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Integrating Harmony and Accountability: A Dual-Engine Ethical Governance Framework and Verifiable Trust Mechanism for Precision Agriculture with Artificial Intelligence

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ABSTRACT

Precision agriculture is gradually becoming a policy tool for countries to promote food security and sustainable governance, with artificial intelligence (AI) playing a key role: through sensors, drones, satellite imagery, and machine learning models, agricultural decisions can be made more precisely to suit soil and climate differences, thereby reducing fertilizer, irrigation, and pesticide inputs. However, embedding AI into agriculture does not necessarily lead to sustainability. On the contrary, the digital infrastructure of precision agriculture may bring about hardware lifecycle carbon footprints and electronic waste; data platforms and algorithms may lead to power concentration, data exploitation, and unfairness to smallholder farmers and diversified farming systems; and may even reinforce monoculture, land concentration, and ecological vulnerability under the guise of an "efficiency narrative."

This article argues that existing AI ethics mostly focus on abstract principles such as transparency, fairness, and privacy, lacking governance tools that can be directly applied to agricultural ecosystems and rural justice; while traditional environmental ethics provides value critique, it often lacks institutionalized operational and accountability mechanisms. To this end, this paper proposes a "dual-engine governance model": using the relational ontology of Eastern ecological ethics and the spirit of restraint embodying the "unity of man and nature" as the value engine to define the purpose, boundaries, and inviolable ecological bottom line of AI intervention in agriculture; and using responsibility, rights, and procedural justice from Western ethics as the procedural engine to transform value requirements into an auditable, appealable, and remedial system. This paper further integrates the dual engines with the concept of "verifiable trust," proposing a set of "AI Environmental Impact Assessment" (AIEIA) methods and workflows for precision agriculture, including indicator design, data governance, model lifecycle auditing, stakeholder participation, and remedial mechanisms. Finally, this paper uses

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scenario-based case studies to demonstrate how AIEIA can reveal backlash effects and data injustice, and proposes policy and industry implementation recommendations to promote agricultural AI towards ecological prosperity rather than merely efficiency optimization.

KEY WORDS: Environmental ethics, precision agriculture, artificial intelligence governance, ecological justice, relational ontology, sustainable AI, data justice, verifiable trust

1. Introduction: The Sustainability Commitment and Ethical Paradox of Precision Agriculture AI

Precision agriculture is often portrayed in public discourse as a solution to "repair agricultural externalities with technology": when fertilizer runoff leads to eutrophication of water bodies, when climate change causes uneven distribution of drought and flood, and when labor shortages cause imbalances in the rural population structure, AI and automation seem capable of simultaneously achieving the dual goals of increased production and carbon reduction through more precise inputs, more real-time predictions, and more efficient management. Especially against the backdrop of global food price volatility, rising geopolitical risks, and frequent extreme weather events, governments and businesses around the world are increasingly inclined to view agricultural digitization as a "technological solution to risk management."

However, understanding precision agriculture as simply "collecting more complete data and making more precise decisions" often overlooks a core fact: agriculture is not a closed production line, but a complex socio-ecological system nested with soil life, watershed hydrology, pollinating organisms, local communities, and market institutions. The intervention of AI will reshape farming methods, capital investment thresholds, knowledge authority, and land use structures; its optimized objective function may unknowingly place certain values (such as maximizing yield and minimizing short-term costs) above other values (such as soil regeneration, local food resilience, and cultural landscape). In other words , AI is not a neutral tool, but a technological-governance apparatus that institutionalizes a specific worldview.

This article refers to this as the "ethical paradox" of precision agriculture AI:

- At the local level, AI may reduce chemical inputs, improve water use efficiency, and reduce the spread of pests and diseases;
- At the system level, it may strengthen single-crop systems, expand data and platform monopolies, and exclude small farmers from capital-intensive technology competition.
- At the life cycle level, it may also shift emissions and pollution from the fields to mining, manufacturing, cloud computing, and electronic waste treatment, forming a "perpetual displacement".

1.1 Research Question

This article focuses on three questions:

1.1.1 **Q1 (Purpose Question):** What kind of agricultural and human-land relationship should precision agriculture AI serve? When should technological intervention be restrained or rejected?

1.1.2 **Q2 (Institutional Issues):** In the multi-party AI supply chain (farmers, platform providers, hardware manufacturers, government, insurance and financial institutions), how should responsibilities be allocated, rights defined and remedies established?

1.1.3 **Q3 (Implementation Issues):** How to transform values such as "harmony, restraint, and relationality" into measurable, auditable, and publicly verifiable governance processes?

1.2 Core Contributions

This article makes three contributions:

1.2.1 **Dual-engine governance model:** using Eastern ecological ethics as the value engine and Western procedural justice as the procedural engine to form a complementary framework.

1.2.2 **Verifiable trust:** Rewrite trust from "believing in technology/brand" to "provable ethical compliance and accountable institutional commitments".

1.2.3 **AIEIA Methodology:** Provides AI-based environmental impact assessment forms and workflows specifically for precision agriculture, covering environmental lifecycle, data governance, bias and equity, rebound effects, chain of responsibility, and grievance redress.

2. Literature Review and Research Positioning: The Discontinuity between AI Ethics, Environmental Ethics, and Agricultural Digitalization

2.1 Deficiencies of the Current AI Ethics Framework

Mainstream AI ethics and governance documents largely revolve around principles such as transparency, explainability, fairness, privacy, security, and accountability. While these principles are important in themselves, they tend to fall short in three ways when applied to precision agriculture:

First, **there is a significant difference in ecological complexity** : farmland is not simply a "user field" for general information systems, but rather part of an ecosystem. Limiting impact assessments to data protection or model accuracy may overlook the cumulative effects on soil microorganisms, biodiversity, and watershed scale.

Second, **the discrepancy in objective functions** : AI ethics often views AI as a tool for a predetermined purpose, focusing on "how to achieve the purpose safely and fairly," while rarely questioning "whether the purpose itself is unjust or unsustainable." In

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agriculture, if the purpose is preset to maximize yield, AI may externalize ecological costs more efficiently.

Third, **the power structure disparity** : Precision agriculture is highly dependent on platforms and supply chains. Data and models are often controlled by a few companies. If the ethical framework does not address platform monopolies, contractual inequalities, and data colonization, it will be difficult to respond to the actual situation of farmers.

2.2 Contributions and Limitations of Environmental Ethics

Environmental ethics offers profound reflections on anthropocentrism, instrumental rationality, and the value of nature, and can point out the fundamental problem of "treating land as a factory." However, in the governance of technology, environmental ethics often encounters the dilemma of "institutional translation."

2.2.1 It can offer norms (how humans should treat nature), but it offers fewer actionable audit metrics, liability definitions, or procedural designs.

2.2.2 In the context of cross-border supply chains and algorithm governance, ethical claims are likely to remain mere pronouncements if specific mechanisms are lacking.

2.3 Implications of Agricultural Digitalization Research

Research on "smart agriculture" reminds us that technology adoption is not simply about improving efficiency, but about changing knowledge and power. When farmers' farming experience is platformized and digitized, farmers may be relegated from "decision-makers" to "executors"; and agricultural data may become tools for financialization and insurance risk control, leading to new exclusion and inequality. This type of research suggests that the ethical issues of precision agriculture AI must be discussed within the socio-technical system and political-economic context.

3. The ethical duality of AI in precision agriculture: from "field efficiency" to "system consequences"

This section does not simplify AI to "the benefits outweigh the drawbacks/the drawbacks outweigh the benefits," but uses multi-level analysis to reveal that the same AI may have opposite effects on different scales.

3.1 First level: Direct benefits (field scale)

Common applications of AI in precision agriculture include:

- **Variable application (VRA)** : Fertilizers and irrigators are applied in zones according to soil and crop conditions to reduce excessive input and loss.
- **Pest and disease image identification** : Use computer vision to identify lesions and pests at an early stage, reducing the need for comprehensive pesticide application.
- **Production and risk forecasting** : Assisting in inventory, harvesting, and logistics planning to reduce waste. At this level, AI appears capable of simultaneously improving economic efficiency and environmental performance.

3.2 Second Layer: Indirect Costs (Infrastructure and Life Cycle)

Once the perspective is broadened to include the supply chain and lifecycle, the benefits are no longer one-way. Precision agriculture requires: sensors, communication equipment, drones, edge computing boxes, cloud servers, batteries, and maintenance services. This hardware possesses:

- **Implicit carbon emissions and resource extraction** : rare earth and metal mining, energy consumption in manufacturing, and emissions from transportation.
- **Replacement and electronic waste** : Agricultural sites are challenging, equipment failure rates are high, and replacement is more frequent.
- **Cloud and model training energy consumption** : If the platform adopts high-frequency image uploads and large model training, the energy cost will be significant. Therefore, AI may shift the environmental burden from "chemical inputs" to "digital inputs".

3.3 Third Layer: Systemic Risk (Institutional and Landscape Scale)

The most challenging aspect is the systemic consequences, particularly including:

3.3.1. Data Injustice and Platform Dependence

Farmers' field data (plot boundaries, soil fertility, yield, inputs, pests and diseases) has extremely high commercial value. If contractual arrangements favor platform providers in controlling this data, farmers may face the following challenges:

- **Locked-in** : Data is not easy to transfer, and the cost of switching platforms is high.
- **Reused** : Data is used for market forecasting, pricing strategies, and even land acquisition analysis, while farmers struggle to share in the profits.
- **Regulatory oversight** : Data may become the basis for insurance underwriting, loan interest rates, or subsidy eligibility, creating new forms of control.

3.3.2 Algorithm bias and incompatibility with diverse farming methods

Models are typically trained with quantifiable metrics, most commonly yield, quality, and input costs, which can lead to two types of biases:

- **Data distribution bias** : Training data often comes from large-scale farms, monocultures, and standardized management; its effectiveness decreases when used for smallholder farmers, mixed crops, and intercropping.
- **Value bias** : If the model does not take into account soil organic matter, biodiversity, pollinating insects, and landscape connectivity, it will regard eco-friendly farming as "noise" and even suggest returning to a highly standardized management model.

3.3.3 Rebound Effect and "Efficiency Reinforcement is Not Sustainable"

Even if AI saves resources in the field, it may trigger a backlash: increased efficiency lowers unit costs, which in turn stimulates increased production, land concentration, or more intensive use. The result is that overall environmental pressure may increase rather than decrease. In particular, when AI makes monoculture more profitable,

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it could accelerate the development of ecologically fragile monoculture landscapes.

4. Theoretical Basis: Ethical Integration of the Dual-Engine Governance Model

This article integrates Eastern and Western ethics in a "complementary" rather than "compromise" manner: the value engine answers "why and what", while the program engine answers "how and by whom".

4.1 Value Engine: Relational Ontology, Harmony Between Man and Nature, and the Principle of Moderation

4.1.1 From Individual to Relationship: Reinterpreting "Farmland"

Relational ontology emphasizes that the world is constituted by relationships; existence is not an isolated point, but a network of interdependent entities. Applied to agriculture, farmland is not a production container that can be arbitrarily manipulated, but a living community jointly generated by soil aggregates, water cycles, mycorrhizal networks, natural enemies of pests, crop genetic diversity, and farmers' labor practices. Therefore, the ethical evaluation of precision agriculture AI cannot solely focus on "how much yield is increased," but must examine whether it:

- Improve or destroy soil life and structure
- Maintain or weaken the connectivity between the watershed and the habitat.
- Supporting or undermining farmers' knowledge and ability to care for the land

4.1.2 Harmony between Man and Nature: Placing "Acceptance" Before "Conquest"

The concept of "harmony between humanity and nature" can be understood as: human activities should be coordinated with the natural order, rather than aiming for complete control. For AI, this means:

- AI should assist in "perceiving" and "responding" to natural signals, rather than reducing nature to a set of variables that can be completely predicted;
- Caution and restraint should be exercised in the face of highly uncertain and irreversible ecological risks;
- The legitimacy of technological intervention is not only about efficiency, but also about whether it enhances system resilience and ecosystem reproduction.

4.1.3 The principle of moderation: minimum footprint and minimum intrusion

The principle of moderation can be translated into three design guidelines:

- **Computational control:** Prioritize low-energy models, edge computing, and data minimization while ensuring that governance objectives are achieved.
- **Hardware control:** Extends equipment lifespan, ensures maintainability and recyclability, and avoids frequent replacements.
- **Governance and restraint:** Preserve farmers' judgment and local knowledge, and avoid monopolizing decision-making power through algorithms.

4.2 Program Engine: Responsibility, Rights, and Procedural Justice

4.2.1 Chain of Responsibility: Breaking down "systemic" issues into accountable roles

The outcomes of precision agriculture AI are typically the result of collaboration among multiple parties: data supply, model training, platform interface design, equipment calibration, farmer operation, agricultural advisory advice, and policy subsidy guidance. The program engine requires that a chain of responsibility be established before deployment, including:

- Risk and Assumption Disclosure: Model Applicability, Data Gap, Error Patterns
- Monitoring and Reporting: Detection Thresholds for Environmental or Economic Damage
- Responsibility allocation: Who bears the repair costs, and who provides technical fixes?
- Insurance or Guarantee: For high-risk situations, it is recommended to use liability insurance or a compensation mechanism.

4.2.2 Rights Bundle: Elevating Farmers from "Users" to "Rights Subjects"

Procedural justice is not just about "fairly distributing outcomes," but also about "fair participation in the process." Precision agriculture AI should at least guarantee:

- **Data rights** : right to know, consent, restriction of use, transfer, deletion, revenue sharing, or collective bargaining.
- **Right to understand** : Provide understandable reasons and uncertainty warnings for key recommendations (application of pesticides, application of fertilizers, cessation of irrigation, harvesting).
- **Right to appeal and redress** : If loss or pollution is caused by model error, there is a clear appeal window, time limit and assessment procedure.
- **Exit right** : Not excluded from subsidies, insurance or market access due to refusal to use the platform.

4.2.3 Auditing and Transparency: Turning Principles into Verifiable Evidence

The program engine emphasizes auditability: it does not substitute declarations for evidence. Its key elements are: metrics, records, third-party audits, and public reporting.

4.3 Verifiable Trust: The Integration Concept of Dual Engines

In the technology field, "trust" is often misunderstood as "users' willingness to adopt." The verifiable trust advocated in this article refers to:

- Trust must be verifiable, not based on brand narrative;
- The method of attestation must be verifiable by interested parties and provide a dispute resolution mechanism;

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- The object of trust is not a single model, but a holistic system encompassing data, hardware, supply chain, operational processes, responsibility, and remedies.

Therefore, verifiable trust has three pillars:

4.3.1 **Value alignment** : The system's purpose and limitations align with ecological harmony and moderation.

4.3.2 **Procedural accountability** : The chain of responsibility is clear, rights are exerciseable, and remedies are available.

4.3.3 **Evidence is verifiable** : indicators are measurable, records are traceable, and audits are reproducible.

5. Scope: Design and Operation of AIEIA (AI Environmental Impact Assessment)

This section proposes AIEIA as a dedicated impact assessment tool for precision agriculture AI. AIEIA is not a replacement for traditional EIA, but rather fills the gap in EIA's lack of assessment terminology for "algorithm-data-platform". AIEIA also differs from general AI risk assessments, incorporating environmental lifecycle and rural justice at its core.

5.1 Scope of Assessment

AIEIA recommends covering at least five areas:

5.1.1 **Field ecological impacts** : soil, water, air, biodiversity

5.1.2 **System lifecycle** : Hardware manufacturing/transportation/power consumption/disposal

5.1.3 **Data governance and rights** : ownership, usage, portability, and shared benefits

5.1.4 **Fairness and Applicability** : Performance Differences Across Different Scales, Farming Methods, and Regions

5.1.5 **Rebound Effects and Landscape Transformation** : Land Concentration, Crop Diversity, Input Intensity, and Social Impact

5.2 Indicator Design Principles

5.2.1 **Measurable:** Prioritize indicators that can be continuously monitored (e.g., SOM trend, groundwater nitrate).

5.2.2 **Comparable:** Indicators must have baselines and references (before and after deployment, regional averages, and comparisons with similar farming methods).

5.2.3 **Attributable factors:** Avoid using only highly macroeconomic indicators; it needs to be able to link AI recommendations with agricultural operations.

5.2.4 **Governable:** When an indicator deteriorates, it must be able to trigger action (adjust the model, restrict a suggestion, or initiate a remedy).

5.3 AIEIA Framework

Table 1 provides an AIEIA framework that can be directly incorporated into papers (this framework can be adjusted according to crop and region).

Table 1 AI-Driven Environmental Impact Assessment (AIEIA) Framework for Precision Agriculture: A Dual-Engine Model Integrating Ethical Principles and Governance Mechanisms

Assessment **Domain**	Core Principle & Guiding **Question**	Procedural Engine (A): Key Performance Indicators & **Metrics**	Program Engine (B): Data Sources & Verification **Methods**	Procedural Engine (C): Governance Actions & Mitigation **Pathways**
1. Agro - ecosystem integrity	**Principle: Relational Integrity.** Does the AI system strengthen rather than weaken the healthy relationships between soil, water, and organisms? Does its objective function go beyond simply maximizing output?	**1a. Soil health** : Soil organic matter (SOM) content (%), microbial activity or diversity indicators (e.g., respiration rate). **1b. Water quality**: Nitrate/phosphate concentrations at key monitoring points (mg/L). **1c. Biodiversity**: Non-crop vegetation cover at farmland edges (%), abundance index of pollinating insects or indicative natural enemies. **1d. Chemical footprint**: Environmental impact quotient (EIQ) or toxicity-weighted application rate of pesticides (kg/ha).	**1a** : Regular soil sampling and analysis reports (compared to baseline). **1b:** Watershed water quality monitoring station data, real-time sensors at field drainage outlets. **1c** : Remote sensing image analysis, field ecological survey records. **1d** : Farmer input purchase and usage records, platform algorithm suggestion logs.	**Prevention** : Incorporate ecological indicators (such as SOM improvement) into the reward function or constraints of the AI model. **Monitoring** : If an indicator deteriorates by more than 5% for two consecutive quarters, trigger an alert and conduct a causal analysis. **Response** : Suspend high-risk recommendations that may lead to further deterioration; require the implementation of ecological compensation measures (such as planting hedges or cover crops).
2. System Lifecycle & Circularity	**Principles: Moderation & Minimal Footprint.** Does the physical	**2a. Energy Footprint:** Total power consumption for model training and inference (kWh/year), data center PUE[1] value.	**2a** : Electricity consumption reports and hardware specifications provided	**Prevention:** Clearly define maintainability and modular design requirements for equipment in procurement

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Assessment **Domain**	Core Principle & Guiding **Question**	Procedural Engine (A): Key Performance Indicators & **Metrics**	Program Engine (B): Data Sources & Verification **Methods**	Procedural Engine (C): Governance Actions & Mitigation **Pathways**
	infrastructure of the system adhere to the principles of resource efficiency and circular economy? Does it avoid unnecessary technological upgrades and waste?	**2b. Hardware Lifecycle:** Average lifespan of equipment (sensors, drones), mean time between failures (MTBF). **2c. Electronic Waste**: Waste equipment recycling rate (%), repair and reuse rate (%). **2d. Computational Efficiency** : Trade-off analysis between model complexity (number of parameters) and accuracy.	by the cloud service provider. **2b** : Equipment procurement and maintenance records, and asset management system data. **2c** : Recycling certificates and third-party recycling audit reports provided by the supplier. **2d** : Technical documents in the Model Card.	specifications; prioritize low-power edge computing solutions. **Monitoring** : Track hardware replacement rates; conduct reviews if rates exceed industry benchmarks. **Response** : Establish an Extended Producer Responsibility (EPR) mechanism, requiring suppliers to be responsible for equipment recycling and proper disposal.
3. Data Justice & Farmer Autonomy	**Principle: Does the Empowerment & Fair Partnership** data governance model empower farmers, or lock them into a platform and exploit the value of their data?	**3a. Data Rights** : Are the terms in the contract regarding data ownership, usage rights, and portability clear and fair? **3b. Lock-in Effect** : Technical barriers and costs for farmers to transfer data to other platforms. **3c. Value Sharing** : Is there a transparent distribution mechanism for the benefits of secondary data utilization (such as market forecasting)? **3d. Governance Participation** : The degree of participation of farmers or their representatives in data governance decisions (e.g., whether there are representative seats).	**3a** : Independent review report of the User Authorization Agreement (EULA) by legal experts. **3b** : Technical testing of API documentation and data export functionality. **3c** : Revenue distribution description in the platform's annual report. **3d** : Bylaws and meeting minutes of the data trust or cooperative.	**Prevention** : Promote standardized data formats and open APIs; design a data architecture with "pre-defined privacy protection." **Monitoring** : Conduct regular anonymous surveys of farmers regarding satisfaction and sense of autonomy. **Response** : Establish data trusts or data cooperatives, where farmers collectively manage their data and negotiate external licensing agreements.
4. Algorithmic Bias & Inclusivity	**Principle: Is the contextual fairness** model equally effective and safe for farmers of different sizes, farming practices (such as organic and mixed cropping), and geographical regions?	**4a. Equal Performance** : Differences in accuracy and false positive/false negative rates between different farmer groups (e.g., smallholder vs. largeholder; monoculture vs. mixed cropping). **4b. Representativeness of Training Data** : The distribution ratio of various farm types and farming methods in the training dataset. **4c. Interpretability** : The degree and quality of comprehensible explanations provided for high-risk recommendations (e.g., application of highly toxic pesticides). **4d. Fault Tolerance** : The stability and safety of the system in the face of unexpected inputs or extreme weather events.	**4a** : Bias Audit Report (Model Clustering Performance Test Report). **4b** : Source and component descriptions in the Datasheet for Datasets. **4c** : Usability testing of the User Interface (UI) and farmer focus group interviews. 4d **:** Stress test and scenario simulation report.	**Prevention** : Invest resources in collecting data from underrepresented groups; design human-machine collaboration loops, retaining the farmer's final veto power. **Monitoring** : Establish a user feedback system to track and analyze model failure cases. **Response** : If the model exhibits significant bias towards a specific group, its application within that group should be restricted until the model is improved and re-validated.

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5. Systemic & Rebound Effects	**Principle: Does the increased efficiency of landscape resilience** technologies inadvertently exacerbate homogenization and land centralization, or make agricultural systems more vulnerable at the macro level?	**5a. Crop diversity:** Changes in the Shannon Index of crop species at the regional scale. **5b. Land use patterns:** Trends in the concentration of farmland management scale within the region (e.g., Gini coefficient). **5c. Total inputs** : Whether total fertilizer/pesticide/water consumption in the region has increased due to expansion despite improvements in unit efficiency (i.e., rebound effect). **5d. Knowledge diversity** : Farmers' reliance on and transmission of traditional agronomic knowledge.	**5a, 5b, 5c** : Long-term tracking analysis combining agricultural statistics, remote sensing imagery, and input sales data. **5d** : Sociological qualitative research, such as in-depth interviews and participatory observation.	**Prevention** : Combine AI deployment with policy tools that encourage diversified farming practices (such as eco-subsidies and crop rotation incentives). **Monitoring** : Establish regional agricultural sustainability dashboards to monitor macro trends. **Response** : If negative systemic effects are detected, policymakers should intervene to adjust market incentives to offset the monoculture pressures induced by technology.

Source: This article was constructed.

Table Explanation: This framework aims to transform abstract ethical principles into actionable governance tools to evaluate and guide the design, deployment, and regulation of precision agriculture AI systems. Its structure closely follows the proposed "dual-engine model": the value engine sets the normative goals the system should pursue (Column 2), while the program engine translates these goals into measurable indicators, verifiable data sources, and concrete governance actions (Columns 3-5). This framework aims to establish a "verifiable trust," ensuring that AI deployment is not merely a technological claim, but an evidence-supported, accountable, and sustainable practice.

Footnotes:

- **PUE (Power** Usage Effectiveness): A measure of energy efficiency in data centers; the closer the value is to 1, the higher the energy efficiency.
- **EIQ (Environmental Impact Quotient):** An index that comprehensively assesses the risks of pesticides to farm workers, consumers, and the ecological environment.
- **Model Card:** A short report that provides information on the performance characteristics, intended use, limitations, and error assessment of an AI model.
- **Datasheet for Datasets:** A document that records information such as the motivation for creating a dataset, its structure, the collection process, and recommended uses, aiming to improve transparency and accountability.

6. AIEIA Workflow: Full Lifecycle Governance from Project Initiation to Exit

AIEIA should be embedded in the AI system lifecycle, rather than a single pre-deployment review. This article proposes a six-stage process:

6.1 Phase One: Project Initiation and Objective Review (Value Gate)

Conduct a value assessment before developing technology to avoid "doing it first and then figuring it out." Key areas to check:

6.1.1 **Is the problem that this AI is supposed to solve truly an ecological and social need, or is it merely for commercial expansion?**

6.1.2 **Are there alternatives with lower footprint and less intrusion (such as agronomic improvement or cooperative equipment sharing)?**

6.1.3 **Is it possible for intervention to cross the line of irreversibility (e.g., in vulnerable watersheds or around conservation areas)?**

Deliverables: Statement of purpose, comparison of alternatives, and preliminary risk map.

6.2 Phase Two: Data Governance by Design

Establish a data rights structure:

6.2.1 **Design the data collection project based on the principle of "minimum necessary data".**

6.2.2 **Clearly define the purpose, retention period, and secondary use of the data.**

6.2.3 **Offers portability, deletion, and collective bargaining (data trust/cooperative).**

6.2.4 **Establish a data quality and deviation detection system (to avoid accepting only data from large-scale agricultural enterprises).**

Deliverables: Data governance charter, consent form, data flow diagram, data sheet.

6.3 Phase Three: Model Design and Control Engineering (Frugal/Moderate AI)

Engineering the principle of moderation:

6.3.1 **Prioritize sufficiency: Choose a simpler model while still meeting the requirements.**

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6.3.2 Prioritize edge computing and tiered upload (to reduce cloud load).

6.3.3 Incorporate ecological indicators into targets or constraints (e.g., fertilization recommendations must meet water quality risk limits).

Deliverables: Model card, energy consumption report, objective function and constraint description.

6.4 Phase Four: Pre-deployment Impact Assessment (Pre-deployment AIEIA)

Establish baselines based on the indicators in Table 1: SOM, water quality, pesticide intensity, equipment LCA, contract terms, and performance cluster testing. If necessary, employ controlled trials or phased deployment to identify attributions.

Deliverables: AIEIA baseline report, risk mitigation plan.

6.5 Phase Five: Post-Deployment Monitoring and Audit (Continuous Audit)

6.5.1 Regularly update ecological and social indicators

6.5.2 Establish a "failure case library" and a backtracking mechanism.

6.5.3 Openness and transparency: Giving back to farmers and communities in an understandable way.

6.5.4 Third-party audit: Audits should be conducted annually for at least high-risk crops/regions.

Deliverables: Quarterly/annual AIEIA reports, audit opinions and improvement records.

6.6 Phase Six: Exit & Extended Responsibility

If the platform terminates its services, farmers switch suppliers, or replace their equipment:

6.6.1 Data portability and format compatibility must be provided.

6.6.2 Equipment recycling, parts supply and maintenance support responsibilities.

6.6.3 Funding will be provided for follow-up monitoring and remediation of pollution or soil degradation that may have delayed effects.

Deliverables: Exit plan, recovery certificate, extended liability clauses.

7. Scenario Example: How AIEIA Reveals "Invisible Risks"

The following two common scenarios demonstrate the role of AIEIA (you can rewrite these as local cases based on your research region when submitting your manuscript).

7.1 Scenario A: Water quality externalities of nitrogen fertilizer recommendation models

A nitrogen fertilizer recommendation model based on satellite vegetation index and soil sensing was implemented in a certain region. In the first quarter after deployment, yields increased and fertilizer application per unit area decreased. While seemingly successful, AIEIA watershed monitoring showed that nitrate peaks actually increased during periods of concentrated rainfall. Further investigation revealed:

- The model was trained on average scenarios and underestimated the "loss risk" of extreme rainfall.
- Fertilization time was advised to be brought forward in order to pursue the growth curve, but short-term weather uncertainties were not taken into account;
- The platform did not disclose the model's failure modes under extreme weather conditions.

AIEIA triggers governance action:

7.1.1 Include "rainfall event risk" in the recommendations' constraints;

7.1.2 During high-risk periods, a more conservative strategy is adopted and manual review is required.

7.1.3 Initiate a chain of responsibility: The platform assumes part of the costs of water quality monitoring and mitigation (such as buffer zone subsidies).

This example shows that focusing solely on "decreased fertilizer application" may overlook key externalities; AIEIA transforms ethical requirements into governable systems through "indicators-thresholds-actions".

7.2 Scenario B: Bias of pest and disease identification systems towards smallholder farmers engaged in mixed cropping

The drone image recognition model performed well in monoculture fields, but had a high misclassification rate in mixed cropping fields, leading to smallholder farmers being advised to apply pesticides unnecessarily. AIEIA's fair evaluation (cluster performance) reveals:

- The training materials almost all come from large-scale monoculture fields;
- The texture and occlusion of mixed-cropping fields increase the uncertainty of the model, but the interface does not show the uncertainty;
- Farmers lack a clear explanation of "why pesticides should be applied," making it difficult for them to reasonably refuse the suggestion.

AIEIA triggers governance action:

7.2.1 Add uncertainty visualization and a "manual confirmation required" prompt to the interface;

7.2.2 Collect data on mixed-operation scenarios and establish on-site calibration;

7.2.3 Set up an appeals and compensation window;

7.2.4 Improve data management: Smallholder data participation training should be rewarded or benefit-sharing provided.

This example highlights that fairness is not just about "models not being discriminatory," but also about "not excluding different farming knowledge and practices from technology."

8. Discussion: Theoretical implications and policy implications of the dual-engine model

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8.1 Why a value engine is needed: to prevent procedural justice from becoming a "whitewash for unsustainable systems"

If only a program engine exists, governance might become: as long as it's transparent, accountable, and contracts are clear, AI can be allowed to more efficiently advance monoculture agriculture. The function of a value engine is to impose directional constraints, requiring AI not only to "harm fewer people" but also to "promote relationship repair." It forces us to incorporate "what agriculture should be" into the design starting point.

8.2 Why a program engine is needed: To prevent harmonious discourse from becoming toothless moral rhetoric.

A value engine alone is prone to remaining at an ideal level: discussing harmony and restraint, but lacking the tools to confront multinational platforms, supply chains, and the power of capital. A process engine provides institutional teeth: chains of responsibility, contractual rights, auditing, and remedies.

8.3 How Verifiable Trust Responds to a "Trust Crisis"

The trust crisis in agricultural AI often stems from three things:

- Farmers don't know how the data is being used.
- Farmers don't know when the model will go wrong.
- When farmers are victimized, they cannot find anyone to hold accountable. Trust needs to be rewritten into an auditable and accountable governance commitment, rather than mere propaganda or goodwill.

8.4 Recommendations for Policy and Industry

8.4.1 **Policy measures include** incorporating AIEIA into the threshold for subsidies, procurement, or demonstration programs; requiring data portability and interoperability; and requiring liability insurance for high-risk recommendations (pesticide/fertilizer application).

8.4.2 **On the industry side:** use model cards/data cards/energy consumption reports as delivery standards; provide uncertainty alerts and human-machine collaboration; and establish a recycling and maintenance system.

8.4.3 **Farmers' organizations:** promote data trusts or cooperative co-management; collectively negotiate contract terms; jointly establish local data collections and common infrastructure models.

9. Main Conclusions, Limitations, and Future Directions of the Research

9.1 Main Conclusions

Precision agriculture AI often justifies itself with the narrative of "less input, more output," but this narrative easily obscures the environmental footprint of digital infrastructure, the redistribution of data and platform power, and the systemic backlash caused by efficiency gains. Without proper governance, AI may merely optimize unsustainable agricultural models rather than guide their transformation.

This paper proposes a dual-engine governance model. It uses the relational ontology of Eastern ecological ethics—the unity of humanity and nature, and the spirit of restraint—as its value engine, providing a teleology and boundaries for AI intervention in agriculture. Simultaneously, it uses Western principles of responsibility, rights, and procedural justice as its procedural engine, establishing auditable, accountable, and remedial institutional arrangements. Both are integrated through "verifiable trust," with AIEIA serving as a concrete tool, ensuring that ethics is not merely a declaration but an operational governance process.

The true revolutionary potential of agricultural AI lies not in more precise nitrogen fertilizer calculations, but in its ability to be designed and managed as a tool to promote soil regeneration, watershed health, and rural justice. Only when we rearrange the "value-procedure-evidence" relationship using a dual-engine framework can AI transform from an efficiency machine into a collaborator for ecological prosperity.

9.2 Limitations and Future Directions

9.2.1 **Indicator availability** : Some biodiversity or soil microbial indicators still face cost and technical barriers; in the future, proxy indicators or stratified monitoring strategies can be developed.

9.2.2 **Attribution difficulties** : Agriculture is greatly affected by climate and market, requiring more sophisticated causal reasoning designs (control areas, differences within differences, time series).

9.2.3 **Cross-domain governance coordination** : AIEIA requires collaboration among environmental, agricultural, and digital governance agencies; in practice, it may face the problem of fragmented authority and responsibility .

9.2.4 **The Global South** : The issues of smallholder farming, land ownership, and data sovereignty are more complex, and further comparative research and localization are needed in the future.

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