PRECISION AGRICULTURE

FARMROOT: AI-IoT Digital Twin for Early Root-Zone Stress Detection and Smart Irrigation

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Abstract

Agricultural monitoring is moving from periodic manual inspection toward continuous, data-driven and predictive management. The proposed FARMROOT concept focuses on a specific problem within this transition: estimating hidden root-zone stress before visible crop symptoms appear and translating that estimate into zone-wise irrigation decisions. This review synthesizes the literature on agricultural Digital Twins, AIoT architectures, smart sensors, soil-moisture prediction, plant-health monitoring, precision irrigation, and low-cost field deployment. The reviewed work shows that IoT sensing can provide continuous measurements of soil moisture, soil temperature, air temperature, humidity, radiation, pH and related variables, while machine-learning and deep-learning models can identify temporal patterns, forecast soil moisture and support irrigation decisions. Digital Twin studies further provide a useful abstraction in which physical agricultural assets are connected to a dynamic digital representation through sensing, communication, historical data, visualization, decision and actuation components. However, the literature is fragmented: some studies predict soil moisture, some classify soil or crop conditions, some monitor plant stress, and others develop Digital Twin architectures, but comparatively little of the reviewed material unifies low-cost multi-sensor root-zone monitoring, early stress-risk estimation, spatial zone representation and irrigation decision support in one field-oriented framework. Based on these findings, FARMROOT is positioned as a conceptual research framework rather than a completed experimental system. The review identifies sensor calibration, ground-truth stress labeling, spatial sampling, temporal prediction, model generalization, connectivity, energy consumption and farmer-oriented decision support as the principal research challenges. A validation framework is proposed using prediction accuracy, early-warning lead time, false-alarm rate, water-use efficiency, sensor reliability, latency and system cost.

Keywords: AIoT; artificial intelligence; digital twin; ESP32; Internet of Things; precision agriculture; root-zone stress; sensor reliability; smart irrigation; soil moisture; time-series machine learning

1 Introduction

The agricultural sector increasingly requires technologies that can improve productivity while using water and other resources more efficiently. The reviewed literature consistently describes a shift from manual, experience-based decisions toward continuous sensing, computational analysis and adaptive management. The Digital Twin literature describes this transition as the connection of physical and digital systems so that the current state can be monitored, analyzed and used for prediction and intervention. In the agricultural context, Digital Twins are therefore relevant not merely as dashboards but as dynamic representations that can connect field observations with forecasts and management actions [1], [2].

IoT provides the sensing and communication foundation for this transition. The literature includes soil-moisture, soil-temperature, air-temperature, humidity, radiation, pH and nutrient measurements. AIoT research further organizes these components into device, connectivity, edge/fog and cloud layers, with intelligence potentially distributed across the architecture [3]. The 2019 soil-moisture prediction study is particularly relevant to FARMROOT because it used field sensor observations and weather information to predict future soil moisture and compared several regression models [4].

Plant-health research broadens the problem beyond irrigation alone. The reviewed plant-health paper describes multimodal sensing, including soil moisture, temperature, humidity, canopy temperature, spectral information and plant physiological indicators, and emphasizes early detection, edge processing and longitudinal data analysis [5]. This perspective is important because a crop may experience a developing environmental or physiological stress condition before obvious visual symptoms become available to a farmer.

FARMROOT is therefore concerned with the intersection of four areas: low-cost IoT sensing, time-series AI, Digital Twin representation and irrigation decision support. The central research question is: Can low-cost multi-sensor IoT observations be transformed into a reliable probability or index of root-zone stress early enough to support an actionable irrigation decision?

The weakest point in this research problem is the definition of ground truth. Soil moisture is an important indicator, but it is not identical to plant stress. Soil texture, rooting depth, crop stage, temperature, atmospheric demand, irrigation history and local field variability can change the relationship between a measured soil value and the actual physiological state of a crop. Therefore, FARMROOT should not claim stress detection solely from a moisture threshold. Instead, it should investigate a validated root-zone stress index or probability supported by agronomic observations and/or independently measured plant-response indicators.

1.1 Objectives of the review

1. Review the role of IoT and AI in continuous agricultural monitoring and intelligent irrigation.
2. Examine Digital Twin concepts and architectures relevant to agricultural field monitoring.
3. Compare sensing modalities and machine-learning approaches relevant to root-zone monitoring and stress estimation.
4. Identify limitations in low-cost sensing, data quality, communication, AI generalization and field deployment.
5. Derive a research gap and conceptual architecture for the FARMROOT framework.
6. Define an evaluation framework suitable for a one-acre experimental deployment.

1.2 Scope and review method

This paper is a focused narrative review based primarily on a selected set of research papers and technical documents relevant to the FARMROOT study. The sources were examined for their objectives, sensing variables, AI methods, communication architectures, Digital Twin concepts, experimental approaches, reported limitations and future directions. This paper does not claim to be a PRISMA systematic review because the source set was selected directly and no independent database screening protocol was applied.

2 Literature review

The reviewed literature can be grouped into five connected research streams: (i) agricultural Digital Twins, (ii) AIoT architectures, (iii) smart sensor and plant-health monitoring, (iv) soil-moisture prediction and smart irrigation, and (v) practical deployment for resource-constrained farms.

2.1 Agricultural digital twins

Atalay defines the Digital Twin as a representation of physical components in a digital environment and frames smart agriculture as a setting where monitoring and computational decision-making can improve resource efficiency [1]. The work identifies the mapping between agricultural production environments and Digital Twin infrastructures and emphasizes monitoring, prediction and automation.

Fuentealba et al. provide a more implementation-oriented Digital Twin model. Their framework identifies physical objects, physical sectors, historical sensing, visualization, Human-Machine Interface, decision, communication, sensors and actuators as important meta-classes [2]. This is highly applicable to FARMROOT: a field can be represented as physical zones, sensor observations can be stored historically, visualization can show zone condition, and the decision component can generate irrigation commands or recommendations.

The Digital Twin concept is therefore more useful for FARMROOT when treated as a dynamic, bidirectional system rather than a static dashboard. The digital representation should receive observations from the field, maintain historical state, use AI predictions, expose risk at the zone level and communicate recommended interventions back to the physical farm.

2.2 AIoT architectures for smart agriculture

The AIoT literature describes IoT as the infrastructure that generates and transports observations and AI as the intelligence that converts observations into decisions. The reviewed thesis distinguishes loosely coupled AIoT, in which IoT data are forwarded to a remote AI system, from tightly coupled AIoT, in which AI capabilities are deployed partly or fully near the devices [3].

A common architecture contains an agricultural device layer, connectivity, edge/fog processing and cloud services. Edge devices can filter, preprocess, encrypt and analyze data before forwarding selected data to the cloud. This is important for FARMROOT because a one-acre field may not require continuous transmission of every raw observation to a remote server. Local filtering and anomaly detection can reduce bandwidth, latency and energy consumption while allowing cloud storage for historical analysis [3], [5].

2.3 Smart sensors and plant-health monitoring

The plant-health literature shows that agricultural stress is inherently multidimensional. The reviewed paper discusses soil moisture, temperature, relative humidity, nutrients, canopy temperature, chlorophyll fluorescence, spectral reflectance and volatile organic compounds as potential indicators [5]. It also describes time-series models and anomaly detection for longitudinal plant-health signatures.

For FARMROOT, a low-cost core sensor set should remain deliberately small: soil moisture, soil temperature, air temperature and relative humidity. Additional variables such as rainfall, radiation, pH or EC can be introduced in later experiments. This prioritizes affordability and makes it possible

to test whether simple scalar sensing can provide sufficient predictive information before adding expensive imaging.

A major issue identified in the reviewed plant-health literature is that low-cost sensors are vulnerable to noise, drift and degradation. The literature recommends calibration, redundancy, anomaly detection, adaptive sampling and edge preprocessing. These are not peripheral engineering details for FARMROOT; they directly influence whether a stress prediction model can be trusted [5].

2.4 Soil-moisture prediction and smart irrigation

Singh et al. developed an IoT-based smart irrigation approach that predicts future soil moisture using field sensor data and weather information [4]. The system measured air temperature, air humidity, soil moisture, soil temperature and radiation. GBRT, Random Forest Regression, Multiple Linear Regression and Elastic Net Regression were evaluated. The reported comparison showed GBRT performing strongly, and the paper reported an R^2 of 0.94 and MSE of 4.04 when soil temperature was included in prediction [4].

The key lesson for FARMROOT is that temporal prediction can be more useful than a simple current-value threshold. The reviewed study explicitly uses historical sensor data and forecast environmental variables to predict upcoming soil moisture [4]. This supports the FARMROOT objective of estimating future stress risk rather than merely reporting current moisture.

Esmail et al. present another IoT and machine-learning irrigation system in which soil moisture, temperature, humidity and rainfall are used to formulate irrigation schedules. Their comparison reports the decision-tree model as the strongest among the evaluated models, while the prototype demonstrates remote monitoring and control [6]. The limitation for FARMROOT is conceptual: an irrigation classification output does not by itself establish hidden root-zone stress or an early-warning lead time.

The 2025 LoRa-based precision agriculture study integrates pH, moisture, temperature, humidity and NPK sensing with a stacked ensemble for soil fertility and an enhanced LSTM for irrigation management [7]. The reported results are 93.37% accuracy for its soil-prediction ensemble and 99.53% for the enhanced LSTM irrigation model [7]. These values demonstrate the potential of ensemble and sequence models, but they should not be directly compared with FARMROOT unless datasets, labels, prediction horizons and evaluation protocols are matched.

2.5 Comparative analysis of reviewed studies

The focus, data, main contribution and relevance of each reviewed source are compared in Table 1.

Table 1. Comparative summary of the reviewed studies.

Source	Primary Focus	Typical Data	Main AI/DT Contribution	Relevance / Limitation for FARMROOT
Atalay [1]	Digital Twin in smart agriculture	DT, monitoring, prediction	Agricultural DT mapping	Not a root-zone stress system
Fuentealba et al. [2]	Digital Twin architecture	Sensors, actuators, history, HMI	Meta-class model	Architecture rather than stress prediction
Muhammed [3]	AIoT architectures	Multiple environmental sensors	Edge/Fog/Cloud	No specific root-zone stress index

Source	Primary Focus	Typical Data	Main AI/DT Contribution	Relevance / Limitation for FARMROOT
Singh et al. [4]	Future soil-moisture prediction	Moisture, soil/air temperature, humidity, radiation	GBRT/RFR/MLR/ ENR	Predicts moisture, not plant stress
Ingole et al. [5]	Automated plant-health monitoring	Soil + environmental + plant sensing	AI, time-series, anomaly detection	Broad multimodal scope; costly modalities possible
Esmail et al. [6]	Smart irrigation	Moisture, temperature, humidity, rainfall	Decision Tree, LR, SVM	Small prototype; no DT/ root-zone model
Savio et al. [7]	Precision agriculture + irrigation	pH, moisture, temperature, humidity, NPK	Stacked ensemble + LSTM + LoRa	Fertility/irrigation rather than hidden stress
Miller et al. [8]	AI + IoT systematic review	Soil, optical, acoustic and other sensors	SVM, CNN, RF and others	Identifies cost/ interoperability/ generalization barriers
El Ouaham et al. [9]	AI/IoT smart-greenhouse review	Environmental + root-zone variables + imaging	ML/DL/ multimodal	Greenhouse focus; less open-field specific
Akhter et al. [10]	AI and collaborative robotics	Soil, climate and crop sensing	ML/DL/ predictive analytics	Robotics emphasis
Slany et al. [11]	AI + IoT water management review	Soil moisture, water/ environmental sensing	SVM, kNN, LSTM, RF, ARIMA etc.	Broad water-management scope

3 Root-zone sensing for early stress estimation

The root zone is a hidden environment. Unlike leaves, roots and the surrounding soil are not directly visible during routine field inspection. Consequently, a FARMROOT system should treat root-zone condition as a latent state inferred from measurable variables. The reviewed literature supports the use of soil moisture, soil temperature, air temperature and humidity as a practical starting point [4], [5], [6].

3.1 Multi-depth soil-moisture sensing

A major improvement over a single soil-moisture measurement is the use of multiple sensing depths. Different depths can represent the upper, middle and lower parts of the effective root zone. The resulting profile can distinguish rapid surface drying from deeper water availability. FARMROOT should therefore consider at least two or three depths during experimental design, with the exact depths determined by crop rooting characteristics and soil conditions.

3.2 Environmental variables

Air temperature and relative humidity provide contextual information about atmospheric demand. Soil temperature can contribute to soil-moisture prediction, as shown by the reviewed 2019 study, where including soil temperature improved the reported GBRT performance [4]. Rainfall and radiation can be included where reliable measurements are available. These variables are particularly

useful for separating short-term moisture decline caused by environmental demand from longer-term soil-water deficits.

3.3 Sensor calibration and reliability

The reviewed literature repeatedly identifies calibration drift, noise, missing data and long-term degradation as major barriers. A low-cost FARMROOT node should therefore perform sensor sanity checks, range validation, timestamp synchronization and missing-value handling before AI inference. A reference measurement method should also be used periodically to estimate field-specific sensor error.

4 AI/ML for root-zone stress estimation

The literature contains several model families suitable for FARMROOT. Classical regression models such as linear regression and Elastic Net are useful baselines. Tree-based models such as Random Forest and Gradient Boosting are attractive because they can represent nonlinear relationships and work well with mixed sensor features [4], [7]. Sequence models such as LSTM are useful where temporal dependence is central to the problem and have been applied to irrigation-related prediction [7].

4.1 Proposed modeling strategy

A staged approach is preferable to immediately selecting a complex deep-learning model. First, establish baseline performance using threshold rules, linear regression, Random Forest and Gradient Boosting. Next, evaluate temporal models such as LSTM or temporal convolution/attention models if the dataset is sufficiently large. Model selection should be based not only on accuracy but also on false alarms, missed stress events, inference latency, energy consumption and interpretability.

4.2 Root-zone stress index

FARMROOT can define an operational Root-Zone Stress Index (RZSI) as a latent or derived state rather than equating one sensor value with stress. A conceptual formulation is:

$$\mathrm{RZSI}(t) = f\left[M(d_1,\ t),\ M(d_2,\ t),\ M(d_3,\ t),\ T_s(t),\ T_a(t),\ RH(t),\ \Delta M(t),\ \mathrm{Rain}(t),\ \mathrm{Irr}(t),\ \mathrm{CropStage}(t)\right] \quad (1)$$

where M(d,t) denotes soil moisture at depth d, Ts is soil temperature, Ta is air temperature, RH is relative humidity, ΔM represents temporal moisture change, Rain represents rainfall and Irr represents irrigation history. The formulation is conceptual; the final feature set and target definition must be experimentally validated.

4.3 Early-warning prediction

The defining characteristic of FARMROOT should be the prediction horizon. Instead of asking whether stress exists now, the model should estimate P(Stress at t+h | observations up to t). Candidate horizons may be several hours or one or more days, depending on crop and sensor sampling interval. Early-warning lead time should then be measured relative to an independently observed stress event.

5 FARMROOT digital twin framework

The Digital Twin architecture synthesized from the reviewed literature can be adapted to a one-acre farm. The physical farm is divided into zones. Each zone contains one or more sensor nodes. Observations move through a communication layer to an edge or cloud analytics service. The Digital Twin stores historical state, displays current conditions, receives AI predictions and generates irrigation recommendations. The architecture follows the sensor–communication–history–visualization–decision–actuation logic identified in the Digital Twin literature [2].

5.1 Proposed FARMROOT layered architecture

The ten layers of the proposed architecture are listed in Table 2.

Table 2. Proposed FARMROOT layered architecture.

Layer	Main Components	Purpose
1. Physical farm layer	Crop, soil, irrigation network, field zones	Actual root-zone state and irrigation actions
2. Sensing layer	ESP32 + moisture, soil temperature, air temperature, RH	Continuous field observations
3. Communication layer	Wi-Fi / LoRa / suitable LPWAN	Reliable sensor-to-gateway transmission
4. Edge processing layer	Filtering, validation, anomaly detection, local inference	Low latency and reduced bandwidth
5. Data layer	Time-series database + historical metadata	Longitudinal farm state
6. AI layer	Stress estimation + moisture forecasting	Stress probability and future condition
7. Digital Twin layer	Zone map, state, predictions, history	Digital representation of the farm
8. Decision-support layer	Irrigation recommendation engine	When, where and how much to irrigate
9. Farmer interface	Dashboard, alerts, zone status	Interpretable actionable information
10. Actuation layer	Pump/valve interface	Optional automated irrigation

5.2 Zone-wise representation

The one-acre experimental field should not be treated as spatially uniform. A zone-based representation allows the Digital Twin to display local differences in moisture and stress risk. For example, each zone can maintain current moisture, recent moisture trend, predicted moisture, stress probability, last irrigation time and recommended action. This directly supports precision irrigation because the decision is localized rather than applied uniformly to the entire field.

6 Intelligent irrigation decision support

The reviewed irrigation literature generally aims to apply water at the appropriate time and quantity. IoT systems supply current field information, while ML can forecast future soil moisture or classify irrigation requirements [4], [6], [7]. FARMROOT should extend this logic by using predicted root-zone stress risk as an additional decision variable.

6.1 Conceptual decision logic

A FARMROOT decision engine can combine current root-zone condition, predicted stress probability, rainfall forecast, recent irrigation, crop stage and soil response. The recommendation may be expressed as a categorical action such as No Irrigation, Monitor, Irrigate Soon or Irrigate Now. A later version can estimate an irrigation quantity. Importantly, these categories should be calibrated experimentally and should not be presented as universal agronomic thresholds.

6.2 Closed-loop digital twin

The Digital Twin becomes most valuable when it closes the loop between sensing and management. Sensor data updates the digital state; the AI model estimates future stress; the decision engine generates a recommendation; the farmer or actuator performs irrigation; and the resulting sensor response becomes new historical data. This creates a feedback loop that can be used to evaluate whether recommendations actually improve water-use efficiency rather than merely improving a machine-learning metric.

7 Discussion

The reviewed sources support the feasibility of each individual FARMROOT component. IoT sensing of soil and environmental variables is established; ML-based soil-moisture prediction is established; smart irrigation decision systems are established; and Digital Twin architectures for agriculture have been proposed. The research opportunity therefore lies in their tighter integration around a clearly defined root-zone stress problem rather than in any single technology.

The first significant distinction is between moisture prediction and stress prediction. The 2019 study predicts future soil moisture [4], while the 2025 LoRa study predicts soil-related and irrigation variables using ensemble and LSTM models [7]. These studies establish a technical basis for forecasting, but FARMROOT should investigate whether a temporal pattern of multi-depth moisture and environmental variables can predict an agronomically meaningful stress event.

The second distinction is between plant-health monitoring and root-zone monitoring. The plant-health literature supports early stress detection and multimodal sensing [5], but expensive imaging and biochemical modalities may conflict with FARMROOT's low-cost objective. FARMROOT can therefore test a deliberately minimal sensor suite and quantify what information is lost or retained by avoiding high-cost modalities.

The third distinction is between a Digital Twin and a dashboard. A dashboard visualizes data, whereas a Digital Twin should maintain a dynamic representation of the physical system and support prediction, simulation or decision interaction. The Digital Twin literature explicitly identifies historical sensing, visualization, decision, communication, sensors and actuators as components of the architecture [2]. FARMROOT should adopt these principles so that the Digital Twin is a functional research component rather than simply a user interface.

8 Research challenges and limitations

8.1 Ground-truth stress labeling

The most difficult issue is establishing when a crop is genuinely stressed. Labels should be tied to agronomic or physiological evidence, not only to an arbitrary soil-moisture threshold.

8.2 Low-cost sensor uncertainty

Low-cost sensors can drift, become noisy and respond differently across soil textures. Calibration and uncertainty handling must be included in the experimental protocol.

8.3 Spatial variability

One acre may contain substantial differences caused by soil texture, topography, irrigation distribution and root density. Zone placement and sensor density therefore affect model validity.

8.4 Temporal drift

Crop stage, weather patterns and management practices change over time. A model trained in one period may not generalize to another period.

8.5 Connectivity

Rural networks can be unreliable. The reviewed AIoT literature supports edge processing and layered architectures to reduce dependence on continuous cloud connectivity [3], [5], [8].

8.6 Energy

Battery-powered nodes must balance sampling frequency, communication and inference. Duty cycling and local preprocessing can reduce energy demand [5], [8].

8.7 Model interpretability

A farmer needs to know why a zone has been classified as high risk. Feature importance, uncertainty estimates or explainable-AI techniques can improve trust.

8.8 Cost and adoption

The reviewed literature repeatedly identifies cost, connectivity, interoperability and digital literacy as barriers for smallholders [5], [8], [9]. FARMROOT should therefore evaluate total system cost, not only model accuracy.

9 Proposed evaluation framework for FARMROOT

The reviewed sources show that accuracy alone is insufficient for a deployable agricultural system. FARMROOT should be evaluated at four levels: sensor reliability, AI prediction, early-warning capability and agronomic/economic utility. The metrics proposed for each level are listed in Table 3.

Table 3. Proposed evaluation framework.

Evaluation Level	Metrics	Purpose
Sensor reliability	MAE/RMSE against reference, missing-data rate, drift, uptime	Establish whether low-cost nodes provide usable observations
Stress classification	Accuracy, precision, recall, F1, ROC-AUC if appropriate	Measure correctness of stress-risk categories
Stress probability	Brier score / calibration error where probabilistic output is used	Check whether predicted probabilities are meaningful

Evaluation Level	Metrics	Purpose
Soil-moisture prediction	MAE, RMSE, R^2	Compare future moisture estimates
Early warning	Lead time, missed-event rate, false-alarm rate	Primary measure of proactive capability
Spatial performance	Zone-level error and consistency	Test spatial robustness across the one-acre field
Irrigation utility	Water applied, water saved, yield/health proxy	Assess practical value
System performance	Latency, packet loss, node uptime, energy use	Evaluate field deployability
Economic feasibility	Hardware cost, maintenance cost, estimated savings	Assess small-farm suitability

9.1 Baseline comparisons

A scientifically convincing study should compare FARMROOT against simple baselines. Recommended baselines include (i) fixed irrigation schedule, (ii) soil-moisture threshold control, (iii) conventional regression, (iv) Random Forest or Gradient Boosting, and (v) a temporal model such as LSTM if sufficient data are available. The goal is not to show that a complex model is always better, but to determine whether added complexity produces meaningful improvements in early-warning lead time and irrigation outcomes.

10 Research gap and proposed contribution

The reviewed studies reveal a fragmented research landscape. Digital Twin papers focus on representation, architecture and interaction. AIoT studies focus on layered sensing, communication and computation. Soil-moisture prediction studies focus on forecasting future water status. Smart irrigation studies focus on irrigation classification or scheduling. Plant-health studies focus on multimodal stress detection. Each area provides important building blocks, but the reviewed material does not establish a single, low-cost, field-oriented framework centered on early root-zone stress probability and zone-wise Digital Twin decision support.

Accordingly, the proposed FARMROOT contribution can be framed around five elements:

1. A low-cost multi-sensor root-zone monitoring architecture suitable for a one-acre experimental field.
2. A temporal AI model that estimates root-zone stress risk rather than only reporting current soil moisture.
3. A zone-wise Digital Twin that maintains current state, historical observations and predicted risk.
4. An irrigation decision-support mechanism that connects stress risk with water-management actions.
5. A field validation protocol that evaluates sensor reliability, early-warning lead time, water use, system latency and cost together.

The contribution should not be stated as the first use of AI, IoT, Digital Twins or machine learning for irrigation. The reviewed literature already demonstrates these individual combinations [1]–[9]. The

defensible contribution is their integration around a specifically defined root-zone early-warning problem under low-cost field constraints.

11 Future research directions

- Develop crop-specific and soil-specific root-zone stress labels using agronomic observations and independent plant-response measurements.
- Investigate multi-depth moisture profiles and spatial interpolation between sensor zones.
- Compare Gradient Boosting, Random Forest, LSTM and attention-based temporal models using identical time-series splits.
- Introduce uncertainty-aware prediction so that the system can distinguish high confidence from ambiguous stress conditions.
- Evaluate edge AI on ESP32-class or gateway hardware for local anomaly detection and low-latency decisions.
- Study adaptive calibration and sensor redundancy for long-duration deployments.
- Integrate rainfall and weather forecasts to avoid unnecessary irrigation immediately before rainfall.
- Extend the Digital Twin from visualization toward what-if simulation of irrigation actions.
- Evaluate water savings and crop response over multiple crop stages and seasons.
- Study transferability across fields and crops using domain adaptation or federated learning where appropriate.

12 Conclusion

This review examined the technical foundations of FARMROOT: AI-based agricultural monitoring, IoT sensing, Digital Twin architectures, root-zone and environmental sensing, soil-moisture prediction and intelligent irrigation. The reviewed literature demonstrates that the necessary technologies are individually mature enough to support an integrated research prototype. IoT can provide continuous observations, machine learning can model temporal relationships, and Digital Twins can organize physical and digital states into a framework for monitoring and decision support [1]–[7].

The central research challenge is not simply constructing another automatic irrigation system. It is determining whether low-cost multi-sensor observations contain sufficient information to estimate hidden root-zone stress before visible symptoms occur, and whether that prediction improves irrigation decisions. This requires reliable ground truth, multi-depth sensing, longitudinal data, spatial validation and an evaluation protocol that goes beyond model accuracy.

FARMROOT is therefore proposed as a research framework in which the physical one-acre field is divided into zones, monitored by low-cost IoT nodes, represented in a Digital Twin, analyzed by temporal AI models and linked to zone-wise irrigation recommendations. The literature also makes clear that calibration, connectivity, energy, data heterogeneity, generalization and adoption must be treated as first-class research variables [5], [8], [9]. If these issues are experimentally addressed, FARMROOT can provide a credible pathway toward affordable and scalable precision irrigation for small and marginal farms.

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