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A Systematic Review of AIoT in Agricultural Environmental Monitoring: A Comparative Analysis of Machine Learning Approaches

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ABSTRACT

Agricultural water management increasingly deploys AIoT systems that integrate IoT sensing with machine learning, yet deployable autonomous irrigation control remains largely unrealized despite widely reported accuracy above 90%. This systematic literature review of 25 peer-reviewed studies (2020–2026), conducted across five databases following PRISMA 2020 guidelines, diagnoses why predictive performance fails to translate into operational autonomy. The analysis identifies six interdependent structural gaps: open-loop prediction architectures, informationally narrow sensing, correlated co-sensor packaging, static non-adaptive models, accuracy–deployability decoupling, and metric inconsistency. These gaps form a dependency chain across data, inference, and actuation layers in which closed-loop integration depends on resolving data adequacy. A parallel finding reveals systematic methodological divergence between national and international research contexts, driven by infrastructure and deployment constraints rather than research quality, with reinforcement learning, hybrid multi-modal architectures, and continual learning largely absent in national studies. This study contributes a reframing of AIoT system maturity by demonstrating that within-study accuracy is misaligned with operational validity. It further establishes environmental generalizability as a more appropriate evaluation criterion, shows that the six structural gaps form a sequential dependency structure that prevents single-gap solutions from producing deployable improvement, and provides directional evidence that reported accuracy and validation scope are inversely related across the corpus, suggesting that current performance claims systematically overstate operational readiness.

INTRODUCTION

Agriculture accounts for ~70% of global freshwater withdrawals, yet water delivery efficiency remains structurally inadequate [1], [2]. As climate variability intensifies, arable land constrains and global food demand rises, the gap between data collection and adaptive water management extends beyond agronomic productivity, reaching into food security, resource sustainability, and rural economic stability [3], [4].

The emergence of the Artificial Intelligence of Things (AIoT) has introduced a compelling technological pathway for closing this gap. AIoT, the convergence of AI and IoT, enables IoT systems to provide data flow to AI techniques for real-time integration, interpretation, and automated prediction, transforming agriculture by addressing smart farm monitoring and efficient agricultural data analysis [5]. AIoT combines automatic decision-making with classic IoT sensing and system controls, where AI is trained to analyze sensor

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data and make informed decisions about irrigation, fertilization, and pest control [6]. While conventional IoT generates data without interpretation, and standalone ML models operate on static datasets without real-time environmental grounding, AIoT architectures offer, in principle, the capacity to sense, interpret, and respond to agricultural conditions continuously and autonomously [7].

Research interest in this domain has grown substantially. The integration of IoT and AI in agriculture has resulted in a sharp increase in peer-reviewed publications between 2022 and 2024, reflecting intensified academic and industrial interest in smart farming solutions driven by global challenges such as climate change, resource scarcity, and labor shortages. Findings from recent reviews reveal significant growth in the use of optical, acoustic, electromagnetic, and soil sensors, alongside ML models such as SVMs, CNNs, and random forests for optimizing irrigation, fertilization, and pest management [8]. Machine learning techniques including KNN, SVM, ANN, and RF have further refined irrigation scheduling, with reported accuracies exceeding 98% in controlled settings [9]. On the surface, this trajectory suggests a field approaching deployable maturity with well-validated technical solutions.

The reality, however, is structurally more complex, and six interrelated structural gaps define the actual distance between the literature and deployable autonomous systems. First, the vast majority of AIoT systems for agricultural monitoring appear to operate as isolated inference components, including prediction models, classification systems, and anomaly detectors without integration into the actuation layer, reflecting an open-loop architectural limitation (G1). The current fragmented approach in smart irrigation, which focuses on individual components rather than the entire system, limits the potential for fully autonomous, real-time, end-to-end irrigation management [10]. Second, the environmental data underpinning these systems is narrower than it appears. Most studies tend to rely on surface soil moisture combined with co-located atmospheric sensors, which are physically correlated and often derived from a single composite module, rather than on informationally independent variables that capture the ecological complexity governing real agricultural water dynamics (G2 and G3) [9]. As a result, many systems are trained on environmental representations substantially narrower than the ecosystems in which they are expected to operate.

Third, model architectures are typically trained on fixed historical datasets and deployed without adaptive mechanisms, limiting their ability to respond to environmental drift, seasonal variation, and sensor degradation (G4). Static supervised models are therefore generally unable to self-correct under the non-stationary conditions inherent to agricultural environments [11]. Fourth, high model accuracy is frequently reported under controlled or single-site evaluation conditions, which may not translate into deployable robustness across heterogeneous field environments (G5). Fifth, the absence of standardized evaluation metrics across studies further limits comparability and prevents cumulative empirical synthesis across the field (G6). These gaps are not independent; rather, they form a dependency structure in which limitations at the data and architectural levels reinforce the absence of operational autonomy at the system level.

These structural limitations are compounded by a contextual divergence that has received no systematic treatment in the existing literature. The uneven global distribution of AIoT innovation reflects a digital divide: research in resource-constrained settings, including most national contexts in developing regions, is disproportionately concentrated on deployment-feasible supervised models applied to localized datasets, while advanced paradigms, including unsupervised learning, hybrid frameworks, reinforcement learning, remain concentrated in well-resourced international research environments [12], [13]. Connectivity constraints, high sensor infrastructure costs, and limited access to multi-site validation environments further widen this methodological divergence [14]. Whether this divergence reflects genuine differences in research quality or structural differences in data infrastructure, deployment constraints, and validation demands has not been systematically examined. This gap matters precisely because internationally developed paradigms cannot be transferred to national or resource-constrained settings without adaptation.

No existing systematic review has examined these structural conditions as an integrated analytical problem. Existing surveys have covered machine learning applications in precision agriculture broadly [8], [15], catalogued IoT sensor deployments and architectures [6], [16], reviewed smart irrigation approaches across paradigms [17], [9], and examined AIoT applications in smart agriculture generally [5], [18]. However, none has simultaneously addressed the distribution of ML paradigms, the informational adequacy of environmental variables, and the system-level gap between predictive performance and operational autonomy within a unified analytical framework, and none has provided a structured comparative analysis of national versus international AIoT research trajectories.

This review addresses these gaps through a PRISMA 2020-compliant Systematic Literature Review of 25 peer-reviewed studies (2020–2026) across five academic databases, structured around four research questions: problem domains addressed by AIoT systems (RQ1), ML paradigm distribution across national and international contexts (RQ2), monitored environmental variables and their informational involvement (RQ3), and structural development directions and research opportunities (RQ4). The central argument is not that current AIoT agricultural systems are technically inadequate, as the accuracy evidence largely suggests otherwise, but that technical performance within narrow evaluation conditions has been systematically conflated with operational readiness for heterogeneous, non-stationary real-world environments. Distinguishing these two is not a semantic concern; it is the prerequisite for directing future research toward the architectural commitments that deployable autonomous agricultural systems actually require.

METHOD

This study employs a Systematic Literature Review (SLR) to critically examine and synthesize the state-of-the-art applications of Artificial Intelligence of Things (AIoT) in agricultural environmental monitoring. The SLR approach was selected to minimize selection bias and to ensure that identification, screening, and synthesis were conducted in a structured and reproducible manner, following the guidelines proposed by Kitchenham and Charters [20]. The research procedure consists of four integrated phases: (1) formulating research questions, (2) executing a comprehensive literature search, (3) establishing eligibility criteria complemented by a Quality Assessment (QA) framework, and (4) conducting a staged article selection process. Reporting adheres to the PRISMA 2020 guidelines [19].

Research Questions

The following four research questions (RQs) were formulated to guide the synthesis:

RQ1: What agricultural problems are most dominantly addressed by AIoT systems, such as environmental condition prediction, classification, anomaly detection, or automatic control?

RQ2: How are Machine Learning approaches distributed and dominated in AIoT research for agricultural environmental monitoring in national and international contexts?

RQ3: What environmental data representations are used in AIoT agricultural monitoring, including variable selection and level of data involvement?

RQ4: What are the development directions and research opportunities for AIoT in agricultural environmental monitoring based on findings from existing literature?

These RQs form a structured analytical framework, progressing from problem identification (RQ1) to methodological and data analysis (RQ2–RQ3), and finally to gap identification (RQ4). Each study was assigned to a single dominant problem category and analyzed across methodological, data, and system dimensions to ensure consistent classification throughout the synthesis.

Search Strategy and Database Selection

The search was conducted across IEEE Xplore, ScienceDirect, SpringerLink, Google Scholar, and national indexing systems (SINTA/Garuda) to capture both international and national variations in AIoT agricultural research. Search strings were constructed using Boolean operators combining IoT/AIoT paradigms, AI/ML techniques, and agricultural contexts, as detailed in Table 1.

Table 1. Search Strategy and Initial Literature Results

Database	Search String	Initial Results
Google Scholar	("AIoT" OR "Sensor Networks") AND ("Pertanian" OR "Irigasi" OR "Smart Farming") AND ("Machine Learning" OR "Deep Learning")	59
National Journals (SINTA/Garuda)	("AIoT" OR "Sensor Networks") AND ("Pertanian" OR "Irigasi" OR "Smart Farming") AND ("Machine Learning" OR "Deep Learning")	28
ScienceDirect	Title, abstract, keywords: ("AIoT" OR "Sensor Networks") AND ("Agriculture" OR "Precision Agriculture") AND ("Deep Learning" OR "Machine Learning")	21
IEEE Xplore	("AIoT" OR "Sensor Networks" OR "IoT") AND ("Agriculture" OR "Smart Farming") AND ("Machine Learning" OR "Deep Learning" OR "Reinforcement Learning")	18
Springer Link	("AIoT" OR "Internet of Things") AND ("Smart Agriculture" OR "Environmental Monitoring") AND ("Deep Learning" OR "Machine Learning")	15
MDPI	Title/Abstract: ("Sensor Networks" OR "IoT") AND ("Agriculture" OR "Irrigation") AND ("Deep Learning" OR "Reinforcement Learning")	13
Total		154

The distribution of results across databases reflects the broad coverage of this search strategy, with Google Scholar and national repositories contributing the largest share, indicating active research activity in both international and national contexts. The deliberate inclusion of SINTA/Garuda is particularly important for capturing Indonesian-context implementations that are often underrepresented in international databases, thereby strengthening the comparative dimension of RQ2. To ensure relevance to AIoT, retrieved studies were further screened for explicit integration of sensing (IoT) and intelligent processing (AI/ML) components within a unified system context. The selection of these databases reflects both their indexing credibility and coverage diversity, ensuring representation of high-impact international research as well as context-specific national studies.

Inclusion and Exclusion Criteria

To ensure selected studies are relevant and methodologically sound, the following criteria were defined prior to screening and applied in conjunction with the QA framework.

Inclusion Criteria:

1. Studies discussing AI, ML, or Deep Learning integrated with IoT or AIoT in smart agriculture contexts.
2. Studies focusing on agricultural environmental monitoring (soil moisture, temperature, irrigation, or related conditions).
3. Studies presenting a clear methodological approach with evaluable outcomes.
4. Peer-reviewed articles, including journals and high-quality conference proceedings.
5. Articles published between 2020–2026.

Exclusion Criteria:

1. Survey or review papers without original methodological or empirical contribution.
2. Studies not relevant to IoT-based agricultural environmental monitoring.
3. Studies lacking sufficient methodological detail or evaluable results.
4. Inaccessible full-text or duplicate publications.

The QA framework supports evidence-weighted synthesis by providing a structured basis for assessing methodological quality across the selected studies. High-quality conference proceedings were included due to their relevance in rapidly evolving fields such as AIoT, where emerging methods are often first introduced prior to journal publication.

Study Selection

The selection process followed the PRISMA 2020 framework across four stages, as illustrated in Figure 1. From 154 initially retrieved articles, 35 duplicates were removed, yielding 119 unique studies. Title and abstract screening excluded 67 irrelevant articles, leaving 52 for full-text assessment. After in-depth evaluation using the QA framework, studies lacking one or more of the following were excluded: quantitative evaluation metrics, IoT hardware integration, or experimental validation. This process resulted in a final set of 25 selected studies.

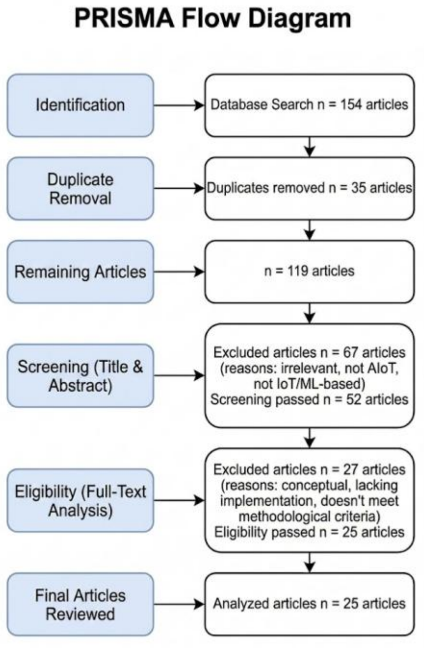

Figure 1. Article Search and Screening Process

This reduction reflects the cumulative effect of applying both topical relevance filters and methodological quality thresholds. The relatively high exclusion rate at the full-text stage (27 of 52 articles) indicates that while the topic attracts broad publication interest, a substantial portion of available literature lacks the empirical depth required for rigorous synthesis. The final corpus of 25 studies therefore represents a concentrated, high-quality dataset that is well-positioned to support meaningful cross-study analysis.

Quality Assessment (QA)

A structured QA framework was applied following the PRISMA-based selection process to provide a graded, multidimensional evaluation of each study's scientific quality. The framework consists of six criteria covering essential dimensions of AIoT agricultural research, defined in Table 2.

Table 2. Quality Assessment Criteria

Code	Quality Question	Rationale
QA1	Does the study clearly define the research problem and objective?	Ensures the study has a clear and focused research direction
QA2	Does the study use real-world or realistic datasets (e.g., IoT or field data)?	Validates the applicability of the study in real-world agricultural environments
QA3	Does the study apply appropriate machine learning, deep learning, or reinforcement learning methods?	Ensures the technical validity of the proposed approach
QA4	Does the study report quantitative evaluation metrics (e.g., accuracy, RMSE)?	Measures the strength and reliability of the reported results
QA5	Does the study implement or simulate a real system (e.g., IoT, control, deployment)?	Assesses the practical relevance and system-level contribution
QA6	Does the study provide comparison or validation (e.g., benchmarking, baseline models)?	Evaluates the robustness of the analysis and model validation

Each criterion was scored using a three-level scheme (Table 3), and studies were classified by total score into quality tiers (Table 4). The QA framework is not applied as an exclusion mechanism but serves as a foundation for evaluating methodological quality across studies.

Table 3. Scoring Definition

Score	Meaning
1	Fully satisfied
0.5	Partially satisfied
0	Not satisfied

The scoring scheme and quality classification are summarized in Tables 3 and 4, providing a structured basis for evaluating the methodological rigor of the selected studies.

Table 4. Quality Level Classification

Total Score Range	Quality Level
5.0 – 6.0	High Quality
3.0 – 4.5	Medium Quality
0 – 2.5	Low Quality

The complete QA results for all 25 studies are presented in Table 5.

Table 5. Quality Assessment Results of Selected Studies

No	Reference	Year	QA1	QA2	QA3	QA4	QA5	QA6	Total Score	Quality Level
1	[21]	2025	1	1	1	1	1	0.5	5.5	High
2	[22]	2025	1	0.5	1	0.5	0.5	0.5	4.0	Medium
3	[23]	2025	1	1	1	1	0.5	1	5.5	High
4	[24]	2025	1	0.5	1	1	1	1	5.5	High

5	[25]	2025	1	1	1	1	0.5	1	5.5	High
6	[26]	2025	1	1	1	1	1	0.5	5.5	High
7	[27]	2025	1	1	1	0.5	0	0.5	4.0	Medium
8	[28]	2024	1	1	1	1	1	1	6.0	High
9	[29]	2025	1	1	1	0.5	0.5	0	4.0	Medium
10	[30]	2025	1	1	1	1	0.5	1	5.5	High
11	[31]	2025	1	1	1	1	0.5	1	5.5	High
12	[32]	2025	1	1	1	1	1	1	6.0	High
13	[33]	2025	1	1	1	1	1	1	6.0	High
14	[34]	2025	1	1	1	1	0.5	1	5.5	High
15	[35]	2025	1	1	1	1	0.5	1	5.5	High
16	[36]	2024	1	1	1	1	1	1	6.0	High
17	[37]	2026	1	1	1	1	1	1	6.0	High
18	[38]	2021	1	1	1	1	1	1	6.0	High
19	[39]	2022	1	0.5	1	1	0.5	1	5.0	High
20	[40]	2023	1	0.5	1	1	0.5	1	5.0	High
21	[41]	2025	1	1	1	1	1	1	6.0	High
22	[42]	2021	1	1	1	1	0	1	5.0	High
23	[43]	2024	1	1	1	1	0	1	5.0	High
24	[44]	2023	1	1	1	1	0.5	1	5.5	High
25	[45]	2025	1	1	1	1	0.5	1	5.5	High

In addition to the QA framework, study quality was further contextualized using external indicators such as citation counts and journal or publisher reputation (e.g., IEEE, Elsevier, Springer). These metrics were not used as strict inclusion criteria but served as supporting evidence to ensure that the selected studies originate from credible and impactful research sources. As shown in Table 5, the majority of selected studies achieved High quality scores (22 of 25), with the remaining three classified as Medium. Notably, the most common area of partial satisfaction is QA5 (system implementation), reflecting a recurring gap between algorithmic performance and real-world deployment, a finding that directly informs the research gaps addressed in RQ4. The consistently high scores across QA1, QA3, and QA4 indicate strong conceptual clarity and technical rigor across the corpus. The QA framework therefore serves as a structured basis for assessing methodological quality and supporting the interpretation of findings across studies.

RESULT AND DISCUSSION

Overview of the Studies

Quality assessment across all 25 selected studies confirms that the corpus meets the methodological standards required for evidence-based synthesis. As shown in Table 5, 22 studies (88%) are classified as high quality, while three studies [22], [27], and [29] fall in the medium-quality range, reflecting partial limitations in quantitative reporting, validation completeness, and deployment scope rather than fundamental methodological flaws. These studies are retained with appropriate evidence weighting; their incomplete metric reporting is revisited as Gap G6 in the discussion of evaluation gaps. No study falls in the low-quality category.

Table 6 reframes the 25 studies as functionally grouped clusters organized across four dimensions, ML paradigm, research scope, environmental variable profile, and system design orientation. Group A unifies the 17 studies sharing a supervised learning foundation with soil–atmosphere sensor inputs, differentiated into classical algorithms (A1), temporal deep learning (A2), and ensemble or multi-modal extensions (A3). Group B isolates the three climate-dominant studies: B1 [22], [29] employs supervised methods; B2 [30] applies an unsupervised paradigm. Group C captures the four IoT data stream anomaly detection systems. Group D identifies the sole study crossing from inference-oriented architecture into closed-loop adaptive control. Supervised learning totals 19 of 25 studies, 17 in Group A and 2 in Group B1; the remaining six are distributed across unsupervised, hybrid, and reinforcement learning paradigms.

Table 6. Summary of National and International Studies on AIoT for Soil, Water, and Air Monitoring — Categorized Format (n = 25)

Sub	Studies	ML Paradigm	Scope	Data & Variable Profile	System Design Orientation
Group A — Supervised Learning with Soil–Atmosphere Sensor Inputs (n = 17)					
A1	[21], [26], [27], [28], [31], [36], [39], [40]	Classical supervised (SVM, RF, DT, TinyML, Logistic Regression)	Nat. + Int.	Soil moisture, temperature, humidity	Prediction / classification; edge-deployable; interpretability-oriented; open-loop
A2	[23], [24], [25], [34], [35], [38]	Deep learning (LSTM, GRU, RNN)	Nat. + Int.	Soil moisture, temperature, humidity, solar radiation	Temporal prediction of irrigation demand or soil moisture; sequence-based modeling; open-loop
A3	[32], [33], [37]	Ensemble / hybrid ML (RF, SVR, XGBoost, ANN, NG-SOM)	Int.	Soil, air quality, crop/plant data, UAV imagery	Extended prediction or disease detection; integrates IoT with multi-source sensing modalities
Group B — Climate-Dominant Modeling (n = 3)					
B1	[22], [29]	Supervised (DL, RF)	Nat.	Rainfall, temperature, humidity	Agricultural productivity or plant growth estimation; no soil sensor; no actuation integration
B2	[30]	Unsupervised (LSTM Autoencoder, OCSVM)	Nat.	Sunlight duration, rainfall	Environmental anomaly detection; detection-only; no downstream control integration
Group C — IoT Data Stream Anomaly Detection (n = 4)					
C1	[41], [42], [43]	Unsupervised (ELSCP, Autoencoder, LoRaWAN AD)	Int.	Real-time IoT data streams	Continuous anomaly detection for data integrity; not directly linked to actuation
C2	[44]	Hybrid (CNN–SVM–LSTM pipeline)	Int.	Multi-sensor heterogeneous IoT streams	Integrated anomaly detection and data correction; represents a more architecturally integrated detection system
Group D — Adaptive Closed-Loop Control (n = 1)					
D1	[45]	Reinforcement learning (PPO)	Int.	Soil moisture, environmental state, irrigation history	Adaptive irrigation policy via iterative environmental interaction; represents the only identified closed-loop architecture

Three distributional patterns emerge. Supervised learning is the methodological center of gravity: classical algorithms in A1 [21], [26], [27], [28], [31], [36], [39], [40] prioritize interpretability and edge-deployment feasibility; deep learning in A2 [23], [24], [25], [34], [35], [38] captures temporal soil moisture dynamics. Group A3 [32], [33], [37] extends this through ensemble and multi-source architectures. Groups B2 and C represent contextually specific deployments, B2 [30] applies unsupervised methods to atmospheric data, Group C [41]-[44] targets IoT data integrity. Reinforcement learning appears solely in Group D [45], architecturally distinct in its closed-loop adaptive control capacity.

Environmental variable coverage concentrates on soil moisture across Groups A1, A2, and D; atmospheric variables function as secondary co-located inputs rather than informationally independent ones [21], [23], [24], [35], [36]. Group B relies exclusively on atmospheric and meteorological variables without soil-sensor integration [22], [29], [30]. Plant-level or multi-modal data remains limited to Group A3 [32], [37]. National studies concentrate within Groups A and B; all methodological departures beyond supervised learning, the unsupervised pipeline in B2, Group C systems, and the RL system in D1, are predominantly international, with [30] as the sole national exception employing an unsupervised paradigm.

RQ1: What agricultural problems are most dominantly addressed by AIoT systems?

The 25 studies address four primary problem domains, each study assigned to a single dominant category to ensure mutually exclusive counting. As shown in Figure 2(a), prediction constitutes the largest domain (n = 10, 40%), followed by decision support/control (n = 6, 24%), anomaly detection (n = 5, 20%), and classification (n = 4, 16%). Within decision support/control, five studies [28], [33], [38], [39], [40] employ supervised learning to generate irrigation recommendations; only [45] (Group D1) employs reinforcement learning as the corpus's sole genuinely closed-loop system. This distribution points to a research landscape that is methodologically mature at the inference layer yet structurally incomplete at the action layer.

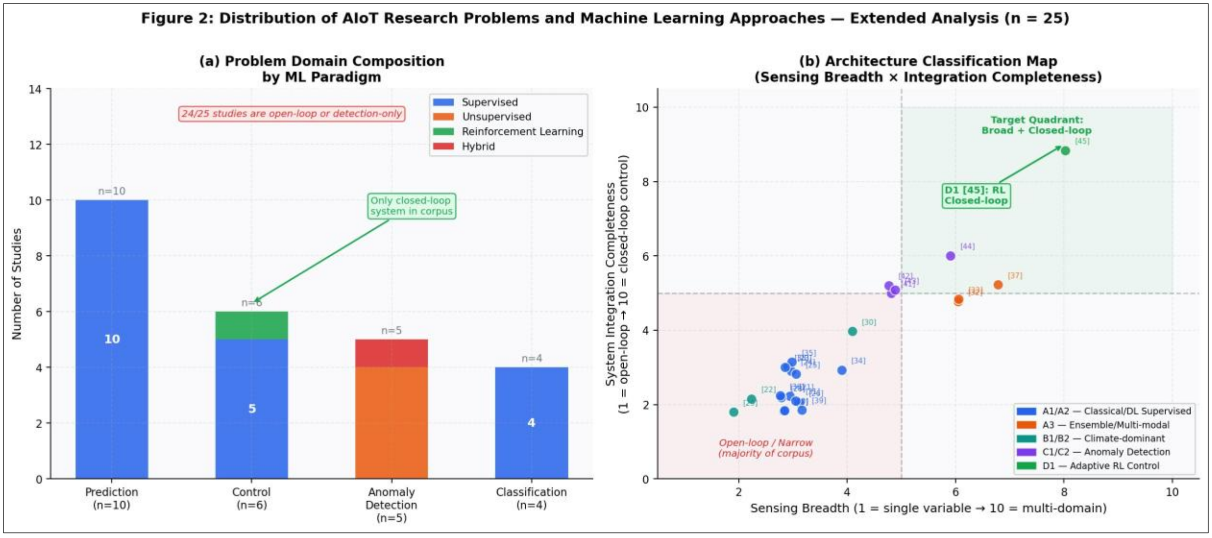

Figure 2. Distribution of AIoT Research Problems and Machine Learning Approaches (n = 25)

Prediction: Technical Depth within an Open-Loop Constraint

Prediction systems (n = 10) target soil moisture estimation and irrigation forecasting across Groups A1 and A2. Group A1 studies [21], [26], [28], [31], [36], [39] deploy classical algorithms, including SVM, Random Forest, Decision Tree, and TinyML-based logistic regression, where interpretability, low computational overhead, and edge-deployment feasibility govern design. Group A2 studies [23], [24], [25], [34], [38] employ LSTM, GRU, and RNN to capture sequential dependencies in time-series IoT data; comparative evaluations consistently indicate LSTM and GRU outperform classical models on time-series data, with GRU offering competitive accuracy at lower computational cost [24], [25].

Despite elevated predictive performance, all systems across Groups A1 and A2 operate open-loop: model outputs inform recommendations but are not linked to actuation mechanisms. This is a systematic characteristic of the entire prediction domain, not an incidental study-level limitation. It is noted that [26] and [40] exhibit a secondary limitation beyond open-loop architecture: their models are trained on fixed historical distributions and do not adapt to environmental drift or seasonal non-stationarity, addressed separately as Pattern P2 in the analysis of structural gaps.

Classification and Anomaly Detection: Complementary Analytical Layers

Classification systems (n = 4), concentrated in Group A1 [27], [28], [31], [36], apply SVM, Random Forest, and Decision Tree to convert continuous sensor readings into discrete categorical outputs. Note that [27] is medium-quality due to incomplete metric reporting, limiting cross-study performance comparison. Computationally efficient and edge-deployable, classification systems occupy a structurally intermediate position: outputs can inform downstream irrigation decisions but require external interpretation to trigger actuation, functioning as analytical converters rather than autonomous decision engines.

Anomaly detection (n = 5) spans two structurally distinct sub-domains. Group B2 [30] applies unsupervised LSTM Autoencoder and One-Class SVM to atmospheric variables for environmental anomaly detection without soil sensor integration or control linkage. Groups C1 and C2 address IoT data stream integrity: three unsupervised systems [41], [42], [43] detect sensor failures and data drift in real-time agricultural streams, complemented by the hybrid CNN–SVM–LSTM pipeline in C2 [44], which integrates detection with active data correction. This distinction matters: B2 detects environmental conditions; C1 and C2 protect data infrastructure. The unsupervised and hybrid paradigm choice across all five studies reflects the practical constraint that labeled anomaly data is inherently scarce in agricultural environments. Crucially, the open-loop characterization applied to prediction systems carries a different architectural meaning here: Group C systems are not designed for actuation, as their purpose is data integrity assurance, and their lack of control linkage reflects a deliberate scope boundary rather than the same design gap characterizing open-loop prediction.

Decision Support and Control: The Autonomy Gap

Decision support and control systems (n = 6) remain structurally underdeveloped despite occupying the most critical position in the AIoT ecosystem. Five studies [28], [33], [38], [39], [40] generate irrigation recommendations via supervised learning, achieving high accuracy but terminating at the recommendation stage with inference and actuation decoupled. Only Group D1 [45] introduces genuine autonomy: the PPO-based reinforcement learning system replaces static input–output mapping with a dynamic irrigation policy learned through iterative environmental interaction, integrating soil moisture state, atmospheric conditions, and irrigation history as a time-evolving state space. Unlike any system in Groups A–C, it generates decisions as a learned behavioral policy enabling sequential decision-making under uncertainty. This is structurally compatible with the non-stationary, feedback-dependent dynamics of real agricultural environments.

Synthesis

The four domains reveal a consistent architectural asymmetry: 24 of 25 studies occupy Groups A, B, and C, all architecturally open-loop or detection-only, while Group D occupies a single entry. It must be emphasized that 'open-loop' and 'detection-only' describe architecturally distinct limitations: prediction systems (Groups A, B1) do not trigger actuation; anomaly detection systems (Groups B2, C) are bounded by deliberate scope. Both represent the absence of closed-loop integration, but for different structural reasons. Figure 2(b) maps this asymmetry spatially across two axes: sensing breadth (1 = single variable, 10 = multi-domain) and system integration completeness (1 = open-loop, 10 = closed-loop control). Groups A1/A2 (blue) and B/climate-dominant (teal) cluster densely in the lower-left quadrant, confirming narrow sensing paired with open-loop inference as the dominant configuration. Ensemble and multi-modal studies in A3 (orange) shift rightward on the sensing axis but remain below the integration threshold. Only study [45] (green, D1) reaches the target quadrant, with broad sensing and closed-loop RL control, isolated from the rest of the corpus. This spatial concentration is not incidental: the lower-left quadrant is structurally easier to publish in, requiring neither multi-modal data infrastructure nor actuation hardware. The central developmental challenge is architecting the closed-loop integration that translates environmental intelligence from Groups A–C into the autonomous agricultural action currently represented by Group D alone.

RQ2: Distribution and Dominance of Machine Learning Approaches in National and International AIoT Research

Having established the dominant problem domains (RQ1), the following discussion examines how these problems are methodologically approached. As shown in Figure 3(a), supervised learning dominates the global corpus, nine national [21]–[29] and ten international [31]–[40] studies, totaling 19 of 25. With one notable exception, almost all methodological diversity beyond supervised learning is concentrated in the international subset: unsupervised approaches in Groups C1 [41], [42], [43], the hybrid CNN–SVM–LSTM in C2 [44], and the RL system in D1 [45] are exclusively international. The sole exception is [30] (Group B2), a national study employing an unsupervised paradigm (LSTM Autoencoder and OCSVM), representing the only national departure from the supervised foundation. No national study occupies Groups C or D.

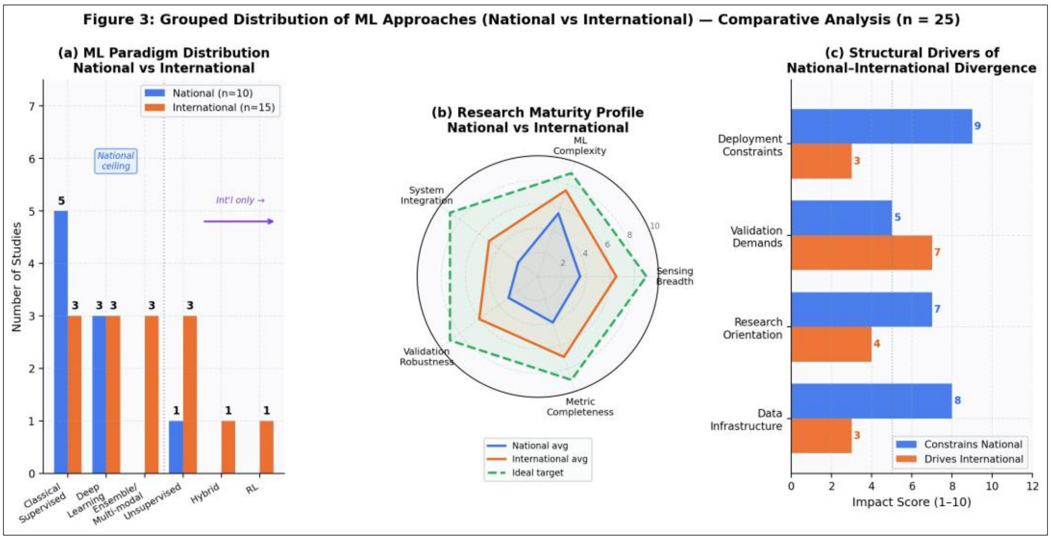

Figure 3. Grouped Distribution of ML Approaches and Research Maturity Profile: National vs International (n = 25)

National Context: Supervised Learning Under Deployment Constraints

Within the national subset (n = 10), supervised concentration is total across nine studies, with [30] as the single unsupervised exception. Group A1 national studies [21], [26], [27], [28] favor classical algorithms where interpretability and computational efficiency are primary criteria, the TinyML implementation in [21] reflects deliberate optimization for on-device inference. Group A2 national studies [23], [24], [25] deploy LSTM and GRU for temporal soil moisture prediction, representing the methodological ceiling of national supervised research: deep learning on sequential data, still operating open-loop. Group B1 studies [22], [29] target agricultural productivity and plant growth estimation on climate-dominant variable profiles without soil sensing or actuation. [30] (B2) applies LSTM Autoencoder and OCSVM to atmospheric data for anomaly detection, representing the sole national unsupervised deployment, but remains detection-only with no control integration. National research thus achieves real-world deployability at the cost of inability to address environmental non-stationarity, multi-source variable integration, or closed-loop decision-making.

International Context: Methodological Diversification and Exploratory Expansion

The international subset (n = 15) extends considerably beyond the supervised foundation. Group A3 [32], [33], [37] introduces ensemble and multi-modal architectures integrating RF, SVR, XGBoost, ANN, and NG-SOM across heterogeneous data sources, modeling plant-environment interactions that single-sensor pipelines are structurally incapable of capturing. Group C systems address IoT data infrastructure reliability: C1 [41], [42], [43] detects real-time stream failures where labeled anomaly data is structurally unavailable; C2 [44] integrates detection with active data correction. Most architecturally distinct is D1 [45], where PPO-based RL replaces static input–output mapping with a decision policy continuously adapted to soil moisture state, atmospheric conditions, and irrigation history. This represents the only system approaching genuine adaptive autonomy.

Structural Drivers of the National–International Divergence

Three intersecting factors drive the systematic divergence. Data infrastructure is most immediate: national studies operate on localized, often single-variable datasets [21], [24], [26], [27], [30], constraining model complexity, while international studies in Groups A3, C, and D operate on multi-source, multi-variable inputs that are prerequisites for ensemble, hybrid, and RL architectures [32], [34], [37], [44], [45]. Research orientation compounds this: national studies optimize for deployable systems within resource constraints; international studies more frequently pursue methodological comparison and architectural exploration. The validation demands of hybrid and RL systems, which require multi-stage evaluation environments and multi-episode training protocols [44], [45], further concentrate advanced paradigms in international work.

Synthesis

The distribution reveals a maturity gradient shaped as much by context as by methodology. Supervised learning across Groups A and B1 is robust and well-validated in both contexts [21]–[29], [31]–[40], but its dominance leaves a structural gap: the paradigms most capable of addressing agricultural complexity, including unsupervised anomaly detection in B2 (the sole national instance) and Groups C1/C2, hybrid multi-modal integration in C2, and adaptive closed-loop control in D1, are predominantly international within the reviewed corpus and largely confined to proof-of-concept deployments. The research maturity radar in Figure 3(b) quantifies this divergence across five dimensions: national studies show notably lower scores on system integration, sensing breadth, and ML complexity relative to international studies, with the gap widest on system integration and narrowest on metric completeness, indicating that national research reports results with comparable rigor but builds less complete systems. Figure 3(c) identifies the structural drivers: deployment constraints score 9 for national versus 3 for international research, and data infrastructure scores 8 versus 3, confirming that the divergence originates in resource and infrastructure conditions rather than differences in research intent or methodological quality. Validation demands and research orientation show smaller but consistent differentials in the same direction. The transition from inference-layer maturity in Group A to action-layer capability in Group D represents the critical underdeveloped axis of the field.

RQ3: Environmental Variables in AIoT Agricultural Monitoring and Their Level of Involvement

While the previous discussion examined methodological approaches, this part focuses on what information these models actually operate on. Variable selection determines model representational depth and system capability. Drawing from the Data & Variable Profile column in Table 6, environmental variables organize into four functional clusters: soil-related (soil moisture, soil type), atmospheric (temperature, humidity, weather/rainfall), water and irrigation flow, and multi-source or advanced data modalities. Figure 4(a) shows frequency and independence scores, Figure 4(b) their relation to quality, and Figure 4(c) multi-variable adequacy.

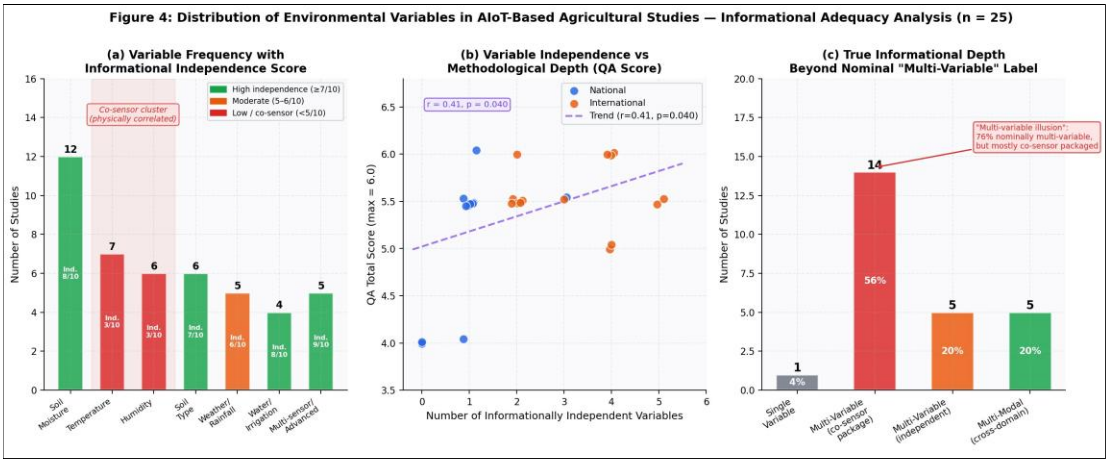

Figure 4. Distribution of Environmental Variables and Informational Adequacy in AIoT Agricultural Studies (n = 25)

As shown in Figure 4(a), soil moisture (n = 12) stands as the single dominant variable, with all others trailing at roughly half that frequency or less. Temperature (n = 7), humidity (n = 6), and soil type (n = 6) form a secondary tier, followed by weather/rainfall (n = 5), multi-sensor/advanced modalities (n = 5), and water/irrigation flow (n = 4). The independence scores in panel (a) show that: soil moisture scores 8/10, confirming high standalone information value, while temperature and humidity carry only 3/10 each, confirming their role as co-sensor co-variates rather than analytically distinct inputs. Water/irrigation flow (9/10) and multi-sensor/advanced configurations (8/10) carry the highest independence but appear in the fewest studies. Figure 4(b) makes the methodological implication explicit: there is a statistically significant positive correlation ($r = 0.41$, $p = 0.040$) between the count of informationally independent variables and total QA score. This means sensing adequacy and methodological rigor are not independent, studies that invest in genuinely independent variable selection also tend to produce more robust, reproducible, and complete research designs.

Soil Moisture as the Gravitational Center

Soil moisture dominates due to a structurally self-reinforcing cycle across Groups A1 and A2: it is the most direct indicator for irrigation decisions, supported by low-cost sensor availability and repeated validation [21], [23]– [28], [31], [34]–[36], [38], [39], [40], [45], creating a research path dependency in which each step reinforces the next: accessible variables are measured, measured variables are modeled, modeled variables are published, and published configurations are repeated, through which soil moisture becomes the default representational unit of agricultural water management while complementary variables receive structurally lower investment. Temperature and humidity appear as secondary variables [21], [23], [24], [35], [36] due to sensor co-location rather than independent analytical justification: composite modules deliver all three variables from a single deployment point. Group B is structurally distinct, studies [22], [29], [30] are exclusively climate-domain, with atmospheric variables as primary inputs and no soil sensor integration. Soil type appears as a classification target in A1 studies [27], [31] rather than a directly sensed variable; water/irrigation flow appears in discharge-oriented systems [24], [26], [33], [36] as output proxies and does not materially broaden the environmental perceptual boundary.

Level of Data Involvement: The Adequacy Illusion

Figure 4(c) shows 19 of 25 studies (76%) nominally multi-variable, yet the panel labels this configuration a “multi-variable illusion”: 56% of all studies fall in the co-sensor packaged category, meaning their multi-variable status reflects sensor packaging rather than genuine informational breadth. The critical move is to examine what multi-variable means within each group. The majority of multi-variable studies in Groups A1 and A2 combine soil moisture with temperature and humidity: variables that are closely correlated and routinely delivered by a single composite sensor module [21], [23], [26], [34], [36]. This inflates apparent diversity while masking redundancy, the multi-variable label describes sensor packaging architecture rather than environmental breadth. Group B's multi-variable configurations [22], [29] combine rainfall, temperature, and humidity, all co-located within standard meteorological station outputs, without introducing any soil-layer or plant-layer information.

The genuinely distinct tier consists of five studies employing multi-source or multi-modal data configurations. It is important to qualify what 'multi-modal' means across these cases, as they differ in representational strategy. Study [37] integrates ground-level IoT sensor readings with UAV-captured leaf imagery analyzing texture and color changes as physiological indicators of sugarcane disease, observing the plant itself rather than only the surrounding abiotic conditions, a qualitatively different strategy opening the model to the biological response layer that conventional soil–atmosphere sensing cannot access. Study [34] extends soil moisture monitoring across five depths (5, 20, 40, 60, and 80 cm) in three distinct soil types, capturing vertical gradients, differential drainage responses, and root-zone heterogeneity.

This is more accurately characterized as multi-depth single-modality rather than multi-modal in the cross-domain sense of [37]; however, it achieves qualitatively different representational depth relative to surface-only configurations and is included in this tier on that basis. Group C2 [44] handles representational heterogeneity of multi-sensor IoT streams through its CNN–SVM–LSTM pipeline. Group D1 [45] integrates soil moisture, environmental state, and irrigation history as RL state space components, treating the temporal sequence of decisions as an environmental variable itself. Group A3 [32] contributes ensemble methods integrating soil, air quality, and crop data. The contrast between these five configurations and the standard soil moisture + temperature cluster in Groups A1/A2 is not a matter of variable count. It is a qualitative difference in what the system is epistemologically capable of representing.

Why Single-Modality Persists

Variable narrowness is structurally driven by three constraints. Sensor economics favor low-cost composite modules delivering correlated soil–atmosphere readings [21], [25], [26], creating an economic path of least resistance reinforcing the dominant sensor configuration. Data complexity scales non-linearly: adding independent sensing modalities increases dimensionality, preprocessing complexity, and validation demands that single-sensor pipelines avoid. In national contexts, implementation-driven research orientation reinforces these constraints by prioritizing deployable systems over the sensor and data infrastructure investment required for multi-modal designs.

Synthesis

The variable landscape has organized itself around what is sensorially convenient rather than what is environmentally representative. Groups A1 and A2, representing 14 of 25 studies, operate on a soil moisture + atmospheric co-variable configuration appropriate for single-season, single-site prediction but systematically underrepresenting the multi-stratum, multi-scale dynamics from which agricultural water stress actually emerges. High reported accuracy may therefore systematically overstate deployable robustness: a model well-fitted to a specific microclimate and soil type will degrade when transferred across different field conditions, seasons, or crop types. The five studies employing multi-source or advanced sensing configurations in Groups A3, C2, and D1 indicate what more robust sensing architectures look like [32], [34], [37], [44], [45], but they remain too few and methodologically diverse to constitute an empirical foundation for generalizable multi-modal AIoT design. Resolving this requires variable selection driven by the representational requirements of the agricultural system being managed rather than the convenience boundaries of available sensor infrastructure.

RQ4: Development Directions and Research Opportunities for AIoT in Agricultural Environmental Monitoring

Supervised learning demonstrates methodological maturity and strong validation across both national and international contexts. However, its dominance constrains architectural progression by anchoring systems in static, inference-oriented paradigms. The preceding analysis shows a field that is technically advanced at the modeling level but structurally incomplete at the system level. Prediction dominates without translating inference into actuation as discussed earlier, supervised learning accounts for 76% of the corpus based on the analysis of the study distribution, and most models rely on environmentally narrow and redundant data representations identified in the variable analysis.

These findings show that high model accuracy coexists with limitations in system integration, validation scope, and environmental representation, as summarized in Table 7.

Table 7. Summary of Key Outcomes and Analytical Limitations Across 25 Selected AIoT Agricultural Studies

Pattern	Studies (n)	Representative Performance	Shared Structural Limitation	Gap Mapped
P1: Open-loop prediction (inference without actuation)	[21], [23], [24], [25], [28], [33], [35], [36], [39] (n=9)	Accuracy 89.68%–99.21%; R^2 up to 0.998; RMSE as low as 0.099	Model outputs inform recommendations but are not linked to actuation mechanisms; no closed-loop validation with irrigation hardware; system terminates at the prediction stage	G1, G5

P2: Static model architecture (no temporal adaptivity)	[26], [38], [40] (n=3)	Accuracy 89.68%–90%+; R² up to 0.95	Offline training followed by fixed inference; model does not adapt to environmental drift, seasonal non-stationarity, or sensor calibration degradation over deployment time	G4
P3: Detection-only systems (no downstream control integration)	[30], [41], [42], [43], [44] (n=5)	F1 0.71–0.82; AUC up to 1.00; AUCPR up to 0.972; accuracy 90%–97.79%	Anomaly detection and data correction outputs are not propagated into decision-making or irrigation control mechanisms; contribution limited to data quality assurance	G1, G3
P4: Narrow validation scope (single-site or simulation-only)	[22], [29], [31], [32], [34], [37] (n=6)	R² 0.79–0.998; accuracy 96%–97.77%	Evaluation conducted on localized or simulated datasets without cross-environment, multi-site, or multi-season validation; deployable robustness under heterogeneous field conditions remains unverified	G2, G5
P5: Incomplete metric reporting (reproducibility gap)	[22], [27], [29] (n=3)	Partial metrics (e.g., accuracy or F1 only); inconsistent and non-standardized reporting across studies	Absence of standardized metric sets prevents cross-study comparison and cumulative empirical synthesis; heterogeneous evaluation protocols across the corpus compound this limitation	G6

Note: Several studies exhibit overlapping limitation patterns. [26] *exhibits dual characteristics: primary assignment to P2 (static model architecture) with open-loop inference (P1) as a secondary characteristic — it therefore appears in the evidence base of both G1 and G4 in Table 8.* [25] *maps primarily to P1 with secondary characteristics of P4 (single-site);* [36] *maps primarily to P1 with secondary characteristics of P2;* [38] *maps primarily to P2 with secondary characteristics of P4. The assignment rule is dominant limitation, but studies with documented secondary characteristics are included in the evidence base of the relevant gap.*

Reading Table 7 by pattern exposes five recurring structural limitation profiles. P1, open-loop prediction, accounts for nine studies including the corpus's highest-performing models (accuracy up to 99.21% [35]; R² up to 0.998 [34]), confirming that inference performance and system architectural completeness operate independently. P2 confirms that well-calibrated models degrade over deployment time when trained on fixed historical distributions [26], [38], [40]. This is a failure mode accuracy metrics cannot detect. P3 demonstrates that anomaly detection outputs, however precise, remain bounded without downstream control integration. This reflects a deliberate scope boundary rather than the same gap as P1. P4 shows accuracy reported under single-site or simulation-only conditions cannot be reliably assumed to transfer across heterogeneous field environments. P5 reveals that three studies [22], [27], [29] exhibit incomplete or non-standardized metric reporting, making cross-pattern comparison structurally impossible. Table 8 maps these patterns onto six structural gaps.

Table 8. Structural Gap Mapping: Evidence Base and Corresponding Development Directions (n = 25)

Gap	Structural Gap	Evidence Base	Development Direction
G1	Open-Loop Prediction Architecture	RQ1 as previously discussed; Limitation column: [21], [23], [24], [25], [26], [33], [35], [36], [38], [39]	Closed-loop AIoT system integration (sensing → inference → actuation as a unified pipeline)
G2	Informational Narrowness of Environmental Data	RQ3 as analyzed in the environmental variable assessment; Fig. 4(a)(b); positive cases: [34], [37]; majority: [21], [23], [24], [25], [26]	Multi-modal sensing frameworks incorporating plant-physiological and subsurface indicators

G3	Multi-Variable Illusion (Correlated Co-Sensors)	RQ3 as evidenced in the variable dependency analysis; Fig. 4(c); co-sensor studies: [21], [23], [26], [36], [38]	Informationally independent feature engineering using mutual information analysis
G4	Static Model Architecture (No Temporal Adaptivity)	RQ2 as examined in the methodological analysis; Limitation column: [26], [36], [38], [40]	Continual/online learning, transfer learning, and Bayesian updating for deployed systems
G5	Accuracy–Deployability Decoupling (Lab vs. Field)	RQ2 & RQ3; Key Outcome vs. Limitation column: [23], [25], [33], [35], [39]	Field-scale multi-site, multi-season validation protocols as a standard evaluation requirement
G6	Metric Inconsistency (Reproducibility Gap)	Key Outcome column: no metric reported in [22], [27], [29]; heterogeneous metrics across corpus	Standardized evaluation benchmarks: required metric sets per task type (regression, classification, control)

Table 8 synthesizes the structural gaps identified across RQ1–RQ3, linking each gap to its empirical evidence and corresponding development directions. Figure 5 visualizes these gaps across three dimensions: panel (a) maps gap severity against the number of affected studies, panel (b) plots reported accuracy against validation scope to expose the accuracy-deployability decoupling of G5, and panel (c) traces the sequential dependency structure showing that resolution must proceed from G2 and G3 through G4 to G1 before G5 and G6 can be addressed.

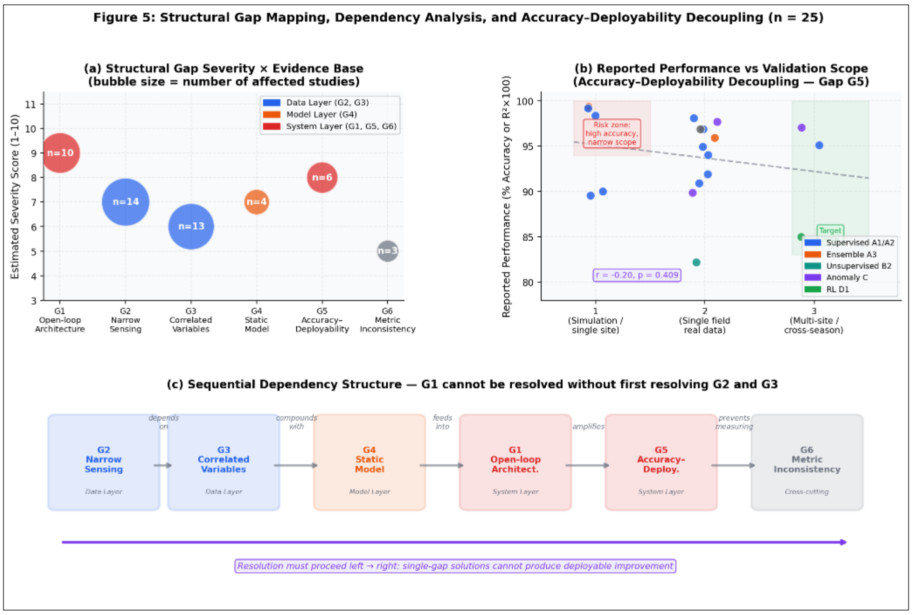

Figure 5. Structural Gap Mapping, Dependency Analysis, and Accuracy-Deployability Decoupling (n = 25)

G1: Open-Loop Prediction Architecture

One of the most pervasive gaps is architectural, and Figure 5(a) confirms its severity: G1 scores 9/10 with the second-largest bubble (n = 10), placing it among the highest-severity gaps alongside G5. At least nine studies in P1, including [21], [23], [25], [26], [33], [36], [38], [39], acknowledge the absence of closed-loop validation or real-time actuation; [26] also contributes as a secondary case. This gap is further compounded by previously identified variable narrowness in environmental data. These patterns indicate a structural interdependency between sensing completeness and control feasibility, inferred from cross-study analysis and sufficiently consistent to warrant recognition. An open-loop architecture cannot respond to its own feedback; prediction without actuation remains analytical rather than operational. The sole exception is [45], where PPO-based RL treats irrigation as a dynamic policy evaluated via cumulative water-use efficiency. This represents a different architectural category, not merely a better model. The development direction is closed-loop pipelines integrating sensing, inference, and actuation from the outset.

G2: Informational Narrowness of Environmental Data

As Figure 5(a) shows, G2 carries a severity score of 7/10 and the largest evidence bubble in the chart (n = 14 affected studies), making it the most broadly distributed gap across the corpus. Plant water stress emerges from soil hydraulic conductivity at depth, atmospheric vapor pressure deficit, stomatal regulation, and root zone structure, none of which surface soil moisture and ambient temperature can reliably represent across heterogeneous field conditions. High accuracy within a specific microclimate may not reliably generalize when underlying environmental processes vary. This is precisely what heterogeneous deployment entails. The five multi-source studies provide the empirical anchor: [34] captures moisture dynamics across five soil depths in three soil types (multi-depth rather than cross-domain multi-modal, but qualitatively superior to surface-only); [37] integrates UAV-captured leaf imagery as a genuine cross-domain physiological signal. The development direction is not 'add more sensors' but the deliberate selection of variables that are informationally independent of existing inputs and that capture the ecological processes surface-only sensing misses.

G3: The Multi-Variable Illusion

G3 is analytically distinct from G2: where G2 concerns which environmental dimensions are absent, G3 concerns whether variables already present are informationally independent. Seventy-six percent of studies nominally achieve multi-variable coverage, but in most cases this means soil moisture combined with temperature and humidity, which are physically correlated variables routinely co-packaged on a single sensor module [21], [23], [26], [36], [38]. Correlated variables may contribute limited additional informational content; under strong correlation, they add little or none. The same studies appear in both G2 and G3 because co-sensor packaging simultaneously narrows the sensing perimeter and inflates apparent data coverage. These are distinct but co-occurring effects of the same structural constraint. The development direction requires mutual information analysis and variance inflation diagnostics as standard data pipeline components, and feature set evaluation based on informational independence rather than input cardinality.

G4: Static Model Architecture

The dominant deployment mode, offline training followed by fixed inference, depends on training and deployment distributions matching. In agricultural systems, this assumption is structurally violated: soil dynamics shift across seasons, sensor calibration drifts, and climate variability introduces non-stationary patterns no historical training set can fully anticipate. [26] and [40] explicitly note that their models 'do not adapt to environmental drift'; [38] acknowledges limited generalizability to unseen environmental conditions. The development direction is the integration of continual learning, including online learning variants, transfer learning for cross-field adaptation, and Bayesian updating mechanisms that allow deployed models to evolve without requiring full retraining.

G5: Accuracy–Deployability Decoupling

Accuracy measures model fit to a training distribution, not robustness to environmental variation. Figure 5(b) makes this decoupling visible: studies concentrated in the left zone (simulation or single-site) report the highest accuracy values, while studies with broader multi-site or cross-season validation consistently show lower but more meaningful performance figures. The negative trend ($r = -0.20$, $p = 0.409$) is directionally consistent but does not reach statistical significance, reflecting the small corpus size rather than an absence of the pattern. Nonetheless, the direction confirms that reported performance and validation scope are inversely related across the corpus, and the studies driving this trend are unambiguous in their own acknowledgments of limited scope. [23] documents $R^2 = 0.95$ while noting the system is 'simulation-oriented without system-level implementation'; [33] achieves 99.21% accuracy while lacking 'closed-loop control and real-time adaptive feedback'; [39] reports 98.3% while its 'focus is limited to model comparison' without real-world deployment validation. The single partial exception is [38], which validates across three geographically distinct locations and introduces genuine cross-environment variation, although its primary limitation as a static model remains. The development direction is to institutionalize multi-site and multi-season field validation as a prerequisite for claiming deployable system performance rather than treating it as a supplementary step.

G6: Metric Inconsistency

The Key Outcome column of Table 7 exposes a metric landscape without a common standard: classification accuracy [21], [26], [35], [39], [40]; regression metrics RMSE/MAE/R^2 [24], [25], [33], [34]; anomaly detection F1 and AUC [30], [42]; policy-based evaluation [45]; and three studies [22], [27], [29] reporting no quantitative metric at all. This heterogeneity is rooted in the same medium-quality studies flagged in §3.1, and it compounds all other gaps: it is impossible to measure whether G1–G5 are being resolved if studies cannot be compared on a common metric basis. The development direction is standardized evaluation protocols, including agreed task definitions, required minimum metric sets per task type (RMSE and R^2 for regression, F1 and AUC for detection, water use efficiency for control), and benchmark datasets enabling cumulative empirical progress.

Synthesis: Where the Maturity Ceiling Actually Is

The conventional shorthand for AIoT agricultural research maturity—model architecture, algorithm performance, and accuracy tables—can misidentify the true maturity ceiling. The binding constraints lie two levels below: at the data layer, where informational narrowness (G2) and redundancy (G3) limit what any model can learn regardless of architecture; and at the system integration layer, where the open-loop gap (G1) prevents accurate forecasts from producing adaptive operational behavior. G4 and G5 intensify these primary constraints by eroding model validity over time and weakening the translation of performance claims into field robustness, while G6 prevents cumulative empirical progress by removing any common evaluative currency.

A more operational measure of AIoT agricultural system maturity is not laboratory accuracy but environmental generalizability: the range of field conditions under which a system maintains operational validity. By this standard, a system achieving 91% accuracy across multiple soil types and seasons is more mature than one achieving 99% on a single held-out validation set from the same field. Evaluated this way, the current corpus is substantially less mature than its reported accuracy suggests. Progress therefore requires simultaneous advances in data sufficiency, closed-loop architecture, and field-scale evaluation; without them, the underlying structural misalignment remains unresolved.

CONCLUSION

This review examined 25 AIoT agricultural studies through four research questions and identified a structural condition that high model accuracy obscures: sophisticated inference coexisting with an unbuilt pathway from prediction to action. Open-loop prediction dominates (nine studies, P1); supervised learning accounts for 76% of the corpus while adaptive paradigms remain largely absent; and 56% of nominally multi-variable studies reflect co-sensor packaging rather than genuine informational breadth (Figure 4(c)). These patterns express the same structural problem: development concentrated at the inference layer while the data and actuation layers remain underdeveloped, as made explicit in Figure 2(b). Critically, this data-layer deficit is not merely quantitative: Figure 4(b) shows informational independence correlates positively with methodological quality ($r = 0.41$, $p = 0.040$), meaning data quality and research rigor are structurally entangled.

This review contributes three analytically distinct findings: that laboratory accuracy is structurally misaligned with operational validity, with environmental generalizability proposed as a more meaningful maturity criterion; that the six structural gaps form a sequentially dependent chain (Figure 5(c)) such that no single-gap solution produces deployable improvement; and that national–international divergence, driven by deployment constraints (9 vs. 3) and data infrastructure (8 vs. 3) rather than research quality (Figure 3(b)(c)), carries direct implications for technology transfer to resource-constrained settings. The dependency structure has clear prioritization consequences. G1 cannot be resolved without first addressing G2–G3, since a closed-loop system fed redundant inputs actuates incorrect decisions more efficiently, not more effectively. G4 compounds silently through seasonal drift, representing a failure mode accuracy metrics cannot detect. G6 prevents the cumulative record needed to verify whether any solution generalizes.

These findings translate into four practical implications. *First*, at the sensing layer, the default soil moisture + temperature + humidity module should be replaced with variable sets selected via mutual information analysis, prioritizing informationally independent inputs such as multi-depth soil profiling [34] or UAV-based plant-physiological signals [37]. *Second*, at the architectural layer, closed-loop integration should be treated as a baseline design requirement, with the PPO-based RL framework in [45] as the closest available template. *Third*, at the evaluation layer, authors should adopt multi-site and multi-season validation as a reporting standard with task-specific minimum metric sets (RMSE and R^2 for regression, F1 and AUC for detection, water use efficiency for control). *Fourth*, for resource-constrained contexts, an incremental pathway is viable: begin with mutual-information-guided variable selection (G2–G3), then progress toward lightweight continual learning (G4) before attempting full closed-loop deployment, aligning with Figure 5(c).

The transition from systems that predict to systems that adapt requires treating sensing breadth, closed-loop integration, and field-scale validation as non-negotiable design requirements. The field possesses the algorithmic tools; what it lacks is the architectural commitment to integrate them. Figure 5(b) makes this urgency visible: reported performance and validation scope follow an inverse directional trend ($r = -0.20$), and though not statistically significant given the corpus size, the pattern is empirically consistent — the studies claiming the highest accuracy are precisely those evaluated under the narrowest conditions. The accuracy tables are not a ceiling to be raised but a mirror that reflects scope, not capability. Without that recognition, the gap between laboratory accuracy and field-deployable intelligence will persist regardless of how high the numbers climb.

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