

IOT-BASED SOIL CONDITION ASSESSMENT IN SMART AGRICULTURE: A REVIEW OF INDICATORS, COMPOSITE INDICES AND DECISION-SUPPORT SYSTEMS

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Abstract - Soil condition assessment is increasingly supported by mechatronic sensing and Internet of Things (IoT) technologies that complement laboratory and field evaluation with continuous and distributed measurements. This review focuses on the complete information chain required for IoT-based soil assessment: indicator selection, sensing and communication, data-quality control, normalization, composite index construction and decision support. Physical, chemical and biological indicators are considered together, while their suitability for continuous monitoring is differentiated. Soil moisture, temperature and electrical conductivity are readily integrated into IoT platforms; pH and nutrient sensing require more rigorous calibration, whereas organic matter, structural and biological indicators often remain periodic laboratory or field inputs. A compact processing framework is proposed in which sensor records are validated, filtered and normalized before aggregation into physical, chemical and biological sub-indices and a conceptual Soil Condition Index (SCI). The SCI is then linked to transparent rule-based alerts and a modular end-to-end architecture connecting sensing nodes, communication, database services and user interfaces. The proposed framework is intended as an interpretation and early-warning layer rather than an autonomous agronomic decision-making system. Its practical application requires local calibration, independent validation and explicit reporting of data completeness. An experimental photovoltaic-powered IoT prototype is also presented to illustrate the practical implementation of the multi-depth sensing, acquisition and 4G communication layers. The review highlights persistent gaps in multi-parameter integration, sensor-data quality control, local calibration and the transformation of raw measurements into transparent decision-support outputs.

Keywords: Soil condition assessment, Smart agriculture, IoT, Soil sensors, Data normalization, Soil Condition Index, Decision support.

1. Introduction

Soil condition influences agricultural productivity, water and nutrient cycling, carbon storage and ecosystem stability. Conventional assessment based on laboratory analysis, manual sampling and expert field observation remains essential for accurate diagnosis, but it is discontinuous in time and may not capture rapid changes caused by irrigation, rainfall, temperature or management operations. IoT-based agriculture complements these methods through smart sensors, embedded systems and wireless

communication that enable continuous or near-real-time monitoring of relevant variables [1–5].

The availability of measurements alone does not ensure useful decisions. Raw values may be noisy, incomplete or context-dependent, and parameters such as moisture, pH and electrical conductivity cannot be interpreted using universal thresholds. A complete technological framework therefore has to connect measurable soil properties with data validation, normalization, composite assessment and transparent decision-support logic. The importance of integrated soil monitoring is also reinforced by Directive (EU) 2025/2360 on soil monitoring and

resilience, which recognizes physical, chemical and biological soil descriptors [6].

This review examines IoT-based soil condition assessment from a technological and methodological perspective. It synthesizes soil indicators, sensing and communication technologies, data-processing methods and decision-support approaches, and proposes a conceptual end-to-end framework in which validated and normalized measurements are aggregated into a hierarchical Soil Condition Index (SCI).

In this paper, “soil condition” refers to the measurable physical, chemical and biological state of the soil at a given time and location, whereas “soil health” is used in the broader sense of the soil's capacity to sustain ecosystem functions over time. Accordingly, the proposed SCI is intended to assess soil condition rather than to represent a comprehensive soil-health index.

The main contribution is the explicit connection between sensing, data quality, composite assessment and interpretable alerts rather than the treatment of IoT as a generic agricultural technology.

2. Review Methodology

This paper is organized as a **structured technological and methodological review** rather than a statistical meta-analysis. The literature was selected around three main themes: (i) physical, chemical and biological indicators used to characterize soil condition; (ii) sensor and IoT technologies for field acquisition and communication; and (iii) methods for transforming raw measurements into validated, normalized and integrated information for soil assessment and decision support. Recent peer-reviewed studies were prioritized, while older foundational works were retained when relevant to sensing platforms, data validation or composite-index methodology.

Studies were included when they addressed measurable soil properties, sensor-based or IoT monitoring, data processing, normalization, composite soil indices or agricultural decision-support systems. Studies focused exclusively on yield prediction, remote sensing without direct soil-condition interpretation, or laboratory agronomy were considered only when they provided information relevant to indicator selection, sensor validation or methodological comparison. This scope is consistent with the paper's objective of linking soil measurements with IoT acquisition, data processing and interpretable assessment.

The review was subsequently organized according to four complementary analytical dimensions. **Soil indicators** define the physical, chemical and biological properties used as the measurable basis of soil-condition assessment.

Sensing and IoT technologies address how these properties can be acquired, digitized and transmitted through connected monitoring systems. **Data processing** covers the validation, filtering, normalization and weighting of heterogeneous measurements to obtain reliable and comparable indicators. Finally, **decision support** considers how processed indicators and composite indices can be translated into interpretable alerts and management-support outputs. These four dimensions provide the methodological structure used to develop the proposed IoT-based soil condition assessment framework.

In addition, an experimental multi-depth IoT monitoring prototype is presented to illustrate the practical implementation of the sensing, acquisition and communication layers of the proposed framework.

3. Soil Condition Assessment: Indicators and Conventional Methods

Soil assessment requires indicators that are agronomically meaningful, measurable and sufficiently sensitive to change. For IoT applications, an additional criterion is whether a parameter can be monitored continuously or must be supplied periodically from laboratory or field measurements [7–10; 11–15].

3.1 Indicator Groups

Physical indicators describe hydrological, thermal and structural behaviour. Soil moisture is central to irrigation and drought assessment, while temperature affects germination, root development and microbial activity. Bulk density, porosity, infiltration, aggregate stability and compaction are also important but are less suitable for continuous low-cost sensing. **Chemical indicators** include pH, electrical conductivity (EC), macronutrients and organic matter; pH affects nutrient availability, EC is widely used as an indicator of dissolved ions and salinity risk, and nutrient information supports fertility management. Organic matter is a chemical/functional indicator with strong links to structure and biological activity, but it is usually determined periodically rather than continuously. **Biological indicators** include microbial biomass or activity, enzyme activity, soil respiration and biodiversity-related variables. They are essential to comprehensive soil-health interpretation but remain difficult to integrate into real-time low-cost IoT platforms; consequently, they are often represented through periodic laboratory or specialized field assessments [16–18].

3.2 Conventional Assessment and IoT Suitability

Laboratory analysis remains the reference approach for texture, pH, organic matter, nutrients, salinity and contamination, while field observations and instruments such as penetrometers, infiltrometers and portable pH/EC meters provide rapid contextual information. IoT monitoring should therefore complement rather than replace classical methods: its main advantage is temporal continuity, spatial distribution and automated acquisition. The main soil-condition indicators, their typical assessment approaches and suitability for IoT monitoring are summarized in Table 1.

Table 1. Soil condition indicators, typical assessment approaches and suitability for IoT monitoring

Indicator	Assessment method	IoT suitability
Physical indicators		
Moisture	Capacitive/resistive, TDR/FDR	High
Temperature	Thermistor/digital probe	High
Compaction /porosity	Field/lab methods	Low-Medium
Chemical indicators		
pH	Electrochemical probe/lab	Medium-High
EC	EC probe	High
N, P, K	Ion-selective/electrochemical/optical/lab	Medium
Organic matter	Lab/optical proxy	Low-Medium
Biological indicators		
Microbial activity/respiration	Biological tests	Low

4. IoT Sensing and Communication Technologies for Soil Monitoring

IoT-based soil monitoring relies on the integration of sensing, embedded acquisition and wireless communication technologies capable of transforming soil properties into digital data and transferring them toward remote processing and decision-support platforms. In this context, sensor selection cannot be considered independently from communication, power consumption and embedded-system requirements.

Not all soil indicators are equally suitable for continuous IoT monitoring. Soil moisture and temperature can generally be acquired at high temporal resolution, whereas pH, electrical

conductivity (EC) and nutrient-related measurements require more careful calibration and interpretation. Structural and biological indicators are less suitable for continuous low-cost acquisition and often remain dependent on periodic field or laboratory measurements [7–10, 19, 20].

4.1. IoT Sensing Layer for Soil Monitoring

The sensing layer represents the physical interface between the soil and the IoT platform. Soil moisture sensors are among the most frequently used devices because of their direct relevance to irrigation and water availability. Resistive and capacitive sensors offer low-cost solutions, while TDR and FDR generally provide higher measurement performance at increased cost and implementation complexity [8–10].

Soil temperature is comparatively easy to monitor continuously using thermistors or digital probes, although measurement depth must be considered because thermal conditions vary significantly along the soil profile. Electrochemical pH sensors and EC probes can also be integrated into IoT monitoring nodes, but their outputs require calibration and contextual interpretation. pH measurements are affected by sensor condition and soil contact, while EC is influenced by moisture, temperature and measurement method. Nutrient-related sensing, including N, P and K, remains more challenging; low-cost implementations are therefore better suited to screening and trend monitoring than to replacing laboratory analysis [7–10, 20]. Overall, moisture and temperature sensors show the highest suitability for continuous IoT monitoring, while pH and EC require stronger calibration and nutrient-related sensing remains more dependent on sensor selectivity and local validation. Structural and biological indicators are generally less suitable for continuous low-cost acquisition. From an IoT perspective, the sensing layer should therefore be modular, combining continuously available variables with periodically updated laboratory or field information when required.

4.2. IoT Communication Technologies and Connectivity

The communication layer is a central component of the IoT architecture because it connects distributed field measurements with the server, database and decision-support platform. Soil-monitoring nodes usually transmit relatively small data packets at predefined intervals, making energy efficiency, communication range and network availability more important than high data rates.

Short-range technologies such as BLE, Zigbee and Wi-Fi are suitable for local or infrastructure-rich environments. BLE offers very low power

consumption, Zigbee supports mesh networking, and Wi-Fi provides straightforward integration with local networks and Internet services.

For distributed agricultural monitoring, long-range technologies are generally more appropriate. LoRaWAN combines low energy consumption with long-range transmission and is well suited to field sensor networks [21]. NB-IoT and LTE-M use cellular infrastructure and allow remote connectivity without a local gateway. Conventional LTE/4G provides direct Internet access and higher data-transfer capability, but at increased energy cost [1–5,12,14]. The main communication technologies considered for IoT-based soil monitoring are compared in Table 2.

Table 2. IoT communication technologies for soil-monitoring systems

Technology (energy)	Typical application	Main limitation
BLE — very low	Node setup/readout	Short range
Zigbee — low	Mesh sensor networks	Routing nodes required
Wi-Fi — medium–high	Local gateway or powered station	Infrastructure dependence
LoRaWAN — very low	Distributed field nodes	Gateway required; low data rate
NB-IoT / LTE-M — low–medium	Remote cellular IoT nodes	Coverage/subscription dependence
LTE / 4G — medium–high	Autonomous stations/gateways	Higher energy demand

Actual communication performance depends on antenna configuration, terrain, vegetation, interference and network coverage; therefore, communication ranges should be considered deployment-dependent rather than fixed values.

For autonomous agricultural stations, 4G communication can be particularly useful because it provides direct server connectivity without requiring local Wi-Fi infrastructure. This option is especially relevant when the monitoring station is supported by photovoltaic power and battery storage.

4.3. Integration within the IoT Monitoring Architecture

Within an IoT soil-monitoring system, sensing and communication operate as consecutive layers of the same architecture: **soil sensors → acquisition unit → embedded controller → IoT communication → server/database**. The sensing

node acquires soil-related variables, associates them with metadata such as timestamp, station identifier and measurement depth, and forwards the measurements through the selected communication interface. The server then receives the transmitted data and provides the input for the validation, filtering and normalization procedures described in Section 5.

This structure is directly reflected in the experimental platform presented in Section 8, where multi-depth soil sensing is combined with an acquisition and conditioning unit, an ESP32 controller and a 4G modem. The IoT architecture therefore provides the technological connection between soil measurement and data interpretation, enabling the subsequent transformation of field measurements into normalized indicators, SCI values and decision-support outputs.

5. Data Processing Pipeline for Soil Condition Assessment

The usefulness of an IoT soil-monitoring system depends not only on sensor availability and connectivity, but also on the quality of the data-processing chain.

Measurements acquired from distributed field sensors may contain missing values, outliers, sensor drift, communication errors or short-term fluctuations. Moreover, soil variables are expressed in different units and numerical ranges and therefore cannot be directly aggregated into a composite assessment.

The proposed IoT data pipeline comprises four successive operations: **data acquisition → quality control → normalization → weighting**. These operations transform raw sensor measurements into reliable and comparable indicators that can subsequently be used by the Soil Condition Index described in Section 6.

5.1. Data Acquisition and Quality Control

Each IoT sensing node should associate the acquired values with metadata required for identification and interpretation. A measurement record should include at least the node identifier, timestamp, measurement depth or location, measured variables and technical status. Data quality is a critical requirement in IoT-based smart agriculture because subsequent processing, alerts and decision-support functions rely directly on automatically acquired sensor measurements. Validation should therefore identify values that are technically impossible, inconsistent with sensor limits or potentially implausible in the monitored context. For a multi-parameter soil-monitoring node, a compact data packet can be represented as:

$$D = \{ID, t, z, M, T, pH, EC, N, P, K, B\} \quad (1)$$

where ID is the station or node identifier, t is the timestamp, z the measurement depth, M moisture, T temperature, EC electrical conductivity, N/P/K nutrient-related values and B denotes battery or system status.

In IoT applications, data-quality control is particularly important because subsequent alerts and decisions are generated automatically from machine-acquired measurements [11,13]. Validation should therefore identify values that are technically impossible, inconsistent with sensor limits or potentially implausible in the monitored context. A basic range check can be expressed as:

$$x_i \in [x_{i,min}, x_{i,max}] , \quad (2)$$

$$\Delta x_i(t) = |x_i(t) - x_i(t-1)| \quad (3)$$

Values outside technical sensor limits can be marked as invalid, whereas unusually large temporal variations should preferably be flagged rather than automatically deleted because actual field events, such as irrigation or rainfall, may also generate rapid changes.

The validation stage may therefore include: range and plausibility checking; missing or duplicated data detection; temporal consistency analysis; comparison between related or neighbouring measurements; periodic verification against manual or laboratory reference data.

After validation, simple filtering procedures such as moving-average or median filters can reduce short-duration sensor noise. For embedded IoT nodes, these methods are particularly suitable because they have low computational requirements. Filtering should nevertheless preserve rapid but real variations in soil conditions.

The output of this stage is therefore not only a measured value, but a **measurement associated with a data-quality status**.

5.2. Data Normalization and Weighting

After quality control, the heterogeneous soil measurements must be transformed onto a common numerical scale before they can be combined. In the proposed framework, each indicator is converted into a normalized score:

$$0 \leq S_i \leq 1$$

where values approaching 1 represent favourable conditions according to the selected reference function, while values approaching 0 represent increasingly unfavourable conditions. For indicators where higher values are favourable within the considered interval, a beneficial-type transformation can be used:

$$S_i = \frac{x_i - x_{i,min}}{x_{i,max} - x_{i,min}} \quad (4)$$

For indicators where increasing values correspond to increasing risk, a cost-type relationship can be applied:

$$S_i = \frac{x_{i,max} - x_i}{x_{i,max} - x_{i,min}} \quad (5)$$

However, several soil parameters, particularly pH, moisture and temperature, are characterized by an **optimal interval** rather than by a monotonically increasing or decreasing relationship. Their normalization can therefore be represented conceptually by four reference values $a < b \leq c < d$:

$$0 \rightarrow \text{linear increase } [a,b] \rightarrow 1 \text{ on } [b,c] \rightarrow \text{linear decrease } [c,d] \rightarrow 0 \quad (6)$$

This formulation allows both deficiency and excess conditions to reduce the normalized score.

The reference intervals should not be considered universal thresholds. They require calibration according to soil type, crop species, phenological stage, measurement depth, climatic conditions and sensor characteristics. The same caution applies to EC because its interpretation depends on the measurement method and local soil conditions.

After normalization, each indicator can be associated with a weighting coefficient w_i , subject to:

$$\sum_{i=1}^n w_i = 1 \quad (7)$$

Equal weighting provides the simplest conceptual implementation, while expert judgement, AHP, entropy-based procedures or data-driven methods may be used when appropriate calibration information is available [15–18, 22].

In an IoT framework, weighting may also reflect **measurement reliability**. A continuously monitored and well-calibrated parameter should not necessarily have the same practical contribution as an intermittently available or less reliable sensor measurement.

5.3. Data Preparation for Composite Soil Assessment

The output of the processing pipeline is a set of validated and normalized soil-condition indicators:

$$S = \{S_1, S_2, \dots, S_n\} \quad (8)$$

together with their corresponding weights:

$$W = \{w_1, w_2, \dots, w_n\} \quad (9)$$

For multi-depth IoT monitoring, each normalized value should also remain associated with its measurement depth:

$$S_i = S_i(z, t) \quad (10)$$

This representation is particularly relevant to the experimental architecture described in Section 8, where soil parameters are acquired at several depths. The processing pipeline can therefore preserve both temporal and vertical information rather than reducing all measurements to a single undifferentiated dataset. The current prototype uses five sensing levels and can generate measurements at 5, 15, 30, 60 and 90 cm. The complete IoT processing chain can thus be summarized as: **raw sensor data** → **metadata association** → **validation** → **filtering** → **normalization** → **weighting** → **SCI input**.

This structure provides the direct connection between the sensing and communication technologies discussed in Section 4 and the hierarchical Soil Condition Index developed in Section 6.

6. Proposed Conceptual Soil Condition Index

The heterogeneous nature of soil measurements makes direct comparison and interpretation difficult, particularly when physical, chemical and biological indicators are acquired using different sensing principles, units and temporal resolutions. Following the validation, filtering and normalization stages described in Section 5, the resulting dimensionless indicator scores can be integrated into a composite assessment framework.

The **Soil Condition Index (SCI)** proposed in this paper is conceived as a hierarchical and transparent interpretation layer rather than as a substitute for laboratory-based soil diagnosis. Its main purpose is to transform multiple normalized indicators into an interpretable score while preserving information on the physical, chemical and biological components that contribute to the overall soil condition.

The proposed approach is consistent with recent soil-quality assessment studies emphasizing the integration of multiple soil properties and the use of composite indices for supporting interpretation [15–18]. Existing soil-quality indices differ in the number and type of indicators considered, as well as in their normalization, weighting and aggregation procedures. Most approaches were developed primarily for periodic soil assessment based on field or laboratory measurements, whereas continuous IoT monitoring introduces additional requirements related to sensor availability, heterogeneous update frequencies and incomplete data. These aspects are particularly relevant when adapting composite-index concepts to connected monitoring systems.

Representative soil-quality indexing approaches are compared with the proposed SCI in Table 3, with

particular emphasis on index construction and IoT relevance.

Table 3. Comparison of representative soil-quality indices and the proposed SCI

Approach	Index construction	IoT relevance
Chaudhry et al. [15]	7 indicators; nonlinear scoring; weighted SQI	Sensor/ML-based estimation; not designed for continuous IoT
Vasu et al. [16]	12 physical, chemical and biological indicators; PCA/expert weighting	Comprehensive, mainly periodic assessment
Islam et al. [22]	Minimum dataset; linear/nonlinear scoring; additive, weighted and Nemoro indices	Method-oriented; not IoT-specific
Proposed SCI	Physical, chemical and biological sub-indices; 0–1 normalization; hierarchical weighting	Explicit IoT integration, missing-data handling, completeness and multi-depth assessment

Compared with conventional SQIs, the proposed SCI embeds normalized and weighted aggregation in an IoT processing chain combining continuous sensor data with periodic field or laboratory information. It additionally addresses missing data, completeness and multi-depth assessment, while requiring local calibration and validation.

6.1. Indicator Groups and Conceptual Structure

The proposed SCI comprises physical, chemical and biological components. Physical indicators include moisture, temperature and structural parameters; chemical indicators include pH, EC, nutrients and organic matter, treated here as a chemical/functional indicator; biological indicators include microbial activity, respiration and related variables. In IoT applications, continuously sensed variables can be combined with periodically updated field or laboratory information.

The three component sub-indices are denoted as: **SCI_P** – physical condition sub-index; **SCI_C** – chemical condition sub-index; **SCI_B** – biological condition sub-index. All indicators used in the calculation are assumed to have been previously converted to normalized scores:

$$0 \leq S_i \leq 1$$

where a value close to 1 represents a favourable condition according to the selected reference function, while a value close to 0 indicates an unfavourable or potentially limiting condition.

The modular structure is particularly relevant for IoT applications because different monitoring stations may contain different sensor configurations. Consequently, the framework does not require all possible soil variables to be continuously available.

6.2. Calculation of the Component Sub-Indices

Each soil-condition component is calculated as a weighted aggregation of the normalized indicators belonging to that group.

For the physical component:

$$SCI_{Ph} = \sum_{i=1}^{n_{Ph}} w_{Ph,i} S_{Ph,i} \quad (11)$$

subject to:

$$\sum_{i=1}^{n_{Ph}} w_{Ph,i} = 1 \quad (12)$$

where $S_{Ph,i}$ represents the normalized physical indicator and $w_{Ph,i}$ its corresponding weight.

For example, when moisture, temperature, compaction and porosity are available:

$$SCI_{Ph} = w_{MSM} + w_{TST} + w_{CSC} + w_{PSP} \quad (13)$$

For a low-cost real-time IoT node where only moisture and temperature are continuously monitored, a simplified physical sub-index may be used:

$$SCI_{Ph, IoT} = w_{MSM} + w_{TST} \quad (14)$$

with:

$$w_M + w_T = 1$$

The chemical sub-index can be expressed as:

$$SCI_{Ch} = \sum_{i=1}^{n_{Ch}} w_{Ch,i} S_{Ch,i} \quad (15)$$

or, for a typical sensor-based configuration:

$$SCI_{Ch} = w_{pH} S_{pH} + w_{EC} S_{EC} + w_{NSN} + w_{pSp} + w_{KSK} \quad (16)$$

subject to:

$$w_{pH} + w_{EC} + w_N + w_p + w_K = 1 \quad (17)$$

The exact set of terms included in Equation (16) depends on sensor reliability and data availability. For example, if the reliability of low-cost NPK sensing has not been independently validated, the chemical sub-index may initially be calculated using only pH and EC, while periodically measured nutrient values can be incorporated when available.

Similarly, the biological component can be represented as:

$$SCI_B = \sum_{i=1}^{n_B} w_{B,i} S_{B,i} \quad (18)$$

A possible implementation based on microbial activity and soil respiration is:

$$SCI_B = w_{MASMA} + w_{SRSSR} \quad (19)$$

where S_{MA} and S_{SR} are the normalized microbial-activity and soil-respiration scores, respectively.

The weighting coefficients should not be considered universal constants. They may be defined using equal weighting, expert knowledge, agronomic guidelines, AHP, entropy-based methods or data-driven procedures, as discussed in Section 5.2. Their final selection should be validated for the intended soil, crop and monitoring objective.

6.3. Overall Soil Condition Index

The complete Soil Condition Index is calculated by combining the three component sub-indices:

$$SCI = \alpha \cdot SCI_{Ph} + \beta \cdot SCI_{Ch} + \gamma \cdot SCI_B \quad (20)$$

$$\alpha + \beta + \gamma = 1 \quad (21)$$

where: α is the weight assigned to the physical component; β is the weight assigned to the chemical component; γ is the weight assigned to the biological component. The hierarchical formulation provides an important advantage compared with the direct aggregation of all indicators into a single equation. It allows the overall SCI to remain interpretable because the contribution of each soil-condition domain can be examined independently.

Similar overall SCI values may result from different limitations; therefore, the monitoring interface should report SCI_{Ph} , SCI_{Ch} and SCI_B together with the dominant limiting indicator. This preserves transparency and prevents the composite score from obscuring the underlying cause of an unfavourable condition.

6.4. Sensor-Based SCI and Handling of Missing Data

A particular challenge in IoT-based soil assessment is that not all indicator groups are updated at the same temporal frequency. Soil moisture, temperature and EC may be monitored every few minutes or hours, whereas organic matter and biological indicators may be updated only after periodic laboratory or field measurements.

The proposed framework therefore distinguishes between a real-time sensor-based SCI and an extended assessment including periodically updated information.

When biological information is unavailable, the real-time SCI may be calculated from the physical and chemical components:

$$SCI_{IoT} = \alpha' SCI_{Ph} + \beta' SCI_{Ch} \quad (22)$$

where:

$$\alpha' + \beta' = 1 \quad (23)$$

The coefficients α' and β' are obtained by renormalizing the available group weights.

A similar procedure can be applied when one individual indicator is temporarily missing. Missing measurements should not automatically be replaced by zero, because, within the proposed normalization scheme, zero represents an unfavourable condition rather than absence of information. If a measurement is missing, two alternatives can be adopted: the missing indicator is temporarily excluded and the remaining weights are renormalized; or, the corresponding sub-index is suspended if insufficient information is available for a reliable calculation.

For example, for a sub-index with available indicators A, the adjusted weights may be written as:

$$w'_i = \frac{w_i}{\sum_{j \in A} w_j} \quad (24)$$

and the available-data sub-index becomes:

$$SCI_A = \sum_{i \in A} w'_i S_i \quad (25)$$

This formulation preserves the mathematical range of the index while avoiding artificial deterioration caused by missing data.

The system should also report an **index completeness indicator**:

$$C = \frac{\sum_{i \in A} w_i}{\sum_{i=1}^n w_i} \quad (26)$$

where $C = 1$ indicates that all expected indicators are available. Thus, the monitoring interface could report, for example: $SCI = 0.72$; data completeness = 85%. This distinction is particularly important in sensor networks because users should be able to differentiate between a low SCI resulting from poor soil conditions and an uncertain SCI resulting from incomplete measurements.

6.5. SCI Classification and Temporal Interpretation

For practical visualization and decision support, the normalized SCI can be mapped onto qualitative soil-condition classes. This classification facilitates rapid interpretation of the composite score and supports the translation of SCI values into practical monitoring actions. A five-level scale is proposed in Table 4.

Table 4. Proposed conceptual interpretation of the Soil Condition Index

SCI class (interval)	Interpretation	Decision-support output
Very good (0.80–1.00)	Favourable condition for the monitored indicators	Maintain current management
Good (0.60–0.79)	Minor limitations may be present	Continue monitoring
Moderate (0.40–0.59)	One or more parameters require attention	Verify limiting indicators
Poor (0.20–0.39)	Significant limitations detected	Recommend corrective assessment and soil testing
Very poor (0.00–0.19)	Severe limitation or high-risk condition	Generate alert and request expert validation

These intervals are introduced as a **conceptual interpretation scale** and should not be considered universal agronomic thresholds.

The value of the classification lies primarily in simplifying communication with the user. However, any warning generated from the SCI should also indicate the limiting indicator or sub-index.

For example, the message: “**SCI = 0.34 – Poor; Primary limitation: SCI_{Ch} ; Dominant indicator: high EC**” is more informative than displaying only the composite score. In addition to the instantaneous SCI value, temporal evolution may provide relevant information about changes in soil condition.

A simple variation indicator can be calculated as:

$$\Delta SCI(t) = SCI(t) - SCI(t-1) \quad (27)$$

where:

$\Delta SCI(t) > 0$ indicates an improving trend;

$\Delta SCI(t) < 0$ indicates a deteriorating trend;

values close to zero indicate relatively stable conditions.

A gradual decrease in SCI may therefore provide an early-warning signal before the index crosses a predefined class boundary. However, short-term variations should be interpreted carefully because soil moisture, temperature and EC may change naturally over short periods following rainfall, irrigation or changes in atmospheric conditions. Trend interpretation should therefore be performed over time windows appropriate to the monitored process.

6.6 Calibration and Validation Requirements

The proposed SCI is a conceptual IoT-oriented soil-condition index that requires local calibration and independent validation. Normalization limits, optimal ranges, indicator and component weights, SCI class boundaries and decision-support thresholds should be adapted to soil type, crop, root-zone depth, climate and management conditions using sensor data together with independent reference information such as laboratory analyses or expert evaluation.

To avoid masking uncertainty, the SCI should be interpreted together with its normalized indicators, physical, chemical and biological sub-indices, data-quality flags, completeness, timestamp and measurement depth. Recent studies also emphasize that indicator selection, normalization, weighting and index-construction methods can significantly influence soil-quality assessment [15–18, 19, 22]. In the proposed framework, these principles are explicitly integrated into the IoT data-processing chain.

Accordingly, the SCI is not proposed as a universal measure of total soil health. Instead, it represents a transparent composite interpretation of the soil parameters available to the monitoring system at a given time and location. This distinction is particularly important for the experimental architecture described in Section 8, where multi-depth sensing can provide a large number of measurements at different soil depths. The same SCI framework can be applied separately to each sensing level, enabling the representation of soil-condition variability along the monitored profile:

$$SCI(z_1), SCI(z_2), \dots, SCI(z_m) \quad (28)$$

where z_m represents the corresponding measurement depth. For the experimental five-level probe, this corresponds to SCI values evaluated at 5, 15, 30, 60 and 90 cm. This depth-dependent formulation is directly applicable to the five-level experimental probe described in Section 8. The output of the proposed SCI module therefore consists of: **validated indicators** → **normalized scores** → **component sub-indices** → **depth-specific or overall SCI** → **condition class** → **limiting indicators**. This output provides the direct input for the decision-support framework discussed in Section 7.

7. Decision-Support Framework for Soil Management

Decision support should combine individual normalized indicators with the SCI because a single composite score cannot explain the cause of a limitation. A transparent rule-based layer is appropriate for early-stage IoT systems because

thresholds can be traced directly to measurements and normalization ranges. Representative rule-based alerts and corresponding management-support outputs are summarized in Table 5.

Table 5. Rule-based alerts and management-support outputs for soil condition monitoring

Condition	Alert	General management-support output
Moisture below lower range	Water deficit	Check irrigation requirement
Moisture above upper range	Excess water	Check drainage/reduce irrigation
pH outside favorable range	Acidic/alkaline condition	Confirm agronomically; assess crop-specific response
EC above calibrated limit	Salinity risk	Check water quality, drainage and salt accumulation
Nutrient indicator below calibrated level	Fertility limitation	Consider laboratory confirmation and nutrient plan
SCI < 0.40	Poor overall condition	Identify limiting sub-index and recommend detailed analysis
Battery/system below limit	Technical warning	Maintenance required

Multi-parameter rules are preferable to isolated thresholds: irrigation interpretation should consider moisture with weather and management conditions; salinity assessment should combine EC with moisture and irrigation history; fertility interpretation should consider nutrients together with pH and organic matter. The system should therefore act as an early-warning and management-support tool rather than an autonomous agronomic authority. Final interventions remain dependent on crop requirements, local soil conditions and expert validation.

8. Proposed IoT-Based Soil Condition Assessment Architecture

8.1. General Architecture

The proposed architecture integrates five functional modules: (1) sensing and embedded acquisition, (2) communication, (3) data management, (4) processing and SCI calculation, and (5) decision support and user interaction. This avoids repeating the detailed algorithms of Sections 5–7 while preserving a complete end-to-end chain. A

sensing node acquires the selected variables, associates them with timestamp, location/depth and technical status, and transmits the data through a short-range, LoRaWAN or cellular link. A gateway or directly connected node stores raw and processed records in a local or cloud database. Validation, filtering, normalization and SCI calculation are then applied before rule-based alerts are generated. Raw values should be retained so historical data can be reprocessed when normalization functions or weights are updated. The complete information flow of the proposed architecture is illustrated in Figure 1.



Figure 1: General architecture of the proposed IoT-based soil condition assessment system

The architecture is modular rather than hardware specific. A low-cost implementation may use moisture, temperature and pH with a basic embedded controller and wireless link; an advanced system may add EC, validated nutrient sensing, multi-depth measurements, weather data, remote sensing and periodic laboratory parameters. The same processing logic can be preserved while the sensing and communication layers scale with field size and budget.

8.2. Experimental IoT Soil Monitoring Prototype

To illustrate the practical implementation of the proposed architecture, an experimental IoT monitoring station was developed for multi-depth soil data acquisition and remote transmission.

The prototype integrates six functional blocks: power supply, soil sensing, data acquisition and control, 4G communication, server and monitoring application, and mobile access. The station is autonomously powered by a photovoltaic panel connected to a charge controller and battery-storage system. A DC-DC converter provides the regulated voltage required by the electronic components, enabling operation during periods of reduced solar radiation and during nighttime.

The experimental IoT soil-monitoring prototype is shown in Figure 2.



Figure 2: Experimental IoT soil-monitoring station developed by the authors.

The prototype integrates photovoltaic power supply and energy storage, embedded data-acquisition and 4G communication electronics, and interfaces for external multi-depth soil sensors.

Soil measurements are acquired using vertical monitoring probe containing five sensing levels positioned at different depths. An illustrative configuration uses depths of 5, 15, 30, 60 and 90 cm. At each level, ten soil-related parameters can be monitored: soil temperature, soil moisture, pH, electrical conductivity, salinity, nitrogen, nitrate, nitrite, phosphorus and potassium. Consequently, a complete acquisition cycle can provide up to 50 individual measurements, allowing both temporal and depth-dependent analysis of soil conditions.

An ESP32 microcontroller coordinates sensor acquisition, performs basic local validation and associates the measurements with timestamps and station identifiers before packaging them for transmission. Basic edge-processing functions can include plausibility checks, detection of non-responsive sensors, local averaging, timestamp generation and station identification. The resulting measurements are structured into a JSON data packet.

Remote transmission is performed through a 4G modem using a SIM-based cellular connection. The communication module enables deployment in agricultural areas without local Wi-Fi infrastructure and can transfer measurements to the remote server using MQTT or HTTP/HTTPS protocols.

At server level, the transmitted measurements are stored in a database and made available to a responsive web interface for real-time visualization, historical analysis and configurable alerts. The web application provides access to current measurements, historical records, graphs and configurable alert thresholds. A responsive browser-based interface also enables access from smartphones without requiring a dedicated native mobile application.

The prototype therefore implements the complete acquisition and communication pathway required by the proposed framework: multi-depth soil sensing → ESP32-based acquisition → local data verification → JSON packaging → 4G transmission → server/database → web/mobile monitoring.

Importantly, the experimental station demonstrates the practical feasibility of the sensing, acquisition and communication layers of the proposed architecture. The complete SCI calculation and decision-support methodology described in Sections 6 and 7 should be considered a subsequent processing layer requiring dedicated field calibration and validation.

9. Discussion

The review indicates that the central problem is no longer the acquisition of soil data, but the transformation of heterogeneous measurements into reliable and interpretable information. IoT platforms can improve temporal coverage, support targeted water and soil management and preserve historical trends, yet their usefulness depends on sensor calibration, spatial representativeness, data quality and agronomic context [1–5,13,18,23].

The experimental photovoltaic-powered prototype provides a practical illustration of the proposed sensing and communication architecture, combining multi-depth soil monitoring, embedded acquisition and 4G data transmission. Although it demonstrates the technical feasibility of these layers, field validation of the complete SCI and decision-support chain remains necessary.

Five gaps remain particularly relevant. First, many systems still monitor only moisture and temperature, while chemical and biological indicators are less continuously accessible. Second, raw values are more commonly displayed than integrated through transparent composite indices. Third, data-quality control is not always explicit despite drift, missing values and communication errors. Fourth, dashboards often provide visualization without showing why a warning was generated. Fifth, thresholds and normalization functions require local calibration because soil, crop and climate conditions are context-dependent [13,15–18].

The proposed framework addresses these gaps conceptually but has limitations. SCI performance depends on the selected indicators and calibration data; incomplete real-time sensing can under-represent biological or structural condition; a composite score can hide different causes of degradation; and the spatial meaning of an SCI remains local unless the sensing design provides adequate coverage. These constraints justify reporting the SCI together with sub-indices, limiting parameters and data completeness.

Future developments should focus on multi-source integration, explainable AI, edge processing and interoperability [24]. Weather, remote sensing, crop images and laboratory data may extend sensor-based assessment, while standardized metadata and data-quality flags can improve the reliability of integrated platforms [1,5,18].

10. Conclusions

IoT technologies enable continuous and distributed soil monitoring, but meaningful assessment requires validated measurements and transparent data integration.

This review links sensing, communication, data-quality control and normalization with a hierarchical SCI and rule-based decision support. The SCI preserves physical, chemical and biological sub-indices, accommodates incomplete data and supports multi-depth interpretation, while the experimental prototype illustrates the sensing and communication architecture. The framework is intended for early warning and management support rather than autonomous agronomic decision-making and requires local calibration and independent validation.

Its main contribution is therefore the integration of conventional composite-index principles into a modular IoT-oriented soil-condition assessment workflow.

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