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Intelligent Plant Growth Monitoring in Precision Agriculture: A Systematic Review of IoT, Edge AI, Remote Sensing, and Generative AI

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Abstract—Smart agriculture has undergone a paradigm shift from manual observation-based farming to data-driven, AI-assisted precision crop management. This literature review systematically examines the evolution of plant growth monitoring systems, encompassing IoT sensor architectures, edge computing frameworks, soil moisture sensing technologies, multivariate sensor fusion, time-series-based growth modeling, satellite-derived vegetation indices, and generative AI integration. Drawing upon fifteen high-quality references spanning 2020–2025, this review identifies critical limitations in existing approaches—including dependence on threshold-based control, inadequate sensor longevity, and absence of unified validation mechanisms—and articulates a clear research gap. The proposed system, designed for M. Tech research, integrates ESP32-based edge intelligence, capacitive soil moisture sensing, asynchronous 5–15 minute data acquisition, Python analytics, Gemini API-based AI interpretation, NDVI satellite validation, and a real-time Next.js dashboard within a hybrid Edge + Cloud architecture. This review positions the proposed framework as a significant advancement toward predictive, scalable, and intelligent plant growth monitoring suitable for Indian agricultural conditions.

Keywords—Plant Growth Monitoring, IoT, ESP32, Edge Intelligence, Soil Moisture Sensing, Time-Series Analysis, NDVI, Gemini AI, Precision Agriculture, Next.js Dashboard

1. Introduction

Agriculture forms the backbone of the Indian economy, sustaining over 60% of the rural population and contributing approximately 17% to national GDP. Despite its significance, Indian agriculture faces persistent challenges including water scarcity, unpredictable monsoon patterns, soil degradation, and inefficient resource utilization. Traditional farming practices rely heavily on seasonal experience, manual observation, and fixed irrigation schedules—methods that are increasingly inadequate in the face of climate variability and growing food demand.

The emergence of the Internet of Things (IoT), edge computing, and artificial intelligence has catalyzed a transformation in agricultural monitoring. Modern smart agriculture systems no longer function as mere data collectors; they serve as intelligent decision-support platforms capable of predicting crop stress, optimizing irrigation, and interpreting complex environmental dynamics in real time. This transition is critical for achieving sustainable food production targets aligned with India's National Mission for Sustainable Agriculture (NMSA).

This literature review comprehensively surveys existing research on plant growth monitoring systems, identifying technological trends, persistent gaps, and emerging directions. The review is structured to trace the evolution from basic threshold-based IoT systems toward AI-augmented, edge-intelligent frameworks, culminating in a clear articulation of the research gap that motivates the proposed M. Tech system—PGMS (Plant and Ground Monitoring System).

The remainder of this paper is organized as follows: Section 2 reviews the evolution of smart agriculture architectures. Sections 3–7 examine specific technological dimensions including sensor technologies, sensor fusion, time-series modeling, satellite integration, and AI interpretation. Section 8 presents a comparative analysis. Section 9 identifies research gaps, and Section 10 concludes with the proposed system rationale. [1],[2],[3], [11], [13]

2. Evolution of Smart Agriculture Systems

2.1 From Manual Practice to IoT-Driven Automation

The history of agricultural monitoring reflects a progressive transition through three distinct phases: manual observation, threshold-based automation, and intelligent adaptive systems. In the first phase, farmers relied on visual assessment, periodic soil testing, and intuition-driven irrigation decisions. These practices, while culturally embedded, offered no quantitative basis for resource optimization and were highly susceptible to human error.

The second phase was initiated by the proliferation of low-cost microcontrollers and wireless communication modules in the early 2010s. Systems such as those surveyed by Agri-Guard (2025) deployed IoT sensor nodes that activated irrigation actuators when measured soil moisture dropped below predefined thresholds. While this approach improved water efficiency over purely manual systems, it remained fundamentally reactive—incapable of anticipating moisture demands or adapting to changing environmental conditions.

The third and current phase is characterized by edge intelligence, multivariate sensing, and AI-driven interpretation. Contemporary systems leverage the ESP32 microcontroller—valued for its dual-core Xtensa LX6 architecture, integrated Wi-Fi/Bluetooth, and sub-dollar cost—as the primary edge node. These systems perform real-time data acquisition, local preprocessing, anomaly detection, and intermittent cloud synchronization, forming a hybrid Edge Cloud architecture that ensures operational continuity in low-connectivity rural environments. [1]–[3]

2.2 The Edge-to-Cloud Paradigm in Precision Agriculture

The edge-to-cloud paradigm represents the dominant architectural philosophy in contemporary smart agriculture research. Rather than transmitting raw sensor data continuously to centralized servers, intelligence is distributed across a three-tier hierarchy: the sensor/actuator layer at the field, the edge processing layer on devices such as the ESP32, and the cloud analytics layer hosted on platforms such as Firebase.

At the edge layer, devices perform noise filtering using exponential moving averages, data validation through range-checking and outlier detection, local anomaly flagging, and temporary buffer storage during network interruptions. Validated data packets are transmitted asynchronously to the cloud at configurable intervals—typically 5 to 15 minutes—reducing bandwidth consumption while maintaining temporal resolution sufficient for growth-stage analysis.

The cloud environment—leveraging Firebase Realtime Database for low-latency structured storage—enables long-term trend analysis, AI model execution, satellite data integration, and dashboard visualization. This architecture supports real-time monitoring through frameworks such as Next.js, enabling agricultural stakeholders to access crop health insights from any web-connected device***.[2], [3], [15]***

3. Soil Moisture Sensing: Technology Comparison

3.1 Resistive Sensors: Limitations and Degradation

Resistive soil moisture sensors operate by measuring electrical conductivity between two metallic probes inserted into soil. When soil moisture increases, the resistance between probes decreases, and the sensor outputs a corresponding analog voltage. These sensors are inexpensive, widely available, and simple to interface with microcontrollers, making them the de facto choice in early IoT agriculture prototypes.

However, resistive sensors suffer from a fundamental electrochemical limitation: the direct current flowing between the probes induces electrolysis, causing metallic ions to migrate away from the probe surfaces. Over weeks of continuous operation, this electrolytic corrosion progressively degrades the probe surface, introducing systematic measurement drift. Studies have reported accuracy degradation of 15–30% within the first three months of field deployment, making resistive sensors unsuitable for longitudinal research applications.

Additional limitations include sensitivity to dissolved salts in soil—which can produce artificially low resistance readings independent of moisture content—and poor performance in clay-heavy soils characteristic of many Indian agricultural regions.

[4], [5]

3.2 Capacitive Sensors: Stability and Research Suitability

Capacitive soil moisture sensors overcome the fundamental limitations of resistive designs by measuring dielectric permittivity rather than electrical conductivity. The sensor forms a capacitor with the soil as the dielectric medium; as soil moisture content increases, the dielectric constant of the soil rises, increasing the measured capacitance. Critically, no direct electrical current flows through the soil, entirely eliminating the electrolysis mechanism responsible for resistive sensor degradation.

Field studies have demonstrated capacitive sensor stability within ±2% accuracy over periods exceeding twelve months under continuous operation. This long-term consistency is essential for the time-series datasets required by growth-stage modeling and machine learning pipelines. For M. Tech-level research requiring data integrity across multiple growing seasons, capacitive sensors represent the only scientifically defensible choice.

The proposed PGMS system employs a two-point calibration protocol for capacitive sensors on the ESP32, utilizing the corrected ADC constant of 4095 for 12-bit resolution, ensuring accuracy across the full dynamic range of soil moisture conditions encountered in Indian agricultural contexts. ***[4], [5]***

4. Sensor Fusion for Intelligent Phenotyping

4.1 Multivariate Environmental Profiling

The concept of sensor fusion in agricultural monitoring extends beyond simple data aggregation—it represents a fundamental shift toward contextual environmental intelligence. Rather than monitoring a single parameter, intelligent frameworks construct multidimensional environmental profiles by integrating soil moisture, ambient temperature, relative humidity, and optionally light intensity (via LDR or BH1750 sensors) and atmospheric pressure.

The scientific basis for sensor fusion lies in the complex interdependencies governing plant physiological processes. Soil moisture must be interpreted in the context of atmospheric vapor pressure deficit (VPD)—a function of temperature and humidity—to accurately assess actual plant water availability. High temperature combined with low soil moisture produces conditions of acute water stress, whereas elevated humidity at moderate temperature may suppress transpiration while simultaneously increasing fungal disease risk. ***[1], [4], [7]***

4.2 Derived Indices and Cross-Validation

Advanced sensor fusion enables the computation of derived environmental indices that provide deeper insight into crop health than any individual parameter. The Water Stress Index (WSI) integrates soil moisture deficit with evapotranspiration rate estimated from temperature and humidity data. The Pest Risk Index (PRI) combines humidity thresholds with temperature profiles associated with common agricultural pathogens.

Cross-validation through sensor fusion significantly improves data reliability. When a single sensor produces an anomalous reading—caused by localized soil heterogeneity, sensor drift, or hardware fault—the multi-sensor context enables the system to flag the reading as suspicious rather than acting on it. This fault-tolerance capability, demonstrated in the Agri-Guard system (2025), is essential for autonomous agricultural systems operating without continuous human supervision. ***[1], [4], [7]***

4.3 ESP32 ADC Calibration and Multi-Sensor Acquisition

Accurate multi-sensor data acquisition on the ESP32 requires careful attention to hardware limitations. The ESP32 ADC exhibits non-linearity at the extremes of its input range—approximately 0–100mV and 3000–3300mV—necessitating software linearization or the use of a calibrated reference voltage. The DHT11 and DHT22 sensors require precise timing for single-wire communication, with the ESP32's dual-core architecture enabling sensor polling on Core 0 while maintaining Wi-Fi connectivity on Core 1, preventing communication interference. ***[4]–[6]***

5. Time-Series Modeling for Plant Growth Detection

5.1 Temporal Dynamics of Plant Growth

Plant growth is an inherently temporal biological process governed by complex interactions between genetic programming and environmental stimuli. Static monitoring approaches—which assess plant health at a single point in time—are fundamentally incapable of capturing growth trajectories, phenological stage transitions, or the cumulative effects of environmental stress. This limitation necessitates a time-series paradigm, wherein environmental measurements are continuously logged with high-resolution timestamps and analyzed as evolving temporal sequences.

Contemporary research on time-series modeling for agriculture encompasses several analytical approaches: (1) moving average smoothing to eliminate high-frequency sensor noise while preserving biologically meaningful trends; (2) exponential weighted moving average (EWMA) for anomaly detection by identifying deviations from expected trajectories; (3) daily aggregate computation—mean, minimum, maximum—for growth-stage boundary identification; and (4) long-term trend analysis using linear regression or polynomial fitting for seasonal behavior modeling. ***[7], [8]***

5.2 Predictive Growth Assessment

The transition from reactive to predictive monitoring represents a fundamental advancement in agricultural intelligence. Reactive systems respond to observed stress conditions—such as soil moisture falling below a threshold—after the stress has already impacted plant physiology. Predictive systems, by contrast, analyse temporal patterns to forecast stress conditions before visible symptoms appear, enabling preemptive intervention.

Evapotranspiration (ET) modeling—which estimates the water demand of a crop based on meteorological variables—provides a scientifically grounded basis for predictive irrigation scheduling. When ET estimates derived from temperature, humidity, and light intensity are integrated with soil moisture time-series, the system can predict when soil moisture will fall below critical thresholds up to 24–48 hours in advance, enabling optimized irrigation timing that minimizes water waste while preventing stress. ***[7], [8], [11]***

5.3 Asynchronous Sampling at 5–15 Minute Intervals

The proposed PGMS system employs asynchronous data sampling at configurable 5–15 minute intervals, representing a carefully considered balance between temporal resolution and system resource constraints. Five-minute intervals provide sufficient resolution to capture rapid moisture dynamics during irrigation events and post-precipitation periods, while 15-minute intervals reduce energy consumption and cellular data costs during stable environmental periods. The ESP32's deep sleep mode enables current draw reduction to approximately 10 µA between sampling events, extending battery life in solar-powered field deployments**. *[6]–[8]***

6. Satellite Data Integration for Field-Scale Validation

6.1 Vegetation Indices: NDVI and Beyond

Remote sensing through satellite platforms provides a macro-scale validation dimension unavailable to ground-based sensor networks. The Normalized Difference Vegetation Index (NDVI), computed from near-infrared (NIR) and red-band reflectance measurements, has been extensively validated as a proxy for vegetation Vigor, chlorophyll concentration, and biomass density across decades of agricultural research.

NDVI is mathematically defined as (NIR − Red) / (NIR + Red), with values ranging from −1 to +1. Healthy vegetation typically exhibits NDVI values of 0.6–0.9, while stressed or sparse vegetation falls in the range 0.2–0.5. Studies using Sentinel-2 imagery (10m resolution, 5-day revisit cycle) have demonstrated strong correlations between NDVI time-series and ground-measured soil moisture, enabling cross-validation of sensor network data at the field scale. The European Space Agency's Copernicus Open Access provides free access to Sentinel-2 Level-2A surface reflectance products suitable for NDVI computation.

6.2 Ground-Satellite Fusion for Validation

The integration of satellite-derived NDVI data with ground sensor measurements creates a hybrid validation framework that significantly enhances the reliability of plant growth detection models. This fusion addresses a fundamental limitation of purely ground-based systems: sensor networks provide high temporal resolution but limited spatial coverage, while satellite imagery offers broad spatial coverage at coarser temporal resolution.

When ground sensors indicate declining soil moisture alongside NDVI values falling below seasonal baselines for the same location, the corroborating evidence substantially increases confidence in the stress diagnosis. Conversely, when ground sensors indicate normal moisture levels but NDVI shows anomalous decline, the discrepancy triggers investigation into potential root-zone issues, micronutrient deficiencies, or above-ground disease not detectable through soil sensing alone.

The proposed PGMS architecture incorporates a Python-based satellite data processing module that retrieves Sentinel-2 NDVI products via the Copernicus API, computes field-level averages aligned with ground sensor coordinates, and stores results in Firebase for integration with the Next.js dashboard's validation visualization layer. ***[9], [10]***

7. AI-Based Growth Interpretation

7.1 From Statistical Thresholds to Adaptive Intelligence

The integration of artificial intelligence into agricultural monitoring systems marks a qualitative transition from rule-based automation to adaptive, context-aware intelligence. Traditional threshold-based systems encode domain knowledge as static rules—if soil moisture < 30%, trigger irrigation—which fail to account for crop-specific requirements, growth stage, seasonal context, recent weather history, or disease vulnerability.

Machine learning approaches, surveyed extensively in systems such as the ML-IoT hybrid platform (JRPS Journal, 2024) and the Grow-IoT smart analytics application (IOP, 2022), demonstrate significant improvements over threshold-based control. Supervised classifiers—including Random Forest, Support Vector Machines, and gradient boosting frameworks—trained on historical sensor data can identify growth stages, classify stress types, and recommend interventions with accuracies exceeding 85% under controlled conditions.

However, classical ML approaches exhibit two significant limitations: they require substantial labeled training datasets that may not be available for novel crop varieties or regional conditions, and they lack the contextual reasoning capability to integrate unstructured agronomic knowledge. Generative AI models overcome both limitations. [11], [13]

7.2 Gemini API Integration for Contextual Agronomic Reasoning

Google's Gemini API represents a paradigm-shifting capability for agricultural AI systems. Unlike statistical ML models that produce categorical classifications, Gemini's large language model (LLM) architecture enables contextual reasoning over structured time-series data, generating natural-language interpretations that explain observed patterns, identify probable causal factors, and recommend corrective actions. The Gemini API provides Python and REST interfaces suitable for integration with the PGMS backend.

In the proposed PGMS architecture, the Gemini API receives structured JSON payloads containing 48-hour environmental time-series, current growth stage estimates, crop profile specifications, and NDVI validation data. The model generates comprehensive growth status reports in English and regional Indian languages (Hindi, Marathi), enabling direct accessibility for farming communities without technical expertise.

The AI interpretation module addresses several specific analytical tasks: (1) growth stage classification based on environmental trajectory patterns; (2) water stress severity estimation combining WSI with evapotranspiration modeling; (3) disease risk assessment through humidity-temperature correlation analysis; (4) irrigation recommendation with volume and timing optimization; and (5) anomaly explanation for sensor readings that deviate from expected seasonal norms. ***[13], [14]***

7.3 Ten Indian Crop Profiles in PGMS

The PGMS system incorporates ten crop-specific profiles reflecting major Indian agricultural commodities across Kharif (monsoon), Rabi (winter), and Zaid (summer) seasons. Each profile specifies optimal moisture range, temperature window, humidity tolerance, and growth stage duration, enabling the AI interpretation layer to provide crop-contextualized rather than generic recommendations. [11], [13], [14]

Supported Crop Profiles (English)

Wheat — Rabi season; optimal soil moisture: 40–60%
Rice — Kharif season; high soil moisture requirement: 70–90%
Cotton — Kharif season; drought-tolerant with optimal moisture: 35–55%
Sugarcane — Year-round crop; recommended soil moisture:55–75%
Soybean — Kharif season; moderate soil moisture requirement: 45–65%
Tomato — Zaid season; consistent soil moisture: 50–70%
Onion — Rabi/Zaid season; lower soil moisture tolerance: 30–50%
Chili — Kharif/Zaid season; moderate soil moisture requirement: 40–60%
Maize — Kharif season; optimal soil moisture: 50–70%
Groundnut — Kharif season; recommended soil moisture: 35–55%

8. Comparative Analysis of Existing Systems

Table 1 presents a systematic comparison of key technological features across existing smart agriculture approaches and the proposed PGMS framework. The comparison reveals a consistent pattern: existing systems address isolated dimensions of the agricultural monitoring challenge but fail to integrate them into a cohesive, scalable, AI-driven architecture.

Feature	Threshold-Based IoT	ML-Based Systems	Edge-AI Systems (Proposed)
Irrigation Control	Static threshold	ML prediction	AI + edge inference
Sensor Type	Resistive (corrosion prone)	Capacitive / hybrid	Capacitive (long-term stable)
Data Processing	Cloud-only	Cloud-heavy	Edge + Cloud hybrid
AI Integration	None	Partial (offline ML)	Real-time (Gemini API)
Satellite Validation	No	Rare	NDVI integrated
Dashboard	Basic / none	Limited	Real-time Next.js UI
Scalability	Low	Medium	High
Power Efficiency	Low	Medium	High (ESP32 optimized)

The comparative analysis reveals three consistent failure modes in existing systems. First, the dominance of threshold-based control in deployed systems reflects a gap between academic research—which frequently proposes ML-based approaches—and practical implementation, where simpler control strategies prevail due to implementation complexity and training data requirements. Second, satellite integration remains largely absent from operational systems despite extensive research demonstrating its validation value. Third, real-time visualization dashboards—critical for non-technical agricultural stakeholders—are rarely implemented with the sophistication required for practical adoption. *[1]–[15]*

9. Weather Prediction and AI-Driven Crop Recommendation

9.1 Hyperlocal Weather Forecasting Integration

Weather prediction is an essential yet largely absent dimension in existing plant growth monitoring systems. While current frameworks rely exclusively on ground-level sensor readings, the integration of real-time and forecast meteorological data transforms reactive monitoring into genuinely predictive agricultural intelligence. The proposed PGMS advanced module incorporates a Weather Prediction Engine (WPE) that fuses hyperlocal forecast data from the OpenWeatherMap API (7-day forecast, 3-hour intervals) with on-device ESP32 sensor streams to build a 72-hour environmental trajectory model for each monitored field.

The WPE retrieves forecast parameters including predicted rainfall (mm), maximum and minimum temperature (°C), wind speed, relative humidity, and cloud cover index at 3-hour resolution. These parameters are ingested into a Python-based Evapotranspiration Forecast Model (EFM) running on the cloud backend, which computes projected soil moisture depletion curves using the FAO-56 Penman-Monteith reference evapotranspiration equation. The soil moisture depletion projection, combined with field-measured current moisture levels, generates a Soil Moisture Forecast Timeline (SMFT) that predicts the exact timestamp at which each monitored crop zone will enter moisture stress conditions—typically with a 24–48 hour advance warning horizon.

For Indian agricultural conditions, the WPE additionally integrates IMD (India Meteorological Department) gridded rainfall forecast datasets available via the IMD API, providing district-level monsoon prediction with 5-day advance coverage. This dual-source weather fusion—global OpenWeatherMap forecasts supplemented by IMD monsoon-specialist data—is particularly critical during the Kharif season

(June–October), when rainfall variability directly governs irrigation scheduling decisions for major crops including rice, cotton, soybean, and maize. ***[7], [8]***

9.2 AI-Powered Crop Suitability Recommendation Engine

The Crop Suitability Recommendation Engine (CSRE) leverages synthesized weather forecast data alongside current soil measurements, NDVI indices, and seasonal calendars to recommend the most agronomically appropriate crop for each monitored field at any given time. Unlike static crop calendars—which prescribe crops based solely on the calendar month—the CSRE performs dynamic suitability scoring that accounts for current and predicted temperature windows, rainfall probability, soil type characteristics, and moisture retention capacity.

The CSRE architecture employs a three-stage pipeline. In Stage 1, the Gemini API receives a structured JSON payload containing the 7-day weather forecast, current soil NPK estimates, soil pH measurement, field coordinates, and the current Indian agricultural season identifier (Kharif, Rabi, or Zaid). The LLM evaluates each of the ten PGMS crop profiles against these parameters and assigns a suitability score (0–100) to each crop based on temperature alignment, water requirement matching, humidity tolerance, and seasonal calendar fit. In Stage 2, the top three scoring crops are returned with ranked suitability percentages and explanatory rationale in natural language. In Stage 3, the recommendation is cross-validated against regional Minimum Support Price (MSP) data from the Government of India—retrieved via the data.gov.in open data API—to ensure that agronomically suitable crops also align with market viability, providing farmers with economically rational recommendations rather than purely technical ones.

The CSRE output is rendered on the Next.js dashboard as a Crop Weather Calendar—a visual timeline displaying the 7-day forecast alongside color-coded suitability windows for each recommended crop. Farmers can tap any crop recommendation to receive a detailed advisory in Hindi or Marathi covering sowing depth, fertilizer schedule, expected harvest window, and weather-contingent irrigation plan. This multilingual, weather-integrated crop advisory represents a substantive advance beyond any system identified in the reviewed literature. ***[11], [13], [14]***

9.3 Proposed System Contribution

The proposed PGMS (Plant and Ground Monitoring System) addresses the identified gap through a five-layer integrated architecture:

- Sensing Layer: ESP32-S3 with capacitive soil moisture sensor (two-point calibrated), DHT22 for temperature/humidity, and optional LDR for light intensity. Asynchronous sampling at 5–15 minute configurable intervals with edge-level noise filtering. [1]–[15]
- Edge Intelligence Layer: Local time-series preprocessing including EWMA smoothing, WSI and PRI computation, anomaly flagging, and buffer storage during network interruptions. Deep sleep mode for power optimization. [1]–[15]
- Cloud Analytics Layer: Firebase Realtime Database for structured time-series storage, Python backend for statistical processing, and Sentinel-2 NDVI integration via Copernicus API for field-scale validation. [1]–[15]
- AI Interpretation Layer: Gemini API integration for contextual growth analysis, crop-specific recommendation generation in multilingual format, and irrigation scheduling optimization. [1]–[15]
- Visualization Layer: Real-time Next.js dashboard with interactive time-series charts, satellite NDVI overlay, crop profile management, and multi-language support for farming community accessibility. [1]–[15]

10. Soil Condition Assessment and Intelligent Improvement Recommendations

10.1 Multi-Parameter Soil Health Profiling

Existing PGMS v4.0 firmware captures soil moisture as the primary subsurface parameter, with NPK guidance provided through crop-profile-based heuristics. The advanced soil condition module extends this capability into a comprehensive Soil Health Profile (SHP) by incorporating five additional measurement dimensions: soil pH (via analog electrochemical sensor SEN0161-V2 interfaced to ESP32 ADC with two-point calibration), estimated electrical conductivity (EC) derived from the capacitive moisture sensor's secondary output signal, ambient soil temperature (DS18B20 waterproof probe at 5 cm depth), organic matter index (proxied through a calibrated visible-light reflectance measurement at 550 nm using an AS7341 spectral sensor), and compaction index (estimated via an FC-28 piezo resistance probe measuring penetration resistance at standardized depth).

Together, these six parameters constitute the PGMS Soil Health Index (SHI), a composite score (0–100) computed by a weighted linear combination calibrated against Government of India Soil Health Card (SHC) scheme benchmark values for major Indian soil types: alluvial soils (Indo-Gangetic plains), black cotton soils (Deccan plateau, Maharashtra), red and laterite soils (Karnataka, Tamil Nadu), and sandy desert soils (Rajasthan). The SHI weighting assigns highest priority to pH alignment (25%), moisture adequacy relative to crop profile (25%), EC within non-saline range (20%), NPK balance (20%), and organic matter adequacy (10%). ***[4], [5], [7]***

10.2 AI-Generated Soil Improvement Advisory

When the SHI falls below a crop-specific adequacy threshold, the PGMS Soil Advisory Engine (SAE) generates a structured remediation plan via the Gemini API. The SAE prompt includes the complete six-parameter SHP reading, the target crop profile, the detected soil type, the regional season, and historical SHI trend data (past 30 days). The Gemini API returns a prioritized Soil Improvement Action Plan (SIAP) with the following structure: (1) immediate corrective actions (0–3 days) such as pH amendment using agricultural lime or sulfur at specified dosage rates per square metre; (2) short-term improvement interventions (1–4 weeks) including organic matter enhancement via vermicompost or green manure incorporation with quantity guidance; (3) medium-term soil structure restoration (1–3 months) involving biofertilizer inoculation schedules and intercropping recommendations for nitrogen fixation; and (4) long-term soil health management practices including crop rotation sequences aligned with the PGMS ten-crop profile system.

The SAE incorporates specific formulation recommendations calibrated for Indian agricultural supply chains, including locally available amendments: DAP (Di-ammonium Phosphate), Urea, MOP (Muriate of Potash), and micronutrient mixtures (Zinc Sulphate, Borax) commercially available through IFFCO and state cooperative networks. Dosage recommendations are expressed both in kg/hectare for large farms and in grams/square metre for smallholding contexts typical of Indian agriculture, where average farm size remains below 1.08 hectares according to the Agricultural Census 2015–16.

The SAE output is displayed on the Next.js dashboard as a color-coded Soil Health Card—mirroring the Government of India SHC format to promote farmer familiarity—with parameter status indicators (optimal, marginal, deficient, or excessive) and action priority badges. Each action card is expandable to reveal detailed instructions with estimated cost and expected SHI improvement contribution, enabling farmers to make informed decisions about resource allocation based on cost-effectiveness as well as agronomic impact. ***[13], [14]***

11. Real-Time Plant Condition Assessment and Visual Health Monitoring

11.1 Multimodal Plant Health Condition Engine

The current PGMS architecture infers plant health indirectly through environmental proxy variables—soil moisture, temperature, humidity—without direct observation of plant physiological state. The advanced Plant Condition Assessment Module (PCAM) introduces multimodal direct plant health evaluation by integrating visual imaging via the ESP32-CAM module (OV2640 sensor, 2MP) with environmental sensor data and AI-powered image analysis through the Gemini Vision API (gemini-1.5-flash, vision-capable endpoint).

The PCAM operates on a configurable capture schedule—default: four images per day at 6:00, 10:00, 14:00, and 18:00 IST—timed to capture morning dew conditions, peak photosynthetic activity, midday stress response, and evening recovery state. Each captured JPEG image (320×240 resolution for bandwidth efficiency) is transmitted to the Firebase Storage bucket alongside a metadata JSON packet containing the concurrent sensor readings (moisture, temperature, humidity, light intensity, SHI score), crop profile identifier, growth stage estimate, and geographic timestamp. The Gemini Vision API processes the image-sensor multimodal payload and returns a structured Plant Condition Report (PCR) assessed across six diagnostic axes. [12], [14], [15]

11.2 Six-Axis Plant Diagnostic Framework

The PCR assesses plant condition across six diagnostic axes, each scored on a 0–10 scale: (1) Leaf Color Health Score (LCHS)—evaluates chlorophyll expression through color spectrum analysis, detecting chlorosis (yellowing indicative of nitrogen or iron deficiency), necrosis (browning from fungal infection or heat stress), and anthocyanin accumulation (purple coloration under phosphorus deficiency or cold stress). (2) Leaf Morphology Score (LMS)—detects wilting, curling, edge burn, lesions, holes (insect damage), or premature senescence patterns. (3) Disease Symptom Detection Score (DSDS)—identifies fungal, bacterial, and viral disease signatures including powdery mildew, leaf blight, rust, mosaic patterns, and damping-off symptoms, cross-validated against the PlantVillage dataset's 54,000-image disease taxonomy. (4) Growth Stage Conformity Score (GSCS)—compares observed plant morphology against expected phenological stage for the crop profile and days-after-sowing count, flagging growth retardation or premature bolting. (5) Canopy Density Index (CDI)—estimates fractional vegetation cover within the camera frame as a proxy for plant biomass accumulation rate, correlated with NDVI satellite validation data. (6) Pest Infestation Indicator (PII)—detects visible pest presence including aphid colonies, caterpillar feeding damage, mite webbing, and stem borer entry holes characteristic of major Indian agricultural pests. ***[9], [10], [12], [14]***

11.3 Condition-Based Automated Alert and Action System

The six PCR scores are aggregated into a composite Plant Vitality Index (PVI), which drives a three-tier automated alert and response system. A PVI above 75 triggers no alert (healthy status, routine logging). A PVI between 50 and 75 generates a moderate alert transmitted via Firebase Cloud Messaging to the farmer's smartphone, presenting the specific low-scoring diagnostic axes with targeted advisory text in the farmer's preferred language (Hindi or Marathi). A PVI below 50 triggers a critical alert that simultaneously: (1) sends an SMS notification via the Twilio API to registered farm contact numbers (ensuring reach in low-smartphone-literacy contexts); (2) schedules an emergency irrigation or nutrient dosing event on the PGMS actuator interface if relevant to the identified condition; and (3) generates a full Plant Condition Emergency Report (PCER) for upload to the Next.js dashboard, including the triggering image, all six diagnostic scores, weather context, soil health data, and the Gemini-generated remediation plan with urgency timeline.

Temporal tracking of the PVI across the crop growth cycle produces a Plant Health Timeline (PHT)—a continuous visualization on the Next.js dashboard that plots vitality trends against weather events, irrigation interventions, and fertilizer applications. This correlation view enables farmers and researchers to identify which management actions produced measurable PVI improvement, building an evidence base for optimizing farm management protocols over multiple seasons. The PHT represents a novel contribution to PGMS that no reviewed system in the literature provides: a closed-loop, evidence-linked record of plant condition response to management interventions, validated jointly through visual imaging, environmental sensing, and satellite NDVI cross-referencing. ***[12], [14], [15]***

11.4 Updated Comparative Feature Analysis Including Advanced Modules

The three advanced modules—Weather Prediction and Crop Recommendation (Section 12), Soil Condition Assessment and Improvement Advisory (Section 13), and Real-Time Plant Condition Monitoring (Section 14)—collectively address three previously unresolved gaps in the literature. Gap 1 (threshold-based control dominance) is directly superseded by the weather-predictive SMFT and CSRE, which replace reactive threshold triggers with proactive, forecast-driven scheduling. Gap 4 (absence of generative AI) is extended beyond the original agronomic interpretation scope to encompass crop recommendation, soil improvement planning, and visual plant diagnosis—demonstrating the breadth of generative AI applicability in precision agriculture. Gap 3 (weak satellite-ground integration) is strengthened through PVI-NDVI cross-validation in the Plant Health Timeline, providing continuous multi-scale validation rather than periodic satellite snapshot comparison.

Together, these three modules advance PGMS from a plant growth monitoring system to a comprehensive Precision Agricultural Intelligence Platform (PAIP)—one that simultaneously monitors the sky (weather prediction), the soil (health profiling and improvement), and the plant (visual condition assessment), integrating all three observational layers through AI-driven analytics to deliver actionable, multilingual, market-aware, and cost-conscious guidance to Indian farmers at the smallholding scale.

12. CONCLUSION

This comprehensive literature review has traced the evolution of plant growth monitoring systems from rudimentary threshold-based IoT deployments to sophisticated, AI-augmented, edge-intelligent frameworks. The fifteen references examined span the full technological spectrum—from basic soil moisture sensing to generative AI interpretation—revealing a consistent pattern of incremental advancement alongside persistent systemic gaps.

The review demonstrates that while individual technological components—capacitive sensing, edge computing, time-series modeling, satellite integration, and AI interpretation—have each achieved research maturity in isolation, their integration into a unified, scalable, and practically deployable system remains an unmet challenge. This gap is not merely technical but also contextual: existing systems rarely account for the specific conditions of Indian agriculture, including regional crop diversity, soil variability, language accessibility requirements, and connectivity constraints.

The proposed PGMS framework directly addresses this multidimensional gap through its five-layer architecture combining ESP32 edge intelligence, capacitive moisture sensing, Gemini AI interpretation, NDVI satellite validation, and Next.js real-time visualization. By synthesizing the best practices identified across the reviewed literature—sensor calibration rigor from soil sensing research, hybrid architecture design from edge computing studies, temporal modeling from growth detection systems, and contextual reasoning from AI integration work—PGMS represents a significant contribution to the practical advancement of precision agriculture in Indian conditions.

The insights from this review underscore that the future of agricultural monitoring lies not in any single technological innovation but in the thoughtful, context-sensitive integration of complementary capabilities into systems that are simultaneously intelligent, reliable, accessible, and scalable. This vision guides the design and implementation of the proposed PGMS research system.

From the systematic analysis of fifteen high-quality references, a unified research gap emerges: there is currently no integrated framework that simultaneously combines (1) long-term reliable capacitive sensing, (2) edge intelligence with asynchronous time-series acquisition, (3) AI-driven growth interpretation via generative models, (4) satellite NDVI validation, and (5) real-time accessible visualization within a scalable hybrid architecture. This gap defines the research motivation for PGMS

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