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ADAPTIVE GOVERNANCE OF ARTIFICIAL INTELLIGENCE IN AGRICULTURE AND FOOD SYSTEMS: A RISK-BASED AND CASE-ORIENTED ANALYSIS

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ABSTRACT

Artificial intelligence (AI) is rapidly transforming agriculture and food systems through applications such as precision farming, autonomous machinery, predictive analytics, and digital supply-chain management. While these technologies promise significant gains in productivity and sustainability, they also raise important governance challenges as regulatory systems struggle to keep pace with rapid technological change. This paper examines how emerging AI governance frameworks apply to the agrifood sector. It reviews key regulatory developments, including the European Union's AI Act, evolving U.S. policy initiatives, and international standards, and analyzes how risk-based regulatory approaches intersect with different categories of agricultural AI applications. The analysis identifies several governance gaps, including the treatment of AI systems that manage critical food infrastructure, limitations in existing safety classifications, and insufficient attention to sustainability-related risks, such as environmental impacts and animal welfare. The paper argues that adaptive governance, characterized by lifecycle monitoring, iterative oversight, standards-based co-regulation, and institutional learning, provides a useful framework for regulating AI systems operating amid technological uncertainty and environmental variability. The findings contribute to the emerging literature on AI governance by identifying pathways for developing adaptive regulatory frameworks for agrifood systems.

KEYWORDS

Artificial intelligence; agriculture; agrifood systems; AI governance; adaptive regulation

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I. Introduction

Artificial intelligence (AI) is rapidly transforming agricultural and food systems, enabling new forms of data-driven decision-making, automation, and predictive analytics across the agrifood value chain. AI-enabled tools are increasingly applied in precision agriculture, autonomous machinery, climate forecasting, and digital traceability systems, with demonstrated potential to improve productivity, resource efficiency, and sustainability (Mana et al., 2024; Wu et al., 2025).[1] Beyond productivity gains, AI deployment in agriculture raises broader questions concerning transparency, accountability, data governance, farmer trust, and the equitable distribution of technological benefits, highlighting that governance challenges extend beyond technical performance (Dara et al., 2022; Gardezi et al., 2023; Ragany et al., 2026). At the same time, global food systems face mounting pressures from climate change, resource constraints, and rising demand, intensifying the need for adaptive and efficient agricultural production systems (IPCC, 2023; World Bank, 2025; OECD, 2026). In this context, AI is increasingly viewed as a critical enabler of resilient and sustainable agrifood systems.[2]

However, the rapid integration of AI into agriculture raises a central governance challenge: how can regulatory systems effectively oversee AI technologies that are dynamic, data-intensive, and embedded across diverse agricultural contexts? This paper addresses how existing and emerging regulatory frameworks can govern AI systems in agriculture and food systems, and what adaptive regulatory approaches are needed to manage their evolving risks while supporting innovation.[3] See also Klerkx et al. (2019) and Ragany et al. (2026) on digital agriculture transformation. In this paper, adaptive governance refers to regulatory approaches that incorporate continuous learning, iterative oversight, stakeholder feedback, and periodic adjustment in response to evolving technologies and risk conditions. Unlike traditional command-and-control regulation, which relies primarily on fixed rules established ex ante, adaptive governance recognizes that emerging technologies such as AI evolve rapidly through ongoing data updates, changing deployment contexts, and novel applications. Effective governance, therefore, requires institutions capable of monitoring outcomes, updating regulatory expectations, and incorporating new information over time (Marchant et al., 2011; National Academies, 2017; OECD, 2024, 2026).

Agriculture provides a particularly important setting for adaptive governance because AI systems operate within highly dynamic environmental, biological, and economic conditions. Machine-

[1] Empirical evidence suggests that AI adoption in agriculture can increase crop yields by approximately 12–45% and reduce input costs (including labor, fertilizer, and water) by up to 25%, while broader projections indicate that digital and AI-enabled technologies could generate tens of billions of dollars annually in additional agricultural value and productivity gains in low- and middle-income countries (Olutumise, 2026; Goedde et al., 2020; World Bank, 2019).

[2] AI-enabled agricultural systems integrate sensing, analytics, and actuation across value chains, raising governance challenges (FAO, 2022; McFadden et al., 2023; Wu et al., 2025).

[3] Recent policy developments reflect a shift toward risk-based AI governance frameworks (OECD, 2023; European Union, 2024).

learning models used for irrigation, pest detection, autonomous machinery, and supply-chain management may perform differently across seasons, regions, crop systems, and climatic conditions. As a result, governance challenges often arise after deployment rather than during initial approval. Static regulatory approaches based on fixed technologies may struggle to address evolving risks, making adaptive governance especially relevant for agricultural AI applications.

AI systems introduce new risks related to data privacy, algorithmic bias, system opacity, and unequal access to digital infrastructure, which may exacerbate existing inequalities within food systems (World Bank, 2025; Yuan & Sun, 2025; Ragany et al., 2026). Despite rapid advances in digital agriculture, empirical and policy research on AI governance in agriculture remains limited relative to sectors such as finance and healthcare, where regulatory frameworks and institutional responses have been more extensively studied. This gap is particularly important given the sector's unique characteristics, including environmental variability, decentralized decision-making, and the critical role of food systems in economic and social stability. Recent reviews similarly argue that while AI offers substantial opportunities for improving agricultural productivity and resilience, governance frameworks must address privacy, algorithmic bias, unequal digital access, transparency, liability, data quality, and stakeholder trust (Omotayo et al., 2025; Ragany et al., 2026).

Existing AI governance frameworks have increasingly adopted risk-based approaches, such as those embodied in the European Union's AI Act, which calibrate regulatory oversight according to system risk and potential harm (OECD, 2023; Val, 2025). However, these frameworks have largely been developed for cross-sectoral applications and face limitations when applied to agriculture, where AI systems interact with environmental and biological processes and fragmented institutional arrangements.[4] Prior research highlights challenges related to data governance, system safety, and regulatory fragmentation, but does not fully address how governance mechanisms operate in practice across different types of agricultural AI systems (Basu et al., 2020; McFadden et al., 2023).

This paper makes three contributions to the emerging literature on AI governance. First, it extends predominantly cross-sectoral AI governance frameworks by situating them within the institutional and environmental context of agriculture. Second, it develops a functional, case-based analytical framework showing how AI governance is activated through existing regulatory regimes rather than through standalone AI statutes. Third, it identifies concrete adaptive regulatory mechanisms such as lifecycle monitoring, embedded compliance, and standards-based oversight that can be operationalized in real-world agricultural applications.

[4] General-purpose AI governance frameworks, including the OECD AI principles and the EU AI Act, are designed to apply across multiple sectors and use cases, which can limit their ability to address sector-specific risks and institutional contexts in domains such as agriculture (OECD, 2023; European Union, 2024).

This article adopts a qualitative, multi-method approach combining regulatory analysis, comparative case studies, and cross-sector comparison. Three agricultural AI applications are examined to explore how governance challenges emerge across different technological contexts. Detailed methodological procedures are described in Section 2. The analysis focuses primarily on the United States, where AI governance is emerging through a combination of agency guidance, technical standards, and sector-specific regulation. The European Union is an important comparative benchmark because the EU AI Act is the most comprehensive risk-based AI regulatory framework currently in force.

The paper proceeds as follows. Section 2 describes the analytical approach and case-study methodology. Section 3 reviews the evolving policy landscape for AI governance in agriculture, focusing on regulatory developments in the United States and the European Union, as well as international frameworks. Section 4 presents three case studies—drone-based monitoring, AI-driven irrigation, and blockchain-enabled traceability—to illustrate how AI governance operates in practice. Section 5 draws comparative lessons from adaptive regulatory approaches in other sectors, including financial technology and digital health. Section 6 concludes with implications for the design of adaptive AI governance frameworks in agriculture and food systems.

II. Methodology

This study adopts a qualitative, multi-method research design to examine how AI governance operates in agriculture and food systems (Creswell & Creswell, 2018; Yin, 2018). The approach integrates policy analysis, case study research, and comparative evaluation to capture both the institutional structure of regulatory frameworks and their practical application across different AI use cases.

a. Research Design

The research combines three complementary components. First, a policy and literature review establishes the regulatory baseline for AI governance in agriculture. This includes analysis of U.S. and European Union regulatory frameworks, international guidelines, and relevant academic literature on AI governance, with particular attention to data governance, machinery safety, and food traceability systems.

Second, the study employs a comparative case study approach to examine how AI governance is operationalized in practice, an approach that is particularly well suited for investigating contemporary phenomena embedded within complex institutional settings (Yin, 2018). Three illustrative cases are selected to capture variation in system function, risk profile, and regulatory interaction: (i) drone-based crop monitoring, (ii) AI-driven irrigation management, and (iii) blockchain-enabled supply-chain traceability. These cases allow for an in-depth assessment of regulatory activation pathways, risk-benefit tradeoffs, and governance challenges across different applications.

Third, a cross-sector comparative analysis draws on adaptive regulatory approaches from other domains, including financial technology and digital health. This component identifies governance mechanisms such as regulatory sandboxes, lifecycle monitoring, and standards-based oversight that may be transferable to agricultural AI systems.

b. Case Selection

The three case studies were selected using a purposive sampling strategy designed to capture variation in the primary functions performed by agricultural AI systems and the regulatory regimes they activate (Patton, 2015). Drone-based crop monitoring represents AI-enabled decision support; AI-driven irrigation management represents systems that may influence or directly control physical infrastructure; and blockchain-enabled traceability represents AI applications embedded within compliance and supply-chain governance. Together, these cases span distinct risk profiles, levels of autonomy, and regulatory contexts, allowing examination of governance challenges across multiple dimensions of agricultural AI. This focus reflects growing recognition that governance challenges arise not only from AI algorithms themselves but also from their interaction with institutional settings, stakeholder behavior, and organizational implementation (Balasooriya & Sedera, 2025).

c. Analytical Framework

The analysis is guided by a functional governance framework that evaluates how regulatory systems are activated based on the characteristics of AI applications rather than sector labels. Specifically, the study assesses AI governance along four dimensions: (i) risk classification and mitigation, (ii) regulatory activation pathways, (iii) documentation and compliance requirements, and (iv) adaptability of regulatory mechanisms over time. The analysis focuses on identifying how AI changes governance requirements and risk profiles relative to conventional agricultural practices rather than quantifying the magnitude of those changes. This analytical approach is consistent with comparative case-study research, which seeks to explain recurring governance patterns and develop transferable conceptual insights rather than estimate population-level causal effects (George & Bennett, 2005; Yin, 2018).

Across case studies and jurisdictions, the analysis focuses on identifying how AI systems trigger existing regulatory regimes, how risks and benefits are distributed, and how adaptive governance tools can support effective oversight amid technological uncertainty.

The study focuses on selected high-impact AI applications in agriculture and on major regulatory frameworks in the United States and the European Union. The case studies are illustrative rather than exhaustive and are intended to highlight representative governance dynamics rather than provide comprehensive sector coverage. As with most qualitative policy analyses (Yin, 2018), the findings are subject to limitations related to evolving regulatory environments and reliance on publicly available information. However, the multi-method approach provides a structured and context-sensitive assessment of AI governance mechanisms in agriculture and food systems.

d. Basis for Cross-Case Inference

The study employs analytical rather than statistical generalization (Yin, 2018). The objective is not to estimate the prevalence of governance outcomes across all agricultural AI systems but to identify governance mechanisms and regulatory challenges that recur across diverse applications. Cross-case inferences are derived through structured comparison using a common analytical framework. Governance principles observed consistently across cases are interpreted as indicative of broader patterns, while findings unique to individual cases are treated as context-specific observations. This approach follows established qualitative case-study methodologies emphasizing theory building and analytical generalization rather than population inference (Yin, 2018; George & Bennett, 2005).

III. Regulatory baselines shaping AI governance in U.S. agriculture: lessons from comparative experience

This section situates AI in agriculture within the broader literature on AI governance, drawing on regulatory, legal, and food systems research to establish the evolving policy baseline. While this article focuses primarily on the United States and the European Union, these jurisdictions are selected because they currently represent the two most influential and contrasting approaches to AI governance. The EU has adopted a comprehensive, legally binding, risk-based regulatory framework through the AI Act, whereas the United States relies on a decentralized system of sector-specific oversight, standards, and agency guidance. Together, these models shape global compliance expectations for technology developers, agricultural exporters, and multinational agrifood firms. Other jurisdictions, including China, the United Kingdom, Brazil, and several emerging economies, are also developing AI governance frameworks, but these largely reflect variations on centralized state-led regulation, sector-specific oversight, or the adaptation of international principles, such as those promoted by the OECD. Accordingly, the U.S.–EU comparison provides an analytically useful baseline for examining how AI governance may evolve in agriculture and food systems. Because the case studies examined in subsequent sections are drawn primarily from U.S. agricultural contexts, the discussion below emphasizes U.S. governance mechanisms while using international developments as comparative reference points.

As of early 2026, AI governance in agriculture and food systems is shifting from predominantly voluntary guidance to more formalized, enforceable compliance regimes. In the US, this transition is shaped by sector-specific strategies, such as the USDA AI Strategy for FY 2025–2026, and by evolving state-level privacy and AI rules (USDA, 2025). In contrast, the EU has adopted a comprehensive, cross-sectoral statute, the EU Artificial Intelligence Act (Hereafter "EU AI Act"), which is being implemented in phases through 2026 **(**European Union, 2024**).** Across both jurisdictions, the emerging baseline for AI in agriculture is explicitly risk-based, with regulatory attention concentrating on safety in autonomous machinery, data governance and privacy, and digitally enabled food traceability (OECD, 2023; Al-Maamari, 2025). This shift

toward risk-based governance reflects broader trends in AI policy frameworks that emphasize proportional regulation based on system functionality and potential harm.[5]

A recurring insight in the literature is that "AI in agriculture" does not constitute a single regulatory object.[6] Agricultural AI systems simultaneously function as data-intensive information technologies, cyber-physical systems embedded in machinery and robotics, and governance tools for food safety and supply chain oversight (Basu et al., 2020; McFadden et al., 2023; Vitale et al., 2025; Ahmad et al., 2025). As a result, AI regulation in this sector rarely takes the form of a single, dedicated statute. Instead, it emerges through the interaction of multiple regulatory regimes[7] that activate depending on what the system does (decision support versus automated actuation), what it affects (personal data, workers, food safety records), and where it is deployed (fields, roads, processing plants, or supply chains) (Al-Maamari, 2025). This regulatory layering reflects broader trends in AI governance, where sector-specific rules, product safety law, and data protection regimes jointly determine compliance obligations. This functional hybridity is well documented in both legal and engineering literatures, which emphasize that agricultural robotics and AI systems operate across overlapping domains of liability, data protection, and safety regulation (Basu et al., 2020).

Agriculture presents distinctive governance challenges because AI systems operate under dynamic environmental conditions, rely on heterogeneous data sources, and directly affect biological production systems. Recent agricultural scholarship likewise emphasizes that responsible AI deployment requires explainability, accountability, fairness, data stewardship, and mechanisms that build trust among farmers and technology providers (Dara et al., 2022; Gardezi et al., 2023). These governance priorities reinforce the functional, multi-regime perspective adopted in this paper, in which AI oversight depends not on the technology itself but on how it interacts with existing regulatory institutions.

This hybridity helps explain why U.S. governance appears fragmented while the EU approach takes the form of a systems-level regulatory architecture.[8] It also aligns with broader observations in digital agriculture research that technological systems integrate sensing, analytics, and actuation across multiple stages of the agricultural value chain, from production to distribution (McFadden et al., 2023). To orient the reader, Table 1 provides a baseline snapshot comparing how key regulatory domains such as general AI governance, data protection, machinery safety, and food traceability are structured in the US, EU, UK, and China.

[5] Risk-based frameworks classify AI systems by harm potential and scale regulatory obligations (OECD, 2023; Val, 2025).
[6] Agricultural AI systems are hybrid socio-technical systems spanning data, machinery, and compliance domains (Basu et al., 2020; McFadden et al., 2023).
[7] AI governance is distributed across overlapping legal domains rather than a single statute (OECD, 2023).
[8] [6] U.S. AI governance is decentralized compared to the EU's harmonized model (OECD, 2023; USDA, 2025).

Table 1: Global AI Governance Models Relevant to Agriculture and Food Systems

Jurisdiction	Governance Model	Key Regulatory Features	Agricultural Relevance
United States	Decentralized, sector-based	Agency guidance, NIST AI RMF, USDA AI Strategy, state privacy laws	Precision agriculture, machinery safety, traceability
European Union	Comprehensive risk-based regulation	EU AI Act, GDPR, Machinery Regulation	High-risk classifications, conformity assessment
United Kingdom	Sector-specific oversight	Existing regulators implement AI principles	Flexible governance for agricultural innovation
China	Centralized state-led governance	Algorithm registration, cybersecurity, and data laws	Large-scale deployment, digital agriculture platforms

Sources: Adapted from USDA (2025–2026 AI Strategy), EU AI Act framework documents, and recent comparative analyses of AI governance regimes (EU, 2024; OECD, 2023; Al-Maamari, 2025; Val, 2025).

a. Adaptive governance as an analytical framework

Adaptive governance differs from conventional regulatory approaches in several respects. Traditional command-and-control regulation typically relies on fixed statutory requirements, prescriptive standards, and periodic enforcement. By contrast, adaptive governance emphasizes ongoing monitoring, iterative adjustment, stakeholder engagement, and institutional learning. It is particularly relevant in settings characterized by uncertainty, complexity, and rapid technological change, where regulators may not be able to anticipate all future risks when establishing rules (Marchant et al., 2011; National Academies, 2017).

Within the AI governance literature, adaptive governance complements rather than replaces risk-based regulation. Risk-based frameworks classify systems according to potential harms and assign corresponding obligations. Adaptive governance focuses instead on how regulatory institutions respond as technologies evolve. The two approaches are therefore complementary: risk-based regulation determines the intensity of oversight, while adaptive governance provides mechanisms to update that oversight in response to new information, evolving risks, and technological advances.

b. The United States: multi-agency governance and indirect regulation

In the United States (US), AI governance in agriculture is best characterized as a distributed, multi-agency system rather than a single binding AI law, operating through federal strategies, agency guidance, technical standards, and sector-specific policies (NIST, 2023; White House, 2025; Baerlocher et al., 2026). Federal policy emphasizes principles such as safety, transparency, bias awareness, and data protection, aligning with internationally recognized frameworks such as the OECD AI Principles (OECD, 2023), and is operationalized through agency guidance, procurement requirements, and program conditions rather than direct statutory mandates. The USDA's AI strategy exemplifies this approach by foregrounding data readiness, documentation, validation, and monitoring across the AI lifecycle (USDA, 2025). This governance-by-process model closely mirrors themes in the academic literature, which repeatedly identify explainability, dataset quality, and auditability as binding constraints on AI deployment in food and environmental contexts (Miller et al., 2025; Vitale et al., 2025). This aligns with the NIST AI Risk Management Framework (NIST, 2023), which emphasizes lifecycle governance.

This functional, activation-based logic is illustrated in Table 2, which maps common agricultural AI system types to the regulatory triggers they are most likely to activate in the US, EU, UK, China, and other international contexts. Rather than cataloging laws, the table shows how AI governance in agriculture emerges through overlapping safety, data, and food-system regimes depending on system design and use.

Data governance represents a second pillar of U.S. AI regulation in agriculture, driven less by federal statute than by state privacy laws and private contractual arrangements.[9] Agricultural AI routinely involves person-linked data (such as worker monitoring), commercially sensitive farm management data, and compliance records tied to traceability and certification. The literature converges on two dominant governance levers: contractual control over data rights and privacy- or security-by-design approaches that limit misuse and enable accountability (McFadden et al., 2023). Wu et al. (2025), for example, show that fragmented data ownership and weak privacy protections constrain dataset sharing, directly shaping which AI systems are trainable, transferable, and certifiable. Recent assessment of U.S. federal policy also identifies data rights, privacy, cybersecurity, and equitable access for small- and medium-scale producers as important unresolved policy issues (Baerlocher et al., 2026).

Safety governance for autonomous and semi-autonomous agricultural machinery further illustrates how standards operate as de facto regulation.[10] In the absence of a unified federal statute, compliance is guided by consensus standards, most notably ISO 18497 (ISO, 2018), as well as tort liability, insurance requirements, and contractual risk allocation. Aby and Issa (2023) document how such standards structure safety expectations around perception, control, and supervision, while also highlighting gaps between standardized test proxies and real-world farming conditions. Once referenced by insurers, procurement rules, or courts, these standards effectively function as enforceable governance instruments. However, compliance with standards alone does not guarantee safety under real-world agricultural conditions (Aby and Issa, 2023; Aquino et al., 2024). This reflects a broader shift toward "soft law" instruments becoming de facto regulatory mechanisms in AI governance.[11]

Finally, food traceability has emerged as a powerful indirect driver of AI governance under Section 204 of the Food Safety Modernization Act.[12] Although not an AI law, FSMA 204 imposes structured, interoperable recordkeeping obligations that increasingly shape AI system design, from data models and audit trails to anomaly detection and digital twins (U.S. Food and Drug Administration (FDA), 2022). The literature treats traceability-oriented AI as both a compliance solution and a new governance challenge, raising questions about data security, interoperability, and computational burden, issues that are central to adaptive regulation (Singh,

[9] U.S. data governance in agriculture is shaped by a combination of state-level privacy statutes (e.g., the California Consumer Privacy Act and the Virginia Consumer Data Protection Act), federal sectoral rules, and private contracting over farm data rights, rather than a single comprehensive federal data protection law (OECD, 2023; USDA, 2025).
[10] Liability relies on product liability, negligence, and contracts rather than AI-specific law (Basu et al., 2020).
[11] "Soft law" refers to non-binding instruments such as technical standards, guidelines, and best practices that can acquire regulatory force when incorporated into contracts, insurance requirements, or judicial reasoning; such instruments are widely recognized as central to the governance of emerging technologies and transnational regulatory regimes (Abbott & Snidal, 2009; OECD, 2023).
[12] Traceability rules shape AI system design via recordkeeping and auditability (U.S. Food and Drug Administration (FDA), 2022; FAO, 2022).

2025; Ahmad et al., 2025). AI applications in grain storage and supply chains raise new regulatory concerns about data security and system reliability (Anukiruthika & Jayas, 2025).

Table 2: Functional Regulatory Activation Across Agricultural AI Systems in the United States, with Comparative International References

AI system type	Primary AI function	Primary risk category	Likely U.S. regulatory triggers	Comparative international reference
Autonomous tractor / robotic weeder	Cyber-physical actuation	Physical safety; harm to people or property	ISO 18497-style safety expectations; product liability; contractual risk allocation; workplace safety regimes	Risk-based classification, machinery safety requirements, conformity assessment, and lifecycle monitoring are increasingly emphasized in the EU and other jurisdictions.
AI decision support for input use/irrigation/fertilizer/chemicals	Recommendations and optimization	Economic, environmental, and resource-management harm	Contractual liability; environmental compliance when recommendations affect pesticide, nutrient, or water-use decisions; state and federal environmental requirements	Growing international attention to accountability, water security, environmental compliance, and resilience of critical agricultural infrastructure.
Vision AI for food quality or safety inspection	Inspection and classification	Food safety and compliance	FDA program expectations; FSMA recordkeeping and audit-trail requirements; verification and validation obligations	International frameworks increasingly emphasize validation, auditability, transparency, and explainable AI for food

AI system type	Primary AI function	Primary risk category	Likely U.S. regulatory triggers	Comparative international reference
				safety and quality assurance systems.
Traceability analytics / blockchain-enabled scoring and alerts	Monitoring, scoring, and alerts	Compliance and supply-chain integrity	FSMA 204 recordkeeping requirements; chain-of-custody accountability; FDA enforcement expectations	Convergence across jurisdictions around data governance, interoperability, cybersecurity, auditability, and cross-border traceability standards.
Digital twin of grain storage or elevator systems	Simulation, prediction, and optimization	Safety, quality, cybersecurity, and infrastructure reliability	Contracts and private standards govern operational liability, food safety programs, cybersecurity expectations, and system reliability	Emerging international focus on cyber-physical resilience, protection of critical food infrastructure, predictive safety monitoring, and lifecycle validation of AI-enabled systems.

Source: Author's synthesis based on OECD (2023); USDA (2025); FDA (2022); European Union (2024); Al-Maamari (2025); Basu et al. (2020); McFadden et al. (2023); ISO (2018).

Note: The table focuses on regulatory activation pathways in the United States while highlighting broader international governance trends. Comparative references draw primarily on developments in the European Union, the United Kingdom, China, and emerging OECD-aligned governance frameworks.

c. The European Union: systems-level AI regulation

The European Union provides an important comparative benchmark because the EU AI Act represents the most comprehensive risk-based AI governance framework currently in force. Unlike the decentralized U.S. approach, the EU integrates AI regulation with data protection, product safety, and food law through a harmonized statutory framework. Agricultural applications embedded in regulated machinery or worker-monitoring systems may be classified as high-risk, thereby triggering obligations for risk management, documentation, conformity assessment, and human oversight. These requirements operate alongside the GDPR.[13] and related product-safety legislation, creating a more centralized and compliance-oriented governance model than that found in the United States (European Union, 2024; OECD, 2023; Al-Maamari, 2025).

Recent OECD analysis shows that AI uptake in European agriculture is concentrating in agricultural robotics, predictive analytics, and crop, soil, and livestock monitoring, while responsible scaling remains constrained by financing, skills, infrastructure, data access, and institutional capacity (OECD, 2026).

d. Comparative perspectives from other jurisdictions

Although the United States and the European Union currently dominate global AI governance debates, other jurisdictions are developing alternative regulatory approaches that could have implications for agriculture and food systems. China has adopted a centralized, state-led model that combines algorithm registration requirements, data governance rules, and sector-specific oversight with broader national technology objectives (Al-Maamari, 2025). This approach enables rapid implementation and large-scale deployment of AI systems but places less emphasis on independent oversight and public transparency than Western regulatory frameworks.

The United Kingdom has pursued a more flexible, sector-specific strategy that relies on existing regulators rather than a dedicated AI statute. This approach emphasizes innovation and regulatory agility while allowing sectoral authorities to tailor governance requirements to specific contexts (Al-Maamari, 2025). In this respect, the UK approach is structurally closer to the decentralized U.S. model than to the EU's comprehensive horizontal framework, although the UK places greater emphasis on coordinating common AI governance principles across existing sectoral regulators. Similarly, Brazil and several emerging economies are developing AI governance frameworks that draw on OECD principles, risk-based oversight, and data protection laws while adapting these concepts to domestic institutional capacities and development priorities.

[13] The General Data Protection Regulation (GDPR) establishes baseline data protection requirements across the European Union, including restrictions on automated individual decision-making and profiling (Articles 13–15, 22), alongside broader obligations relating to transparency, accountability, and data governance (European Union, 2016).

Despite these differences, a common pattern is emerging across jurisdictions. Most frameworks increasingly emphasize risk assessment, transparency, accountability, and lifecycle governance rather than technology-specific prohibitions. This convergence suggests that agricultural AI governance is likely to evolve through a combination of international norms, technical standards, and sector-specific regulatory adaptations rather than through a single globally harmonized framework.

e. Cross-cutting themes in the literature

Across jurisdictions, several cross-cutting governance themes recur in the literature. A recent review of AI governance in agriculture similarly identifies liability, transparency, privacy and security, algorithmic bias, data quality, and inclusive stakeholder participation as core elements of sector-specific governance (Ragany et al., 2026). Consistent with this broader synthesis, three cross-cutting issues emerge most prominently from the regulatory literature reviewed in this paper. First, liability and accountability remain central, particularly when AI-driven decisions generate economic, environmental, or safety harms (Aquino et al., 2024; Al-Maamari, 2025). Legal analyses emphasize that liability is typically resolved through a combination of standards, documentation, and contractual allocation of responsibility, making written agreements and audit trails critical governance artifacts (Basu et al., 2020).

Second, explainability and traceability emerge not merely as ethical ideals but as functional compliance requirements (Singh, 2025). In agri-food systems, transparent decision logic is often necessary for audits, incident response, and regulatory review, especially where AI outputs affect food safety or farm incomes.

Third, dataset standardization and interoperability constitute a hidden regulatory bottleneck (Miller et al., 2025; Yuan and Sun, 2025). While regulators can mandate documentation and audits, fragmented data ecosystems raise compliance costs and disproportionately burden smaller actors (Mana et al., 2024). The literature suggests that without progress on shared data standards, adaptive regulation risks reinforcing structural inequalities in AI adoption by increasing compliance burdens and limiting access to high-quality datasets (OECD, 2023; World Bank, 2025).

These recurring documentation and evidence requirements are summarized in Appendix Table 1, which links core governance concepts such as risk assessment, explainability, and data governance to the concrete artifacts typically requested by regulators, insurers, and auditors. Collectively, these themes reinforce the view that effective governance of agricultural AI extends beyond technical performance to encompass transparency, accountability, data stewardship, interoperability, stakeholder engagement, and adaptive institutional arrangements capable of evolving alongside technological change (Omotayo et al., 2025). Together, these governance mechanisms help build stakeholder trust by making AI systems more transparent, accountable, and auditable across agricultural decision contexts. This synthesis provides the conceptual

foundation for the adaptive regulatory framework and case study analysis developed in the following sections.

IV. Case Studies: Operationalizing Adaptive Regulation for AI in Agriculture and Food Systems

This section applies the analytical framework developed in Section 2 to three agricultural AI applications representing distinct functions, risk profiles, and regulatory contexts. To translate conceptual analysis into institutional practice, this section develops three case studies of AI systems reshaping agriculture and food systems: (1) drone-based crop monitoring, (2) AI-driven irrigation management, and (3) blockchain-enabled supply-chain traceability. Each case demonstrates how AI governance is activated through existing regulatory regimes, how risks and benefits are distributed, and how adaptive mechanisms can balance innovation with accountability. The selected cases also correspond to major application areas identified in recent European policy analysis, including predictive analytics, automated agricultural systems, and crop and soil monitoring (OECD, 2026).

The case studies evaluate AI systems relative to the conventional technologies and management practices they are designed to supplement or replace. The governance question is therefore not whether risks exist in absolute terms, since many agricultural activities already involve operational, environmental, and compliance risks, but whether AI changes the likelihood, scale, speed, or distribution of those risks. Throughout the analysis, regulatory pressure points are assessed relative to these existing baselines, with attention to both risk reduction and the emergence of new forms of governance concern.

a. Case Study 1: Drone-Based Crop Monitoring

i. Vignette

A midwestern grain farm deploys unmanned aerial vehicles (UAVs) equipped with multispectral and thermal sensors. Machine-learning models process imagery to detect crop stress, nutrient deficiencies, and pest outbreaks (Wu et al., 2025; Mana et al., 2024), generating variable-rate application maps for fertilizer and pesticide use. Although the AI does not directly actuate machinery, its outputs materially influence regulated decisions, raising governance concerns around decision-support AI systems (OECD, 2023).[14]

ii. Baseline Comparison

The relevant baseline is conventional crop monitoring based on manual field scouting, farmer experience, agronomist recommendations, and, in some cases, satellite imagery. Many of the risks identified in Table 3, including pesticide misapplication, inaccurate diagnosis of crop stress,

[14] Agricultural drones operate under aviation, environmental, and data regulations (Wu et al., 2025; OECD, 2023).

and non-compliance with pesticide labels, already exist under traditional decision-making systems. The governance significance of AI-enabled drone monitoring lies not in creating entirely new risks, but in altering their scale and propagation. Errors embedded in algorithmic recommendations may be rapidly disseminated across large areas, while highly accurate systems may substantially reduce input misuse and environmental impacts. Regulatory attention, therefore, focuses on validating model performance, documenting decision logic, and ensuring that AI-assisted recommendations remain consistent with existing compliance obligations.

iii. Risk-Benefit Profile

Table 3: Risk-Benefit Profile

Dimension	Potential Benefits	Governance Risks / Regulatory Pressure Points
Productivity	Earlier detection of stress; improved timing of interventions	Overreliance on model outputs in heterogeneous conditions
Environmental performance	Reduced chemical inputs via precision targeting	Inaccurate prescriptions leading to over-application or drift
Worker safety	Reduced manual scouting exposure	UAV flight safety and exposure risks
Data governance	Field-level performance insights	Data ownership disputes; cybersecurity vulnerabilities
Compliance	Machine-generated documentation	Misalignment with pesticide label restrictions

Source: FAO (2022); Wu et al. (2025).

iv. Adaptive Governance Roadmap

Adaptive governance begins with the functional activation of regulation. Because UAV-generated prescriptions shape pesticide and fertilizer applications, environmental, labeling, and occupational regimes are implicated, consistent with the multi-regime governance of AI-enabled agricultural systems documented in the literature (Basu et al., 2020; McFadden et al., 2023). Oversight, therefore, requires mapping how these standards apply when AI outputs guide regulated conduct and embedding compliance constraints within system design.

A second component involves updating legacy risk assumptions. Many pesticide drift and exposure models were developed for conventional application methods. They may not fully capture UAV-specific operating characteristics, a limitation widely noted in safety assessments of automated agricultural systems (Aby & Issa, 2023). Targeted empirical data collection and periodic reassessment allow regulatory benchmarks to evolve alongside technological practice.

Third, compliance obligations can be translated into machine-readable guardrails within prescription tools, preventing recommendations that violate regulatory limits (OECD, 2023; ISO, 2018). This shifts enforcement from ex post correction to ex ante design.

Finally, lifecycle monitoring is essential. As models are retrained across seasons and environments, continuous documentation and drift detection enable iterative alignment with safety and environmental objectives (National Academies, 2017; OECD, 2023). This case highlights how even non-autonomous AI systems can trigger regulatory oversight when their outputs shape compliance-relevant decisions, underscoring the importance of governance frameworks that account for indirect system effects.

b. Case Study 2: AI-Driven Irrigation Management

i. Vignette

A specialty crop producer adopts an AI-based irrigation platform integrating soil sensors, weather forecasts, and evapotranspiration models (Wu et al., 2025; Mmbando, 2025). In some configurations, the system directly actuates pump controls. Errors may result in crop loss, groundwater depletion, or infrastructure damage.[15]

ii. Baseline Comparison

The appropriate baseline for comparison is conventional irrigation scheduling based on farmer judgment, fixed calendars, extension recommendations, or rule-based sensor systems. Risks such as under-irrigation, over-irrigation, crop stress, and infrastructure failure are not unique to AI-enabled systems. However, AI changes the decision architecture by increasing automation and reducing direct human involvement in routine operational decisions. While AI may improve responsiveness to changing weather and soil conditions, model errors, sensor failures, or cybersecurity breaches can propagate more rapidly through automated systems than through conventional management approaches. Consequently, governance concerns focus less on the existence of irrigation risk itself and more on the degree of autonomy, accountability, and resilience embedded within the decision process.

[15] AI control systems raise accountability and reliability concerns (Mana et al., 2024; OECD, 2023).

iv. *Risk-Benefit Profile*

Table 4: Risk-Benefit Profile

Dimension	Potential Benefits	Governance Risks / Regulatory Pressure Points
Water efficiency	Reduced over-irrigation; improved water productivity	Model failure under extreme weather conditions
Climate resilience	Dynamic adaptation to variability	Sensor malfunction risks
Labor efficiency	Automated scheduling	Automation bias and reduced oversight
Infrastructure stability	Coordinated water management	Cybersecurity threats; cascading risk
Liability exposure	Documented optimization decisions	Unclear liability allocation for automated harm

Source: FAO (2022); World Bank (2025).

v. *Adaptive Governance Roadmap*

Adaptive oversight begins with proportionate risk scaling. Recommendation systems primarily raise economic and environmental risks, whereas automated control systems introduce safety and infrastructure concerns. Regulatory intensity should therefore reflect system autonomy and harm potential, consistent with risk-based AI governance frameworks that scale obligations according to these factors (European Union, 2024).

Embedded safeguards form the second pillar. Human override mechanisms, confirmation thresholds, and emergency shutdown features reduce automation bias and limit cascading harm when anomalies occur (Aby & Issa, 2023). Third, lifecycle validation ensures accountability. Structured hazard analyses, validation across diverse conditions, and drift monitoring clarify the boundaries of model performance and support post-incident review (Wu et al., 2025; National Academies, 2017).

Finally, resilience and cybersecurity are integral. Because irrigation platforms rely on networked sensors and infrastructure (OECD, 2024; World Bank, 2025), security baselines and incident protocols are necessary to prevent digital vulnerabilities from producing physical or

environmental damage. Adaptive regulation here rests on calibrated oversight, embedded safeguards, and continuous validation. This case demonstrates that increasing system autonomy fundamentally alters the regulatory profile of AI applications, requiring a shift from informational oversight to safety-critical governance.

c. Case Study 3: Blockchain-Enabled Supply Chain Traceability

i. Vignette

A produce distributor implements a blockchain-based traceability system that records harvesting, packing, shipping, and receiving events, supporting compliance with FSMA 204 requirements (U.S. FDA, 2022; Anukiruthika & Jayas, 2025).[16] AI analytics flag anomalies and contamination risks, supporting compliance with FSMA 204 requirements (U.S. FDA, 2022; Anukiruthika & Jayas, 2025).

ii. Baseline Comparison

The relevant comparators are traditional traceability systems based on paper records, enterprise resource planning systems, and manually maintained supply chain documentation. Traceability failures, data errors, and incomplete audit trails have long been recognized as challenges in food safety governance. AI-enabled blockchain systems can improve the speed, transparency, and accuracy of traceback processes, but they also introduce new governance concerns related to data interoperability, algorithmic scoring, cybersecurity, and the persistence of erroneous information within distributed ledgers. Regulatory scrutiny, therefore, focuses on whether digital systems improve accountability relative to existing approaches while maintaining mechanisms for error correction and oversight.

[16] Blockchain systems support compliance in food safety and supply chains (McFadden et al., 2023; FDA, 2022).

iii. Risk-Benefit Profile

Table 5: Risk-Benefit Profile

Dimension	Potential Benefits	Governance Risks / Regulatory Pressure Points
Food safety	Faster traceback and targeted recalls	False-positive alerts harming suppliers
Regulatory compliance	Structured CTE and KDE documentation	Interoperability challenges
Consumer trust	Increased transparency	Exposure of sensitive commercial information
Supply-chain efficiency	Reduced recall costs	Immutable erroneous data risks
Cross-border trade	Alignment with digital compliance expectations	Jurisdictional data protection conflicts

Source: FAO (2022); World Bank (2025).

iv. Adaptive Governance Roadmap

Governance begins with regulatory anchoring. Ledger architecture should align directly with critical tracking events and key data elements required by food safety law, ensuring that the digital infrastructure supports existing compliance obligations (FDA, 2022). Second, embedded data quality controls are essential. Because distributed ledgers amplify data permanence, validation checks, periodic audits, and calibrated anomaly detection reduce the risk of entrenched inaccuracies (OECD, 2023). Third, institutional clarity supports accountability. Contractual provisions defining data entry responsibilities and correction procedures are as important as technical robustness in multi-actor ecosystems (Basu et al., 2020; McFadden et al., 2023).

Finally, interoperability and staged implementation promote durable adoption. Standardized data schemas and phased rollout reduce fragmentation and allow oversight practices to mature incrementally (OECD, 2023; World Bank, 2025). Adaptive regulation thus integrates digital innovation into established food safety governance while preserving trust. This case illustrates how AI governance may be embedded within existing regulatory infrastructures, with digital systems becoming integral to compliance rather than external to it.

d. Cross-Case Insights

Across all three cases, governance risks are best understood relative to existing agricultural practices rather than as entirely novel hazards. In most instances, AI modifies the scale, speed, autonomy, and distribution of risks already present in agricultural production and food-system management.

The governance principles identified below emerge from structured comparison across the three cases using the common analytical framework described in Section 2. Regulation is activated functionally rather than categorically (OECD, 2023; Val, 2025): AI systems are governed based on what they do, whether influencing pesticide application, actuating infrastructure, or generating traceability records rather than by virtue of being labeled "AI." As a result, governance typically arises through environmental, safety, and food-system regimes rather than through stand-alone AI statutes.

Documentation serves as core governance infrastructure (National Academies, 2017; Wu et al., 2025). Hazard analyses, validation reports, audit trails, and traceability logs operationalize accountability and enable institutional review in systems that evolve through retraining and redeployment. Effective oversight also requires proportionate scaling (EU, 2024; OECD, 2023). Decision-support tools raise different concerns than autonomous control systems; therefore, adaptive regulation calibrates intensity in response to autonomy, risk, and systemic impact.

Finally, governance must be iterative (Marchant et al., 2011; OECD, 2024). Because AI systems change with data and deployment context, static ex ante rules are insufficient. Continuous monitoring and periodic reassessment sustain regulatory alignment over time. Together, these insights reinforce the paper's central claim: adaptive governance in agriculture rests on functional regulatory activation, documentation-based accountability, proportionate oversight, and institutional learning. The following section builds on these principles to articulate a consolidated adaptive regulatory framework.

The conclusions drawn from these cases should be interpreted as analytical rather than predictive. The selected applications are intended to illustrate variation across agricultural AI systems rather than provide a representative sample of all AI technologies used in agriculture. Nevertheless, because the cases span different levels of autonomy, regulatory exposure, and operational function, the recurring governance themes identified here provide a useful basis for developing broader adaptive governance principles and for guiding future empirical evaluation.

V. Comparative Lessons from Adaptive Regulation in Other Sectors

Comparative experience from other technology-intensive sectors offers valuable insights into adaptive governance mechanisms relevant to agriculture. Domains such as financial technology

(fintech), digital health, and autonomous systems have faced challenges similar to those emerging in agricultural AI, including rapid technological innovation, uncertainty regarding system risks, and the need to balance experimentation with public safeguards (Marchant et al., 2011; OECD, 2023). These sectors have developed governance mechanisms such as regulatory sandboxes, lifecycle monitoring, and standards-based oversight that help manage technological uncertainty while maintaining accountability and public oversight (Abbott & Snidal, 2009; Marchant et al., 2011; OECD, 2023). Because agricultural AI systems likewise evolve through ongoing model updates and deployment across diverse environmental and operational contexts, these adaptive regulatory approaches provide useful lessons for designing governance frameworks that support both innovation and responsible oversight (Krause, 2025; Wu et al., 2025).

a. Regulatory Sandboxes and Controlled Experimentation

One widely cited adaptive governance mechanism is the regulatory sandbox, first developed in financial technology regulation in jurisdictions such as the United Kingdom and Singapore (OECD, 2023; World Bank, 2020). Sandboxes allow firms to test innovative technologies under temporary regulatory supervision, typically with limited-scale deployment, defined risk controls, and structured reporting obligations (OECD, 2023; Krause, 2025). This approach enables regulators to observe real-world system behavior while maintaining safeguards for consumers and markets.

Several lessons from fintech sandboxes are relevant for agricultural AI. First, sandbox environments provide regulators with empirical evidence about technology performance, reducing the information asymmetry that often characterizes emerging technologies. Second, sandbox participation encourages early dialogue between developers and regulators, allowing governance expectations such as documentation standards, transparency requirements, and safety protocols to be integrated into system design. Third, sandbox frameworks create institutional learning loops in which insights from experimental deployments inform future regulatory guidance and standards (Krause, 2025; OECD, 2023).

Applied to agriculture, sandbox-style mechanisms could support pilot deployments of AI-enabled systems such as autonomous machinery, decision-support platforms, or digital traceability infrastructure. Similar experimentation frameworks have been proposed for robotics and autonomous agricultural systems, where regulatory uncertainty and safety concerns complicate large-scale deployment (Basu et al., 2020; Wu et al., 2025).

b. Iterative Approval and Lifecycle Oversight in Health Technologies

A second instructive model comes from the regulation of digital health technologies and medical AI systems. In these domains, regulators increasingly recognize that machine-learning models evolve through retraining and continuous data updates (OECD, 2023; National Academies,

2017). Traditional one-time approvals, therefore, struggle to ensure safety over the full lifecycle of AI-enabled products.

To address this challenge, regulators have begun adopting iterative or lifecycle-based oversight models (Marchant et al., 2011; OECD, 2024). These frameworks typically combine initial approval based on documented performance with ongoing post-deployment monitoring, periodic revalidation, and requirements for documenting model updates. The objective is to ensure that regulatory oversight evolves alongside the technology itself.

The underlying principle, continuous validation rather than static certification, has clear relevance for agricultural AI systems. Many agricultural applications, such as crop prediction models, irrigation optimization systems, or pest detection algorithms, rely on datasets that change across seasons, regions, and climate conditions. Lifecycle governance mechanisms that incorporate performance monitoring and documented model updates, therefore, offer a more realistic regulatory structure for these technologies (FAO, 2022; Wu et al., 2025).

c. Co-Regulation and Standards-Based Governance

Adaptive governance in several sectors also relies heavily on co-regulation and standards-based oversight. Rather than relying exclusively on statutory rules, regulators often incorporate technical standards developed by industry bodies or professional organizations into compliance frameworks (Abbott & Snidal, 2009; OECD, 2023). These standards translate high-level regulatory objectives such as safety, reliability, and transparency into testable engineering requirements.

This model is particularly visible in sectors involving cyber-physical systems. In agriculture, safety governance for automated machinery already relies heavily on consensus standards that guide system design, testing, and risk assessment (Aby & Issa, 2023; ISO, 2018). Once incorporated into procurement requirements, certification schemes, or liability frameworks, such standards effectively function as enforceable governance instruments.

Standards-based governance may therefore provide a practical pathway for regulating AI-enabled agricultural technologies. Because these systems combine digital analytics with physical operations, regulatory frameworks that integrate technical standards with legal oversight can provide flexibility while maintaining safety and accountability (Basu et al., 2020; OECD, 2023).

Taken together, these sectors differ in how regulatory authority is exercised and how uncertainty is managed (Table 6). Fintech emphasizes controlled experimentation through sandbox environments, health technologies prioritize lifecycle monitoring and post-market oversight, and autonomous systems rely heavily on technical standards and safety validation. These differences reflect variation in risk tolerance, institutional capacity, and the consequences of system failure, offering a structured basis for translating adaptive governance approaches into the agricultural context.

Table 6: Adaptive Regulatory Mechanisms Across Sectors

Sector	Adaptive regulatory tool	Key lesson for agricultural AI governance
Financial technology (fintech)	Regulatory sandboxes	Controlled experimentation allows regulators to observe emerging technologies under supervision while generating empirical evidence to guide future rulemaking.
Digital health and medical AI	Iterative approval and lifecycle monitoring	AI systems require ongoing validation and monitoring because models evolve through retraining and data updates.
Autonomous systems and robotics	Standards-based safety frameworks	Technical standards translate safety principles into testable engineering requirements and can function as de facto regulatory instruments.
Cross-sector AI governance	Risk-based and adaptive regulatory frameworks	Governance should scale with system autonomy and risk while incorporating feedback loops and institutional learning.

Source: Adapted from OECD (2023); Marchant et al. (2011); National Academies (2017).

d. Transferable Governance Principles

Across these sectors, several common governance principles emerge that are directly applicable to AI regulation in agriculture and food systems (OECD, 2023; National Academies, 2017).

First, adaptive regulation emphasizes controlled experimentation, allowing regulators to observe system performance in supervised environments before widespread deployment. Second, oversight increasingly occurs across the technology lifecycle, combining ex ante evaluation with ongoing monitoring and iterative adjustment. Third, governance frameworks frequently rely on collaborative arrangements between regulators, industry actors, and standards bodies to translate regulatory objectives into operational safeguards (Marchant et al., 2011; OECD, 2024).

The broader international experience also suggests that agricultural AI governance is likely to remain institutionally diverse. Whereas the EU relies on comprehensive statutory regulation and the United States emphasizes distributed sectoral oversight, jurisdictions such as China and the United Kingdom illustrate alternative pathways based on centralized state coordination or regulator-led flexibility. Emerging economies, including Brazil and India, are increasingly drawing on OECD principles and international standards while adapting governance frameworks to local agricultural priorities and institutional capacities. These differences underscore the importance of adaptive governance mechanisms that can operate across diverse legal and regulatory environments.

These lessons reinforce the central premise of this study: effective governance of AI systems requires regulatory institutions capable of learning alongside technological change. By adapting mechanisms such as regulatory sandboxes, lifecycle monitoring, and standards-based co-regulation, policymakers can develop oversight frameworks that maintain accountability while supporting innovation in agriculture and food systems (OECD, 2023; Val, 2025; Werner, 2024).

Recent reviews likewise conclude that successful agricultural AI governance requires technical safeguards to be complemented by institutional capacity, stakeholder participation, transparent data governance, and continuous policy adaptation as technologies evolve (Omotayo et al., 2025).

VI. Conclusion

This paper examined how emerging regulatory frameworks are responding to the rapid integration of artificial intelligence (AI) technologies across agriculture and food systems. As AI-enabled tools, ranging from autonomous machinery and precision agriculture platforms to predictive analytics and digital supply-chain systems, become increasingly embedded throughout the agrifood value chain, regulators face the challenge of ensuring that governance frameworks remain effective amid rapid technological change and uncertainty.

The analysis focused primarily on emerging U.S. approaches to agricultural AI governance while drawing comparative lessons from the European Union's risk-based regulatory framework and broader international developments. These frameworks increasingly rely on risk-based regulatory approaches, in which oversight is calibrated according to the potential harms associated with specific AI applications. Within the agrifood sector, many AI systems fall into categories related to safety components of agricultural machinery, decision-support systems, and digital infrastructure that supports food supply chains.

At the same time, the study identified several important governance gaps in current regulatory approaches. Some AI systems with potentially significant implications for food security and agricultural resilience, such as those that manage critical food infrastructure or supply chain logistics, may fall outside existing high-risk classifications. In addition, current definitions of

"safety components" tend to focus primarily on mechanical hazards, potentially overlooking broader agrifood risks, including food safety, environmental impacts, biodiversity loss, and animal welfare concerns. More fundamentally, risk-based frameworks often struggle to keep pace with the dynamic nature of AI systems, which evolve through continuous data updates and adaptive learning.

To address these challenges, the paper drew lessons from adaptive regulatory approaches developed in other technology-intensive sectors such as financial technology, digital health, and autonomous systems. Comparative analysis suggests that governance tools, including regulatory sandboxes, lifecycle monitoring, and standards-based co-regulation, can help regulators manage technological uncertainty while maintaining effective oversight. These mechanisms emphasize regulatory learning, iterative supervision, and collaboration between regulators, industry actors, and standards bodies, features that are particularly relevant for governing rapidly evolving agricultural technologies. The practical effectiveness of this approach, however, depends on institutional capacity for retrospective review and on mechanisms that translate post-deployment evidence into regulatory adjustment.

The study contributes to the emerging literature on AI governance in agriculture in several ways. It provides a structured overview of how agricultural AI applications intersect with existing regulatory frameworks, identifies key governance gaps that may arise as AI becomes more deeply embedded in food systems, and highlights adaptive regulatory tools that may support more flexible and responsive oversight. By bringing the agrifood sector into broader debates on AI governance, where attention has largely focused on finance, healthcare, and digital platforms, the paper also helps extend the scope of current regulatory scholarship.

Looking ahead, effective governance of AI in agriculture will require regulatory frameworks that can evolve alongside technological change. Agricultural systems involve complex interactions among technological, environmental, and socio-economic factors, meaning that AI regulation must address not only technical risks but also broader societal values related to food security, environmental sustainability, and rural livelihoods. Ensuring that regulatory institutions can evolve alongside AI innovation will be critical for harnessing the benefits of these technologies while safeguarding the resilience, sustainability, and security of global food systems.

Future research could extend this framework to other agricultural AI applications with different functions, levels of autonomy, and regulatory exposure. Promising areas include autonomous farm machinery and robotics, AI-enabled livestock management, precision pesticide and fertilizer application, and AI-supported food processing and quality assurance. Comparative analysis across these applications could further test and refine the function-based and adaptive risk-governance framework developed here.

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Appendix

Appendix Table 1: Evidence and documentation checklist for AI systems in agriculture

Evidence artifact	Why it matters	Link to literature / policy sources
Hazard analysis & risk assessment (e.g., HARA, FMEA, FTA)	Demonstrates systematic identification, evaluation, and mitigation of safety and operational risks associated with AI-enabled systems.	Aby & Issa (2023) summarize core risk-analysis methods and their limitations in AI-enabled and automated systems.
Standard conformance mapping (e.g., ISO 18497 clauses → test cases)	Translates voluntary or consensus standards into auditable, testable claims that can be assessed by regulators or insurers.	ISO 18497 scope and principles for agricultural field-operation safety (ISO, 2018).
Model documentation (data provenance, performance bounds, validation results, drift monitoring)	Enables accountability, reproducibility, post-incident review, and ongoing oversight of model behavior over time.	Wu et al. emphasize transparency, traceability, and lifecycle documentation for AI governance.
Data governance plan (access control, privacy protections, retention, bias and misuse risks)	Reduces legal, ethical, and operational risks related to data use; supports scalability across jurisdictions and supply chains.	Dataset governance and privacy constraints are highlighted by Wu et al. and related AI governance literature.
Traceability logs (lot- and event-level linkage; immutable audit trails where feasible)	Supports regulatory traceability requirements, rapid recalls, and post-event investigations across food supply chains.	FDA FSMA traceability compliance framework (U.S. Food and Drug Administration, 2022).