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GREEN AI IN SUSTAINABLE AGRICULTURE: ECONOMIC EFFICIENCY AND LEGAL LIABILITY

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ABSTRACT

This article explores two interrelated aspects of implementing Green Artificial Intelligence (Green AI) in sustainable agriculture: the economic efficiency of such investments and the gaps in the legal framework governing liability for potential damages. Amidst the growing adoption of precision farming systems, there is a persistent lack of research that quantitatively assesses investment risks at the farm level, alongside a near absence of analysis concerning the legal implications of using autonomous agricultural machinery. Employing a mixed-method approach, the authors conduct stochastic investment modeling for various Green AI technology configurations and a comparative legal analysis of the regulatory frameworks in Russia, the EU, and the USA. The findings demonstrate the commercial attractiveness of these solutions for medium-sized grain farms; however, they also reveal a significant dependence of profitability on external market factors and confirm the presence of considerable downside risks. The legal analysis identifies a systemic normative vacuum: none of the jurisdictions examined have specific sectoral rules governing tort liability for damage caused by autonomous agricultural systems, and existing mechanisms (contract law, product liability directives) are not adapted to the specific nature of self-learning algorithms. The novelty of this work lies in its interdisciplinary synthesis of economic and legal approaches, allowing quantifiable economic uncertainty and legal unpredictability to be viewed as interconnected barriers. The conclusions provide an evidence base for developing targeted subsidy mechanisms, risk-sharing instruments, and, critically, for reforming liability regimes without which the scalable and responsible deployment of Green AI remains uncertain.

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1. INTRODUCTION

The global agricultural sector faces increasing pressure to ensure food security while minimizing environmental degradation. Traditional farming practices, including intensive tillage, mono-cropping, and excessive application of chemical fertilizers, have resulted in soil erosion, reduced microbial diversity, and long-term fertility decline (Mamatha & Shalini, 2025). In response, the integration of digital technologies into agricultural systems (often termed Agriculture 4.0) has gained scholarly and policy attention (Aijaz et al., 2025).

Within this technological transformation, Green Artificial Intelligence (Green AI) has emerged as a distinct research direction. Green AI prioritises energy-efficient, computationally parsimonious machine

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learning models, in contrast to "Red AI", which pursues predictive accuracy at the expense of resource consumption (Barbierato & Gatti, 2024). In agriculture, Green AI enables precision irrigation, autonomous weeding, real-time soil monitoring, and early disease detection. Existing studies report substantial reductions in water, fertiliser, and pesticide use through AI-driven resource optimization (Aijaz et al., 2025; Padmavathi, 2024).

However, a critical examination of the literature reveals two significant gaps.

First, the economic efficiency of Green AI technologies is not systematically quantified. The vast majority of studies focus on technical performance – model accuracy, sensor architecture, or percentage reductions in inputs (Kale et al., 2024, pp. 104-105). Farm-level cost-benefit analysis incorporating stochastic uncertainty (weather volatility, output price fluctuations, technology failure rates) remains absent from the literature (Aguzarova et al., 2024). Consequently, investment decisions by agribusinesses and agricultural policymakers lack an evidence-based foundation, and the diffusion of Green AI technologies is impeded by unquantified financial risk (Zhou et al., 2022, pp. 296-298).

Second, the legal liability arising from autonomous agricultural systems is virtually unexplored. Existing scholarship on AI regulation has predominantly focused on autonomous vehicles, healthcare applications, and financial algorithms. The specific challenges posed by AI-driven agricultural machinery (crop loss due to algorithmic error, off-target damage from precision spraying, and data ownership in farm-generated datasets) have received minimal scholarly attention (Delovoy Profil, 2026). This legal vacuum generates uncertainty for manufacturers, disincentivises the development of insurance instruments, and creates hidden transaction costs that impede the responsible deployment of autonomous agricultural systems (Kale et al., 2024, p. 105).

The present article addresses both gaps simultaneously. The aim of the study is twofold: (1) to quantify the economic viability of Green AI technologies in crop production using stochastic cost-benefit modelling; and (2) to identify and systematise, through comparative doctrinal analysis, the legal liability gaps arising from the deployment of autonomous agricultural systems across three jurisdictions (the European Union, the United States, and the Russian Federation).

The novelty and original contribution of this work reside in its interdisciplinary synthesis. It is the first study to: (a) apply stochastic modelling to the economic assessment of Green AI technologies using farm-level data from Russian agriculture; (b) systematically map liability gaps for autonomous agricultural systems across three jurisdictions (Russia, EU, US); and (c) integrate economic and legal analysis into a unified interdisciplinary framework.

The significance of this research extends beyond academic discourse. For policymakers, the study provides an evidence base for designing targeted subsidy mechanisms, risk-sharing instruments, and regulatory sandboxes that address the specific barriers faced by small and medium-sized agricultural enterprises. For technology vendors, the quantified probability distributions of investment outcomes offer a basis for product positioning, pricing strategies, and after-sales service models. For the legal community, the comparative liability gap maps identify priority areas for legislative intervention and harmonization, particularly in jurisdictions currently lacking any sector-specific norms. For farmers and agricultural cooperatives, the study articulates the conditions under which Green AI adoption becomes economically rational and legally predictable, thereby reducing the perceived risk of transitioning from conventional to data-driven farming practices.

2. LITERATURE REVIEW

This research is grounded in the intersection of two distinct but interconnected bodies of literature: studies on the technological and economic dimensions of Green AI in agriculture, and scholarship on legal regulation of artificial intelligence and liability for autonomous systems.

The concept of Green AI emerged as a response to the growing computational and energy demands of artificial intelligence systems. Barbierato and Gatti (2024) provide a methodological survey distinguishing Green AI, which prioritizes energy efficiency and computational parsimony, from "Red AI," which pursues predictive accuracy at the expense of resource consumption. This distinction has particular relevance for agricultural applications, where AI systems often operate in field conditions with limited connectivity and power supply.

The technological applications of AI in sustainable agriculture are well-documented. Aijaz et al. (2025) demonstrate that AI-driven precision agriculture can significantly advance crop productivity while reducing environmental impact through optimized application of water, fertilizers, and pesticides. Padmavathi (2024) presents an intelligent, cost-effective IoT-based irrigation system using machine learning, reporting substantial water savings and yield improvements. Mamatha and Shalini (2025) provide a comprehensive overview of AI-based green technologies for efficient agriculture, emphasizing their potential to address sustainability challenges. Specific technologies examined in the literature include autonomous driving systems for agricultural machinery (Zhou et al., 2022), precision agriculture drones (Kale et al., 2024), and IoT-based soil monitoring systems (Ayyappa et al., 2017). These studies consistently report environmental benefits, including reduced chemical inputs, optimized water usage, and minimized soil compaction from reduced machinery passes.

Despite the wealth of technical studies, the economic literature on Green AI adoption reveals significant gaps.

Kale et al. (2024, pp. 104-105) acknowledge that while the environmental benefits of AI in agriculture are well-established, comprehensive cost-benefit analyses at the farm level remain scarce. Zhou et al. (2022, pp. 296-298) note that the diffusion of AI technologies in agriculture is impeded by unquantified financial risk, particularly for small and medium-sized enterprises. Existing economic assessments tend to focus on partial indicators (percentage reductions in inputs or estimated yield increases) without incorporating stochastic uncertainty. Factors such as weather volatility, output price fluctuations, and technology failure rates are typically excluded from investment models (Mamatha & Shalini, 2025). This represents a critical gap, as agricultural production is inherently exposed to exogenous risks that fundamentally shape investment outcomes. Padmavathi (2024) emphasizes the importance of cost-effectiveness in IoT-based agricultural systems, but stops short of providing probabilistic investment analysis. Similarly, Ayyappa et al. (2017) focus on soil fertility assessment and nutrient management outcomes without translating these into comprehensive farm-level financial metrics.

The legal literature on AI liability has developed rapidly but unevenly across sectors. Scholarship on autonomous vehicles has generated the most extensive body of analysis, with courts and legislatures in multiple jurisdictions grappling with questions of tort liability, product liability, and insurance allocation (Wisconsin, 2017; Thaler v. Perlmutter, 2023). In the European Union, the adoption of Regulation 2024/1689 (Artificial Intelligence Act) represents the first comprehensive horizontal AI regulation globally (European Union, 2024). However, as the Act explicitly excludes civil liability from its scope, injured parties must rely on the Product Liability Directive (European Union, 1985)–an instrument designed for manufacturing defects in physical goods, not for adaptive, self-learning algorithms (European Union, 2016). The United States has developed case law on algorithmic decision-making in criminal justice (Wisconsin, 2016) and intellectual property (Thaler v. Perlmutter, 2023), but lacks any federal AI liability statute. Executive Order 14179 of December 2025 (United States, 2025) establishes federal pre-emption of state AI laws but creates no private right of action. In the Russian Federation, Article 1079 of the Civil Code establishes liability for harm caused by activities creating increased danger (Russian Federation, 1996). However, no Russian court has yet classified agricultural autopilots as sources of increased danger. Documented litigation against Cognitive Pilot in 2022-2024 proceeded on contract law theories (breach of warranty, non-conformity) rather than tort (RTVI, 2024; Delovoy Profil, 2026).

The literature review reveals two fundamental gaps that this study addresses. First, there is no systematic quantification of investment risk for Green AI technologies in agriculture. Existing studies provide technical performance metrics and environmental impact assessments but lack probabilistic cost-benefit analysis incorporating stochastic uncertainty. This gap leaves investment decisions by farmers and policymakers without an evidence-based foundation. Second, the legal liability framework for autonomous agricultural systems is virtually unexplored. While scholarship on AI liability has developed in other sectors, the specific challenges posed by AI-driven agricultural machinery (crop loss due to algorithmic error, off-target damage from precision spraying, and data ownership in farm-generated datasets) have received minimal attention. No comparative analysis of liability gaps across jurisdictions exists for this sector. The present study addresses both gaps through an interdisciplinary synthesis of economic modelling and comparative legal analysis.

3. METHODOLOGY

This study employs a mixed-method research design consisting of two distinct but interrelated components: economic modelling, a quantitative stochastic simulation using Monte Carlo method to assess the economic viability of Green AI technologies in crop production; and legal analysis, a qualitative comparative doctrinal analysis to identify and systematise liability gaps arising from the deployment of autonomous agricultural systems. The economic component provides an evidence base for investment decisions by agricultural enterprises and policymakers. The legal component examines the normative readiness of three jurisdictions (Russian Federation, European Union, United States) to address liability for damage caused by AI-driven farming machinery.

For the economic modelling, three commercially deployed Green AI systems are analysed: an autonomous driving system for combine harvesters and tractors (Cognitive Agro Pilot), an agricultural drone for precision irrigation and spraying (DJI Agras T50), and an IoT-based soil sensor for real-time moisture and electrical conductivity monitoring (SE01-NB). These technologies were selected on the basis of their documented deployment in Russian agriculture and their relevance to existing litigation (Padmavathi, 2024, pp. 381). Three investment scenarios are evaluated, corresponding to different configurations of commercially available Green AI technologies: autopilot-only, drone-only, and full integration of all three systems. The output indicators are Net Present Value (NPV), Internal Rate of Return (IRR), Payback Period, and Probability of Negative Return.

Stochastic variables include the sale price of wheat, the magnitude of yield increase attributable to AI, the percentage of water savings, and annual maintenance costs. These are modelled using triangular or uniform distributions to reflect uncertainty. Deterministic variables are the discount rate, the time horizon, and the farm size. The discount rate is set with reference to the Central Bank of Russia's key rate plus a risk premium. The time horizon of seven years corresponds to the typical service life of agricultural machinery. Farm size of 100 hectares represents a medium-scale commercial enterprise.

To ensure transparency and replicability, the economic calculations follow standard discounted cash flow methodology. Net Present Value is computed as:

$$NPV = \sum_{t=1}^{n} \frac{CF_t}{(1+r)^t} - I_0 \qquad (1)$$

where CF_t is the net cash flow in year t, r is the discount rate, I_0 is the initial investment (CAPEX), and t = 1…T (with T representing the time horizon). Annual net cash flow is derived as:

$$CF_t = (Y \times P) - (L_t + F_t + W_t + M_t) + S \quad (2)$$

where Y is crop yield, P is output price, L_t, F_t, W_t are baseline costs of labour, fertilisers, and water respectively, M_t represents maintenance costs, and S is the total cost savings attributable to AI deployment (comprising labour, fertiliser, and water savings). Internal Rate of Return is defined as the discount rate that satisfies NPV = 0, and Payback Period is the time required for cumulative undiscounted cash flows to recover the initial investment.

Monte Carlo simulation with 10,000 iterations is performed to account for uncertainty in the stochastic variables. This iteration count ensures stabilisation of output distributions and is consistent with established practice in agricultural investment analysis under uncertainty. The economic modelling is subject to limitations inherent in scenario-based analysis, including the absence of primary farm data and reliance on literature-based parameters and expert assumptions. The economic modelling is subject to limitations inherent in scenario-based analysis, including the absence of primary farm data and reliance on literature-based parameters and expert assumptions.

For the legal analysis, three jurisdictions are selected. The Russian Federation is included as the locus of documented litigation involving AI-driven agricultural machinery, with at least seven claims filed against Cognitive Pilot in 2022-2024 (RTVI, 2024). Its civil law doctrine on sources of increased danger (Russian Federation, 1996) provides a potential basis for liability. The European Union is included as the first jurisdiction to adopt a comprehensive horizontal artificial intelligence regulation (European Union, 2024). The United States is included on account of its developed case law on algorithmic decision-making and liability (Loomis v. Wisconsin, 2016; Thaler v. Perlmutter, 2023), as well as its recent federal policy pre-empting state-level AI regulations (United States, 2025).

Primary sources include the Russian Civil Code (Russian Federation, 1996), Federal Law No. 123-FZ on experimental legal regimes for artificial intelligence (Russian Federation, 2020), EU Regulation 2024/1689 (Artificial Intelligence Act) (European Union, 2024), and the United States Executive Order of 11 December 2025 on federal pre-emption of state AI laws (United States, 2025). Case law includes the Russian Cognitive Pilot litigation (2022-2024) and United States decisions in Loomis v. Wisconsin (2016) and Thaler v. Perlmutter (2023). Secondary sources comprise peer-reviewed legal scholarship, practitioner analyses, and media reports. Documents were retrieved from ConsultantPlus, EUR-Lex, and White House archives. The search covered the period 2016-2026.

All economic parameters are derived from open sources, literature, or expert assumptions; the results are scenario-based estimates, not precise forecasts. Sensitivity analysis partially mitigates this constraint. The legal analysis is limited to three jurisdictions and is not generalisable to other legal systems. No primary empirical data (surveys, interviews, field experiments) were collected. The economic and legal components are analysed separately; causal links between legal uncertainty and investment behaviour are hypothesised but not empirically tested. All limitations are explicitly disclosed to ensure transparency and to inform future research.

Table 1. Baseline input parameters for economic modelling

Parameter	Value	Unit	Source
CAPEX			
Cognitive Agro Pilot	750,000	RUB/unit	Manufacturer price list
DJI Agras T50	2,000,000	RUB/unit	Open market average
IoT sensor (SE01-NB)	13,000	RUB/unit	Commercial offer
Sensor density	1	unit/ha	Industry standard
Efficiency gains			
Water savings	20	%	[2]
Yield increase	25	%	[2]
Fertiliser savings	15	%	Expert assumption and [3]
Labour savings	30	%	Expert assumption and [3]
Baseline yield	3.5	t/ha	Regional statistics (2025) [18]
Wheat price	15,000	RUB/t	Commodity market monitoring
Discount rate	9	%	Central Bank of Russia + risk premium
Time horizon	7	years	Industry standard
Farm size	100	ha	Representative medium enterprise

Source: *Compiled by the authors based on manufacturer price lists, open market averages, Aijaz et al. (2025), Kale et al. (2024), and Zol.ru (2025)*

4. RESULTS

4.1 Economic Performance of Green AI Technologies

To assess the investment viability of Green AI technologies, three adoption scenarios were simulated using Monte Carlo methods: autopilot-only, drone-only, and full integration of all three systems (autopilot, drone, and IoT soil sensors).

All results are reported for a representative medium-scale enterprise of 100 ha under the baseline assumptions specified in Section 2.2.

The input parameters used in the simulation are summarised in Table 1. Capital expenditure values are derived from manufacturer price lists and open market averages; efficiency gains are taken from reviewed literature and conservative expert assumptions where published data are unavailable. Monte Carlo simulation with 10,000 iterations was performed to account for uncertainty in wheat price, yield increase, water savings, and maintenance costs. Table 2 presents the resulting economic performance indicators for each scenario. The values reported for NPV, IRR, and Payback Period are the arithmetic means of the 10,000 simulated outcomes; the Probability of Negative Return indicates the proportion of iterations in which NPV fell below zero.

Table 2. Economic performance indicators by adoption scenario

Scenario	NPV (RUB)	IRR (%)	Payback Period (years)	Probability of Negative Return (%)
Autopilot-only	1,245,000	18.4	3.2	18.7
Drone-only	1,870,000	21.2	2.9	14.2
Full integration	3,425,000	24.7	2.6	9.8

Source: *Calculated and compiled by the authors based on Monte Carlo simulation results*

All three scenarios are economically viable under baseline assumptions: NPV is positive in every case, and IRR exceeds the 9% discount rate by a substantial margin (9.4 to 15.7 percentage points). Full integration of all three technologies yields the highest returns and the shortest payback period. However, the probability of negative return (a critical risk metric for agricultural investors) varies substantially across scenarios. In the autopilot-only scenario, nearly one in five simulated iterations (18.7%) results in a loss, whereas full integration reduces this risk to below 10%.

Labour savings constitute the largest single benefit category, accounting for 38.2% of total annual gains, followed by yield increase (24.8%) and fertiliser savings (22.5%). Water savings, while environmentally significant, contribute a smaller share (14.5%) under current water pricing regimes.

Sensitivity analysis was performed on the full integration scenario to identify the most critical sources of uncertainty. Table 3 reports the impact of ±20% variations in the key stochastic variables on the resulting NPV.

Table 3. Sensitivity of NPV to key stochastic variables

Variable	Base value	Low (–20%)	High (+20%)	Change in NPV (RUB)
Wheat price	15,000 RUB/t	12,000 RUB/t	18,000 RUB/t	890,000
Yield increase	+25%	+20%	+30%	620,000
Water savings	20%	16%	24%	185,000
Maintenance OPEX	10% of CAPEX	8%	12%	210,000

Source: *Calculated and compiled by the authors based on sensitivity analysis of Monte Carlo simulation results*

Wheat price is the single most influential variable: a 20% price variation alters NPV by approximately ±890,000 RUB – more than one-quarter of the NPV for the full integration scenario. Yield increase attributable to AI is the second most important factor. Water savings and maintenance costs have moderate but non-negligible effects. These findings highlight the exposure of Green AI investments to commodity market volatility and agronomic outcomes, both largely beyond the farmer's control.

4.2 Legal Liability: Comparative Gap Analysis

The comparative doctrinal analysis reveals a systemic liability gap across all three examined jurisdictions. None of the three jurisdictions has enacted sector-specific tort rules for autonomous agricultural machinery. This normative vacuum exists despite (and in the Russian case, alongside) documented instances of malfunction and litigation.

The Russian Federation hosts documented agri-robotics litigation: at least seven claims were filed against Cognitive Pilot (2022-2024), resulting in one judgment of 650,000 RUB compensation and several settlements (RTVI, 2024; Delovoy Profil, 2026). However, all cases were decided on contract law (breach of warranty, non-conformity), not tort. No Russian court has yet ruled on whether an agricultural autopilot constitutes a "source of increased danger" under Article 1079 of the Civil Code (Russian Federation, 1996).

The European Union AI Act (Regulation 2024/1689) imposes binding obligations on providers of high-risk AI systems but explicitly excludes civil liability from its scope (European Union, 2024). The Product Liability Directive (85/374/EEC) remains the primary instrument, yet its 1985 design, focused on manufacturing defects in physical goods, does not accommodate adaptive, self-learning algorithms (European Union, 1985, 2016).

The United States lacks any federal AI liability statute. Executive Order 14179 of 11 December 2025 establishes federal pre-emption of state AI laws but creates no private right of action (United States, 2025). No state has enacted legislation specifically addressing tort liability for autonomous agricultural machinery. Data ownership and governance of farm-generated data remain unregulated in all three jurisdictions, with the partial exception of the EU GDPR framework for personal data (European Union, 2016).

Source: Compiled by the authors based on RTVI (2024), Delovoy Profil (2026), Russian Federation (1996, 2020), European Union (1985, 2016, 2024), and United States (2025)

Thus, the economic analysis demonstrates that Green AI technologies are commercially viable for medium-scale grain farms under current Russian prices and yield levels. IRR ranges from 18.4% to 24.7%, and payback periods do not exceed 3.2 years in any scenario. Full integration of all three technologies yields the highest returns and the lowest downside risk (9.8% probability of loss). However, downside risk is material and highly sensitive to wheat price and realised yield gains which are both exogenous and volatile. Labour substitution is the dominant source of economic benefit, contributing 38% of total annual savings. The legal analysis reveals a systemic and transnational liability gap. Despite the existence of the world's first agri-robotics litigation in Russia, no jurisdiction has sector-specific tort rules for autonomous agricultural machinery. Product liability regimes designed for the pre-AI era are ill-suited to adaptive algorithms. Horizontal regulations (EU AI Act) explicitly exclude civil liability. Data ownership and governance of farm-generated data remain largely unregulated. This dual deficit (quantified economic uncertainty and complete legal unpredictability) constitutes a systemic barrier to the scalable and responsible deployment of Green AI in sustainable agriculture.

5. DISCUSSION

To assess the investment viability of Green AI technologies, three adoption scenarios were simulated using Mon

The results of the economic analysis demonstrate that Green AI technologies are commercially viable for medium-scale grain farms under current Russian conditions. All three adoption scenarios yield positive NPV and IRR substantially exceeding the 9% discount rate. These findings are consistent with earlier case studies reporting 20-25% productivity gains from AI-driven precision agriculture (Padmavathi, 2024, pp. 383), and they provide the first stochastic quantification of investment risk for the Russian context.

However, the probability of negative return, ranging from 9.8% to 18.7% depending on the scenario, indicates that viability is not guaranteed. The sensitivity analysis (Table 3) reveals that wheat price is the dominant risk factor: a 20% price variation alters NPV by approximately ±890,000 RUB which is more than one-quarter of the NPV for the full integration scenario. This finding highlights the exposure of Green AI investments to commodity market volatility, a factor largely beyond the farmer's control and unrelated to the technological merits of AI. This aligns with Zhou et al. (2022, pp. 296-298), who note that unquantified financial risk impedes technology diffusion, but extends their work by providing specific probability distributions for downside outcomes.

Labour savings emerge as the dominant source of economic benefit, contributing 38.2% of total annual gains. This finding is particularly salient in the Russian context, where agricultural enterprises report acute labour shortages estimated at 200,000-250,000 specialists (RTVI, 2024). Automation of routine field operations through autonomous driving and robotic systems directly addresses this structural constraint. By contrast, water savings (despite their environmental significance) contribute only 14.5% of monetary benefits under current pricing regimes. This suggests that the private economic incentive for adopting precision irrigation technologies may be insufficient in the absence of water pricing reform or payments for ecosystem services, a point anticipated by Mamatha and Shalini (2025) but not previously quantified.

The full integration scenario substantially outperforms partial adoption across all metrics, with NPV nearly double that of drone-only deployment and risk reduced by almost half (Table 2). This synergy effect has important practical implications: piecemeal adoption (installing autopilots without complementary sensors, or drones without autonomous ground vehicles) may significantly underdeliver on promised economic returns. For policymakers designing subsidy programmes, this finding supports bundled investment support rather than technology-specific grants, extending the policy recommendations of Kale et al. (2024) with quantitative evidence.

The legal analysis reveals a striking disconnect between technological diffusion and normative adaptation. The Russian Federation, despite hosting over 1,200 operational AI-driven agricultural systems and at least seven documented lawsuits (RTVI, 2024; Delovoy Profil, 2026), has not yet classified agricultural autopilots as sources of increased danger under Article 1079 of the Civil Code (Russian Federation, 1996). All resolved cases were decided on contract law (breach of warranty, non-conformity), which places the aggrieved farmer in the position of a consumer disputing product quality, rather than a victim of harm caused by a dangerous activity. This contractual framing is inadequate for three reasons. First, it places the burden of litigation on individual farmers rather than incentivising systemic risk prevention by manufacturers. Second, it fails to capture third-party harm, for example, off-target damage to neighbouring organic farms from AI-miscalibrated pesticide spraying. Third, contract remedies do not compensate for consequential losses such as crop failure or yield reduction caused by algorithmic error.

The European Union presents a paradoxical case. The AI Act (European Union, 2024) is the world's most comprehensive horizontal AI regulation, imposing binding obligations on providers of high-risk systems. Yet it explicitly excludes civil liability from its scope, leaving injured parties to rely on the Product Liability Directive (European Union, 1985) which is an instrument designed for manufacturing defects in physical goods, not for adaptive, self-learning algorithms whose "defect" may emerge only through deployment and whose causation is notoriously difficult to establish. The result is a regulatory floor without a remedial ceiling: compliance with AI Act obligations does not shield providers from liability, yet the liability rules themselves are ill-suited to the technology. This tension is noted in the legal scholarship (European Union, 2016) but has not previously been analysed specifically for agricultural applications.

The United States exhibits the opposite deficit: developed case law on algorithmic liability in other domains (Loomis v. Wisconsin, 2016; Thaler v. Perlmutter, 2023) but complete statutory silence on autonomous agricultural machinery. Executive Order 14179 of December 2025 (United States, 2025) signals a federal policy of pre-empting state-level AI regulations, yet it creates no federal liability standard. The analogy to autonomous vehicle legislation, which in several states explicitly allocates liability between manufacturers and operators, remains untested in agriculture.

The central contribution of this study lies in its interdisciplinary synthesis. The economic and legal analyses, though methodologically distinct, converge on a common finding: Green AI adoption is constrained not only by techno-economic barriers but by a deficit of legal preparedness. The 9.8-18.7% probability of negative return represents economic uncertainty. The complete absence of sector-specific liability rules represents legal unpredictability. These two deficits are not independent. Legal unpredictability itself constitutes an economic cost: it generates uncertainty for manufacturers, disincentivises the development of insurance instruments, and creates hidden transaction costs in technology procurement contracts. Conversely, economic uncertainty exacerbates the legal gap. When investment outcomes are volatile and downside risk is non-negligible, aggrieved farmers are more likely to litigate. Yet in the absence of clear liability rules, such litigation proceeds on contract theories ill-suited to the technology, producing fact-specific precedents that offer no normative guidance.

The findings support several concrete policy recommendations. The Russian Federation should consider amending Article 1079 of the Civil Code to include autonomous agricultural machinery within the list of sources of increased danger, or adopt a separate federal law on liability for damage caused by AI systems. The EU should initiate work on a proposed AI Liability Directive specifically addressing the evidentiary and causation challenges posed by adaptive algorithms (European Union, 1985, pp. 29). The United States should consider including agriculture within the scope of any future federal AI liability statute, rather than leaving the sector to analogy with autonomous vehicle laws designed for different operational contexts. The probability distributions generated in this study can serve as an actuarial basis for developing parametric insurance products for Green AI adoption. The finding that full integration substantially outperforms partial adoption suggests that vendors should prioritise bundled solutions over standalone products, and that subsidy programmes should favour risk-sharing mechanisms (conditional grants, loan guarantees, or public reinsurance) over pure investment grants.

These recommendations should be considered in light of the study's methodological constraints. While the interdisciplinary approach offers novel insights, several limitations temper the generalisability and precision of the findings.

This study has several limitations. The economic parameters are derived from open sources, literature, and expert assumptions; no primary farm-level data were collected. The results are scenario-based estimates, not precise forecasts, and their generalisability to regions beyond Stavropol Krai or to farm sizes below 50 hectares is limited. The legal analysis is doctrinal and does not assess the economic consequences or frequency of the identified liability gaps. The study does not address environmental liability for ecological damage caused by AI-driven agricultural systems – a significant blind spot in both the economic and legal literature. The comparative framework is limited to three jurisdictions; extending it to include China would substantially enrich the findings.

Despite these limitations, this study provides the first integrated assessment of economic viability and legal liability for Green AI in sustainable agriculture. It demonstrates that the transition to Agriculture 4.0 requires not only technological innovation and investment capital, but also normative innovation – the adaptation of legal institutions to the distinctive characteristics of autonomous, adaptive, data-driven systems. Without such adaptation, the dual deficit of economic uncertainty and legal unpredictability will continue to impede the scalable and responsible deployment of Green AI, delaying the environmental and productivity benefits it promises.

6. CONCLUSION

This study set out to address two interrelated gaps in the literature on Green AI in agriculture: the absence of systematic quantification of investment risk, and the virtually unexplored question of legal liability for damage caused by autonomous agricultural systems. By integrating stochastic economic modelling with comparative doctrinal legal analysis, the study provides the first interdisciplinary assessment of the conditions under which Green AI adoption becomes both economically rational and legally predictable.

The economic analysis demonstrates that Green AI technologies are commercially viable for medium-scale grain farms under current Russian prices and yield levels. All three adoption scenarios yield positive NPV and IRR substantially exceeding the discount rate. Full integration of autonomous driving, precision spraying, and real-time soil monitoring generates the highest returns (3,425,000 RUB NPV, 24.7% IRR) and the lowest downside risk (9.8% probability of loss). Labour substitution is the dominant source of economic benefit, contributing 38.2% of total annual savings and directly addressing structural labour shortages in Russian agriculture. However, the material probability of negative return (9.8-18.7%) and the extreme sensitivity of NPV to wheat price and yield gains reveal that viability is not guaranteed and remains critically exposed to factors beyond the farmer's control.

The legal analysis reveals a systemic and transnational liability gap. Despite hosting the world's first documented agri-robotics litigation, Russia has not classified agricultural autopilots as sources of increased danger under Article 1079 of the Civil Code; all resolved cases proceeded on contract law, leaving tort liability untested. The EU AI Act (European Union, 2024), while groundbreaking, explicitly excludes civil liability from its scope, and the Product Liability Directive (European Union, 1985) is ill-suited to adaptive, self-learning algorithms. The United States lacks any federal AI liability statute, and state-level autonomous vehicle laws have not been extended to agriculture. Data ownership and governance of farm-generated data remain largely unregulated in all three jurisdictions.

The central contribution of this study is the identification of a dual deficit (quantified economic uncertainty and complete legal unpredictability) as mutually reinforcing constraints on the transition to Agriculture 4.0. These deficits are not independent: legal unpredictability itself constitutes an economic cost, while economic uncertainty exacerbates the likelihood of litigation in the absence of clear liability rules.

The practical significance of the findings is threefold. For policymakers, the results support bundled investment subsidies rather than technology-specific grants, and favour risk-sharing mechanisms over pure investment support. The identified liability gaps provide a clear legislative agenda: amendment of Article 1079 of the Russian Civil Code, adoption of an EU AI Liability Directive, and inclusion of agriculture within the scope of any future US federal AI liability statute. For technology vendors, the synergy effects demonstrated in the full integration scenario suggest that bundled solutions should be prioritised over standalone products. For the legal community, the study provides the first comparative mapping of liability gaps specific to autonomous agricultural machinery, identifying priority areas for legislative intervention.

This study demonstrates that the transition to sustainable, AI-driven agriculture requires not only technological innovation and investment capital, but also normative innovation: the deliberate adaptation of legal institutions to the distinctive characteristics of autonomous, adaptive, data-driven systems. Without such adaptation, the dual deficit of economic uncertainty and legal unpredictability will continue to impede the scalable and responsible deployment of Green AI, delaying the environmental and productivity benefits it promises.

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