



Machine Learning and IOT-Driven Decision Support Systems in Agriculture: A Systematic Review of Tabular Telemetry and Predictive Modeling

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Abstract— Decision Support Systems (DSS) in precision agriculture have evolved from static rule-based engines into data-driven frameworks powered by Internet of Things (IoT) telemetry and supervised machine learning. While recent literature increasingly focuses on deep learning and volatile commodity forecasting, empirical farm-level deployments rely heavily on structured tabular telemetry—comprising soil macronutrients (N, P, K), moisture dynamics, potential of hydrogen (pH), and local microclimate variations.

This systematic review synthesizes research published between 2018 and 2026, evaluating non-deep machine learning paradigms tailored for tabular agro-telemetry across 58 peer-reviewed studies. We analyze multi-tier system architectures spanning low-power field acquisition, edge preprocessing, and predictive inference engines.

Comparative benchmarking indicates that tree-based ensembles (Random Forest, XGBoost, LightGBM) consistently outperform kernel methods and linear baselines, yielding classification accuracies between 94.2% and 99.4% for crop suitability and fertilizer recommendation while maintaining sub-millisecond inference latencies suitable for resource-constrained edge gateways. Support Vector Machines (SVM) with radial basis function (RBF) kernels offer competitive stability on small-sample regime topologies.

Finally, we highlight critical deployment challenges, including sensor calibration drift, missing data imputation under intermittent connectivity, and edge compute trade-offs, outlining viable architectural directions for resilient

agro-decision frameworks

Keywords— Precision agriculture; Decision support systems; Agro-telemetry; Random Forest; XGBoost; Support vector machines; Edge computing.

1. INTRODUCTION

Global agricultural production faces compounding challenges from arable land degradation, climate variability, and freshwater scarcity. Traditional agronomic practices rely on periodic manual soil testing and empirical rules of thumb, often resulting in misallocated chemical fertilizers and inefficient irrigation regimes.

The advent of Precision Agriculture (PA) and the Internet of Things (IoT) provides continuous temporal data acquisition through in-situ field telemetry. Modern farm telemetry captures essential parameters including soil macronutrients (Nitrogen [N], Phosphorus [P], Potassium [K]), electrical conductivity (EC), moisture content, and micro-meteorological variables.



To translate this multidimensional data into actionable agronomic interventions, automated Decision Support Systems (DSS) have become central to smart farming architectures. While high-dimensional deep learning architectures—such as Convolutional Neural Networks (CNNs) for leaf pathology detection and Recurrent Neural Networks (RNNs) for commodity pricing—have received substantial attention, practical deployment at the field level is predominantly governed by structured tabular telemetry.

Tabular agro-telemetry features low feature dimensionality ($D \in [5,15]$), moderate sample sizes, and strong feature-target non-linearities. For such workloads, deep networks present excessive parameterization, susceptibility to overfitting, and significant computational overheads that hinder deployment on edge microcontrollers.

Consequently, traditional machine learning paradigms—notably tree-based ensembles (Random Forest, Gradient Boosting, XGBoost) and kernel classifiers (Support Vector Machines)—remain the industry standard for tabular agro-inference.

Despite growing literature on smart farming, existing surveys broadly aggregate unconstrained computer vision tasks with macro-economic pricing models, obscuring technical nuances in tabular telemetry processing, preprocessing requirements, and embedded inference pipelines.

This review provides a systematic synthesis of tabular machine learning architectures in agricultural decision support.

The primary contributions of this paper are:

1. A structured taxonomy of four-tier smart agriculture DSS architectures, tracing the pipeline from field acquisition to edge-cloud inference.
2. A methodological comparison of algorithmic paradigms (Tree Ensembles, Kernel Formulations, and Parametric Baselines) evaluated on agro-telemetry datasets.
3. An analysis of edge-to-cloud trade-offs, identifying persistent open challenges in telemetry imputation, latency, and sensor degradation.

II. LITERATURE REVIEW

Early agricultural DSS implementations relied on deterministic multi-criteria decision models and lookup tables mapped to static agronomic zones. While computationally trivial, these systems lacked adaptability to real-time micro-climatic fluctuations.

The integration of low-power sensor nodes enabled empirical statistical modelling. However, linear baselines (such as Multiple Linear Regression and Naive Bayes) generally struggle to capture non-linear biochemical interactions, such as the relationship between soil pH, moisture dynamics, and nutrient assimilation.

Recent research has prioritized non-linear machine learning frameworks. Support Vector Classifiers (SVC) equipped with non-linear Radial Basis Function (RBF) kernels have demonstrated strong generalizability across constrained soil-test sample regimes by maximizing the margin hyperplane. Concurrently, tree ensemble architectures have gained widespread adoption due to their scale invariance and capability to handle mixed categorical-continuous agronomic features.

Several studies evaluate the performance of Random Forest (RF) against Extreme Gradient Boosting (XGBoost) for crop selection based on N-P-K balances, with gradient boosting methods showing marginal predictive advantages at the expense of hyperparameter sensitivity.

A recurring gap in prior survey literature is the conflation of vision-based phenotyping with telemetry-driven operational DSS. In operational environments, sensor-driven agro-DSS faces unique challenges: high sensor noise floors, packet dropouts across LPWAN channels, and strict energy budgets on battery-powered edge transceivers.

This review addresses these aspects by concentrating on the end-to-end telemetry-to-decision pipeline.

III. METHODOLOGY

This systematic review adheres to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 guidelines.

A. Search Strategy and Corpus Extraction

A comprehensive literature search was conducted across five major bibliographic databases: IEEE Xplore,



ScienceDirect, SpringerLink, MDPI, and Scopus, targeting publications from January 2018 through 2026. The search syntax combined Boolean operators with targeted keywords:

Query = ("Smart Agriculture" v "Precision Farming")
 $\wedge$ ("Decision Support System"
 $\vee$ "Crop Recommendation"
 $\vee$ "Irrigation Scheduling")
 $\wedge$ ("Machine Learning"
 $\vee$ "Random Forest" v "SVM"
 $\vee$ "XGBoost")
 $\wedge$ ("Telemetry" v "Soil Sensors"
 $\vee$ "IoT")

The initial query execution yielded $n = 642$ records. Following automated and manual deduplication, 188 redundant records were removed, leaving $n = 454$ unique publications for primary title and abstract screening.

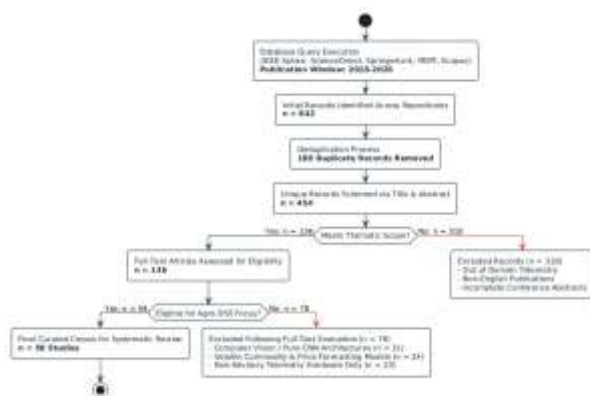


Figure 1: PRISMA-2020 Systematic Literature Selection Flow

B. Inclusion and Exclusion Criteria

Articles were evaluated against explicit methodological criteria:

- **Inclusion Criteria:** (i) Peer-reviewed journal articles or complete conference papers; (ii) Direct utilization of structured, tabular agro-telemetry (e.g., NPK, soil moisture, temperature, humidity, rainfall); (iii) Implementations containing verifiable empirical machine learning models for agronomic decision support.
- **Exclusion Criteria:** (i) Pure computer-vision architectures dedicated exclusively to leaf disease segmentation or plant phenotyping

via RGB/spectral imagery ($n = 31$ excluded); (ii) Economic, supply-chain, or commodity market price forecasting models ($n = 24$ excluded); (iii) Sensor hardware and circuit designs lacking an analytical decision-support layer ($n = 23$ excluded).

Applying these constraints during the full-text evaluation narrowed the corpus down to 58 core studies for in-depth comparative synthesis.

IV. RESULTS AND DISCUSSION

A. Architectural Decomposition of Agro-DSS

Across the analysed corpus, deployable smart agriculture DSS frameworks converge onto a structured four-tier pipeline:

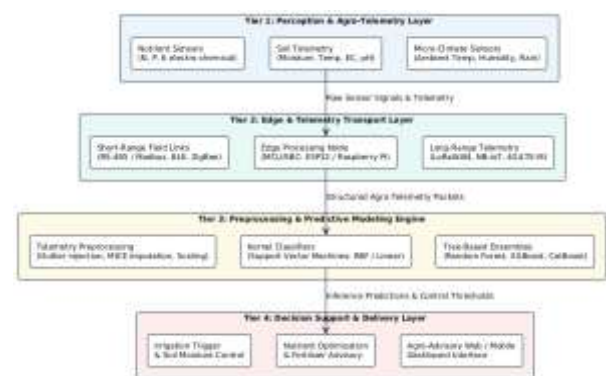


Figure 2: Multi-Tier Architectural Taxonomy for Agriculture DSS

- 1. Perception & Agro-Telemetry Layer:** Deploys electrochemical ISFET or optical NPK sensors alongside digital capacitive soil moisture probes, electrical conductivity (EC) sensors, and meteorological arrays.
- 2. Edge & Telemetry Transport Layer:** Bridges sensor interfaces via short-range field links (RS-485 Modbus, BLE) to edge compute nodes (e.g., ESP32, STM32, or Raspberry Pi). Uplinks to the cloud are handled through low-power wide-area networks (LoRaWAN, NB-IoT) or cellular connectivity (4G/LTE-M).
- 3. Preprocessing & Inference Engine:** Applies data conditioning—including median filtering for noise reduction, Multivariate Imputation by Chained Equations (MICE) for packet dropouts, and Min-Max scaling. The



conditioned vector is then evaluated against trained predictive models.

4. **Decision Support & Delivery Layer:** Translates raw model inferences into agronomic advisories—such as dynamic irrigation trigger times, crop suitability rankings, and stoichiometric fertilizer application rates—delivered via web and mobile interfaces.

B. Comparative Analysis of Machine Learning Paradigms

Tabular agro-telemetry analysis shows divergence in model performance based on training set scale, feature cardinality, and model capacity:

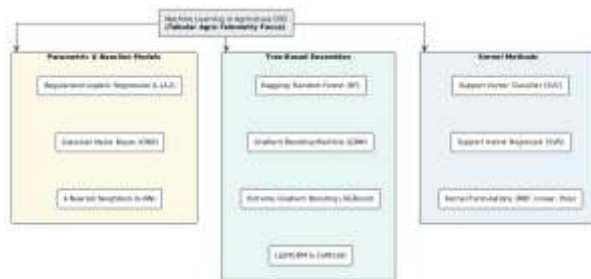


Figure 3: Algorithmic Taxonomy of Tabular ML Models

Table I: Comparative Performance Matrix of Tabular ML Models in Agro-DSS

Model Architecture	Representative Paradigm	Typical Accuracy (%)	Inference Latency (Edge)	Training Complexity	Resilience to Missing Data	Primary Agronomic Application
Random Forest (RF)	Bagging Ensemble	95.4 – 98.1	Low (~1.8 ms)	Moderate	High (Surrogate splits)	Crop Suitability Recommendation
XGBoost / LightGBM	Gradient Boosting	96.8 – 99.4	Moderate (~3.5 ms)	Moderate-High	High (Native NaN handling)	Dynamic Yield & Irrigation Trigger
Support Vector Machine (SVC)	Kernel Method (RBF)	91.2 – 95.6	Moderate (~4.2 ms)	High ($O(N^3)$ to $O(N^2)$)	Low (Requires complete vector)	Soil Fertility Classification
Gaussian Naive Bayes (GNB)	Probabilistic Generative	82.0 – 87.5	Ultra-low (~0.2 ms)	Minimal	Moderate	Rapid Baseline Screening
Logistic Regression (L1/L2)	Linear Parametric	80.5 – 86.0	Ultra-low (~0.1 ms)	Minimal	Low	Binary Frost / Stress Warning

Tree-based ensembles (Random Forest, XGBoost) demonstrate the highest overall classification accuracy and empirical robustness. Their decision-tree topology matches the orthogonal, threshold-based physical

constraints common in crop cultivation (e.g., specific ranges for soil moisture and temperature). Additionally, gradient boosting frameworks naturally accommodate missing sensor attributes during packet loss without requiring computationally expensive imputation steps.

While kernel methods (SVM with RBF) perform well on small, well-curated experimental datasets, their inference latency scales unfavourably with the number of support vectors. This creates runtime bottlenecks when running on low-power edge microcontrollers.

C. Edge vs. Cloud Deployment Trade-offs

Deploying DSS logic requires balancing response latency, power availability, and network reliability:

- **Cloud-Centric Pipelines:** Offer unconstrained compute capacity for periodic batch retraining and large ensemble operations. However, they introduce vulnerabilities to intermittent connectivity in rural environments.
- **Edge-Native Pipelines:** Executing quantized tree models (e.g., via TensorFlow Lite for Microcontrollers or compiled C headers) on ESP32/ARM Cortex-M nodes enables offline operation and immediate actuation for closed-loop irrigation. Memory constraints (< 512 KB SRAM), however, limit model depth and hyperparameter tuning.

D. Open Challenges

1. **Sensor Calibration Drift:** Optical and electrochemical NPK sensors exhibit drift over time due to biofouling and soil moisture fluctuations, introducing non-stationary noise into static inference models.
2. **Tabular Data Scarcity:** Agronomic datasets remain sparse across regional microclimates, limiting cross-geographic model generalizability.
3. **Interpretability & Agronomic Trust:** Farmers frequently reject black-box recommendations; integrating SHAP (Shapley Additive Explanations) or tree feature attribution into user interfaces remains an ongoing development area.



V. CONCLUSION

This review synthesized machine learning and IoT architectures dedicated to tabular agro telemetry within agricultural Decision Support Systems.

The comparative synthesis highlights that tree-based ensembles (Random Forest, XGBoost) offer the most balanced combination of high predictive accuracy, missing-data handling, and low inference latency, making them well-suited for edge and near-edge farm environments. Kernel methods provide strong baselines in data-constrained settings but face memory and runtime constraints on embedded microcontrollers.

Future research should prioritize automated on-device sensor recalibration routines, standardized open tabular agro-benchmarks, and explainable AI interfaces to improve user adoption in real-world farming environments.

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