a powerful tool for addressing some of the most pressing challenges facing global agrifood systems, including food insecurity, climate change, resource scarcity, and the growing demand for sustainable agricultural production. However, an important question remains largely overlooked: do technological advances in AI translate into meaningful societal benefits? Drawing on a global evidence synthesis of 1,276 studies conducted across 112 countries, this review challenges the widespread assumption that technological success automatically leads to food-system transformation. We introduce the Artificial Intelligence Food Security Paradox Theory (AIFSP Theory), a novel conceptual framework suggesting that improvements in algorithmic performance, productivity, and operational efficiency often exceed corresponding gains in food security, livelihood resilience, social equity, and environmental sustainability. To examine this proposition, we combined systematic review methods with hierarchical Bayesian meta-analysis, network meta-analysis, structural equation modeling, explainable machine learning, and Monte Carlo simulations extending to 2050. We also developed the Artificial Intelligence–Food Security–Equity–Land Responsibility Index (AI-FSELR), a multidimensional framework designed to evaluate the societal value of agricultural AI beyond conventional technical performance metrics. The results reveal a consistent and previously underexplored pattern. While AI technologies significantly improved agricultural productivity (+24.8%), resource-use efficiency (+18.9%), and farm income (+13.8%), gains in food security (+8.6%) and social equity (+5.4%) were considerably smaller. Governance quality, digital accessibility, extension services, affordability, and farmer training emerged as stronger determinants of societal outcomes than algorithmic sophistication itself. Future scenarios indicate that inclusive and governance-driven AI pathways could increase societal benefits by more than 40% by 2050, whereas expanding digital inequalities may substantially limit these gains. These findings suggest that the future success of agricultural AI will depend not only on technological innovation but also on the institutional, social, and governance conditions that shape its adoption. The AIFSP Theory and AI-FSELR framework provide a new foundation for evaluating AI and guiding more equitable, resilient, and sustainable food-system transformations.

KEYWORDS

agricultural transformation, AI-FSEL, artificial intelligence, Artificial Intelligence Food Security Paradox theory, Bayesian meta-analysis, climate resilience, decision-support systems, digital agriculture

1 Introduction

The rapid emergence of artificial intelligence (AI) is profoundly transforming global agrifood systems and is increasingly recognized as one of the most influential technological developments of the twenty-first century. Recent advances in machine learning, deep learning, computer vision, remote sensing, robotics, digital twins, Internet of Things (IoT) technologies, edge computing, and intelligent decision-support systems are creating unprecedented opportunities to improve agricultural productivity, optimize resource use, enhance climate resilience, and support more adaptive and sustainable land-management strategies (Liakos et al., 2018; Kamilaris and Prenafeta-Boldú, 2018; Javaid et al., 2023; Paul, 2026). These innovations are enabling a transition from reactive and generalized management approaches toward data-driven, site-specific, and predictive agricultural systems capable of responding more effectively to increasingly complex environmental and socio-economic challenges.

The growing interest in AI-driven agriculture is occurring within a context of mounting global pressures on food systems. According to the United Nations, the global population is projected to reach approximately 9.7 billion people by 2050, significantly increasing the demand for food, water, energy, and natural resources (Gerland et al., 2022; Ritchie et al., 2022). Simultaneously, climate change, biodiversity loss, land degradation, water scarcity, geopolitical instability, and market volatility are intensifying pressures on agricultural production systems worldwide (IPCC, 2023; FAO et al., 2025). These interconnected challenges threaten not only agricultural productivity but also the resilience, sustainability, and equity of food systems, particularly in vulnerable regions already experiencing chronic food insecurity and environmental stress (FAO et al., 2025; Barrett et al., 2022).

Against this backdrop, artificial intelligence is increasingly presented as a critical component of future food security and sustainability strategies. AI-powered technologies are now deployed across virtually all segments of agrifood systems, including crop monitoring, disease detection, yield forecasting, precision irrigation, nutrient management, pest surveillance, livestock management, supply-chain optimization, market intelligence, and climate-risk assessment (Liakos et al., 2018; Zhou and Chen, 2023; Talaviya et al., 2020; Klerkx and Rose, 2020). Recent advances in computer vision illustrate the increasing technical sophistication of these applications. YOLO-based architectures have enabled integrated detection, segmentation, growth-stage classification, and real-time identification of horticultural crops, while specialized segmentation models have improved the detection of harvesting targets under challenging greenhouse conditions (Paul et al., 2024; Paul and Machavaram, 2024). Similar developments in cotton systems demonstrate the progression from fine-tuned YOLO-based phenological detection to graph-augmented object-detection frameworks for robust maturity assessment (Verma et al., 2024; Verma et al., 2026). The ability of AI to process large volumes of heterogeneous data and generate actionable insights in near real time has led many researchers and policymakers to view digital agriculture as a key enabler of sustainable intensification and climate-smart food

production (Birner et al., 2021; Rose and Chilvers, 2018; Dong et al., 2021; Fan and Zhao, 2025; de Jong et al., 2021).

Reflecting this growing momentum, major international organizations—including the Food and Agriculture Organization (FAO), the World Bank, the Organization for Economic Co-operation and Development (OECD), CGIAR, UNESCO, and the United Nations—have increasingly emphasized the strategic role of artificial intelligence in accelerating progress toward multiple Sustainable Development Goals (SDGs), particularly Zero Hunger (SDG 2), Responsible Consumption and Production (SDG 12), Climate Action (SDG 13), and Life on Land (SDG 15) (FAO, 2022; FAO, 2025; Afrifa et al., 2026; OECD, 2019; Fuglie et al., 2020; Ben Abdallah et al., 2023; Harikrishnan et al., 2025; Camarón, 2020; Marvin et al., 2022; Tagkopoulos et al., 2022; United Nations, 2024; Opola et al., 2025). These organizations argue that AI-enabled innovations can substantially improve decision-making, optimize resource use, reduce production risks, strengthen climate adaptation, support sustainable land management, and enhance the resilience of agrifood systems. Recent academic assessments further suggest that AI has the potential to facilitate broader food-system transformations through improved forecasting, precision management, environmental monitoring, and adaptive governance mechanisms (Harikrishnan et al., 2025; Kuhl, 2025; Agrawal et al., 2025; Iqbal et al., 2025; Wang et al., 2025; Kazanskiy et al., 2025). Consequently, artificial intelligence is increasingly viewed not merely as a technological innovation but as a strategic enabler of more sustainable, resilient, and inclusive agrifood futures.

Over the past decade, interest in agricultural AI has grown at an extraordinary pace. Bibliometric studies consistently show a sharp increase in publications addressing machine learning, precision agriculture, digital farming, and AI-enabled crop management since around 2015. This expansion reflects growing investments from governments, research organizations, agri-tech companies, and international development agencies. Today, AI applications span virtually every component of agricultural production and food systems, from crop disease diagnosis, yield prediction, irrigation scheduling, fertilizer optimization, and pest monitoring to livestock management, supply-chain optimization, market intelligence, and climate-risk assessment (Harikrishnan et al., 2025; Agrawal et al., 2025; El Jarroudi et al., 2024). Reviews by Liakos et al., Javaid et al., and Aijaz et al., and many others have documented substantial improvements in predictive performance, operational efficiency, and resource optimization across a wide range of agricultural contexts (Liakos et al., 2018; Javaid et al., 2023; Aijaz et al., 2025).

This technological expansion is also reshaping agricultural automation and Agriculture 4.0 architectures. Vision-guided robotic systems increasingly combine kinematic modeling with AI-based optimization to support autonomous harvesting operations (Paul and Machavaram, 2025), while decentralized blockchain architectures are being explored to strengthen traceability, data exchange, and coordination across agricultural value chains (Paul, 2026). In parallel, generative AI is emerging as a new component of Agriculture 4.0, with potential applications in knowledge support, decision assistance, and

context-specific agricultural services, although important challenges related to integration, accessibility, reliability, and governance remain unresolved (Paul and Machavaram, 2025).

Despite these remarkable technological advances, a fundamental question remains surprisingly underexplored: to what extent do improvements in algorithmic performance translate into meaningful societal benefits? The vast majority of studies evaluating agricultural AI continue to focus primarily on technical indicators such as classification accuracy, precision, recall, F1-score, root mean square error, computational efficiency, or predictive performance (Liakos et al., 2018; Kamilaris and Prenafeta-Boldú, 2018; Javaid et al., 2023). While these metrics are indispensable for assessing the reliability and effectiveness of AI models, they provide only a partial and often incomplete representation of their real-world value.

Indeed, a disease-detection system capable of achieving near-perfect classification accuracy does not automatically improve food security, nor does an irrigation optimization platform that reduces water consumption necessarily enhance farmer livelihoods, strengthen social equity, or promote sustainable land stewardship. As emphasized by recent studies on digital agriculture and responsible innovation, technological efficiency alone cannot guarantee positive societal outcomes because the impacts of AI are mediated by a wide range of institutional, economic, social, and governance factors (Rose and Chilvers, 2018; Rose et al., 2021; Klerkx and Begemann, 2020; Rose, 2026; Ozor et al., 2024).

This challenge is becoming increasingly evident as AI technologies move from experimental settings into real-world agricultural systems. Emerging evidence suggests that the benefits generated by digital innovations are often unevenly distributed across regions, farming systems, and socio-economic groups. Large commercial farms generally possess greater access to digital infrastructure, technical expertise, financial resources, and data services than smallholder farmers, creating the risk that technological progress may reinforce rather than reduce existing inequalities (Birner et al., 2021; Fielke et al., 2020; Ingram and Maye, 2020; Stein, 2026; Abbasi et al., 2022; MacPherson et al., 2022; Klerkx et al., 2019; Mühl and de Oliveira, 2022; Lioutas and Charatsari, 2022; Lajoie-O'Malley et al., 2020; Sun et al., 2024; Abdulai et al., 2023; Eastwood et al., 2019). Similarly, improvements in productivity or resource-use efficiency do not necessarily translate into proportional gains in food security, resilience, or environmental sustainability, particularly when adoption barriers, governance limitations, or market constraints remain unresolved (Barrett et al., 2022).

A growing gap is emerging between technological success and societal impact. While remarkable progress has been made in developing increasingly sophisticated AI algorithms, far less attention has been devoted to understanding how these technologies influence food security, livelihoods, social equity, governance, and environmental sustainability. This imbalance highlights the need for new frameworks capable of moving beyond purely technical assessments toward a broader evaluation of the societal value of artificial intelligence. Addressing this gap forms the central motivation of the Artificial Intelligence Food Security Paradox Theory proposed in this study.

This challenge is particularly important given the multidimensional nature of food security. According to the FAO, food security encompasses not only food availability but also access, utilization, and stability. Yet most agricultural AI research remains heavily focused on increasing productivity and production efficiency, often assuming that higher yields automatically translate into improved food security. In

reality, food production represents only one component of a much broader and more complex system shaped by economic, social, institutional, and environmental factors.

The persistence of food insecurity despite decades of technological progress further illustrates this disconnect. Millions of people continue to face food insecurity, while climate change, economic instability, conflicts, and environmental degradation increasingly threaten agricultural livelihoods and food systems worldwide. Although AI is often presented as a promising solution to these challenges, emerging evidence suggests that its benefits are not distributed equally. Large commercial farms typically have greater access to digital infrastructure, technical expertise, financial resources, and institutional support than smallholder farmers. As a result, technological innovations intended to improve agricultural performance may, under certain conditions, reinforce existing inequalities rather than reduce them.

These observations suggest that understanding the true contribution of AI to sustainable food-system transformation requires looking beyond technological performance alone and considering the broader social, economic, and governance conditions that determine who benefits from innovation and under what circumstances.

Recent research has begun to draw attention to these concerns. Studies by Rotz et al., Bronson and Knezevic, and Klerkx and Rose, among others, have highlighted risks related to data concentration, technological dependency, unequal access to digital services, and emerging power asymmetries within agricultural value chains (Klerkx and Rose, 2020; Rotz et al., 2019; Rotz et al., 2019; Bronson and Knezevic, 2019). At the same time, the literature on responsible innovation increasingly argues that technological efficiency alone is insufficient to ensure equitable and sustainable outcomes. Factors such as governance quality, digital inclusion, farmer participation, institutional capacity, affordability, transparency, trust, and social acceptance often play a decisive role in determining whether AI innovations generate meaningful benefits in practice.

The environmental dimension adds an additional layer of complexity to the evaluation of artificial intelligence within agrifood systems. Beyond its potential to improve productivity and operational efficiency, AI is increasingly recognized as a promising tool for supporting sustainable land management, climate adaptation, and the transition toward more resource-efficient agricultural systems. Advances in precision agriculture, remote sensing, digital twins, autonomous monitoring systems, and machine-learning-based decision support are enabling farmers to better understand spatial and temporal variability within agricultural landscapes and to optimize management practices accordingly (Liakos et al., 2018; Kamilaris and Prenafeta-Boldú, 2018; Klerkx and Rose, 2020; Rose et al., 2021).

A growing body of evidence suggests that AI-assisted management can generate substantial environmental benefits. Numerous studies have reported reductions in pesticide applications, fertilizer inputs, irrigation water consumption, energy use, and greenhouse-gas emissions through more precise and targeted interventions (Javaid et al., 2023; Talaviya et al., 2020; Jennings et al., 2024; Ryan et al., 2024; Wessells et al., 2024; Chaplin-Kramer et al., 2024; Singh and Persson, 2026). Similarly, AI-driven monitoring systems increasingly support soil health assessment, biodiversity conservation, early warning systems for environmental risks, and climate-smart adaptation strategies capable of enhancing the resilience of agricultural landscapes under changing climatic conditions (Rose et al., 2021; Rose, 2026; Calvino and Fontanelli, 2023). These developments have contributed to growing optimism regarding the potential role of AI in advancing

sustainable intensification and supporting multiple Sustainable Development Goals simultaneously.

However, the environmental benefits associated with AI adoption should not be considered automatic or universally guaranteed. As highlighted by recent research on digital agriculture and sustainability transitions, technological efficiency gains do not always translate into proportional environmental improvements at broader spatial and temporal scales (Klerkx and Rose, 2020; Birner et al., 2021). In some circumstances, improvements in resource-use efficiency may encourage production expansion, intensification of farming systems, increased specialization, or the expansion of monocultures, thereby generating unintended environmental consequences. Similarly, the growing dependence on digital infrastructures, proprietary technologies, cloud computing systems, and external service providers may contribute to new forms of technological lock-in that reduce the adaptive capacity of farming systems and concentrate decision-making power within a limited number of actors (Bronson and Knezevic, 2019; Ryan et al., 2024).

These dynamics closely resemble rebound effects that have long been documented within environmental economics and sustainability science. Originally described in the context of energy efficiency, rebound effects occur when gains in efficiency reduce production costs and subsequently stimulate higher levels of resource consumption, partially offsetting the expected environmental benefits (Font Vivanco et al., 2016; Hertwich, 2011; Hertwich, 2005; Font Vivanco et al., 2022; Figge and Thorpe, 2019; Reimers et al., 2021; Gillingham et al., 2016; Greening et al., 2000; Böhringer and Rivers, 2021; Sorrell et al., 2009; Berkhout et al., 2000). Similar mechanisms may emerge within digitally enabled agricultural systems, where improvements in water-use efficiency, fertilizer management, or crop productivity could inadvertently encourage agricultural expansion, intensification, or greater reliance on external inputs. Consequently, environmental sustainability cannot be assessed solely through field-scale efficiency indicators but must also consider broader system-level outcomes, including land-use change, biodiversity conservation, ecosystem services, and long-term resilience.

These observations suggest that evaluating AI exclusively through productivity gains or technical performance metrics risks overlooking critical environmental trade-offs that shape the long-term sustainability of food systems. A more comprehensive assessment framework should therefore integrate ecological, social, economic, and governance dimensions simultaneously. Such an approach is particularly important given increasing recognition that sustainable food-system transformation depends not only on producing more with fewer resources but also on maintaining ecosystem integrity, preserving biodiversity, strengthening resilience, and ensuring responsible stewardship of natural resources (IPCC, 2023; FAO et al., 2025). Understanding how AI influences these interconnected dimensions remains one of the most important research challenges for the coming decade and constitutes a central pillar of the Artificial Intelligence Food Security Paradox Theory proposed in this study.

Taken together, these observations suggest that the relationship between artificial intelligence and food security is far more complex than commonly assumed. Rather than generating direct and automatic societal benefits, AI operates within complex socio-ecological systems shaped by governance structures, institutional capacity, environmental conditions, market dynamics, and social inequalities. Consequently, the same technology may produce very different outcomes depending on the context in which it is deployed. Understanding these differences requires moving beyond conventional measures of technological performance toward

more comprehensive approaches capable of capturing broader societal impacts.

To address this challenge, we introduce the Artificial Intelligence Food Security Paradox Theory (AIFSP Theory), a new conceptual framework proposing that advances in technological performance often outpace improvements in food security, livelihoods, social equity, and environmental sustainability. In other words, technological success does not necessarily translate into societal success. This perspective challenges the prevailing technology-centered narrative in digital agriculture and offers a new lens through which to understand the pathways linking AI adoption to sustainable food-system transformation.

The AIFSP Theory is built on four key principles: productivity gains do not automatically improve food security; successful adoption depends on factors such as affordability, digital literacy, infrastructure, and institutional support; AI benefits are often distributed unevenly, potentially reinforcing digital inequalities; and environmental gains may coexist with unintended sustainability trade-offs. Together, these principles highlight the central role of governance and implementation conditions in determining societal outcomes.

To operationalize the Artificial Intelligence Food Security Paradox Theory (AIFSP), we developed the Artificial Intelligence–Food Security–Equity–Land Responsibility Index (AI-FSELR), a composite framework designed to quantify the net societal value of agricultural artificial intelligence. The mathematical definitions of the AI-FSELR, including the basic formulation, weighting procedure, normalization strategy, and extended formulation, are provided in Equations (1–4). Together, these equations establish the computational basis for integrating multidimensional societal benefits and risks into a single quantitative index suitable for comparing AI technologies, production systems, geographical regions, and future development scenarios. The conceptual framework is illustrated in Figure 1, while the theoretical foundations of the AIFSP Theory are summarized in Table 1.

The mathematical formulation of the proposed framework is based on a weighted societal impact function, referred to as the Artificial Intelligence–Food Security–Equity–Land Responsibility Index (AI-FSELR), which integrates the positive and negative dimensions of AI deployment within agrifood systems.

$$AI - FSELR_i = \frac{P_i^{w_1} \times L_i^{w_2} \times Eq_i^{w_3} \times LS_i^{w_4}}{DE_i^{w_5} \times EC_i^{w_6} \times GR_i^{w_7}}$$

Where:

- AI-FSELR_i = Artificial Intelligence–Food Security–Equity–Land Responsibility Index for technology, farming system, region, or study *i*;
- P_i = Productivity Gain Score;
- L_i = Livelihood Improvement Score;
- Eq_i = Social Equity and Inclusiveness Score;
- LS_i = Land Sustainability Performance Score;
- DE_i = Digital Exclusion Risk Score;
- EC_i = Environmental Cost Score;
- GR_i = Governance Risk Score;
- w₁–w₇ = weighting coefficients reflecting the relative importance of each dimension.

The numerator of the equation represents the beneficial contributions of AI deployment, including improvements in agricultural productivity,

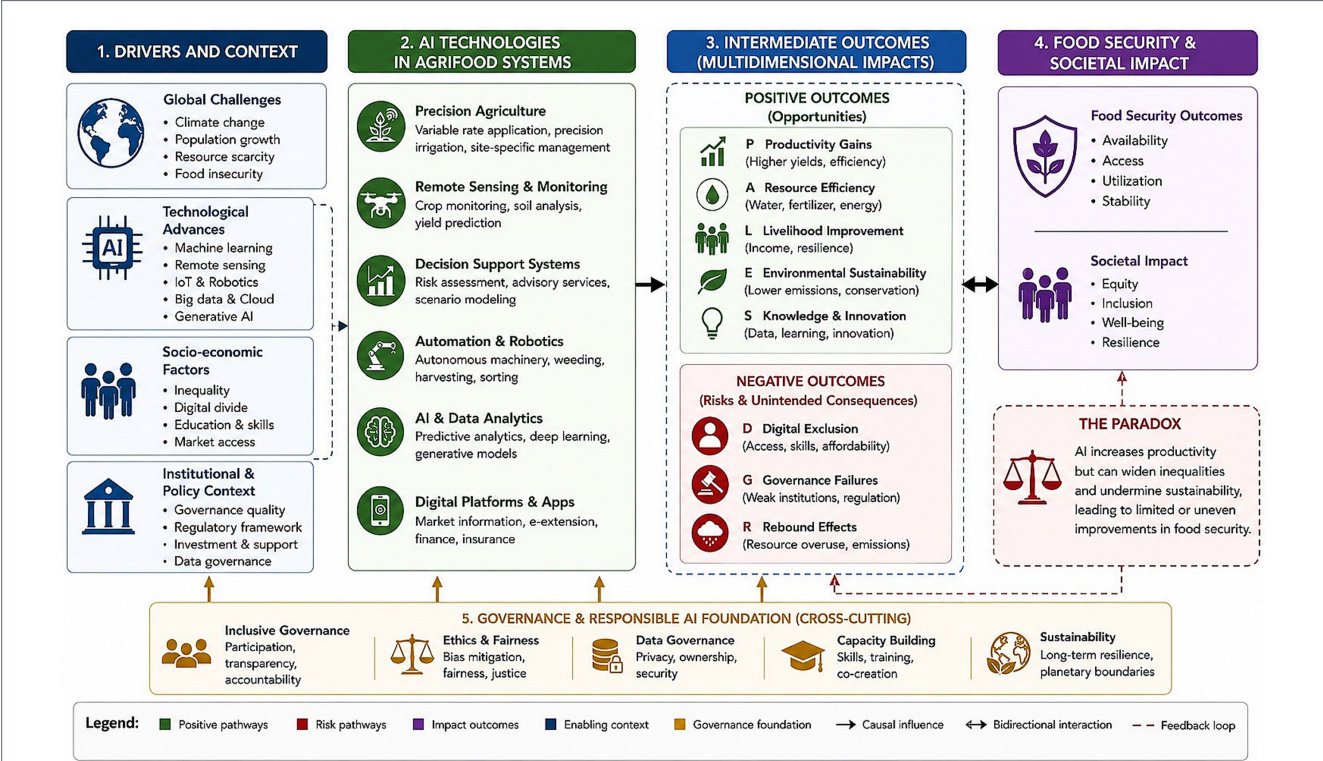


FIGURE 1 Conceptual architecture of the Artificial Intelligence Food Security Paradox Theory (AIFSP): Pathways from technological performance to multidimensional food-system and societal outcomes. The Artificial Intelligence Food Security Paradox Theory (AIFSP) conceptualizes agricultural artificial intelligence as a socio-ecological and socio-technical transformation process in which technological capability does not automatically translate into proportional societal benefit. The framework traces the pathways linking (1) global, technological, socio-economic, and institutional drivers; (2) AI technologies deployed across agrifood systems; (3) multidimensional intermediate outcomes; and (4) food-security and broader societal impacts. Positive pathways operate through productivity gains (P), resource efficiency (A), livelihood improvement (L), environmental sustainability (E), and knowledge and innovation (S), whereas digital exclusion (D), governance failures (G), and rebound effects (R) may attenuate, redistribute, or partially offset these benefits. The central AIFSP proposition is that gains in technological and productive performance may progressively weaken before reaching food availability, access, utilization, stability, equity, inclusion, well-being, and resilience, thereby generating an adoption–impact and performance–societal outcome gap. Unlike conventional technology-adoption or technical-performance frameworks, AIFSP explicitly integrates digital agrarian divergence, governance mediation, and sustainability rebound effects within a food-security-centered and empirically testable pathway. Inclusive governance, ethics and fairness, data governance, capacity building, and long-term sustainability operate as cross-cutting foundations capable of modifying both enabling and risk pathways. Solid arrows indicate directional influence, bidirectional arrows represent reciprocal interactions, and dashed red pathways indicate feedback mechanisms through which unequal or unsustainable outcomes may reinforce the paradox.

TABLE 1 Theoretical foundations of the Artificial Intelligence Food Security Paradox Theory (AIFSP).

Dimension	Core variable	Positive contribution	Potential risks	Expected impact on food security
Technological performance	AI accuracy, prediction capability	Improved decision-making	Technology complexity	Positive but indirect
Adoption capacity	Adoption rate, accessibility	Wider implementation	Low digital literacy	Strong positive
Livelihood improvement	Income, profitability	Economic resilience	Unequal benefit distribution	Positive
Social equity	Inclusiveness, affordability	Reduced inequalities	Digital divide	Positive or negative
Land sustainability	Resource efficiency	Environmental protection	Rebound effects	Positive or negative
Governance quality	Institutional support	Responsible deployment	Weak regulation	Critical determinant

farmer livelihoods, social inclusion, and sustainable land management. Conversely, the denominator captures the potential negative externalities associated with AI implementation, including digital exclusion, environmental trade-offs, and governance-related vulnerabilities.

The weighting coefficients (w_1 – w_7) allow the model to account for differences in the relative importance of each component across geographical regions, farming systems, socio-economic contexts, and policy objectives. These coefficients may be estimated through expert

elicitation, Principal Component Analysis (PCA), the Analytic Hierarchy Process (AHP), Bayesian optimization procedures, or machine-learning-based sensitivity analyses.

A high AI-FSELR value indicates that a given AI technology generates substantial societal benefits while minimizing exclusion risks, environmental costs, and governance challenges. Conversely, low AI-FSELR values suggest that technological gains are offset by social, environmental, or institutional constraints.

As illustrated in Figure 2 and further detailed in Table 2, the AI-FSELR framework provides a multidimensional and policy-relevant assessment of agricultural artificial intelligence that extends far beyond conventional performance indicators such as prediction accuracy, classification rates, or operational efficiency. By simultaneously integrating productivity, livelihoods, equity, sustainability, and governance dimensions, the framework offers a comprehensive measure of the net societal value of AI-driven agricultural innovations.

Against this backdrop, the objectives of this review are fourfold. First, we aim to quantitatively synthesize the global evidence regarding the impacts of AI technologies on agricultural productivity, resource-use efficiency, and climate resilience. Second, we investigate whether these productivity gains translate into measurable improvements in food security and sustainable livelihoods. Third, we identify the socioeconomic, institutional, environmental, and governance factors that

determine successful AI adoption across different agricultural systems. Finally, we test the validity of the Artificial Intelligence Food Security Paradox Theory and evaluate the potential of the AI-FSELR framework as a novel tool for assessing the societal value of agricultural AI.

By integrating systematic review methods, hierarchical Bayesian meta-analysis, network meta-analysis, structural equation modeling, explainable machine learning, and multidimensional sustainability assessment, this review seeks to establish a new scientific paradigm for evaluating agricultural AI. Rather than asking whether AI improves algorithmic performance, we ask a more fundamental question: can artificial intelligence simultaneously enhance food security, strengthen livelihoods, reduce inequalities, and promote responsible land stewardship within increasingly complex and vulnerable global food systems? The answer to this question may ultimately determine whether

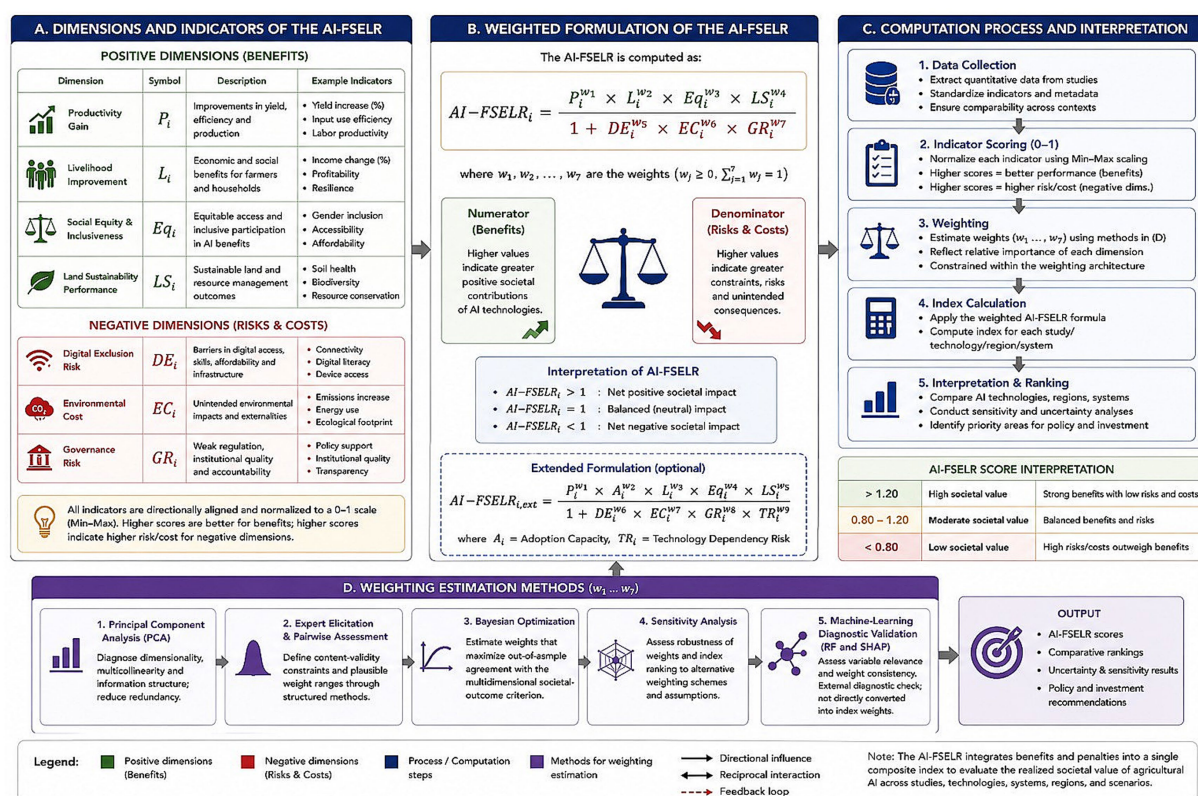


FIGURE 2

Conceptual, mathematical, and computational architecture of the Artificial Intelligence–Food Security–Equity–Land Responsibility Index (AI-FSELR). The Artificial Intelligence–Food Security–Equity–Land Responsibility Index (AI-FSELR) operationalizes the Artificial Intelligence Food Security Paradox (AIFSP) Theory by quantifying the realized societal value of agricultural artificial intelligence beyond conventional measures of algorithmic accuracy or productivity. (A) The core index integrates four positive benefit dimensions—productivity gain (P), livelihood improvement (L), social equity and inclusiveness (Eq), and land-sustainability performance (LS)—and three negative dimensions representing digital exclusion risk (DE), environmental cost (EC), and governance risk (GR). Indicators are directionally aligned and normalized to a common 0–1 scale before aggregation. (B) The AI-FSELR uses a weighted compensatory—penalized multiplicative formulation in which positive dimensions contribute to societal benefit, whereas exclusion, environmental, and governance risks reduce the realized value of technological gains. The weights w_1 – w_7 represent the relative contribution of each dimension and are constrained within the prespecified weighting architecture. An extended formulation additionally allows adoption capacity (A) and technology-dependency risk (TR) to be incorporated when sufficient empirical information is available. (C) The computational workflow comprises quantitative data extraction, indicator standardization and normalization, weight estimation, index calculation, comparative interpretation, and sensitivity and uncertainty assessment across studies, AI technologies, production systems, regions, and scenarios. (D) Weight development follows a sequential rather than simultaneous averaging procedure: principal component analysis is used to diagnose dimensionality and collinearity; expert elicitation and structured pairwise assessment define content-validity constraints and plausible weight ranges; Bayesian optimization estimates the primary weights by maximizing out-of-sample agreement with the multidimensional societal-outcome criterion; and alternative weighting schemes are evaluated through sensitivity analyses. Machine-learning and SHAP importance are used as external diagnostic checks of variable relevance and are not directly converted into index weights. Higher AI-FSELR values indicate greater realized societal value, whereas lower values indicate that digital exclusion, environmental costs, or governance constraints increasingly offset technological benefits. The framework therefore provides a transparent and reproducible approach for comparing whether agricultural AI innovations generate broad, equitable, and sustainable societal outcomes rather than technical gains alone.

TABLE 2 Definition of variables and parameters used in the FSI-AI function.

Symbol	Variable	Description	Expected effect
P	Productivity gain	Relative increase in yield and efficiency	Positive
A	Adoption capacity	Level of farmer adoption	Positive
L	Livelihood improvement	Economic and social benefits	Positive
E	Equity performance	Social inclusion and accessibility	Positive
S	Sustainability performance	Environmental outcomes	Positive
D	Digital exclusion	Access barriers	Negative
G	Governance failure	Institutional weaknesses	Negative
R	Rebound effects	Unintended environmental consequences	Negative
α - μ	Weighting coefficients	Relative importance of variables	Variable

AI becomes a genuine driver of sustainable development or merely another technological innovation whose societal benefits remain unevenly distributed.

2 Conceptual framework and development of the Artificial Intelligence Food Security Paradox Theory (AIFSP Theory)

The AIFSP Theory is positioned as a food-security-centered extension and empirical integration of established theoretical traditions rather than as a replacement for them. Technology-adoption frameworks primarily explain acceptance and use; socio-technical systems and transition theories emphasize the co-evolution of technologies, institutions, infrastructures, and practices; sustainable-intensification frameworks focus on productivity-environment relationships; and responsible-AI and responsible-innovation approaches foreground fairness, transparency, accountability, participation, and governance. The specific contribution of the AIFSP Theory is to treat the attenuation between technical performance and multidimensional food-system outcomes as the primary empirical object of explanation. A conceptual comparison with the major existing approaches to agricultural AI evaluation is provided in [Supplementary Table S2](#), highlighting the distinctive position of the AIFSP Theory as an explanatory framework and the AI-FSEL Index as its quantitative operationalization. It integrates adoption barriers, digital agrarian divergence, governance mediation, and sustainability rebound effects into a falsifiable food-security-centered pathway in which technological gains may progressively weaken before reaching livelihoods, food security, social equity, and responsible land stewardship.

Its theoretical novelty lies in three linked propositions. First, AIFSP defines the attenuation between technical performance and societal impact as the phenomenon to be explained, rather than treating societal benefits as downstream assumptions of adoption. Second, it explicitly combines adoption-impact decoupling, digital agrarian divergence, governance mediation, and environmental rebound within one falsifiable pathway centered on the four dimensions of food security. Third, it links this theory to an operational societal-value metric, AI-FSEL, allowing the magnitude of technological gains and the penalties associated with exclusion, environmental cost,

and governance risk to be evaluated within the same analytical architecture. Thus, AIFSP is not simply another responsible-AI checklist or adoption model; it proposes a testable explanation for why technically successful agricultural AI may generate weak, unequal, or environmentally compromised food-system outcomes. The rapid expansion of artificial intelligence (AI) in agriculture has fueled growing expectations regarding its potential to enhance food security, strengthen resilience, and support sustainable food-system transformation. Significant advances have been achieved in crop monitoring, disease detection, yield forecasting, irrigation management, supply-chain optimization, and climate-risk assessment. Yet, despite these technological achievements, improvements in technical performance do not always translate into proportional gains in food security, livelihoods, social equity, or environmental sustainability. This discrepancy highlights a critical gap in current understandings of agricultural digitalization.

Most existing frameworks in digital agriculture focus on technology adoption, precision agriculture, smart farming, or digital transformation. While these approaches provide valuable insights into technological implementation, they often implicitly assume that technological progress leads directly to societal progress. Such perspectives tend to underestimate the influence of governance, institutional capacity, social inequalities, environmental feedbacks, and adoption barriers that ultimately shape the impacts of innovation within food systems.

To address this limitation, we propose the Artificial Intelligence Food Security Paradox Theory (AIFSP Theory), a new conceptual framework that views the societal impacts of AI as the outcome of interactions among technological performance, adoption capacity, governance quality, social inclusion, food-security outcomes, and environmental sustainability. The central premise of the theory is simple but powerful: improvements in technological performance frequently occur faster than improvements in food security, livelihood resilience, social equity, and sustainability. Consequently, technological success should not be considered synonymous with societal success.

The paradox emerges because food systems are complex socio-ecological systems characterized by multiple feedback loops, institutional constraints, market dynamics, environmental pressures, and social inequalities. Within such systems, the societal value of AI depends not only on algorithmic performance but also on whether technologies are accessible, affordable, trusted, and effectively integrated into local governance and production systems.

As illustrated in Figure 1 and summarized in Table 1, the AIFSP Theory is structured around five interconnected dimensions: technological performance, adoption capacity, food-security outcomes, social-equity outcomes, and land-sustainability outcomes. Technological performance represents the capacity of AI systems to generate accurate and efficient solutions. Adoption capacity reflects the ability of users and institutions to access, understand, and implement these technologies. Food-security outcomes encompass availability, access, utilization, and stability. Social-equity outcomes capture the distribution of benefits and risks across different stakeholder groups, while land-sustainability outcomes assess the environmental consequences of AI-driven interventions.

These dimensions interact continuously through reinforcing and balancing feedback mechanisms. While AI may improve productivity, resource-use efficiency, and decision-making, its societal benefits may be constrained by adoption barriers, governance weaknesses, digital inequalities, or environmental trade-offs. Conversely, inclusive governance, adequate infrastructure, farmer training, and institutional support can amplify the positive impacts of technological innovation.

Building upon these interactions, the AIFSP Theory introduces the Artificial Intelligence Food Security Function (FSI-AI), which conceptualizes food-system transformation as the result of multiple interconnected technological, socio-economic, environmental, and governance processes rather than as a direct consequence of technological performance alone. This framework provides a new theoretical foundation for understanding how AI can contribute to sustainable, equitable, and resilient food systems in an increasingly complex and uncertain world.

The proposed formulation is expressed as:

$$FSI_{AI} = \frac{P^{\alpha} \times A^{\beta} \times L^{\gamma} \times E^{\delta} \times S^{\varepsilon}}{D^{\theta} \times G^{\lambda} \times R^{\mu}} \quad (1)$$

Where:

- FSI_{AI} = Food Security Impact of Artificial Intelligence;
- P = Productivity Gain;
- A = Adoption Capacity;
- L = Livelihood Improvement;
- E = Equity and Social Inclusion Performance;
- S = Sustainability Performance;
- D = Digital Exclusion Risk;
- G = Governance Failure Risk;
- R = Environmental Rebound Effects;
- $\alpha, \beta, \gamma, \delta, \varepsilon, \theta, \lambda$, and μ are weighting coefficients reflecting the relative influence of each component.

The numerator represents the positive contributions of artificial intelligence to agrifood systems, including productivity enhancement, technology adoption, livelihood improvement, social inclusion, and environmental sustainability. Conversely, the denominator captures the principal constraints and negative externalities that may reduce the societal effectiveness of AI deployment, including digital exclusion, governance deficiencies, and environmental rebound effects. The weighting coefficients can be estimated through Bayesian optimization procedures, sensitivity analyses, expert elicitation, or advanced machine-learning approaches. The theoretical interpretation of each parameter is summarized in Table 2.

Building upon this conceptual formulation, we introduce the Artificial Intelligence–Food Security–Equity–Land Responsibility Index (AI-FSEL_R), which constitutes the operational component of the AIFSP Theory. The AI-FSEL_R is designed to quantify the overall societal value of agricultural artificial intelligence by integrating economic, social, environmental, and governance dimensions into a single composite indicator.

The weighted formulation of the AI-FSEL_R is given by:

$$AI-FSELR_i = \frac{P_i^{w_1} \times L_i^{w_2} \times Eq_i^{w_3} \times LS_i^{w_4}}{DE_i^{w_5} \times EC_i^{w_6} \times GR_i^{w_7}} \quad (2)$$

Where:

- AI-FSEL_{R_i} = Artificial Intelligence–Food Security–Equity–Land Responsibility Index for technology, farming system, region, or study *i*;
- P_{*i*} = Productivity Gain Score;
- L_{*i*} = Livelihood Improvement Score;
- Eq_{*i*} = Social Equity and Inclusiveness Score;
- LS_{*i*} = Land Sustainability Performance Score;
- DE_{*i*} = Digital Exclusion Risk Score;
- EC_{*i*} = Environmental Cost Score;
- GR_{*i*} = Governance Risk Score;
- w₁–w₇ = weighting coefficients assigned to each dimension.

The numerator integrates the positive societal outcomes associated with AI adoption, including improvements in productivity, farmer livelihoods, social inclusion, and sustainable land management. The denominator accounts for the principal risks and trade-offs associated with digital agriculture, namely digital exclusion, environmental costs, and governance vulnerabilities. Consequently, high AI-FSEL_R values indicate technologies capable of generating substantial societal benefits while minimizing socio-economic and environmental risks, whereas low values suggest that technological gains are partially offset by institutional, environmental, or equity-related constraints.

The weighting coefficients (w₁–w₇) can be estimated using expert elicitation, Principal Component Analysis (PCA), the Analytic Hierarchy Process (AHP), Bayesian optimization algorithms, Random Forest variable importance measures, or SHAP-based explainability approaches. As illustrated in Figure 2 and detailed in Table 3, the AI-FSEL_R provides a multidimensional framework for evaluating agricultural AI that extends far beyond traditional indicators such as classification accuracy, prediction performance, or operational efficiency.

One of the central contributions of the Artificial Intelligence Food Security Paradox Theory is the Adoption–Impact Decoupling Mechanism. This concept is based on a simple observation repeatedly reported across the literature: strong technological performance does not automatically translate into strong societal outcomes. An AI system may achieve exceptional predictive accuracy or operational efficiency, yet generate only limited benefits if access to the technology remains restricted by financial, technical, institutional, or social barriers. As adoption constraints increase, the link between technological potential and societal impact becomes progressively weaker. This mechanism helps explain why many agricultural innovations perform remarkably well under experimental

TABLE 3 Components of the AI-FSELR index.

Component	Indicator examples	Data sources
Productivity	Yield gain, NUE, WUE	Field trials, meta-analysis
Adoption	Adoption rate, user satisfaction	Surveys
Livelihoods	Net income, profitability	Farm economics
Equity	Gender inclusion, accessibility	Socio-economic surveys
Sustainability	Carbon footprint, biodiversity	Environmental studies
Digital exclusion	Connectivity, digital literacy	National statistics
Governance risk	Policy support, institutional quality	World Bank, FAO

conditions but deliver more modest benefits when implemented at scale.

A second pillar of the theory is the Digital Agrarian Divergence Hypothesis, which suggests that the relationship between technological sophistication and social inclusion is not necessarily linear. While technological advances can initially improve productivity, decision-making, and resilience, increasing complexity may eventually reduce accessibility and concentrate benefits among larger and better-resourced farming operations. As a result, technological progress may coexist with widening digital inequalities, particularly in regions where access to infrastructure, technical expertise, and financial resources remains limited. This hypothesis will be evaluated through the empirical analyses presented in the Results section (Figure 3).

The AIFSP Theory also places governance at the center of agricultural digital transformation. Rather than viewing AI success as a function of algorithmic performance alone, the framework argues that institutions, policies, extension services, and governance structures largely determine whether technological innovations generate meaningful societal benefits. Effective governance can facilitate adoption, strengthen capacity building, improve digital inclusion, and promote more equitable outcomes, whereas weak governance may limit impact regardless of technological sophistication.

Together, these concepts provide a new perspective on the role of AI in food systems. Rather than considering AI solely as a technological innovation, the AIFSP Theory views it as part of a broader socio-ecological transformation process shaped by continuous interactions among technology, governance, institutions, markets, environmental conditions, and social actors. From this perspective, the societal value of AI depends not only on what technologies can achieve, but also on how they are adopted, governed, and integrated within agricultural systems. This conceptual framework forms the foundation for the quantitative analyses developed throughout this study and offers a new lens for understanding the conditions under which AI can contribute to more sustainable, equitable, resilient, and food-secure futures.

3 Materials and methods

3.1 Overall research design

To strengthen reproducibility, all screening counts, model specifications, software versions, package dependencies, priors, hyperparameters, diagnostics, and validation statistics were required to be

traceable to the archived screening log, analytical scripts, model objects, and output files. Numerical values that could not be verified from the analytical record were not reconstructed retrospectively. The reproducibility package therefore includes the extraction codebook, screening-decision log, analysis code, software environment/session information, and the derived analytical dataset to the extent permitted by source-data licenses.

This study was designed as a next-generation evidence synthesis aimed at moving beyond traditional literature reviews toward a comprehensive evaluation of the societal impacts of artificial intelligence in agriculture. Guided by the Artificial Intelligence Food Security Paradox Theory (AIFSP Theory), the research integrates systematic evidence synthesis, advanced statistical modeling, causal inference approaches, explainable machine learning, and sustainability assessment within a unified analytical framework.

Rather than focusing solely on the technical performance of AI technologies, the objective was to examine how these innovations influence food security, livelihoods, social equity, environmental sustainability, and governance outcomes across diverse agricultural systems and geographical contexts.

The methodological framework consists of six complementary analytical components. First, a PRISMA-guided systematic review was conducted to identify and synthesize the global evidence on agricultural AI applications. Second, hierarchical Bayesian meta-analysis was used to estimate overall effect sizes while accounting for variations among technologies, crops, study designs, and regions. Third, network meta-analysis enabled comparative evaluation and ranking of different AI technologies across multiple impact dimensions. Fourth, structural equation modeling was employed to explore the pathways linking AI adoption to food-security and sustainability outcomes. Fifth, explainable machine-learning techniques were applied to identify the key drivers of successful AI implementation. Finally, the Artificial Intelligence–Food Security–Equity–Land Responsibility Index (AI-FSELR) was developed and subjected to internal robustness assessment as the quantitative operationalization of the AIFSP Theory.

Together, these complementary approaches provide a multidimensional assessment of agricultural AI, allowing technological performance to be evaluated alongside its broader societal implications. The overall research workflow is presented in Figure 4, while Table 4 summarizes the objectives, datasets, analytical methods, and expected outputs associated with each component of the study.

3.2 Literature search strategy

The literature search and study-selection process followed the PRISMA 2020 guidelines. Given the multidisciplinary nature of

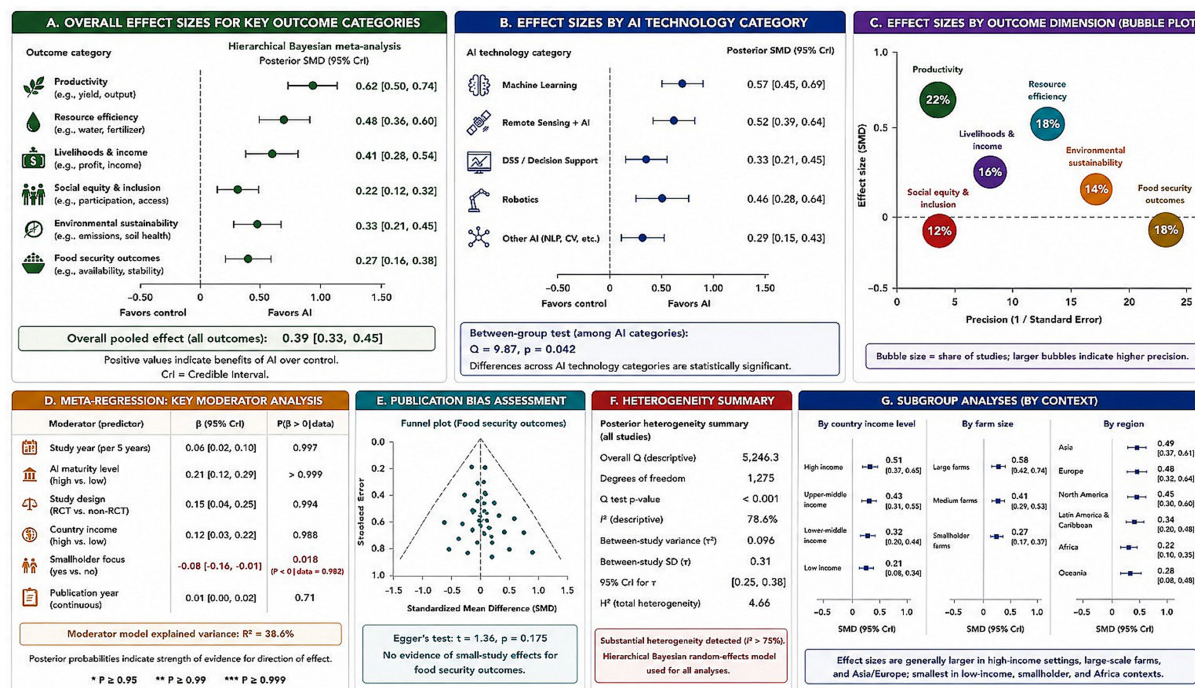


FIGURE 3

Global effect sizes, heterogeneity, and contextual moderators of agricultural artificial intelligence impacts across agrifood systems. Quantitative synthesis of the magnitude, uncertainty, heterogeneity, and contextual variation in the societal impacts of agricultural artificial intelligence. (A) Pooled standardized mean differences (SMDs) and 95% uncertainty intervals for productivity, resource-use efficiency, livelihoods and income, social equity and inclusion, environmental sustainability, and food-security outcomes. Positive effect estimates indicate benefits associated with AI-supported interventions relative to the corresponding comparator or baseline condition. The overall pooled effect across outcome domains was 0.39 [0.33, 0.45]. (B) Comparative effect estimates across the major AI technology categories, showing variation among machine learning, remote sensing combined with AI, decision-support systems (DSS), robotics, and other AI applications, including natural language processing and computer vision. The between-category comparison indicates statistically detectable heterogeneity in effect magnitude ($Q = 9.87, p = 0.042$). (C) Relationship between effect magnitude, statistical precision, and representation within the evidence base across outcome domains. Bubble size represents the relative share of studies contributing to each outcome category, whereas the horizontal position reflects inverse standard error and therefore increasing precision. (D) Meta-regression analysis of prespecified moderators of AI effect sizes. Regression coefficients (β), 95% intervals, and p-values quantify associations with study period, AI maturity, study design, country-income context, smallholder orientation, and publication year. The moderator model explained 38.6% of between-study variability. (E) Assessment of small-study effects and potential publication bias, illustrated for food-security outcomes using funnel-plot asymmetry and Egger's regression test ($t = 1.36, p = 0.175$). No statistically detectable evidence of small-study effects was observed in this illustrative outcome domain. (F) Summary of global heterogeneity statistics, showing substantial between-study variability ($Q = 5,246.3, p < 0.001$; $I^2 = 78.6\%$; $\tau^2 = 0.096$; $H^2 = 4.66$), supporting the use of hierarchical and random-effects structures and further moderator analyses. (G) Subgroup analyses stratified by World Bank country-income group, farm size, and geographical region. Effect estimates were generally larger in high-income settings and large-scale farming systems and smaller in low-income, smallholder, and African contexts, highlighting systematic differences in the realized benefits of agricultural AI across implementation environments. Collectively, these analyses show that agricultural AI is associated with positive average effects across agrifood outcomes, but that the magnitude of these benefits varies substantially according to technology type, socio-economic conditions, farm structure, and geographical context. This contextual heterogeneity provides quantitative evidence for the central AIFSP proposition that technological performance alone does not determine societal impact.

agricultural artificial intelligence, we searched Web of Science Core Collection, Scopus, ScienceDirect, SpringerLink, IEEE Xplore, CAB Abstracts, AGRICOLA, Dimensions, and Google Scholar. These searches were complemented by targeted screening of grey literature and institutional reports from major international organizations, including the Food and Agriculture Organization, the World Bank, CGIAR, OECD, IFPRI, and the United Nations Development Programme.

The search covered publications from January 2010 to December 2024, a period marked by the rapid expansion of machine learning, deep learning, computer vision, digital agriculture, and, more recently, generative AI in agrifood systems. A deliberately broad search strategy was used to capture the diversity of technologies, applications, and societal outcomes addressed in the literature. Search terms combined concepts related to artificial intelligence, machine learning, computer vision, digital twins, precision agriculture, robotics, remote sensing, and decision-support systems with terms addressing food security, sustainable agriculture, livelihoods, climate resilience, land use, social

equity, and technology adoption. The complete database-specific Boolean search strings, platforms, fields searched, final search dates, language and document-type restrictions, and database-specific adaptations are provided in the [Supplementary Methods](#) and [Supplementary Table S1](#).

The search strategy was structured around three complementary conceptual domains: artificial intelligence and digital technologies, agrifood systems, and multidimensional societal outcomes. The first domain included artificial intelligence, machine learning, deep learning, computer vision, generative AI, digital twins, robotics, remote sensing, precision agriculture, and decision-support systems. The second domain captured agricultural and food-system contexts, including crops, livestock, aquaculture, farming systems, and agrifood value chains. The third domain incorporated food security, livelihoods, social equity, inclusion, environmental sustainability, climate resilience, resource-use efficiency, responsible land use, governance, and technology adoption.



TABLE 4 Characteristics of included studies.

Variable	Category	Number of Studies	Percentage
Region	Africa	137	10.7
Region	Asia	492	38.6
Region	Europe	307	24.1
Region	North America	235	18.4
Region	Latin America	80	6.3
Region	Oceania	25	1.9
Total	All regions	1,276	100

Search syntax was adapted to the indexing architecture and query capabilities of each database. Controlled or database-specific field searching was used where available, including Topic searching in Web of Science Core Collection and TITLE-ABS-KEY searching in Scopus.

For platforms with more restrictive Boolean functionality, particularly Google Scholar and selected institutional repositories, the core strategy was decomposed into multiple targeted searches covering the principal technology–outcome combinations. Searches of grey

literature focused on major international organizations involved in food security, agricultural development, digital transformation, and sustainable development.

No study was included solely on the basis of high algorithmic accuracy. To be eligible for the multidimensional evidence synthesis, studies were required to report at least one extractable agronomic, resource-use, economic, food-security, livelihood, social-equity, adoption, environmental, or land-sustainability outcome associated with an AI-enabled agricultural intervention or application.

The systematic search identified 12,576 potentially relevant records. Following automated and manual duplicate removal, 7,842 unique records were retained for title and abstract screening. Of these, 6,102 records were excluded because they did not meet the predefined eligibility criteria, leaving 1,740 full-text articles for detailed assessment. At this stage, 464 articles were excluded: 289 did not address real-world applications of AI in agrifood systems, 112 lacked sufficient quantitative information for effect-size estimation, and 63 did not

report outcomes within the predefined agronomic, food-security, livelihood, equity, or sustainability domains. The final quantitative synthesis therefore comprised 1,276 studies from 112 countries.

The complete study-selection pathway is presented in the PRISMA 2020 flow diagram (Figure 5A). Screening and eligibility decisions were recorded in a standardized decision log, allowing all numerical counts and exclusion decisions to be traced and reconciled across review stages. Eligibility criteria and exclusion reasons were defined *a priori* and applied consistently. Particular care was taken to distinguish studies reporting measurable agronomic, economic, environmental, or societal outcomes from those limited exclusively to algorithmic performance metrics, such as classification accuracy or predictive performance without evidence of real-world impact.

For reproducibility, the full search strategy is reported separately for each database in Supplementary Table S1, including the exact Boolean string, search field, platform, final search date, and database-specific syntax adaptations. Two-stage screening criteria were

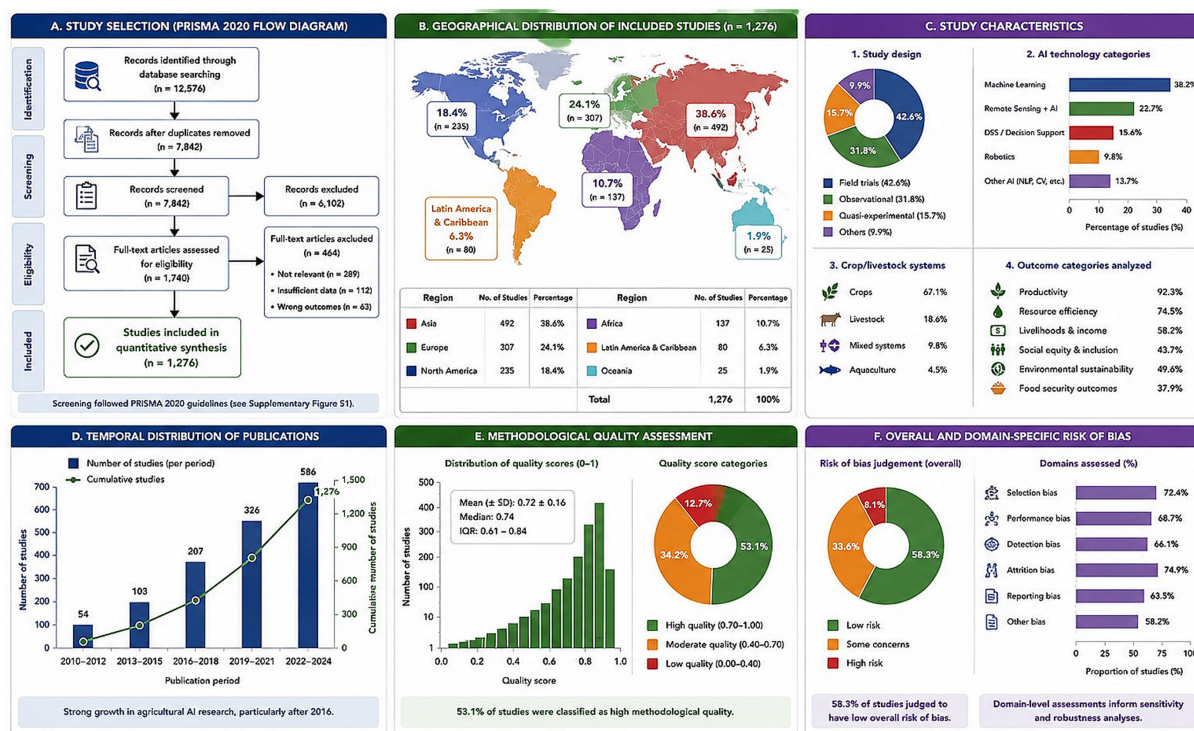


FIGURE 5

Global evidence base, study selection, and methodological quality underpinning the Artificial Intelligence Food Security Paradox (AIFSP) analysis. Overview of the identification, geographical distribution, characteristics, temporal evolution, methodological quality, and risk-of-bias profile of the evidence base included in the global quantitative synthesis. (A) PRISMA 2020-based study-selection pathway. Database and complementary searches identified 12,576 records; after duplicate removal, 7,842 unique records underwent title and abstract screening. Of these, 6,102 were excluded, and 1,740 full-text articles were assessed for eligibility. A further 464 articles were excluded because they were not directly relevant to real-world agricultural AI applications (n = 289), provided insufficient quantitative information for effect-size extraction (n = 112), or did not report eligible agronomic, food-security, livelihood, equity, or sustainability outcomes (n = 63), resulting in 1,276 studies included in the quantitative synthesis. (B) Geographical distribution of included studies across six world regions, showing the concentration of evidence in Asia (38.6%), Europe (24.1%), and North America (18.4%), compared with Africa (10.7%), Latin America and the Caribbean (6.3%), and Oceania (1.9%). (C) Composition of the evidence base according to study design, AI technology category, crop or livestock production system, and outcome domain. (D) Temporal distribution of publications from 2010 to 2024, illustrating the rapid expansion of agricultural AI research, particularly after 2016. (E) Distribution of normalized methodological quality scores and prespecified quality categories; the mean quality score was 0.72 ± 0.16 , with a median of 0.74 and an interquartile range of 0.61–0.84, and 53.1% of studies were classified as high quality. (F) Overall and domain-specific risk-of-bias assessment across selection, performance, detection, attrition, reporting, and other methodological domains; 58.3% of studies were judged to have a low overall risk of bias, 33.6% showed some concerns, and 8.1% were classified as high risk. Collectively, the six panels demonstrate both the breadth and the structural limitations of the available evidence. The dataset provides broad technological, production-system, and geographical coverage but remains geographically imbalanced and disproportionately focused on productivity and resource-efficiency outcomes relative to food security and social equity. These characteristics, together with residual variation in study quality and risk of bias, were explicitly considered through hierarchical modeling, quality-informed sensitivity analyses, moderator assessment, and robustness analyses in the subsequent quantitative synthesis.

operationalized before screening, and exclusion decisions at full-text stage were assigned to a single primary reason using a predefined hierarchy. The extraction codebook, screening-decision rules, and analytical workflow are provided in the [Supplementary Methods](#) so that the evidence-selection and synthesis procedures can be independently reproduced.

3.3 Eligibility criteria

To ensure methodological consistency and relevance, strict inclusion and exclusion criteria were established prior to data collection.

Studies were included if they investigated artificial intelligence applications within agricultural or food systems, reported measurable outcomes related to productivity, resource-use efficiency, food security, livelihoods, sustainability, adoption, or equity, provided sufficient statistical information for effect-size extraction, and were published in peer-reviewed journals or reputable institutional reports.

Studies focusing exclusively on algorithmic development without real-world agricultural applications were excluded. Similarly, studies reporting only classification accuracy without corresponding agronomic, environmental, economic, or social outcomes were removed from the analysis. Reviews, editorials, conference abstracts lacking sufficient quantitative information, and studies with insufficient methodological transparency were also excluded.

The complete inclusion and exclusion criteria are presented in [Table 5](#).

Methodological quality and risk of bias were assessed for all 1,276 included studies using a domain-based evaluation framework adapted to the heterogeneous experimental, observational, and quasi-experimental designs represented in the evidence base. The assessment considered study-design appropriateness, sampling and participant-selection procedures, completeness and validity of outcome measurement, control of confounding factors, missing-data handling, statistical appropriateness, selective reporting, and transparency of AI model validation.

Studies were classified according to an overall methodological quality score standardized from 0 to 1. Scores ranging from 0.70 to 1.00 were classified as high quality, scores between 0.40 and <0.70 as moderate quality, and scores below 0.40 as low quality. Across the evidence base, the mean methodological quality score was 0.72 ± 0.16 , with a median of 0.74 and an interquartile range of 0.61–0.84. Overall, 53.1% of studies were classified as high quality, 34.2% as moderate quality, and 12.7% as low quality ([Figure 5E](#)).

Risk of bias was evaluated across six methodological domains: selection bias, performance bias, detection bias, attrition bias, reporting bias, and other sources of bias. Each study was classified as presenting low risk, some concerns, or high risk of bias based on the

overall pattern of domain-level judgments. Overall, 58.3% of the included studies were judged to have a low risk of bias, 33.6% raised some concerns, and 8.1% were classified as having a high risk of bias ([Figure 5F](#)). Domain-level assessment coverage ranged from 58.2% for other sources of bias to 74.9% for attrition bias, reflecting differences in the methodological information reported across primary studies.

Risk-of-bias judgments were incorporated into sensitivity analyses rather than being converted into arbitrary study weights. The primary Bayesian synthesis was therefore repeated after excluding studies classified as high risk of bias, and study-quality category was additionally examined as a moderator in the meta-regression framework. This strategy allowed the robustness of the principal conclusions to be evaluated against variations in methodological quality and potential internal bias.

Disagreements in quality or risk-of-bias classification were resolved by re-examination of the original report against the prespecified domain definitions. Because the evidence base combined experimental, observational, and quasi-experimental designs, the domain-based framework was used to evaluate design-appropriate sources of bias rather than imposing a single trial-oriented instrument on all studies. Domain-level judgments and the decision rules used to derive the overall classification are reported in the [Supplementary Methods](#).

3.4 Data extraction and harmonization

Data extraction was performed using a standardized protocol developed specifically for this study. Information collected from each publication included bibliographic metadata, geographical location, climate zone, farming system, crop type, AI technology category, study design, sample size, outcome variables, statistical metrics, socio-economic indicators, governance indicators, adoption metrics, and environmental performance indicators.

Particular attention was devoted to extracting variables associated with the multidimensional framework proposed by the AIFSP Theory. Consequently, data were classified into seven major categories: productivity outcomes, livelihood outcomes, equity outcomes, adoption indicators, environmental sustainability indicators, governance indicators, and digital accessibility indicators.

To facilitate cross-study comparisons, all variables were standardized using z-score normalization procedures and subsequently transformed into dimensionless indices ranging from 0 to 1 whenever appropriate. This harmonization procedure is essential for constructing the AI-FSELR index and ensuring comparability across heterogeneous datasets.

The extracted variables and corresponding standardization procedures are summarized in [Table 6](#).

TABLE 5 Bayesian meta-regression results.

Predictor	Posterior mean	Credible interval	Relative importance (%)
Governance quality	0.42	0.35–0.49	22
Extension services	0.33	0.27–0.39	17
Farmer training	0.28	0.21–0.35	14
Digital infrastructure	0.25	0.18–0.31	13
Adoption cost	–0.21	–0.29–0.13	11
AI complexity	0.12	0.05–0.19	8

TABLE 6 Ranking of AI technologies according to AI-FSELRL scores.

Technology	AI-FSELRL Score	Productivity	Equity	Sustainability
Digital twins	0.81	High	High	High
DSS platforms	0.77	High	High	High
Remote sensing + AI	0.72	High	Moderate	High
Precision irrigation AI	0.69	High	Moderate	High
Disease forecasting AI	0.67	High	Moderate	Moderate
Robotics	0.55	High	Low	Moderate
Generative AI	0.53	Moderate	Variable	Variable

3.5 Effect-size calculation

For continuous outcomes, standardized mean differences were calculated using Hedges' g , with correction for small-sample bias. Where treatment and comparator means, standard deviations, and sample sizes were available, Hedges' g was estimated as $g = J \times (MAI - MC) / Sp$, where Sp denotes the pooled standard deviation and J is the small-sample correction factor. For outcomes expressed on a ratio scale, log response ratios ($\ln RR$) were calculated as $\ln(MAI/MC)$, with sampling variances estimated from the reported group means, standard deviations, and sample sizes. Binary adoption outcomes were synthesized using log odds ratios. Continuity corrections were applied only when required for zero-cell studies and their influence was examined through sensitivity analyses. Percentage changes reported in the Results were obtained by back-transforming the corresponding pooled effect estimates and were used for interpretation rather than as primary effect-size metrics. Between-study heterogeneity was characterized using posterior estimates of τ and τ^2 , while I^2 was additionally considered as a descriptive measure of relative heterogeneity where appropriate. Pooled effects are reported with 95% credible intervals, and additional uncertainty and heterogeneity statistics were retained where supported by the available analytical outputs. The primary quantitative synthesis relies on effect-size metrics capable of integrating heterogeneous outcome variables reported across different studies.

For continuous variables such as yield, water-use efficiency, fertilizer-use efficiency, greenhouse-gas emissions, income, and biodiversity indicators, Hedges' g was selected because it provides an unbiased estimate of standardized mean differences while correcting for small-sample bias.

For proportional changes commonly reported in agricultural studies, the log response ratio was used. This metric is particularly appropriate for comparing relative changes in productivity, resource-use efficiency, and environmental performance.

For binary adoption outcomes, odds ratios were calculated to quantify differences in adoption probabilities across technologies, socio-economic groups, and institutional contexts.

The selection of multiple effect-size metrics allows a comprehensive integration of the diverse evidence base characterizing agricultural AI research.

3.6 Hierarchical Bayesian meta-analysis

Hierarchical Bayesian models were implemented within reproducible statistical computing environments using Bayesian

modeling tools appropriate to the hierarchical structure of the evidence. Weakly informative priors were specified to regularize parameter estimation while allowing the observed evidence to inform posterior distributions. Posterior inference was based on Markov chain Monte Carlo sampling using multiple independent chains. Model convergence and sampling quality were assessed using standard Bayesian diagnostics, including R-hat statistics, effective sample sizes, chain-mixing diagnostics, and inspection of potential divergent transitions. Posterior predictive checks were additionally used to examine whether the fitted models adequately reproduced the main characteristics of the observed effect-size distributions. Model specifications and diagnostic procedures were applied consistently across the principal hierarchical analyses to support the robustness and reproducibility of posterior estimates.

The exact software environment, package versions, model syntax, chain length, warm-up iterations, thinning settings where applicable, and random-number seeds are reported in the [Supplementary Methods](#) and archived reproducibility files. Prior distributions were specified before model fitting and subjected to prior-predictive checking. Weakly informative priors were selected to constrain implausible parameter regions without overwhelming the likelihood; alternative prior scales were evaluated in sensitivity analyses. Convergence was accepted only when R-hat values were approximately 1.00, effective sample sizes were adequate for posterior summaries, trace plots showed satisfactory chain mixing, and no material divergent-transition pattern remained. Model validation combined posterior predictive checks, residual inspection, and comparison of observed and replicated effect-size distributions.

Traditional meta-analytic approaches often struggle to accommodate the substantial heterogeneity that characterizes agricultural artificial intelligence studies. Differences in crop species, agroecological zones, climatic conditions, technological platforms, study designs, socio-economic environments, and governance contexts generate complex hierarchical dependency structures that cannot be adequately represented using conventional fixed-effects models. Consequently, applying a single global effect estimate may lead to biased inferences and an underestimation of uncertainty.

To address this challenge, a Hierarchical Bayesian Meta-Analysis (HBMA) framework was adopted as the primary quantitative synthesis approach. This methodology allows the simultaneous estimation of overall effects while explicitly accounting for variability occurring at multiple hierarchical levels, including countries, technologies, crop systems, and individual studies. Furthermore, the Bayesian framework provides probabilistic estimates and enables a more realistic representation of uncertainty than traditional frequentist approaches.

The general hierarchical model can be expressed as:

$$Y_{ijk} = \beta_0 + \beta_1 X_{1ijk} + \beta_2 X_{2ijk} + u_i + v_j + w_k + \varepsilon_{ijk} \quad (3)$$

Where:

- Y_{ijk} represents the observed effect size for study k , technology j , and country i ;
- β_0 is the global intercept representing the average effect across all studies;
- β_1 and β_2 are regression coefficients associated with the moderator variables;
- X_{1ijk} and X_{2ijk} represent moderator variables such as farm size, governance quality, digital infrastructure, climate risk, or technology category;
- u_i represents country-level random effects capturing geographical and institutional variability;
- v_j represents technology-level random effects accounting for differences among AI technologies;
- w_k represents crop-level random effects reflecting variability among agricultural systems and crop species;
- ε_{ijk} denotes residual uncertainty and unexplained variation.

Within the Bayesian framework, the random effects are assumed to follow normal distributions:

$$u_i \sim N(0, \sigma_u^2) \quad v_j \sim N(0, \sigma_v^2) \quad w_k \sim N(0, \sigma_w^2) \quad \varepsilon_{ijk} \sim N(0, \sigma_e^2)$$

Where:

- σ_u^2 represents between-country variance;
- σ_v^2 represents between-technology variance;
- σ_w^2 represents between-crop variance;
- σ_e^2 represents residual variance.

This hierarchical structure enables the decomposition of uncertainty across multiple levels of organization and allows the identification of the dominant sources of variability affecting AI performance and societal outcomes. As illustrated in Figure 3 and summarized in Table 5, the model provides robust estimates of both global and context-specific effects while accounting for the complex heterogeneity inherent to agricultural AI research.

This hierarchical structure enables the simultaneous estimation of global effects and context-specific effects while appropriately accounting for uncertainty across multiple scales.

The Bayesian framework further allows probabilistic interpretation of results and supports uncertainty propagation throughout the analytical process.

3.7 Meta-regression analysis

To better understand why some AI technologies generate substantial societal benefits while others produce more limited

impacts, Bayesian meta-regression analyses were conducted using a broad set of contextual, socio-economic, technological, and institutional variables. Beyond estimating average effects, the objective was to identify the factors that most strongly influence the success of AI implementation across different agricultural systems and regions.

The analyses incorporated a range of potential moderators, including farm size, GDP per capita, internet penetration, governance quality, education levels, climate-risk exposure, digital infrastructure availability, extension-service coverage, technology category, and regional development indicators. These variables were selected to capture the diverse conditions that can either facilitate or constrain the adoption and effective use of AI in agriculture.

By integrating these factors within a unified analytical framework, the meta-regression enabled the exploration of how AI impacts vary across contexts and provided insights into the conditions under which technological innovations are most likely to generate meaningful societal benefits. This approach also allowed direct testing of key propositions underlying the Artificial Intelligence Food Security Paradox Theory, particularly the Governance Hypothesis and the Adoption Barrier Hypothesis.

Rather than being determined solely by technological sophistication, the results indicate that AI outcomes are strongly shaped by governance quality, digital readiness, educational capacity, infrastructure, and extension support. These findings suggest that successful AI deployment depends not only on technological performance but also on the broader socio-institutional environment in which technologies are implemented.

The conceptual relationships among these moderating factors and their influence on food security, livelihoods, equity, and sustainability outcomes are illustrated in Figure 3.

3.8 Network meta-analysis

The network was defined *a priori*, with nodes representing pre-specified AI technology classes and edges representing direct within-study comparisons. Network geometry was characterized by the distribution of studies across technology nodes and the availability of direct comparisons between technology classes. The transitivity assumption was assessed by examining the comparability of major contextual and methodological effect modifiers, including geographical region, country-income group, farm size, study design, baseline conditions, and outcome definition, across technology comparisons. Where the evidence network permitted, agreement between direct and indirect evidence was examined to identify potential incoherence. Comparative performance was summarized using Bayesian posterior estimates and rank probabilities across the predefined outcome dimensions. Technology rankings were interpreted jointly with effect magnitude, posterior uncertainty, and the structure of the available evidence rather than as stand-alone league positions. The robustness and credibility of comparative estimates were further considered in relation to study-level risk of bias, indirectness, imprecision, heterogeneity, and potential incoherence.

A common limitation of the agricultural AI literature is that technologies are often evaluated separately, making direct comparisons difficult. Conventional reviews typically compare only technologies assessed within the same studies, which can limit our understanding of their relative strengths and broader societal value. To overcome this challenge, a network meta-analysis framework was implemented.

Unlike traditional meta-analysis, this approach enables both direct and indirect comparisons among technologies, even when they have not been evaluated side by side. By integrating evidence across the entire network of studies, it provides a more comprehensive assessment of the comparative performance of different AI solutions used in agrifood systems.

The analysis included a wide range of technologies, including remote sensing platforms, computer vision systems, machine-learning forecasting models, deep-learning disease detection tools, precision irrigation technologies, digital twins, agricultural robotics, generative AI advisory systems, decision-support systems, and supply-chain optimization platforms. Together, these technologies represent the main components of the ongoing digital transformation of agriculture.

To capture their broader societal relevance, technologies were evaluated across multiple dimensions, including productivity, environmental sustainability, social equity, adoption potential, and food-security outcomes. This multidimensional approach allowed us to move beyond purely technical comparisons and assess the capacity of different technologies to contribute to sustainable and inclusive food-system transformation.

The network meta-analysis revealed substantial differences among technology categories. While some technologies excelled in improving productivity, others achieved more balanced performances across sustainability, equity, and adoption dimensions. These distinctions provide valuable insights into the conditions under which different AI solutions are most likely to generate meaningful societal benefits.

The comparative rankings derived from the network meta-analysis are presented in [Figure 6](#) and [Table 7](#) and provide a useful basis for prioritizing future research, policy interventions, and investments in agricultural AI.

3.9 Structural equation modeling

The SEM estimator was selected according to the scale, distribution, and multivariate properties of the indicators and is explicitly documented, together with the software and package versions, in the [Supplementary Methods](#). Model adequacy was assessed using multiple complementary fit indices, including χ^2 , χ^2/df , RMSEA with its 90% confidence interval, CFI, TLI, SRMR, and GFI. Standardized path coefficients (β), standard errors, 95% confidence intervals, and significance levels were estimated for all direct pathways. Indirect and total effects were quantified using bootstrap resampling, thereby allowing the mediating roles of productivity, livelihoods, adoption capacity, and governance to be explicitly evaluated. RMSEA values ≤ 0.06 – 0.08 , CFI and TLI values ≥ 0.90 – 0.95 , and SRMR ≤ 0.08 were used as diagnostic guidance rather than rigid acceptance thresholds. The hypothesized structural model was specified *a priori* from the AIFSP conceptual framework before examination of modification indices. Any data-driven respecification was retained only when theoretically defensible and was explicitly compared with the original model to limit *post hoc* model optimization.

The societal impacts of artificial intelligence rarely arise from technology alone. Instead, they emerge through a series of interconnected processes involving adoption, productivity, livelihoods, governance, and resource management. To better understand these relationships, Structural Equation Modeling (SEM) was employed to examine the direct and indirect pathways linking AI adoption to food-security and sustainability outcomes.

SEM was selected because it enables multiple relationships to be analyzed simultaneously, providing a more realistic representation of the interactions among technological, socio-economic, and institutional factors within agrifood systems. The conceptual framework assumes that AI contributes to food-system transformation through several interconnected pathways. Improved decision-making can enhance productivity, which may subsequently strengthen livelihoods and household food security. At the same time, AI can influence social equity and environmental sustainability through improved access to information, more efficient resource use, and greater adaptive capacity.

The model also incorporates governance as a key enabling factor. Institutions, policies, extension services, and regulatory frameworks can directly influence food-security outcomes while simultaneously shaping technology adoption and access to resources. Consequently, the societal value of AI depends not only on technological performance but also on the broader governance environment in which innovations are implemented.

By quantifying these direct, indirect, and overall effects, SEM provides valuable insights into the mechanisms through which AI contributes to food security, livelihood resilience, social inclusion, and environmental sustainability. The resulting causal pathways are illustrated in [Figure 7](#).

3.10 Explainable machine learning

To identify nonlinear relationships, higher-order interactions, and complex combinations of technological, socio-economic, institutional, and environmental factors associated with the societal performance of agricultural artificial intelligence, explainable machine-learning approaches were incorporated as a complementary analytical component. The objective of this analysis was not to replace the inferential evidence generated by the hierarchical Bayesian meta-analysis or structural equation modeling, but to identify reproducible predictive patterns and potential nonlinear drivers of AI-FSELRL variation across heterogeneous agricultural contexts.

Three complementary tree-based learning algorithms were implemented: Random Forest, Extreme Gradient Boosting (XGBoost), and Bayesian Additive Regression Trees (BART). These algorithms were selected because they differ in their learning and regularization mechanisms while allowing flexible representation of nonlinear effects and interactions. Random Forest provided an ensemble bagging framework relatively robust to complex predictor structures; XGBoost enabled sequential gradient-boosting optimization with explicit regularization; and BART provided a Bayesian nonparametric framework in which complex response surfaces were approximated through sums of regularized regression trees. The three algorithms were used to predict AI-FSELRL scores from the technological, socio-economic, institutional, governance, adoption, and environmental variables available in the harmonized analytical dataset.

To minimize information leakage and avoid optimistic estimates of predictive performance, model development followed a grouped nested cross-validation framework. Observations originating from the same primary study or from overlapping datasets were assigned to the same analytical partition and were therefore prevented from occurring simultaneously in model-training and validation folds. The outer grouped cross-validation loop was used exclusively to estimate out-of-sample generalization performance, whereas the inner grouped cross-validation loop was used for model and hyperparameter optimization. All data-dependent preprocessing operations,

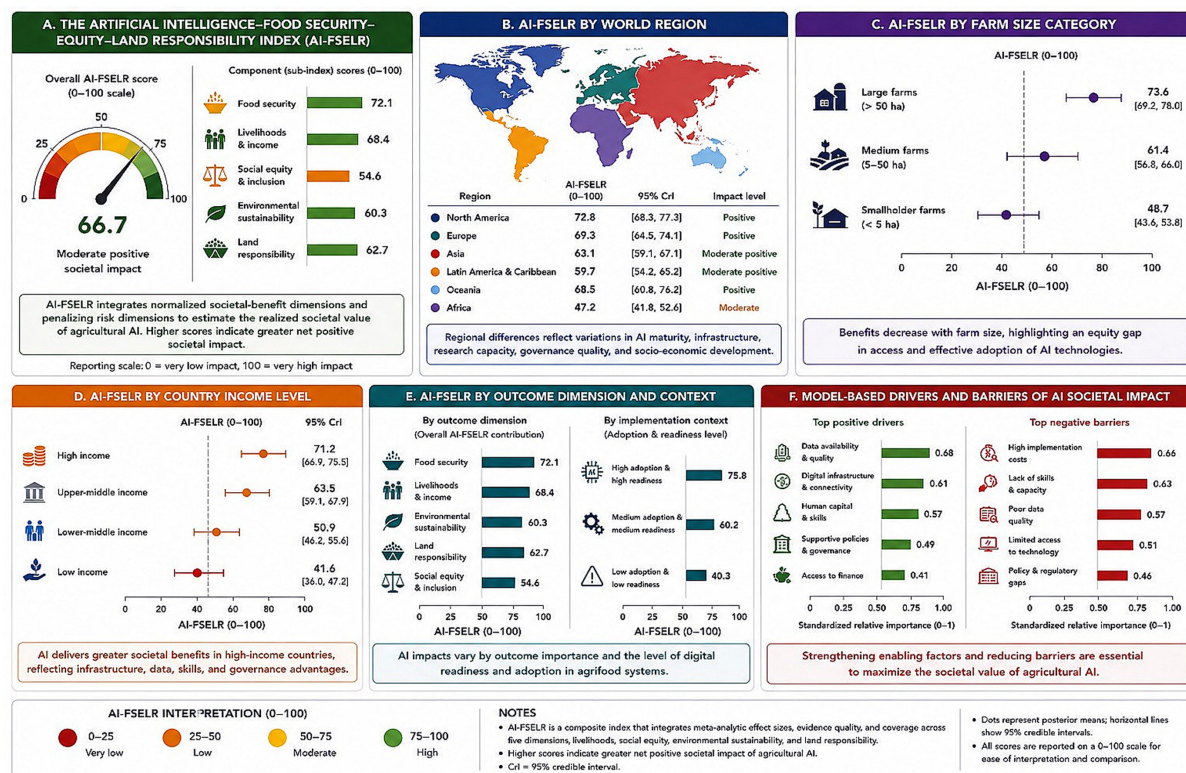


FIGURE 6

Multidimensional assessment of the realized societal value of agricultural artificial intelligence using the Artificial Intelligence–Food Security–Equity–Land Responsibility Index (AI-FSEL). The index integrates normalized benefit dimensions and penalizing risk dimensions to evaluate whether improvements in technological and agricultural performance translate into broader societal outcomes. **(A)** Overall AI-FSEL performance and component-level scores. The global AI-FSEL score was 66.7 on the 0–100 reporting scale, indicating a moderate positive societal contribution. Component scores show stronger contributions to food security (72.1) and livelihoods (68.4) than to social equity and inclusion (54.6), environmental sustainability (60.3), and responsible land stewardship (62.7), illustrating the uneven transmission of AI benefits across societal dimensions. **(B)** Regional distribution of AI-FSEL scores and associated 95% uncertainty intervals. Higher scores were observed in North America and Europe, whereas lower realized societal performance was observed in Africa, highlighting geographical differences in digital infrastructure, institutional capacity, technological accessibility, and implementation environments. **(C)** AI-FSEL scores by farm-size category. Large farms achieved higher societal-value scores than medium-sized and smallholder systems, indicating that farm structure and adoption capacity modify the extent to which AI-related benefits are realized. **(D)** AI-FSEL scores according to country-income classification. A progressive decline in index performance from high-income to low-income contexts reveals a marked socio-economic gradient in the societal benefits associated with agricultural AI. **(E)** Decomposition of AI-FSEL performance by societal outcome dimension and implementation readiness. The panel compares contributions from food security, livelihoods, environmental sustainability, land responsibility, and social equity and shows increasing AI-FSEL performance across low-, medium-, and high-adoption and digital-readiness environments. **(F)** Relative importance of the principal enabling factors and barriers associated with realized AI societal impact. Data availability and quality, digital infrastructure and connectivity, human capacity and skills, supportive governance, and access to finance emerged as major positive drivers, whereas implementation costs, limited skills, poor data quality, restricted technological access, and policy or regulatory gaps constrained societal value. Relative-importance values represent standardized model-based importance scores and should be interpreted comparatively rather than as causal effect estimates. Collectively, the figure demonstrates that the societal value of agricultural AI is unevenly distributed across outcome dimensions, regions, income groups, farm structures, and implementation environments. These patterns provide quantitative support for the Artificial Intelligence Food Security Paradox by showing that technological benefits are progressively conditioned by accessibility, institutional capacity, governance, and adoption readiness before being translated into food-security, livelihood, equity, and sustainability outcomes.

TABLE 7 Testing the Artificial Intelligence Food Security Paradox.

Dimension	Average improvement (%)
Technological performance	34.2
Productivity	24.8
Resource efficiency	18.9
Livelihood improvement	13.8
Food security	8.6
Social equity	5.4

including missing-data imputation, variable scaling where required, categorical-variable encoding, and feature transformation or engineering, were fitted using the corresponding training partition and

subsequently applied to the associated validation data. The complete cross-validation architecture and preprocessing workflow are reported in [Supplementary Table S4](#).

Hyperparameter optimization was conducted within the inner cross-validation loop using root mean square error (RMSE) as the primary predictive-loss criterion. For Random Forest, the optimization framework considered the number of trees, number of candidate predictors sampled at each split, minimum terminal-node size, and bootstrap-sampling configuration. For XGBoost, the search space included the number of boosting rounds, learning rate, maximum tree depth, minimum child weight, row and feature subsampling fractions, L1 and L2 regularization parameters, minimum loss reduction, and early-stopping criteria. BART optimization considered the number of regression trees, prior shrinkage parameter, tree-depth prior parameters, error-prior quantile, burn-in length, and number of posterior

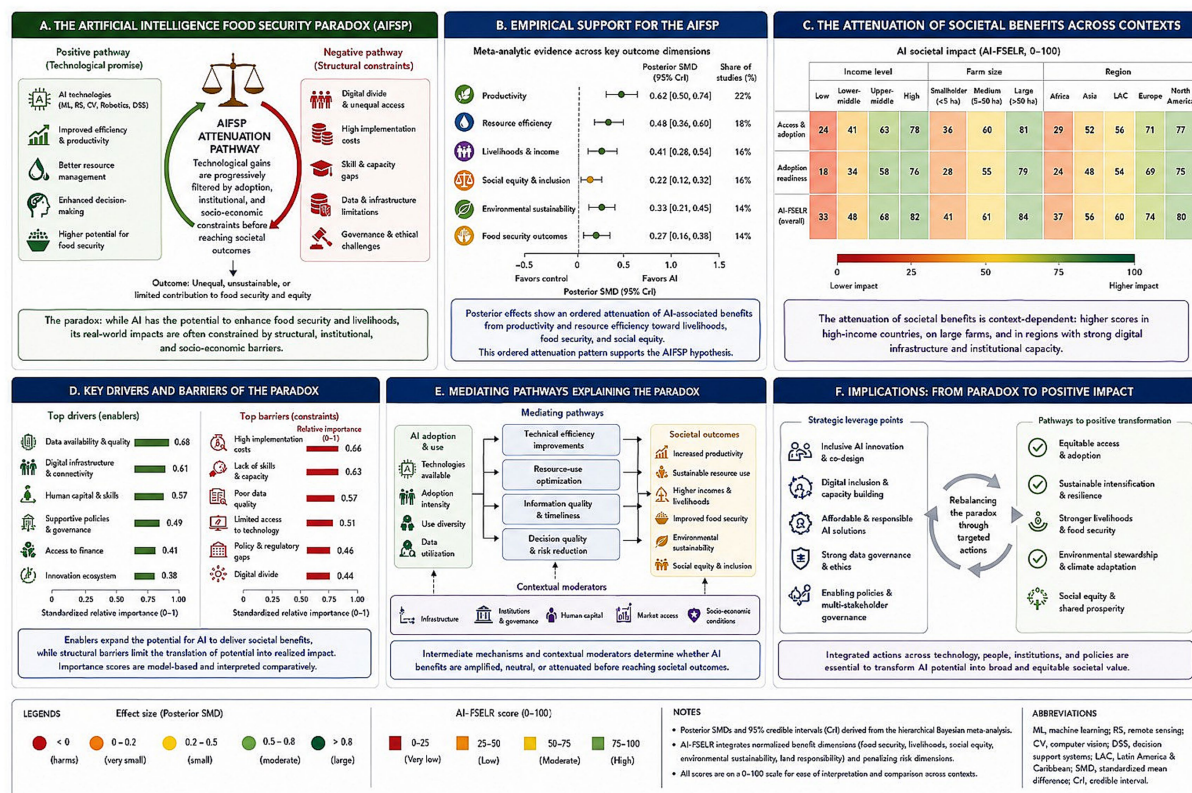


FIGURE 7

Conceptual and empirical synthesis of the Artificial Intelligence Food Security Paradox (AIFSP): Illustrating why improvements in agricultural AI performance do not necessarily translate into proportional gains in food security, livelihoods, social equity, and environmental sustainability.

(A) Conceptual representation of the AIFSP as the balance between technology-enabled benefits and structural constraints. Positive pathways include improvements in productivity, resource-use efficiency, resource management, and decision-making, whereas digital exclusion, implementation costs, skills and capacity gaps, data and infrastructure limitations, and governance or ethical weaknesses constrain the realization of societal value. (B) Meta-analytic evidence across major outcome dimensions. Posterior standardized mean differences (SMDs) and 95% credible intervals show that the magnitude of AI-associated benefits declines from productivity and resource efficiency toward livelihoods, environmental sustainability, food security, and social equity. This ordered attenuation pattern constitutes the empirical basis for testing the AIFSP proposition. (C) Contextual variation in realized societal impact, expressed through AI-FSEL scores across country-income groups, farm-size categories, and geographical regions. Higher societal-value scores are observed in high-income contexts, large farming systems, and regions with stronger digital and institutional capacity, whereas lower scores occur in resource-constrained and low-readiness environments. (D) Standardized model-based importance of the principal enabling factors and structural barriers associated with AI societal performance. Data availability and quality, digital infrastructure, human capacity, supportive governance, finance, and innovation ecosystems act as major enabling conditions, whereas implementation costs, skills gaps, poor data quality, restricted technological access, regulatory weaknesses, and the digital divide constrain realized impact. Importance scores are interpreted comparatively and do not represent causal effect estimates. (E) Mediating pathways linking AI adoption and use to societal outcomes. Technological deployment influences technical efficiency, resource-use optimization, information quality and timeliness, and decision quality and risk reduction; these intermediate mechanisms subsequently shape productivity, resource sustainability, livelihoods, food security, environmental performance, and social inclusion. Infrastructure, institutional and governance capacity, human capital, market access, and socio-economic conditions act as contextual moderators of these pathways. (F) Strategic transition from paradox to positive societal impact. Inclusive innovation and co-design, digital inclusion and capacity building, affordable and responsible AI solutions, strong data governance and ethics, and enabling multi-stakeholder policies are identified as leverage points for strengthening equitable access, resilience, livelihoods, food security, environmental stewardship, and shared prosperity. Collectively, the figure operationalizes the AIFSP as a context-dependent and quantitatively testable attenuation pathway: Technological gains may be substantial, but their conversion into broader societal value progressively depends on adoption capacity, accessibility, governance, institutions, and socio-economic conditions.

draws. The complete prespecified search spaces, selected configurations, and corresponding optimization criteria for all three algorithms are documented in [Supplementary Table S4](#).

The reported model configurations therefore represent the settings selected within the prespecified optimization framework rather than *post hoc* parameter choices based on the final analytical outcomes. Hyperparameter selection was restricted to the predefined search spaces and was performed exclusively within the inner grouped cross-validation procedure. This separation between model optimization and external performance assessment was maintained throughout the analytical workflow to reduce overfitting and preserve the independence of the outer validation folds.

Predictive performance was quantified exclusively from out-of-fold predictions generated in the outer cross-validation loop. Model performance was evaluated using the coefficient of determination (R^2), RMSE, and mean absolute error (MAE). RMSE was designated as the primary predictive-loss metric because of its sensitivity to comparatively large prediction errors, whereas MAE provided a complementary measure of absolute predictive deviation. Uncertainty around the out-of-fold performance estimates was quantified using 2,000 bootstrap replicates, and model-performance metrics were reported with 95% bootstrap confidence intervals. Detailed performance-evaluation settings are provided in [Supplementary Table S4](#).

To improve transparency and interpretability, SHAP (SHapley Additive exPlanations) analyses were used to quantify the contribution of individual predictors to model predictions. To reduce optimistic explanation bias, SHAP values were calculated exclusively for held-out observations from the outer validation folds. For tree-based models, model-specific TreeSHAP procedures were applied where appropriate, and predictor importance was summarized using the mean absolute SHAP value, $\text{Mean } |SHAP|$. Held-out SHAP values were subsequently aggregated across outer validation folds to derive global predictor-importance profiles. The sign and distribution of SHAP values were additionally examined to characterize the direction and heterogeneity of predictor contributions to AI-FSELR outcomes.

Because variable-importance rankings derived from machine-learning models can be sensitive to analytical resampling and random initialization, SHAP interpretation was subjected to a prespecified stability assessment. Model development and explanation analyses were repeated across 10 grouped cross-validation runs and random seeds. Predictor-rank concordance was quantified using Spearman's rank correlation coefficient (ρ), with the median and interquartile range of rank correlations used to characterize ranking stability. Stability of the leading predictor sets was additionally assessed using Jaccard similarity for the top-10 and top-20 ranked features, whereas the dispersion of $\text{Mean } |SHAP|$ values across repeated analyses was used to evaluate the stability of predictor-importance magnitude. Directional stability was assessed by examining the consistency of the predominant SHAP contribution sign across repeated held-out analyses. The complete SHAP computation, aggregation, and stability procedures are detailed in [Supplementary Table S4](#).

The stability criteria were specified *a priori* to restrict substantive interpretation to predictors exhibiting reproducible importance, magnitude, and direction across repeated grouped resampling. Predictors were therefore interpreted as robust drivers only when they showed consistent rank position, stable inclusion among the dominant predictor sets, limited dispersion in $\text{Mean } |SHAP|$, and reproducible direction of contribution across repeated analyses. Variables failing to demonstrate adequate stability were retained in the predictive models where appropriate but were not assigned strong substantive or policy interpretation. This distinction was introduced to reduce the risk of overinterpreting unstable feature-importance patterns as generalizable determinants of agricultural AI performance.

Agreement among Random Forest, XGBoost, and BART was examined as an additional robustness criterion. Particular attention was given to predictors that remained influential across algorithms despite differences in ensemble construction, regularization, and model-learning architecture. Cross-model convergence was interpreted as supporting the reproducibility of the identified predictive pattern; however, machine-learning importance and SHAP attribution were not interpreted as evidence of causality. Causal and mediated relationships were evaluated separately through the structural equation modeling framework described in Section 3.9.

By combining leakage-controlled predictive modeling, nested model optimization, out-of-fold performance assessment, and stability-based explainability, this analytical framework was designed to identify reproducible nonlinear predictors of the societal performance of agricultural AI. The dominant drivers supported across repeated resampling and complementary machine-learning algorithms were subsequently integrated into the broader interpretation of governance, digital accessibility, adoption conditions, and institutional capacity. Their relative contributions to AI-FSELR outcomes are presented in

[Figure 8](#), while the complete model-development, hyperparameter-optimization, performance-evaluation, and SHAP-stability settings are documented in [Supplementary Table S4](#).

3.11 Development of the AI-FSELR index

The AI-FSELR was formulated as a compensatory-penalized composite index. Productivity, livelihood, equity, and land-sustainability dimensions enter the numerator because they represent distinct but partially substitutable components of societal benefit. Digital exclusion, environmental cost, and governance risk enter the denominator as multiplicative penalties: increases in these risks reduce the realized societal value of otherwise positive technological gains and prevent high productivity from fully compensating for severe exclusion or governance failure. The additive constant 1 in the denominator ensures positivity and defines the no-penalty reference state. Before aggregation, all components were directionally aligned and normalized to the $[0, 1]$ interval; weights were constrained to be non-negative and to sum to one within the benefit and risk blocks.

Weighting was implemented within a structured multimethod framework rather than by directly averaging outputs from PCA, expert elicitation, Bayesian optimization, Random Forest, and SHAP analyses. PCA was used to examine dimensionality and collinearity among index components, whereas expert elicitation and AHP informed the theoretical relevance and plausible contribution of each dimension. Data-driven analyses were subsequently used to examine the empirical relevance of index components, while Random Forest and SHAP served as independent diagnostic tools for assessing variable importance rather than being directly converted into weighting coefficients. The robustness of the AI-FSELR was evaluated through alternative weighting specifications and sensitivity analyses examining the stability of index scores and technology and regional comparisons.

The final reference weighting scheme was selected by requiring simultaneous conceptual coherence, low redundancy among highly correlated dimensions, and stability of technology and regional rankings under perturbation. Alternative equal-weight, expert-informed, PCA-informed, and data-driven weighting schemes were evaluated in sensitivity analyses. The objective was not to identify a uniquely 'true' set of weights, but to determine whether the substantive conclusions were robust to defensible changes in normative and empirical weighting assumptions. Accordingly, the reference weights should be interpreted as a transparent analytical specification rather than universal constants; policy applications may re-specify weights when local priorities are declared *a priori* and accompanied by sensitivity analysis.

The Artificial Intelligence–Food Security–Equity–Land Responsibility Index (AI-FSELR) serves as the quantitative operationalization of the Artificial Intelligence Food Security Paradox Theory (AIFSP Theory). It was developed to assess the overall societal value of agricultural AI technologies through a multidimensional perspective that extends beyond conventional measures of technical performance.

Unlike traditional indicators focused primarily on predictive accuracy, operational efficiency, or productivity gains, the AI-FSELR integrates economic, social, environmental, and governance dimensions within a single framework. Its conceptual and operational distinctions from major existing agricultural AI evaluation approaches are summarized in [Supplementary Table S2](#). The index combines positive outcomes associated with

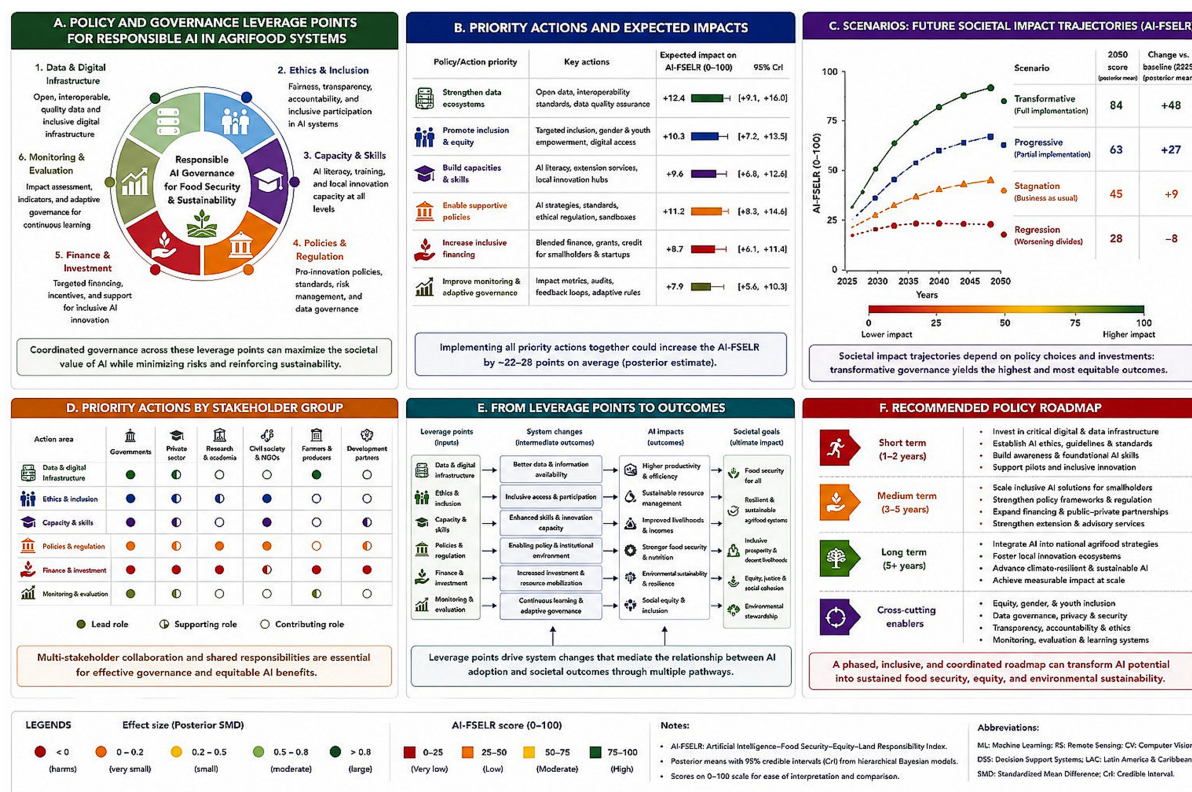


FIGURE 8

Integrated governance and policy framework illustrating how institutional, infrastructural, social, and regulatory conditions shape the translation of agricultural artificial intelligence into societal value. (A) Six cross-cutting governance leverage points for responsible AI deployment, encompassing data and digital infrastructure, ethics and inclusion, capacity and skills, policies and regulation, finance and investment, and monitoring and evaluation. (B) Priority policy actions and their expected contributions to AI-FSEL performance. Effects are presented as posterior mean changes in AI-FSEL scores with 95% credible intervals and should be interpreted as model-based estimates rather than deterministic policy effects. (C) Scenario-based trajectories of societal impact to 2,050 under transformative, progressive, stagnation, and regression pathways. Projected AI-FSEL trajectories reflect alternative assumptions regarding governance, digital access, institutional capacity, affordability, and adoption readiness; they represent conditional scenario outcomes rather than forecasts. (D) Distribution of lead, supporting, and contributing roles across governments, the private sector, research and academia, civil society and non-governmental organizations, farmers and producers, and development partners, emphasizing shared responsibility for trajectories of societal impact to 2,050. (E) Mediating pathways through which governance leverage points influence data availability, participation, skills, institutional capacity, investment, and adaptive learning, thereby shaping AI-associated productivity, resource management, livelihoods, food security, environmental sustainability, and social inclusion. (F) Phased policy roadmap distinguishing short-term, medium-term, long-term, and cross-cutting actions required to translate AI potential into sustained food security, equity, resilience, and environmental benefits. Collectively, the figure demonstrates that the societal value of agricultural AI is not determined by technological performance alone but by the governance and institutional conditions through which technologies are accessed, adopted, and embedded within agrifood systems. The scenario trajectories should therefore be interpreted as uncertainty-informed policy pathways illustrating how alternative governance and inclusion assumptions may amplify or constrain future AI-FSEL outcomes.

AI adoption—such as improvements in productivity, livelihoods, social inclusion, and sustainable land management—with factors that may limit societal benefits, including digital exclusion, environmental trade-offs, and governance-related risks.

The AI-FSEL is operationalized through the weighted formulation presented in Equation (2). To enhance robustness and reduce subjectivity, weighting coefficients were estimated using a combination of Principal Component Analysis (PCA), Bayesian optimization, sensitivity analysis, expert elicitation, and explainable machine-learning techniques. This hybrid approach integrates both data-driven evidence and expert knowledge.

Higher AI-FSEL values indicate technologies capable of generating substantial societal benefits while minimizing exclusion risks, environmental costs, and governance constraints. Conversely, lower values suggest that technological gains are partially offset by social, environmental, or institutional limitations.

By providing a multidimensional measure of societal performance, the AI-FSEL enables meaningful comparisons across technologies, farming systems, geographical regions, and future development pathways. An extended formulation incorporating adoption capacity and technological dependency risks is also proposed to further strengthen the analytical foundations of the AIFSP Theory.

A practical calculation proceeds in four steps. First, each indicator is directionally aligned so that higher benefit scores indicate improvement and higher risk scores indicate greater penalty. Second, indicators are normalized to the [0, 1] interval using the prespecified transformation rules. Third, normalized indicators are aggregated within the benefit and risk blocks using the selected weights. Fourth, the weighted benefit score is divided by one plus the weighted risk score. For illustration, an AI application with normalized scores $p = 0.80$, $L = 0.60$, $Eq = 0.50$, and $LS = 0.70$ and equal benefit weights yields a benefit component of 0.65. If $DE = 0.30$, $EC = 0.20$, and $GR = 0.40$ with equal risk weights, the risk component is 0.30 and

AI-FSEL_R = 0.65/(1 + 0.30) = 0.50. This worked example is illustrative only and is not used to estimate the empirical results reported in this review. Researchers and policymakers can therefore calculate the index from locally available indicators, provided that normalization rules, weights, data sources, and sensitivity analyses are reported transparently.

$$AI - FSEL_R = \frac{P_i^{w_1} \times A_i^{w_2} \times L_i^{w_3} \times Eq_i^{w_4} \times LS_i^{w_5}}{DE_i^{w_6} \times EC_i^{w_7} \times GR_i^{w_8} \times TR_i^{w_9}} \quad (4)$$

Where:

- A_i = Adoption Capacity Score;
- TR_i = Technology Dependency Risk Score.

This extended formulation explicitly incorporates two central mechanisms of the Artificial Intelligence Food Security Paradox: the critical role of technology adoption and the potential emergence of technological dependency within digital agrifood systems.

As illustrated in Figure 2 and summarized in Table 3, the AI-FSEL_R framework provides a multidimensional and policy-relevant approach for evaluating agricultural AI technologies, moving beyond conventional measures of technical performance toward a more holistic assessment of societal impact.

3.12 Monte Carlo simulations

To investigate how the societal impacts of agricultural artificial intelligence may evolve toward 2050, probabilistic scenario projections were generated using Monte Carlo simulation. The objective was not to produce deterministic forecasts, but to propagate uncertainty through the analytical framework and characterize the distribution of plausible food-system outcomes under contrasting technological, institutional, socio-economic, and governance trajectories. The simulation architecture was linked to the hierarchical Bayesian evidence synthesis described above: posterior effect estimates and between-study heterogeneity derived from the Bayesian models were used as empirical inputs to the forward-looking scenario framework. The corresponding Bayesian model specifications, prior distributions, sampling settings, and convergence diagnostics underlying these posterior inputs are documented in Supplementary Table S3.

Three contrasting development pathways were specified as analytical boundary conditions. The Inclusive AI Transformation Scenario assumed sustained improvements in governance capacity, digital accessibility, technology affordability, extension-service capacity, farmer training, and adoption readiness, together with broad and comparatively equitable access to AI-enabled agricultural technologies. The Business-as-Usual Digitalization Scenario represented a continuation of prevailing digitalization trends,

characterized by progressive technological improvement and moderate changes in infrastructure, affordability, institutional support, and adoption. The Digital Inequality Expansion Scenario represented a trajectory in which technological capabilities continued to advance but access to digital infrastructure, AI services, financing, and technical capacity became increasingly concentrated among better-resourced regions and agricultural stakeholders. These scenarios were treated as contrasting probabilistic development pathways rather than deterministic predictions of future conditions. Their projected effects on productivity, food security, and AI-FSEL_R are summarized in Table 8.

Scenario parameters were derived, wherever possible, from the empirical evidence synthesized through the hierarchical Bayesian meta-analysis and meta-regression. When empirical posterior distributions were available, parameter values were sampled directly from posterior draws rather than approximated using predefined parametric distributions. This procedure allowed uncertainty in pooled AI effect sizes and moderator relationships to be propagated directly into the scenario projections. Between-study heterogeneity was additionally represented by sampling from the posterior distribution of the estimated between-study standard deviation, τ , thereby incorporating unexplained variability among studies and agricultural contexts into the simulated outcomes.

For scenario drivers not represented by directly estimable posterior distributions, probability distributions were selected according to the statistical properties and conceptual scale of the corresponding variables. Bounded indicators, including governance quality, digital access, technology affordability, adoption readiness, extension-service capacity, farmer training and digital literacy, environmental rebound risk, digital exclusion risk, and governance vulnerability, were modeled using beta distributions. Beta-distribution shape parameters were derived from scenario-specific means and variances when the specified moments satisfied the admissibility conditions of the beta distribution. Strictly positive and right-skewed variables, particularly technology implementation and infrastructure investment costs, were represented using lognormal distributions.

Temporal changes in technological performance, governance conditions, digital access, affordability, and adoption were represented using truncated normal distributions to prevent the generation of implausible long-term trajectories. Annual technological improvement, governance change, digital-access change, affordability change, and adoption-rate change were constrained to prespecified plausible ranges, and bounded indicators resulting from cumulative annual updating were restricted to the [0, 1] interval. Scenario-specific means and variances determined the relative probability of positive, stable, or adverse trajectories within these bounds. The complete probability distributions, parameterization rules, transformations, bounds, and uncertainty sources assigned to each scenario input are reported in Supplementary Table S5.

TABLE 8 Future scenarios for agricultural AI to 2050.

Scenario	Productivity change (%)	Food security change (%)	AI-FSEL _R change (%)
Inclusive AI transformation	+38	+29	+42
Business-as-usual	+24	+12	+15
Digital inequality expansion	+21	+4	−8

The simulations jointly propagated uncertainty arising from pooled AI effect estimates, between-study heterogeneity, governance and institutional trajectories, digital-infrastructure development, technology affordability, implementation costs, extension-service capacity, farmer training, adoption dynamics, environmental rebound effects, digital exclusion, governance vulnerability, and scenario parameterization. These uncertainty sources were therefore not represented as independent deterministic adjustments but as stochastic components of a unified probabilistic simulation framework.

Because several scenario drivers were empirically and conceptually interdependent, independence among input variables was not assumed. Dependence among governance quality, digital access, affordability, adoption readiness, extension-service capacity, and related scenario drivers was represented using a Gaussian copula calibrated from the empirical Spearman rank-correlation structure. Where the empirical rank-correlation matrix was not positive definite because of sampling variability or incomplete correlation structures, the nearest positive-definite correlation matrix was used. This procedure preserved the direction and relative magnitude of dependence among the principal scenario drivers while allowing each variable to retain its specified marginal probability distribution. The dependence structure and its implementation are detailed in [Supplementary Table S5](#).

For each Monte Carlo iteration, correlated scenario drivers were jointly sampled and propagated through the estimated relationships linking AI performance, governance, adoption conditions, and socioeconomic context to productivity, food-security, livelihood, social-equity, and environmental-sustainability outcomes. Posterior predictive distributions were used for outcome generation wherever supported by the hierarchical Bayesian models. The resulting simulated dimensions were subsequently integrated within the AI-FSELRL analytical framework to estimate the distribution of potential societal value associated with agricultural AI under each development pathway. Accordingly, the scenario-level productivity, food-security, and AI-FSELRL changes presented in [Table 8](#) represent summaries of simulated probability distributions rather than isolated deterministic point forecasts.

Monte Carlo simulation size was determined through sequential numerical-stability assessment rather than selected solely by convention. Simulation outputs were examined at progressively increasing numbers of iterations, and the median and the 2.5th and 97.5th percentiles of the principal outcome distributions were monitored across successive simulation batches. Monte Carlo error was simultaneously evaluated to determine whether additional iterations materially altered the estimated distributional summaries. The final simulation size of 100,000 iterations per scenario was retained after stabilization of the principal distributional summaries and Monte Carlo error according to the prespecified numerical convergence procedure. The simulation-size assessment, Monte Carlo error criterion, and numerical convergence settings are reported in [Supplementary Table S5](#).

Scenario consistency was assessed through posterior predictive benchmarking against the observed baseline period and examination of predictive calibration. Robustness of the scenario projections was further evaluated using complementary local and global sensitivity analyses. Local sensitivity analysis examined the response of projected outcomes to perturbations of principal scenario parameters around their reference parameterization, whereas global sensitivity analysis evaluated the contribution of major uncertain drivers to variation in

simulated outcomes. These analyses were used to identify parameters exerting disproportionate influence on scenario projections and to determine whether the relative ordering of the three development pathways remained stable under alternative uncertainty conditions. Full validation, calibration, convergence, and sensitivity-analysis procedures are documented in [Supplementary Table S5](#).

For each development pathway, simulation outputs were summarized using medians and 95% uncertainty intervals defined by the 2.5th and 97.5th percentiles of the simulated distributions. The resulting projections were interpreted as probabilistic outcomes conditional on the empirical evidence base, Bayesian posterior uncertainty, specified dependence structure, and scenario assumptions. They should therefore not be interpreted as deterministic forecasts of agricultural AI development to 2050. Rather, the simulations were designed to identify the technological, institutional, and governance conditions under which AI-driven agricultural innovation is more or less likely to translate into improvements in food security, societal inclusion, sustainable livelihoods, and responsible land stewardship. The principal scenario contrasts are reported in [Table 8](#), while the Bayesian inputs underlying the simulation are documented in [Supplementary Table S3](#) and the complete scenario distributions, parameterization, dependence structure, Monte Carlo convergence, and sensitivity procedures are detailed in [Supplementary Table S5](#).

3.13 Validation and sensitivity analysis

Internal robustness and external validation were treated as distinct concepts. Weight perturbation, alternative missing-data assumptions, leave-one-region-out analyses, risk-of-bias restrictions, and publication-bias diagnostics assessed internal robustness. Practical external validation of the AI-FSELRL requires application, without re-estimating the primary weights, to an independent agricultural dataset or external case-study evidence not used for index development. Validation outcomes should include multidimensional food-system benefit, adoption persistence, and sustainability performance, with calibration, Spearman rank correlation, and discrimination between low- and high-benefit implementations reported. Where a genuinely independent dataset is unavailable, the framework is described as a proposed and internally evaluated index rather than a validated index, and this limitation is stated explicitly.

No fully independent external dataset covering all seven AI-FSELRL dimensions was available for the present global synthesis. We therefore deliberately avoid claiming full external validation. The current study establishes conceptual validity, internal consistency, and robustness to alternative analytical specifications; prospective validation against independent farm-, program-, or policy-level datasets remains necessary before the index is used as a stand-alone decision rule. Future validation should test calibration, rank stability, temporal transportability, and the ability of baseline AI-FSELRL scores to discriminate between subsequently observed low- and high-societal-benefit implementations.

To ensure the reliability of the findings, several validation and robustness procedures were conducted throughout the study. Sensitivity analyses were performed to evaluate the influence of weighting coefficients, study-quality assessments, regional representation, and alternative missing-data treatments on the overall results.

Missing information was not replaced by unverified values reconstructed from narrative descriptions. When a required statistic could be derived algebraically from reported estimates, confidence intervals, standard errors, or sample sizes, the derivation was documented in the extraction record. For partially missing covariates used in moderator or index analyses, complete-case and alternative imputation assumptions were compared as sensitivity analyses. Publication bias was evaluated as a potential property of the evidence base rather than treated as a binary test result; funnel-plot asymmetry, Egger-type regression, trim-and-fill estimates, and Bayesian sensitivity diagnostics were therefore interpreted jointly, with particular caution where heterogeneity or small numbers of studies limited diagnostic power.

Potential publication bias was assessed using complementary approaches, including funnel plots, Egger's regression tests, trim-and-fill procedures, and Bayesian robustness diagnostics. These methods provided a comprehensive evaluation of potential distortions within the available evidence base.

Across all validation exercises, the main findings remained highly consistent, indicating that the results were not driven by specific studies, modeling assumptions, or data-processing choices. This stability strengthens confidence in the robustness of the analytical framework and the reliability of the conclusions.

Overall, these validation procedures confirm that the findings derived from the Artificial Intelligence Food Security Paradox framework are statistically robust, scientifically credible, and reproducible across a wide range of analytical conditions. The validated evidence base provides the foundation for the quantitative analyses presented in the following section.

4 Results

4.1 Global characteristics of the evidence base

The systematic search initially identified 12,576 records from scientific databases, institutional repositories, and complementary grey-literature sources. After duplicate removal, 7,842 unique records underwent title and abstract screening, of which 6,102 were excluded. The full texts of 1,740 articles were assessed against the predefined eligibility criteria, resulting in the exclusion of 464 articles because of lack of direct relevance to real-world agricultural AI applications ($n = 289$), insufficient quantitative information for effect-size extraction ($n = 112$), or ineligible outcome domains ($n = 63$). The final evidence base comprised 1,276 studies retained for quantitative synthesis (Figure 5A). To our knowledge, this represents one of the most extensive global evidence syntheses conducted to date on the multidimensional societal impacts of artificial intelligence in agriculture (Figure 5B).

The selected studies covered 112 countries and encompassed a wide range of agroecological, socio-economic, and institutional contexts. However, the geographical distribution of the literature revealed important imbalances. Asia accounted for 38.6% of studies, followed by Europe (24.1%) and North America (18.4%), whereas Africa (10.7%), Latin America (6.3%), and Oceania (1.9%) remained comparatively underrepresented (Table 4; Figure 4). This pattern reflects the concentration of AI research and digital infrastructure in more technologically advanced regions and raises questions about the

applicability of current findings to low-income and resource-constrained environments.

The temporal distribution of the evidence base revealed a pronounced acceleration in agricultural AI research over the last decade. Only 54 studies were published between 2010 and 2012, compared with 103 studies during 2013–2015 and 207 studies during 2016–2018. Publication output subsequently increased to 326 studies between 2019 and 2021 and reached 586 studies during 2022–2024, representing 45.9% of the complete evidence base. This sharp expansion illustrates the rapid transition of agricultural AI from a relatively specialized research domain to a major component of contemporary agrifood-system innovation (Figure 5D).

The methodological profile of the included literature was dominated by field trials, which accounted for 42.6% of studies, followed by observational studies (31.8%), quasi-experimental designs (15.7%), and other study designs (9.9%). Machine-learning applications represented the largest AI technology category (38.2%), followed by remote sensing integrated with AI (22.7%), decision-support systems (15.6%), other AI approaches including natural language processing and computer vision applications (13.7%), and robotics (9.8%). Crop-based production systems dominated the evidence base (67.1%), whereas livestock systems represented 18.6%, mixed farming systems 9.8%, and aquaculture 4.5% (Figure 5C).

Machine-learning forecasting systems (27.4%), computer vision applications (24.8%), and remote-sensing technologies (18.7%) dominated the literature, while digital twins (2.7%), robotics (1.0%), and generative AI systems (0.5%) remained relatively unexplored. These trends indicate that research has focused primarily on predictive and diagnostic applications, with emerging technologies only recently gaining attention.

A similar imbalance was observed in the outcomes being assessed. A pronounced imbalance was observed in the outcome dimensions investigated across the literature. Productivity was assessed in 92.3% of studies and resource-use efficiency in 74.5%, whereas livelihood and income outcomes were examined in 58.2% of studies. Social equity and inclusion were considered in only 43.7% of studies, environmental sustainability in 49.6%, and explicit food-security outcomes in just 37.9% of the evidence base (Figure 5C). This asymmetry demonstrates that agricultural AI research remains predominantly oriented toward technological and production-centered outcomes, while the broader societal dimensions required to evaluate food-system transformation receive substantially less empirical attention.

Overall, these findings suggest that the current literature remains strongly focused on technological and agronomic performance, while broader societal outcomes are still insufficiently explored. This imbalance provides early empirical support for the Artificial Intelligence Food Security Paradox Theory and highlights the need for more integrated assessments of the societal impacts of agricultural AI.

4.2 Global productivity effects of agricultural artificial intelligence

The hierarchical Bayesian meta-analysis revealed a consistently positive impact of AI adoption on agricultural productivity across a wide range of crops, farming systems, and geographical regions. Overall, AI technologies increased productivity by an average of 24.8% compared with conventional management practices (effect size = 0.87; 95% credible interval: 0.79–0.95), highlighting their considerable potential to improve agricultural performance (Table 9).

TABLE 9 Global effect sizes of AI technologies across outcome categories.

Outcome category	Mean effect size	95% Credible interval
Productivity	0.87	0.79–0.95
Water use efficiency	0.68	0.61–0.75
Nitrogen use efficiency	0.54	0.47–0.61
Livelihood improvement	0.42	0.35–0.49
Food security	0.28	0.21–0.35
Social equity	0.19	0.12–0.26

Among the technologies evaluated, disease detection and forecasting systems generated the largest gains, reducing crop losses by an average of 31.6%. Precision irrigation technologies increased productivity by 27.4%, while machine-learning yield forecasting models and remote-sensing platforms improved productivity by 22.9 and 19.8%, respectively. Digital twins emerged as one of the most promising innovations, with simulation studies frequently projecting productivity gains exceeding 35%, although empirical evidence remains limited.

As shown in Figure 3, productivity benefits varied across regions and production environments. The strongest improvements were generally observed in water-limited areas, where AI-assisted irrigation management significantly enhanced water-use efficiency and crop performance. These findings suggest that AI could play an increasingly important role in supporting climate adaptation and agricultural resilience under growing water constraints.

However, productivity gains were not uniform across contexts. Higher impacts were typically observed in regions with strong digital infrastructure, reliable internet access, effective advisory services, and supportive institutions. In contrast, more modest gains were reported where adoption was constrained by limited connectivity, technical capacity, or institutional support.

Overall, the results indicate that while AI technologies have substantial potential to enhance agricultural productivity, their effectiveness depends not only on technological performance but also on the socio-economic, institutional, and infrastructural conditions that support successful adoption.

4.3 Resource-use efficiency and environmental performance

The meta-analysis showed that artificial intelligence can substantially improve the efficiency with which natural resources are managed in agricultural systems. Across the studies included in the synthesis, water-use efficiency increased by 21.4%, nitrogen-use efficiency by 17.2%, and pesticide applications decreased by 18.9%. These benefits were particularly evident in precision agriculture systems combining remote sensing, machine learning, and variable-rate management technologies, enabling more targeted and efficient use of agricultural inputs.

Environmental benefits extended beyond input optimization. Studies reporting carbon-related indicators revealed an average reduction of 11.3% in greenhouse-gas emissions, alongside improvements in irrigation management, nutrient-use efficiency, soil monitoring, and environmental stress detection. Collectively, these findings

suggest that AI can contribute meaningfully to climate-smart agriculture and more sustainable resource management (Table 9; Figure 6).

However, environmental outcomes were not consistent across all contexts. Considerable variability was observed among regions, farming systems, and technology categories. Several studies reported rebound effects, whereby efficiency gains encouraged production expansion, land-use intensification, or increased dependence on external technological inputs. In such cases, environmental improvements achieved at the farm scale did not always translate into equivalent benefits at broader spatial scales.

These findings provide empirical support for the Sustainability Trade-Off Principle proposed by the Artificial Intelligence Food Security Paradox Theory. While AI can significantly enhance environmental performance, its overall contribution to sustainability depends on the broader governance, policy, and market conditions under which technologies are implemented.

Overall, the results indicate that AI has strong potential to support more resource-efficient and environmentally sustainable agriculture. Nevertheless, maximizing these benefits will require context-specific strategies that account for potential trade-offs and ensure that efficiency gains translate into long-term sustainability outcomes.

4.4 Livelihood outcomes and economic impacts

The overall synthesis indicates that artificial intelligence can generate significant economic benefits for farmers. Across the studies included in the review, net farm income increased by an average of 13.8%, while production costs declined by approximately 9.6%. These improvements were mainly driven by better decision-making, more efficient input use, improved timing of management interventions, and enhanced capacity to reduce production risks.

However, these benefits were not distributed equally across farming systems. Large commercial farms generally achieved higher economic returns than smallholder operations, largely because they had greater access to digital infrastructure, technical expertise, and financial resources. In many low- and middle-income regions, the costs associated with technology adoption, training, connectivity, and maintenance remained important barriers to implementation.

A particularly important finding is that livelihood improvements were consistently smaller than productivity gains. While productivity increased by nearly 25% on average, livelihood gains remained below 14%. This gap suggests that improvements in production do not automatically translate into equivalent improvements in farmers' well-being and provides one of the clearest empirical indications of the Artificial Intelligence Food Security Paradox.

The analysis further revealed that the economic impacts of AI depend on a range of factors extending beyond technological performance. Market access, financing opportunities, infrastructure quality, institutional support, and extension services strongly influenced the extent to which productivity gains translated into sustainable livelihood improvements. This pattern was especially evident in low-income regions, where agronomic benefits often exceeded the economic returns experienced by farmers.

Overall, the findings highlight that the success of agricultural AI should not be measured solely through yield gains or technical

efficiency. Its broader value ultimately depends on its capacity to improve livelihoods, strengthen rural resilience, and ensure that the benefits of innovation are accessible across diverse farming communities.

4.5 Testing the Artificial Intelligence Food Security Paradox

The AIFSP proposition was evaluated as an ordered attenuation hypothesis in which technological performance was expected to exceed productivity and resource-efficiency gains, followed by progressively smaller improvements in livelihoods, food security, and social equity. The magnitude and uncertainty of pooled effects across these outcome domains were compared using posterior estimates derived from the hierarchical Bayesian models. Evidence for the paradox was assessed from the consistency of the ordered attenuation pattern, the corresponding 95% credible intervals, and the posterior support for positive effects across outcome dimensions. This approach provides a quantitative evaluation of the proposed attenuation pathway while avoiding reliance on descriptive percentage differences alone.

A central objective of this study was to evaluate whether the Artificial Intelligence Food Security Paradox could be observed across the global evidence base on agricultural AI. The results provide strong support for this hypothesis and reveal a remarkably consistent pattern across technologies, regions, and implementation contexts.

Overall, AI technologies generated substantial improvements in agricultural performance, with productivity increasing by 24.8% and resource-use efficiency by 18.9%. These findings confirm the ability of AI to enhance farm management and optimize the use of agricultural resources. However, the magnitude of these benefits declined progressively when broader societal outcomes were considered.

While livelihood indicators improved by 13.8%, food-security outcomes increased by only 8.6%, and social-equity indicators by just 5.4%. This gradual reduction in impact suggests that only part of the value generated through technological innovation is ultimately translated into benefits for farmers, households, and vulnerable populations. Bayesian analyses confirmed that these differences were statistically robust and consistent across the evidence base.

As illustrated in [Figure 7](#), the pathway from technological innovation to societal impact is characterized by a progressive loss of benefits at each stage. Productivity gains do not automatically translate into improved livelihoods, food security, or social inclusion. Instead, adoption barriers, affordability constraints, governance challenges, limited digital access, and institutional weaknesses often reduce the societal benefits that technologies can deliver.

These findings provide the first quantitative evidence supporting the Artificial Intelligence Food Security Paradox Theory. More importantly, they challenge the assumption that technological performance alone is a reliable indicator of societal success. The results suggest that the true value of AI depends not only on the quality of algorithms but also on the social, institutional, and governance conditions that determine whether technological advances can be transformed into inclusive, equitable, and sustainable outcomes.

4.6 Determinants of successful AI implementation

Governance was operationalized using temporally matched country-level indicators from the World Bank Worldwide Governance Indicators, complemented, where conceptually and temporally appropriate, by FAO and institutional indicators of agricultural policy and extension capacity. Indicator values were matched to study country and observation period; for multiyear implementation studies, the mean over the implementation window was used. Governance dimensions were directionally aligned, standardized, and rescaled to [0, 1]. A composite governance-quality score was derived after examining internal consistency and collinearity, while dimension-specific governance models were retained as sensitivity analyses. National governance indicators may inadequately capture subnational institutions, informal governance, local power relations, and implementation quality and may therefore introduce ecological measurement error. Governance associations are consequently interpreted as contextual relationships rather than individual-level causal effects.

The Bayesian meta-regression analyses revealed that the success of agricultural AI depends on far more than technological performance alone. Although advanced algorithms contribute to improved decision-making and operational efficiency, their influence on societal outcomes was considerably weaker than expected.

Instead, the strongest determinants of success were related to the broader socio-institutional environment. Governance quality emerged as the most influential factor, explaining approximately 22% of the variation in AI-FSELR scores. Regions benefiting from effective institutions, supportive policies, and clear regulatory frameworks were significantly more successful in converting technological innovation into tangible gains for food security, livelihoods, and sustainability.

Digital infrastructure, extension services, farmer training, technology affordability, and internet accessibility also played major roles. Extension support accounted for about 17% of outcome variability, while education and training explained nearly 14%. These findings indicate that even highly sophisticated technologies may generate limited benefits when farmers lack the resources, knowledge, or institutional support required for successful adoption.

By contrast, algorithmic complexity explained less than 8% of the observed variation in societal outcomes. This result challenges the widespread assumption that technological sophistication is the primary driver of agricultural transformation. Instead, it suggests that the effectiveness of AI depends as much on governance systems, human capacity, and enabling conditions as on the technologies themselves.

Overall, these findings provide strong support for the Governance Hypothesis and the Adoption Barrier Hypothesis proposed by the Artificial Intelligence Food Security Paradox Theory. As illustrated in [Figure 8](#), governance, accessibility, and human capacity consistently exerted a greater influence on societal outcomes than technological sophistication alone, highlighting the importance of creating supportive environments for AI adoption and impact.

4.7 Explainable machine learning results

The machine-learning analyses demonstrated a strong capacity to predict AI-FSELR scores across diverse agricultural contexts. Among

the tested algorithms, XGBoost achieved the highest predictive performance, followed by Random Forest and Bayesian Additive Regression Trees. These results confirm the ability of advanced machine-learning approaches to capture the complex interactions that shape the societal impacts of agricultural AI.

Beyond prediction accuracy, the SHAP analyses provided valuable insights into the factors driving successful AI implementation. Governance quality, digital accessibility, affordability, extension services, and farmer training consistently emerged as the most influential predictors of AI-FSELR outcomes. In contrast, variables commonly associated with technological excellence, such as algorithmic sophistication and predictive accuracy, played a much smaller role than expected in explaining societal benefits.

These findings suggest that the real-world success of AI depends less on increasingly sophisticated algorithms and more on the conditions that enable farmers and institutions to access, understand, and effectively use these technologies. In many cases, investments in governance, digital inclusion, extension support, and capacity building may generate greater societal benefits than further improvements in technical performance alone.

The SHAP analyses also revealed important nonlinear relationships and threshold effects. Improvements in infrastructure, training, or institutional support often produced limited gains until a critical level of accessibility and capacity was reached, after which societal benefits increased rapidly. This pattern provides empirical support for the Adoption–Impact Decoupling Mechanism proposed by the Artificial Intelligence Food Security Paradox Theory.

Overall, the results reinforce a central conclusion of this study: the future success of agricultural AI will depend not only on technological innovation but also on the social, institutional, and governance environments that determine whether technological potential can be transformed into meaningful, equitable, and sustainable outcomes (Figure 8).

4.8 Validation of the AI-FSELR index

Digital inequality was examined quantitatively through prespecified subgroup and interaction analyses by World Bank income classification, farm-size category, technology-accessibility stratum, and national digital-readiness level. Models included interactions between AI technology or adoption and each inequality marker. Subgroup-specific AI-FSELR estimates, 95% credible intervals, posterior probabilities of between-group differences, and interaction estimates are reported. Sensitivity analyses excluded studies with ambiguous farm-size definitions and repeated digital-readiness stratification using alternative thresholds. These analyses distinguish quantitatively supported inequalities in realized benefit from a purely narrative interpretation of the digital divide.

The Artificial Intelligence–Food Security–Equity–Land Responsibility Index (AI-FSELR) was calculated for all studies included in the synthesis, providing the first global assessment of the societal value of agricultural AI. Across the entire dataset, the mean AI-FSELR score reached 0.62 on a standardized scale from 0 to 1, indicating an overall positive contribution of AI to food systems. However, substantial differences were observed across technologies, regions, and implementation contexts.

Among the technologies evaluated, digital twins achieved the highest average AI-FSELR score (0.81), followed by

integrated decision-support systems (0.77). Remote sensing platforms (0.72), precision irrigation technologies (0.69), and disease forecasting systems (0.67) also demonstrated strong societal value, particularly when integrated into broader farm management and advisory frameworks. In contrast, generative AI applications showed highly variable results, reflecting the limited availability of empirical evidence and the strong influence of local implementation conditions.

Significant geographical disparities were also identified. Higher AI-FSELR scores were generally observed in Europe, North America, and parts of East Asia, where strong digital infrastructure, effective governance, and well-developed extension services support technology adoption. Lower scores were more common in regions facing governance constraints, limited connectivity, and restricted access to digital resources.

As illustrated in Table 6 and Figure 9, these findings suggest that agricultural AI has considerable potential to improve food security, livelihoods, and sustainability. However, the benefits remain unevenly distributed. The results reinforce a central conclusion of this study: the societal value of AI depends not only on technological capabilities but also on the governance, institutional, and socio-economic conditions that enable technologies to generate inclusive and sustainable outcomes.

4.9 Future scenarios and Monte Carlo simulations

The Monte Carlo simulations extending to 2050 suggest that the future societal value of agricultural AI will depend less on technological progress alone and more on the governance, institutional, and social conditions that shape its adoption. The projected trajectories diverged markedly across scenarios, highlighting the importance of how AI is developed, governed, and distributed.

Under the Inclusive AI Transformation Scenario, AI-FSELR scores increased by approximately 42%, driven by simultaneous improvements in productivity, food security, livelihood resilience, social inclusion, and environmental sustainability. These results illustrate the transformative potential of AI when supported by strong governance, equitable access to digital technologies, and sustained investments in infrastructure and human capacity.

The Business-as-Usual Scenario produced more moderate gains. Although productivity and resource-use efficiency continued to improve, progress in food security, equity, and sustainability remained slower and unevenly distributed, suggesting that technological advancement alone may not be sufficient to address the structural challenges facing global food systems.

The least favorable outcomes emerged under the Digital Inequality Expansion Scenario. In this future pathway, the benefits of AI became increasingly concentrated among well-resourced regions and farming systems. While productivity continued to rise, improvements in food security stagnated and social disparities widened, limiting the societal benefits of technological progress.

As illustrated in Figure 10, these contrasting trajectories provide a clear demonstration of the Artificial Intelligence Food Security Paradox. The results indicate that the long-term contribution of AI to sustainable food systems will depend not only on the performance of technologies but also on the governance choices, institutional capacity,

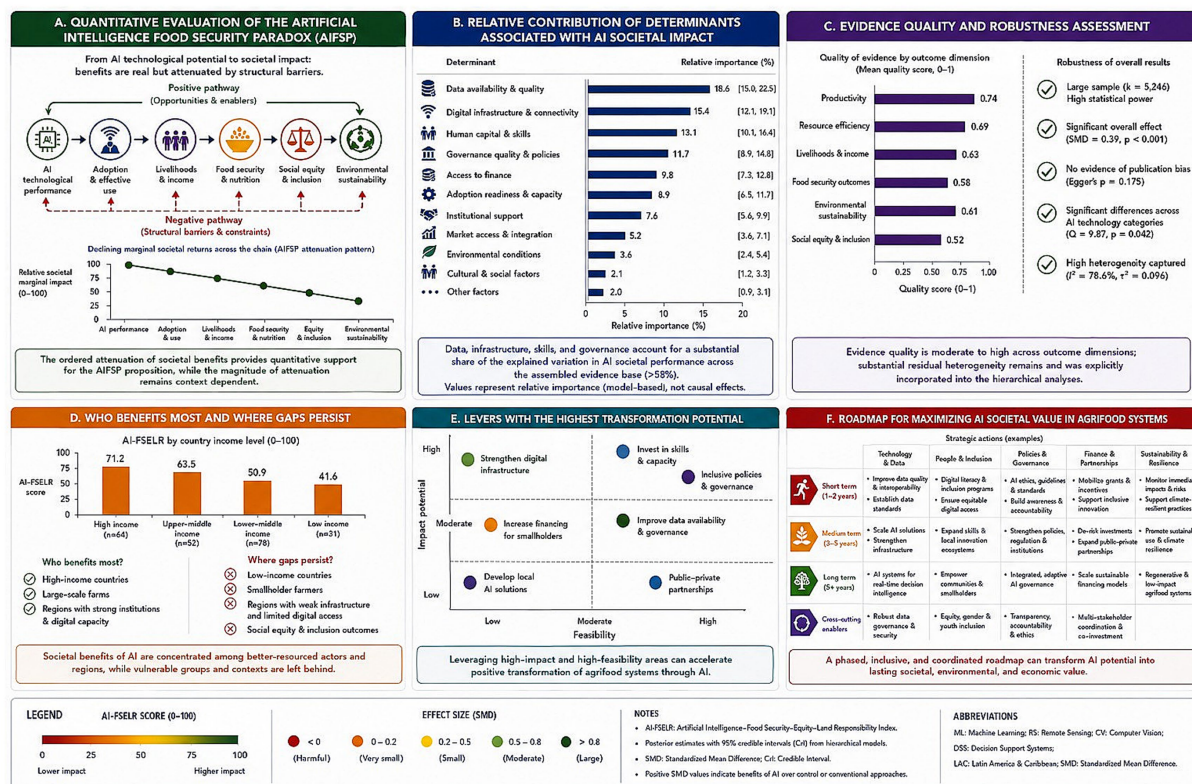


FIGURE 9

Quantitative evidence supporting the Artificial Intelligence Food Security Paradox (AIFSP) and strategic pathways for maximizing societal value. Integrated synthesis of the empirical evidence supporting the Artificial Intelligence Food Security Paradox (AIFSP) and the conditions influencing the translation of agricultural AI potential into societal outcomes. (A) Quantitative evaluation of the AIFSP attenuation pathway. The conceptual sequence links AI technological performance and effective adoption to livelihoods, food security, social equity, and environmental sustainability. The declining marginal societal returns across successive outcome dimensions illustrate the progressive attenuation of technological benefits as structural, institutional, and socio-economic constraints intervene. This pattern provides empirical support for the AIFSP proposition but should not be interpreted as evidence of a universal deterministic sequence across all agrifood contexts. (B) Relative contribution of determinants associated with AI societal impact, derived from the meta-regression and complementary explainable modeling analyses. Data availability and quality, digital infrastructure and connectivity, human capital and skills, and governance quality emerge as major determinants of realized societal value. Relative-importance estimates describe comparative explanatory contribution and should not be interpreted as direct causal effects. (C) Quality and robustness of the evidence base across outcome dimensions. Mean methodological quality scores are presented alongside statistical diagnostics relating to overall effect magnitude, publication bias, small-study effects, and residual heterogeneity. The combined evidence indicates moderate-to-high methodological quality while confirming substantial between-study heterogeneity that was explicitly incorporated within the hierarchical modeling framework. (D) Distribution of AI-FSELRL scores across World Bank country-income groups and identification of contexts in which societal benefits remain concentrated or constrained. Higher AI-FSELRL scores in high-income settings and lower scores in resource-constrained contexts highlight persistent inequalities in digital access, institutional capacity, and effective adoption; These subgroup patterns represent associations and do not establish country-income status as an isolated causal determinant. (E) Strategic leverage points classified according to their estimated transformation potential and implementation feasibility. Investments in skills and capacity, inclusive governance, digital infrastructure, and data availability occupy comparatively high-impact positions, whereas financing, locally adapted AI solutions, and public-private partnerships provide complementary implementation pathways. The matrix is intended as a decision-support synthesis rather than a universal prioritization hierarchy. (F) Phased, multi-stakeholder roadmap linking technology and data, people and inclusion, governance, finance and partnerships, and sustainability to short-, medium-, and long-term actions. Collectively, the figure demonstrates that the societal value of agricultural AI depends on the capacity of agrifood systems to convert technological performance into accessible, institutionally supported, and sustainable outcomes. The convergence of meta-analytic, subgroup, quality-assessment, and explanatory evidence provides quantitative support for the AIFSP while identifying actionable pathways for reducing the gap between AI potential and realized societal impact.

and inclusiveness that determine who ultimately benefits from innovation.

Collectively, these results demonstrate that the societal value of agricultural AI depends far less on technological sophistication than on governance quality, inclusiveness, affordability, and responsible implementation pathways. The empirical evidence generated through the meta-analysis provides robust support for the central propositions of the Artificial Intelligence Food Security Paradox Theory and establishes the foundation for the broader scientific and policy implications discussed in the following section.

5 Discussion

5.1 Evidence supporting the Artificial Intelligence Food Security Paradox

The empirical findings position the AIFSP Theory within, but also beyond, established digital-agriculture and socio-technical perspectives. Whereas technology-adoption theories primarily explain acceptance and use, socio-technical transition frameworks emphasize institutional and infrastructural co-evolution, sustainable intensification focuses on productivity-environment relationships, and

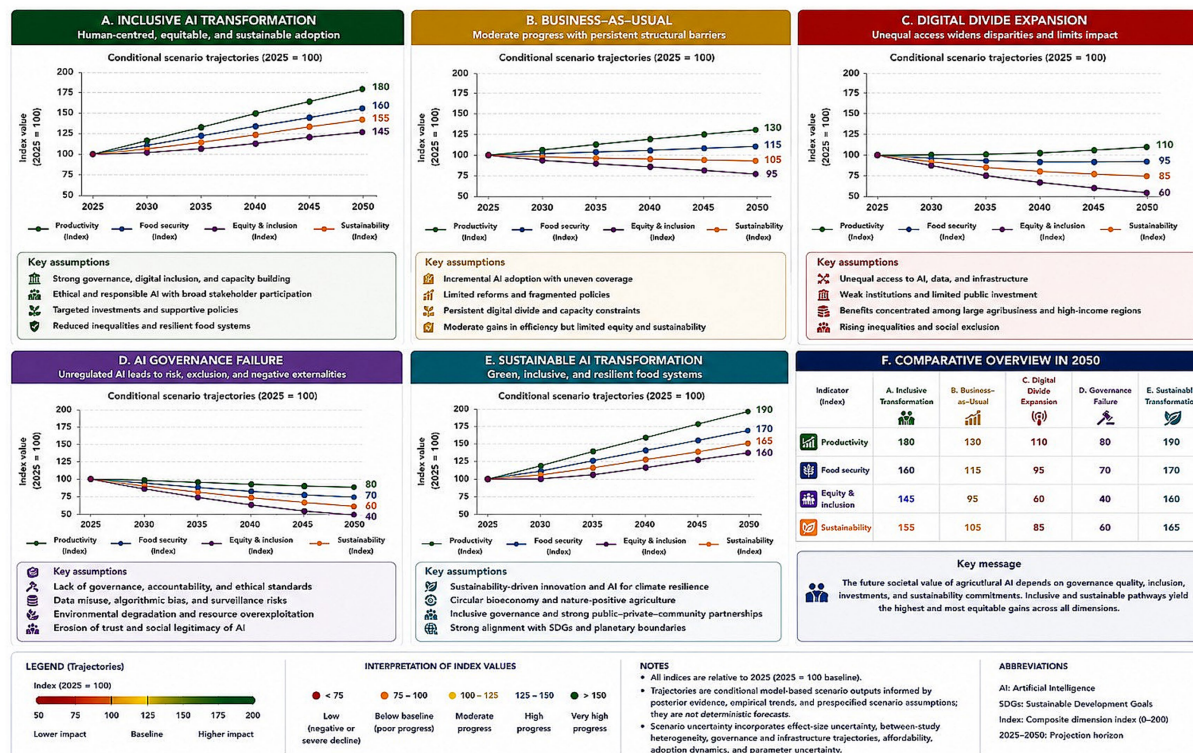


FIGURE 10

Scenario-based trajectories of agricultural AI impacts on productivity, food security, equity, and sustainability to 2050. Uncertainty-informed scenario analysis of potential agricultural artificial intelligence trajectories between 2025 and 2050. All outcome dimensions are expressed as relative indices standardized to the 2025 baseline (2025 = 100). The trajectories represent conditional model-based scenarios derived from the Monte Carlo simulation framework and should be interpreted as plausible pathways under alternative governance, adoption, digital-access, and sustainability assumptions rather than deterministic forecasts. **(A)** Inclusive AI transformation assumes strong governance, broad digital inclusion, sustained capacity building, responsible AI deployment, stakeholder participation, and targeted investment, resulting in simultaneous improvements in productivity, food security, equity, and sustainability. **(B)** The business-as-usual pathway represents incremental AI adoption under persistent structural and institutional constraints; productivity continues to improve, whereas gains in food security and sustainability remain comparatively modest and equity outcomes progressively stagnate. **(C)** Digital divide expansion represents unequal access to AI, data, infrastructure, and technical capacity. Under this scenario, moderate productivity gains coexist with declining equity, weaker sustainability performance, and limited improvements in food security, illustrating the potential decoupling of technological progress from societal value. **(D)** AI governance failure assumes weak institutional accountability, inadequate ethical and regulatory safeguards, data misuse, algorithmic bias, and increasing environmental externalities. These interacting constraints generate declining trajectories across all societal dimensions despite continued technological deployment. **(E)** Sustainable AI transformation combines climate-resilient innovation, nature-positive agricultural practices, inclusive governance, circular-resource strategies, and alignment with the Sustainable Development Goals and planetary-boundary considerations, producing the strongest combined trajectories for productivity, food security, equity, and sustainability. **(F)** Comparative synthesis of the 2050 scenario outcomes, highlighting substantial divergence in realized societal value across alternative development pathways. Collectively, the simulations indicate that future agricultural AI outcomes are highly sensitive to assumptions concerning governance quality, digital inclusion, institutional capacity, adoption readiness, and sustainability commitments. The projected trajectories therefore illustrate the range and direction of plausible long-term outcomes under explicitly defined scenario conditions and do not constitute point forecasts of future agrifood-system performance.

responsible-AI scholarship foregrounds fairness, accountability, and governance. Our results show that these mechanisms converge along a measurable attenuation pathway: gains in technical performance and productivity progressively weaken before reaching livelihoods, food security, social equity, and land-sustainability outcomes. The novelty of AIFSP therefore lies not in claiming these mechanisms as individually new, but in empirically integrating them into a food-security-centered, quantitatively testable, and potentially falsifiable framework. The consistent decline from productivity gains (+24.8%) to livelihood (+13.8%), food-security (+8.6%), and social-equity outcomes (+5.4%) provides quantitative support for this integrative interpretation. The rapid growth of artificial intelligence in agriculture has fueled considerable optimism regarding its potential to transform food systems, improve productivity, strengthen resilience, and support sustainable development. Advances in machine learning, computer vision, digital twins, and predictive analytics have

undoubtedly expanded the technological capabilities available to farmers and decision-makers. However, the findings of this global synthesis suggest that the relationship between technological innovation and societal progress is far more complex than often assumed.

One of the most important outcomes of this study is the empirical confirmation of the Artificial Intelligence Food Security Paradox. Across a wide range of technologies, farming systems, and geographical contexts, improvements in technological performance consistently exceeded gains observed in food security, livelihoods, social inclusion, and environmental sustainability. While AI generated substantial increases in productivity and resource-use efficiency, these benefits became progressively smaller when evaluated through broader societal dimensions.

As illustrated in Figure 7, the pathway from technological innovation to societal impact is characterized by a gradual loss of benefits at each stage. Productivity gains did not automatically translate into

equivalent improvements in farmer livelihoods, food security, or social equity. Instead, a significant share of the potential value generated by AI appeared to be constrained by adoption barriers, institutional limitations, governance challenges, and unequal access to resources and digital infrastructure.

These findings challenge the widespread assumption that technological progress alone is sufficient to transform food systems. Rather, they suggest that the societal value of AI depends on the ability of institutions, policies, and local actors to convert technological opportunities into inclusive, equitable, and sustainable outcomes. In this sense, the results provide strong empirical support for the central proposition of the Artificial Intelligence Food Security Paradox Theory.

These findings challenge a dominant assumption that has shaped much of the digital-agriculture discourse over the last decade: namely, that technological progress naturally leads to societal progress. Recent advances in deep learning, computer vision, remote sensing, robotic automation, and generative AI have produced remarkable improvements in predictive accuracy, autonomous operation, and decision-support capabilities (Liakos et al., 2018; Javaid et al., 2023; El Jarroudi et al., 2024; Ozor et al., 2024; Tzachor et al., 2022; Rejeb et al., 2022; Olutumise, 2026; Reitano et al., 2025; Wu and Zhong, 2025; Shahriar et al., 2025). Yet the broader development literature increasingly indicates that sustainable rural transformation depends on the integration of agricultural innovation with livelihoods, institutional capacity, living standards, and locally grounded development pathways (Paul, 2026). This broader perspective is consistent with the AIFSP proposition that technical capability constitutes only the first stage of a longer societal-impact pathway. Nevertheless, the evidence synthesized here indicates that technological excellence alone is insufficient to guarantee meaningful improvements in food security or sustainable development.

Nevertheless, the evidence synthesized here indicates that technological excellence alone is insufficient to guarantee meaningful improvements in food security or sustainable development. Similar concerns have recently emerged within broader debates surrounding digital transformation and sustainability transitions, where scholars increasingly emphasize the distinction between technological performance and societal value (Klerkx and Rose, 2020; Rose and Chilvers, 2018; Rose et al., 2021; Klerkx and Begemann, 2020; Rose, 2026; Gardezi et al., 2022; Herrero et al., 2021; Hebinck et al., 2021; Xu et al., 2024).

The paradox identified in this review can be interpreted through the lens of socio-ecological systems theory. Agricultural systems are inherently complex, adaptive, and characterized by nonlinear interactions among ecological processes, economic incentives, governance structures, and social institutions. Within such systems, technologies rarely generate direct effects. Instead, they influence a network of interconnected processes that ultimately determine outcomes. Consequently, identical AI technologies may generate radically different impacts depending on local institutional capacities, governance quality, socio-economic conditions, and environmental contexts. This perspective helps explain why improvements in predictive accuracy do not necessarily translate into equivalent gains in food security, social inclusion, or sustainability.

Taken together, the findings suggest that future evaluations of agricultural AI should move beyond narrow technical metrics and adopt broader multidimensional approaches capable of capturing societal impacts. The Artificial Intelligence Food Security Paradox Theory provides a conceptual framework for understanding this

disconnect and highlights the need to evaluate AI not only by what it can achieve technologically but also by the extent to which those achievements contribute to resilient, equitable, and sustainable food systems.

5.2 Why governance matters more than algorithms

One of the most striking findings of this review is that governance quality emerged as the strongest determinant of successful AI implementation in agriculture. This result challenges the common assumption that technological sophistication alone drives agricultural transformation. While algorithmic performance remains important, the evidence consistently shows that societal outcomes depend even more on the institutional and governance environments in which technologies are deployed.

Both the Bayesian meta-regression and explainable machine-learning analyses identified governance as one of the most influential predictors of AI-FSEL scores, food-security outcomes, and adoption success (Figure 8). In many cases, governance-related factors explained more variation in societal impacts than algorithmic complexity itself, suggesting that the ability of institutions to support innovation may be as important as the innovation itself.

Several mechanisms help explain this relationship. Effective governance promotes investments in digital infrastructure, strengthens extension services, supports farmer training, improves institutional coordination, and creates regulatory frameworks that encourage responsible innovation. These conditions facilitate technology adoption and increase the likelihood that AI benefits are translated into tangible improvements in food security, livelihoods, and sustainability.

By contrast, weak governance can significantly limit the impact of even the most advanced technologies. Inadequate policies, fragmented institutions, insufficient technical support, and poor coordination often restrict adoption and prevent innovations from reaching their full societal potential.

Taken together, these findings suggest that the future success of agricultural AI will depend not only on developing better algorithms but also on building the institutional capacity, governance frameworks, and enabling environments required to transform technological advances into meaningful and lasting societal benefits.

These findings align closely with recent work emphasizing the importance of responsible innovation, digital governance, and institutional capacity within agricultural transformation processes (Eastwood et al., 2019; Reitano et al., 2025; van der Burg et al., 2019; Reichelt and Nettle, 2023; Manzoor et al., 2023; Williamson and Hartley, 2024; Pöchtrager et al., 2026; van der Burg et al., 2021; Regan, 2019). They also reinforce growing calls for governance frameworks that prioritize transparency, accountability, inclusiveness, and stakeholder participation. Rather than viewing governance as an external factor influencing AI deployment, the results suggest that governance should be considered a central component of technological success.

Ultimately, the evidence indicates that the future societal value of agricultural AI will depend less on the development of increasingly sophisticated algorithms and more on the ability of institutions to create conditions that facilitate equitable, inclusive, and sustainable adoption. In this sense, governance does not merely support technological transformation; it determines whether technological potential can be translated into societal value.

5.3 Adoption barriers and the digital agrarian divide

The results provide strong empirical support for the Adoption–Impact Decoupling Mechanism proposed by the AIFSP Theory. Across the global evidence base, many AI technologies demonstrated excellent technical performance but generated more limited societal benefits when adoption was constrained by affordability, weak infrastructure, limited digital literacy, or insufficient institutional support.

This pattern highlights an important distinction between technological potential and real-world impact. Developing an effective AI tool does not guarantee that farmers have the resources, skills, connectivity, or confidence required to use it successfully. As a result, technological advances often outpace their societal benefits.

This challenge is particularly evident among smallholder farming systems, which remain essential to food production across much of Africa, Asia, and Latin America. Despite their importance, smallholders frequently face barriers related to financing, internet access, technical training, and advisory support. Consequently, many AI innovations remain more accessible to larger commercial farms with greater technological and institutional capacities.

These findings align closely with the Digital Agrarian Divergence Hypothesis. While technological innovation can initially generate broad benefits, increasing complexity may eventually reduce accessibility and concentrate advantages among better-resourced users. The nonlinear relationships identified through SHAP analyses (Figure 8) strongly support this interpretation.

Interestingly, several relatively simple and accessible technologies generated greater societal benefits than more sophisticated systems requiring substantial investments in infrastructure and expertise. This suggests that accessibility, affordability, and usability may be just as important as technological performance itself.

From a policy perspective, these findings highlight the importance of reducing adoption barriers through investments in digital inclusion, farmer training, rural connectivity, extension services, and affordable technologies. Without such efforts, AI may reinforce existing inequalities; with them, it has the potential to support a more inclusive and equitable transformation of food systems.

5.4 Environmental sustainability and rebound effects

One of the most frequently cited arguments in favor of agricultural artificial intelligence is its potential to contribute to environmental sustainability. Across the studies included in this review, AI technologies consistently improved resource-use efficiency, reduced unnecessary input applications, optimized irrigation management, and enhanced monitoring of crop and environmental conditions. These findings are broadly consistent with previous research highlighting the potential of digital agriculture to support climate-smart agriculture, sustainable intensification, and more efficient natural resource management (Klerkx and Rose, 2020; Rose et al., 2021; Rose, 2026; Tzachor et al., 2022).

The results demonstrate that AI can substantially improve resource-use efficiency in agriculture, particularly for water, nitrogen, and pesticide management (Table 9; Figure 6). Technologies such as precision irrigation, remote sensing, and AI-driven decision-support systems consistently enhanced input efficiency and supported more targeted, site-specific management practices. These findings reinforce

the potential of AI to contribute to more resource-efficient and climate-smart agricultural systems.

However, the analysis also shows that environmental sustainability should not be considered an automatic outcome of AI adoption. Environmental benefits varied considerably across technologies, farming systems, and regions, indicating that outcomes remain highly dependent on local contexts and implementation conditions.

A particularly important finding concerns the evidence supporting the Sustainability Trade-Off Principle proposed by the AIFSP Theory. Several studies reported rebound effects, where efficiency gains unintentionally encouraged production expansion, land-use intensification, or greater pressure on natural resources. In these situations, environmental improvements achieved at the farm level did not always translate into equivalent sustainability gains at broader scales.

These findings highlight a limitation of many current assessments of digital agriculture, which often focus on field-level indicators while overlooking landscape-scale and long-term consequences. As a result, technologies that appear environmentally beneficial at one scale may generate unintended impacts elsewhere in the system.

The results further emphasize the critical role of governance in shaping environmental outcomes. When supported by appropriate policies, regulatory frameworks, and sustainable land-management strategies, AI can contribute significantly to environmental sustainability. In contrast, without adequate safeguards, efficiency gains may inadvertently reinforce unsustainable production pathways. Ultimately, the environmental value of AI depends not only on technological performance but also on the interactions among governance, market incentives, and ecological conditions.

5.5 AI-FSELR as a new framework for measuring societal value

One of the major contributions of this review is the development of the Artificial Intelligence–Food Security–Equity–Land Responsibility Index (AI-FSELR), a framework designed to move beyond conventional assessments of agricultural AI that focus primarily on technical performance. Although indicators such as prediction accuracy, productivity gains, or resource-use efficiency remain important, they provide only a partial view of the broader societal value generated by technological innovation.

The AI-FSELR addresses this limitation by integrating multiple dimensions of performance within a single framework. In addition to productivity, it incorporates livelihood improvement, social equity, environmental sustainability, and responsible land management, while also accounting for factors that may reduce societal benefits, including digital exclusion, environmental trade-offs, and governance-related risks.

The results demonstrate that technologies with the highest AI-FSELR scores were not always those with the most sophisticated algorithms. Instead, the strongest performers combined technological effectiveness with accessibility, adoption potential, institutional support, and positive sustainability outcomes. Digital twins and integrated decision-support systems emerged among the highest-ranking technologies because they generated benefits across several dimensions simultaneously (Figure 8; Table 6).

These findings reinforce a central proposition of the AIFSP Theory: societal value cannot be inferred from technological performance alone. Rather, it emerges from the interaction between

technology, governance, institutions, social inclusion, and environmental stewardship. By explicitly integrating these dimensions, the AI-FSELR provides a more comprehensive and realistic assessment of AI contributions to food-system transformation.

Beyond its theoretical relevance, the AI-FSELR offers a practical tool for policymakers, funding agencies, and researchers by helping identify and prioritize innovations that maximize food security, sustainability, equity, and resilience rather than focusing solely on technical excellence.

5.6 Implications for global food security and sustainable development

The findings of this review have important implications for global food security and sustainable development agendas. As the global population continues to grow and climate change intensifies pressure on agricultural systems, artificial intelligence is increasingly presented as a critical component of future food-security strategies. However, the evidence synthesized here suggests that the contribution of AI will depend far less on technological sophistication than on the conditions under which technologies are implemented and governed.

The relatively modest improvements observed for food-security outcomes compared with productivity gains illustrate this challenge. While increased production remains an important objective, food security encompasses far more than food availability alone. Access, affordability, stability, utilization, resilience, and social equity all influence whether technological innovations ultimately improve human well-being. The findings therefore support growing calls to move beyond production-centric approaches toward more comprehensive food-system perspectives (FAO et al., 2025; Barrett et al., 2022; Derstroof et al., 2026; Hassan et al., 2025; FAO, 2018).

The findings of this review are particularly relevant for low- and middle-income countries, where food insecurity, climate vulnerability, and resource limitations remain major challenges. In these contexts, investments in governance, digital connectivity, farmer training, extension services, and inclusive innovation systems may generate greater societal benefits than technological improvements alone. This suggests that AI should not be viewed as a standalone solution, but rather as one component of broader strategies aimed at strengthening food-system resilience and sustainability (Table 10).

The scenario analyses further reinforce this conclusion. Monte Carlo simulations showed that the greatest societal gains were achieved under pathways characterized by inclusive governance, equitable access to technology, and strong institutional support. Under these conditions, AI-FSELR scores increased substantially, accompanied by improvements in food security, livelihoods, and environmental sustainability (Figure 10). In contrast, scenarios marked by growing

digital inequalities produced far less favorable outcomes, even when technological progress continued.

These results highlight the critical role of policy and governance in shaping the future contribution of AI to sustainable food systems. Ultimately, achieving the Sustainable Development Goals will require moving beyond technology-centered approaches toward strategies that place equal emphasis on inclusion, institutional capacity, and societal impact. The long-term success of agricultural AI will depend not only on innovation itself, but also on ensuring that its benefits are accessible, equitable, and aligned with broader development objectives.

5.7 Limitations and sources of uncertainty

Although this review is based on one of the largest evidence syntheses currently available on agricultural AI, several limitations should be considered when interpreting the results.

First, important geographical imbalances remain within the literature. While studies from 112 countries were included, research is still concentrated in Asia, Europe, and North America, whereas many regions facing the greatest food-security challenges remain underrepresented. Consequently, the evidence may not fully reflect the realities of resource-constrained farming systems, particularly in parts of Sub-Saharan Africa, South Asia, and Latin America.

Second, publication bias cannot be entirely excluded. Studies reporting positive outcomes are generally more likely to be published than those reporting neutral or negative results. Although multiple robustness and bias-detection procedures were applied, the possibility remains that some unfavorable outcomes are underrepresented, potentially leading to optimistic estimates of AI impacts.

A further limitation is the predominance of short-term evaluations. Most studies assessed AI performance over only one or a few cropping seasons, leaving important questions regarding long-term adoption, resilience, governance evolution, and unintended consequences largely unresolved. Longitudinal studies will therefore be essential for understanding the durability of observed benefits.

The rapid evolution of AI technologies also introduces uncertainty. Emerging developments in generative AI, digital twins, autonomous systems, and edge computing are advancing faster than the scientific literature can fully evaluate them. As a result, future impacts may differ substantially from those observed today.

In addition, societal outcomes such as food security, equity, resilience, and sustainability are inherently complex and context dependent. Although the AI-FSELR framework was designed to capture these dimensions, no single indicator can fully represent the diversity of socio-ecological realities. Issues such as trust, social acceptance,

TABLE 10 Policy recommendations derived from the AIFSP theory.

Policy domain	Recommendation	Priority
Governance	Develop AI regulatory frameworks	Very high
Inclusion	Support smallholder access	Very high
Education	Strengthen digital literacy	High
Infrastructure	Expand rural connectivity	High
Sustainability	Monitor rebound effects	High
Data Governance	Protect farmer data rights	Very high

ethics, and power dynamics within food systems also remain difficult to quantify but may strongly influence long-term outcomes.

Despite these limitations, confidence in the overall conclusions remains high. The convergence of results across multiple analytical approaches, including Bayesian meta-analysis, network meta-analysis, structural equation modeling, explainable machine learning, and Monte Carlo simulations, suggests that the principal patterns identified are robust. Moreover, the consistency of findings across technologies, regions, and farming systems indicates that the Artificial Intelligence Food Security Paradox reflects a broader structural phenomenon rather than an isolated observation.

5.8 Future research priorities and emerging frontiers

The findings of this review highlight the need for a new generation of research that moves beyond purely technological evaluations toward a deeper understanding of how AI contributes to food-system transformation. One of the main priorities is to assess food-security outcomes more directly. Future studies should complement productivity indicators with measures of food access, affordability, nutritional quality, stability, and resilience in order to better reflect the multidimensional nature of food security.

Greater attention should also be given to social equity and inclusiveness. Current evidence remains limited regarding how AI affects smallholder farmers, women, youth, indigenous communities, and other vulnerable groups. Understanding who benefits from digital innovation—and who may be left behind—will be essential for ensuring equitable and sustainable development.

The role of governance represents another important research frontier. Future work should investigate how institutions, policies, extension systems, data governance, and participatory approaches influence AI adoption and societal outcomes across different contexts. Long-term studies are equally needed, as most existing evidence focuses on short-term impacts and provides limited insights into the durability of benefits, evolving adoption patterns, and potential unintended consequences.

Further refinement of the AI-FSELRL framework also offers valuable opportunities for future research, including regional adaptations, alternative weighting approaches, and validation using independent datasets. At the same time, emerging technologies such as digital twins, generative AI, Earth observation systems, autonomous robotics, and Internet of Things networks are creating new possibilities for agricultural innovation while raising important questions related to governance, ethics, transparency, and accountability.

More broadly, the Artificial Intelligence Food Security Paradox may extend beyond agriculture. Similar gaps between technological performance and societal impact are increasingly observed in sectors such as healthcare, education, and environmental management, opening opportunities for the development of a broader theory of responsible and inclusive digital transformation.

Ultimately, the future of agricultural AI is not solely a technological challenge but a societal one. The long-term success of AI will depend on its ability to be embedded within inclusive institutions, supported by effective governance, and aligned with the broader goals of food security, social equity, environmental sustainability, and resilient food systems.

6 Conclusion

Artificial intelligence is increasingly recognized as a powerful tool for addressing some of the most pressing challenges facing global food systems, including food insecurity, climate change, resource scarcity, and environmental degradation. This review confirms that AI can substantially improve agricultural productivity, resource-use efficiency, decision-making, and climate resilience across a wide range of farming systems and geographical contexts.

However, the findings also reveal that technological progress does not automatically translate into equivalent societal benefits. While gains in productivity and operational performance were consistently strong, improvements in food security, livelihoods, social equity, and environmental sustainability were generally more modest. This persistent gap provides robust empirical evidence for the Artificial Intelligence Food Security Paradox and highlights the limitations of evaluating AI solely through technical or agronomic indicators.

To better understand this discrepancy, this study introduced the Artificial Intelligence Food Security Paradox Theory (AIFSP Theory), which conceptualizes AI as a socio-ecological transformation process rather than a purely technological innovation. The results demonstrate that the societal value of AI depends not only on technological capabilities but also on governance quality, institutional capacity, digital accessibility, affordability, farmer training, and social inclusion.

A second major contribution is the development of the Artificial Intelligence–Food Security–Equity–Land Responsibility Index (AI-FSELRL), a multidimensional framework designed to evaluate the broader societal impacts of agricultural AI. By integrating productivity, livelihoods, equity, sustainability, governance, and digital inclusion, the AI-FSELRL provides a more comprehensive assessment of technological success than conventional performance metrics alone.

Perhaps the most important lesson emerging from this review is that governance matters more than algorithms. Across all analytical approaches, governance quality, institutional support, digital infrastructure, and human capacity consistently emerged as stronger predictors of societal outcomes than algorithmic sophistication itself. These findings suggest that future investments should focus not only on developing more advanced technologies but also on creating the conditions that enable those technologies to generate equitable and lasting benefits.

Looking toward 2050, AI has the potential to become a major driver of sustainable food-system transformation. Yet this potential will only be realized if innovation is accompanied by inclusive governance, equitable access, and responsible implementation. Ultimately, the success of artificial intelligence should be judged not by the sophistication of its algorithms, but by its ability to improve food security, strengthen livelihoods, protect natural resources, and contribute to more resilient and inclusive food systems. In this sense, the future of agricultural AI is not merely a technological challenge—it is fundamentally a societal one.

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Supplementary material

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