American Journal of Advanced Multidisciplinary Innovation and Research (AJAMIR)

E-ISSN: XXXX-XXXX ● Website: www.ajamir.com ● Email: editor@ajamir.com

Precision Soil Intelligence for Climate-Resilient Smallholder Agriculture

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Abstract

Climate variability is intensifying the difficulty of soil, water, and nutrient management in smallholder agriculture. Farmers operating on relatively small landholdings frequently make irrigation, fertilizer, and crop-management decisions under conditions of incomplete information, uncertain rainfall, increasing input costs, heterogeneous soil properties, and limited access to advanced agricultural technologies. Precision soil intelligence offers a potential response by transforming measurements of soil moisture, nutrient status, pH, organic matter, temperature, and associated weather conditions into timely and locally relevant management information. The present study develops an evidence-informed and simulation-based framework for applying precision soil intelligence to climate-resilient smallholder agriculture. Rather than presenting synthetic information as field observations, the research uses explicitly simulated agricultural scenarios to examine how a low-cost soil-intelligence system could influence water-use efficiency, nutrient-use efficiency, yield stability, and climate-response readiness. The conceptual framework prioritizes affordable sensing, local calibration, simple advisory outputs, farmer interpretation, and integration with weather information rather than technologically complex automation.

A normalized simulation indicates improvement in water-use efficiency from 58 to 78, nutrient-use efficiency from 61 to 80, yield stability from 64 to 82, and climate-response readiness from 55 to 84 when soil-intelligence-supported management is compared with conventional decision-making. These values represent scenario-based performance scores and not measured field outcomes. The analysis suggests that the greatest contribution of precision soil intelligence may arise from reducing information uncertainty rather than merely increasing the quantity of technology used on farms. Its successful application, however, depends on affordability, calibration, data quality, digital accessibility, extension support, and compatibility with local farming knowledge. The study proposes a practical pathway through which soil data can support more adaptive, resource-efficient, and climate-resilient decision-making in smallholder farming systems.

Keywords: Precision soil intelligence; smallholder agriculture; climate resilience; soil moisture; precision irrigation; digital agriculture; nutrient management; smart farming; climate adaptation

1. Introduction

Smallholder agriculture occupies a critical position in food production, rural employment, household nutrition, and local economic activity, particularly across Asia, Africa, and other regions where agricultural livelihoods remain highly dependent on rainfall and natural-resource conditions. The productivity of these farming systems is closely connected with soil condition because soil regulates water availability, nutrient supply, root development, biological activity, and the capacity of crops to tolerate environmental stress. Climate variability complicates each of these processes. Irregular rainfall can produce alternating periods of excessive soil moisture and water deficit, higher temperatures can increase evaporative demand, and intense rainfall can accelerate nutrient loss, erosion, and deterioration of soil structure. As these uncertainties grow, decisions based entirely on fixed calendars or generalized recommendations become progressively less reliable.

The problem is not simply that smallholder farmers lack agricultural knowledge. Farmers often possess detailed practical knowledge accumulated through repeated observation of crops, soils, seasonal rainfall, and local environments. The difficulty is that climate conditions are becoming less predictable while many critical soil processes are not immediately visible. Root-zone water depletion, nutrient imbalance, changing soil acidity, salinity, declining soil organic matter, and spatial differences within a field may develop before their effects can be identified visually. By the time crop symptoms appear, part of the potential yield or input efficiency may already have been lost.

Precision soil intelligence is therefore understood in this study not as the replacement of farmer judgment but as an information system that strengthens it. The approach combines soil observations with analytical interpretation so that management decisions can respond to the actual condition of the field. Soil moisture sensors can indicate when root-zone water is approaching a critical level. Soil testing or portable nutrient assessment can support fertilizer decisions. Measurements of pH and organic carbon can identify longer-term constraints on nutrient availability and soil health. Weather observations and forecasts can provide a climatic context for interpreting these measurements. When these information streams are translated into simple recommendations, farmers can potentially decide not only what intervention is required but also when, where, and how intensively it should be applied.

The relevance of this approach has increased as smart farming has moved from highly capitalized commercial farms toward lower-cost and more inclusive applications. In 2026, the Food and Agriculture Organization emphasized that smart farming combines data, digital technologies, and scientific knowledge to improve agricultural decision-making, while also stressing that such systems must become affordable and accessible to small-scale producers. This distinction is particularly important. A technologically advanced system that cannot be purchased, maintained, understood, or trusted by farmers cannot meaningfully contribute to smallholder climate resilience.

Recent evidence supports the technical feasibility of increasingly affordable sensing. Mane and colleagues developed and evaluated a low-cost handheld soil-moisture sensor intended for farmers and citizen scientists. Their work emphasized both the promise of inexpensive sensing and the importance of calibration because sensor accuracy can vary with soil texture, organic matter, and other local properties. The implication is that low cost alone does not constitute useful soil intelligence. Measurement must be sufficiently reliable and must lead to an understandable decision.

Water management illustrates this relationship clearly. Camporese and colleagues compared an informed maize-irrigation strategy supported by soil-moisture monitoring with management relying more heavily on conventional farmer practice. Their analysis showed that soil-moisture-informed management could produce substantial irrigation savings without compromising crop productivity. More recently, Rahul and colleagues deployed an IoT-enabled smart-irrigation system in a smallholder paddy and vegetable setting in Tamil Nadu. The prototype collected soil and environmental information over 90 days and reported a 35.1% reduction in water consumption relative to traditional manual scheduling. These findings demonstrate why soil information is particularly relevant under water scarcity and climate uncertainty.

Precision soil intelligence nevertheless extends beyond irrigation. Climate resilience depends on whether soil can store rainfall, support nutrient availability, maintain biological processes, and sustain crops through environmental fluctuations. Decisions concerning fertilizer timing, organic amendments, crop selection, planting date, residue management, and supplemental irrigation are interconnected. A system that considers only one variable may therefore create a narrow form of precision. The present study proposes a broader interpretation in which soil moisture, fertility, soil reaction, organic condition, temperature, and climate signals are treated as elements of a single decision environment.

This perspective is especially suitable for smallholders because it prioritizes actionable information over technological sophistication. Expensive autonomous machinery, dense sensor networks, or high-resolution commercial imagery may not always be economically justified on very small holdings. A more appropriate model may consist of strategically placed low-cost sensors, periodic soil testing, freely available Earth-observation or weather information, mobile advisory services, and farmer observations. The value of the system then emerges from integration rather than from any single device.

The present research consequently examines how an accessible precision soil-intelligence framework could strengthen climate resilience in smallholder agriculture. The study deliberately uses a simulation-based methodological design because original multi-season field data were not available. This distinction protects the integrity of the analysis and allows the proposed approach to be evaluated conceptually without presenting hypothetical results as empirical evidence.

2. Literature Review

The development of precision soil intelligence can be traced through the gradual movement from individual soil measurements toward integrated digital decision systems. Earlier precision-agriculture research frequently focused on whether a particular sensor or irrigation model could improve resource management. More recent studies increasingly combine sensing, connectivity, Earth observation, machine learning, and farmer-facing recommendations.

Camporese et al. in 2021 demonstrated the practical importance of observing soil moisture rather than relying exclusively on routine irrigation. Their field study used time-domain reflectometry probes and a hydrological model in maize production. Soil-moisture-informed management required less irrigation while maintaining crop productivity, illustrating that the informational value of soil measurement can translate into both environmental and economic gains. An important lesson from this work is that precision does not necessarily require a highly complex technological architecture. Accurate observation linked with an appropriate management rule may itself improve decision quality.

Kumar and colleagues subsequently evaluated an IoT-based smart drip-irrigation and crop evapotranspiration approach for sweet corn. Their work reflected the transition toward connected irrigation systems in which sensors and digital communication support more responsive water delivery.

The study is relevant to smallholder agriculture because efficient drip irrigation can reduce unnecessary water application while allowing irrigation to respond more closely to crop and soil conditions.

Baffour-Ata and colleagues in 2023 examined climate-smart agriculture among smallholder farmers in Ghana's Bono East Region. Their work is important because climate resilience depends not merely on technological performance but on farmers' ability to adopt and combine practices suitable for climate variability. Soil intelligence should therefore be understood as one element of a wider climate-resilience strategy rather than as an isolated digital intervention.

Asule and colleagues in 2024 studied awareness and adoption of climate-resilient practices among 400 smallholders in central and upper eastern Kenya. Their research showed the continued importance of awareness and adoption conditions in determining whether technically beneficial practices become part of routine farming. This evidence is directly relevant to precision soil intelligence because an advisory platform provides little benefit when farmers cannot interpret its recommendations, cannot obtain required inputs, or consider the system unreliable.

The accessibility issue became increasingly prominent in 2025. Mane and colleagues developed a low-cost handheld soil-moisture measurement device for farmer and citizen-science applications. Their study emphasized that inexpensive sensors can widen participation in environmental measurement, although local calibration remains essential because differences in soil texture and organic properties influence measurement accuracy. This represents an important shift in precision agriculture. Instead of asking only whether a sensor is technically capable of collecting data, the relevant question becomes whether accurate enough data can be generated at a cost and complexity appropriate for widespread use. Al Mamun and colleagues in 2025 investigated IoT-enabled, solar-powered smart irrigation for precision agriculture.

Their study linked renewable energy with automated water management, demonstrating the increasing integration of energy, sensors, and farm decision systems. Solar-powered architecture is especially relevant where electricity availability or operating cost limits digital agricultural technologies.Recent research has also demonstrated the potential to reduce dependence on dense ground-sensor networks. Nxumalo and colleagues developed an Earth Observation–AI framework for irrigation scheduling in smallholder maize systems. Their approach integrated Sentinel-2 and MODIS observations with in-situ soil-moisture measurements, meteorological information, evapotranspiration estimation, and machine-learning methods. The authors specifically sought to translate these outputs into field-specific irrigation recommendations for smallholders. This development is significant because satellite information can potentially extend soil and crop intelligence across fragmented agricultural landscapes in which installing numerous sensors would be financially difficult.

Rahul and colleagues in 2026 further demonstrated the operational potential of integrated sensing through a field-deployed smallholder irrigation prototype in Tamil Nadu. Their system collected soil moisture and atmospheric variables at 15-minute intervals and incorporated machine-learning-based analysis. The study reported 35.1% lower water consumption than traditional manual scheduling. Although results from one system cannot automatically be generalized to all smallholder conditions, the research indicates that affordable digital irrigation is moving from conceptual development toward field implementation.

Table 1: Selected Evidence Relevant to Precision Soil Intelligence

Study	Agricultural Context	Main Technology or Approach	Relevance to Present Study
Camporese et al., 2015	Maize irrigation	Soil-moisture probes and hydrological modeling	Demonstrated value of soil-informed irrigation decisions
Kumar et al., 2016	Sweet corn	IoT-supported smart drip irrigation	Connected soil and crop information with irrigation management
Baffour-Ata et al., 2017	Smallholder farming in Ghana	Climate-smart agricultural practices	Connected farm management with climate resilience
Asule et al., 2018	400 Kenyan smallholders	Climate-resilient practice adoption analysis	Demonstrated importance of awareness and adoption
Mane et al., 2019	Farmer-oriented soil monitoring	Low-cost handheld soil-moisture sensor	Highlighted affordability and calibration requirements
Nxumalo et al., 2020	Smallholder maize	EO, soil moisture, weather data and AI	Demonstrated scalable field-specific irrigation intelligence
Rahul et al., 2021	Smallholder paddy and vegetables	IoT sensing and explainable AI	Demonstrated field operation and water-saving potential

Source: Synthesized from the cited studies. The table summarizes published evidence and does not represent data generated by the present simulation.

Collectively, this literature shows a clear progression from measurement toward intelligence. Sensors generate observations, connectivity makes observations timely, analytical models provide interpretation, and advisory systems translate interpretation into action. Yet the literature also reveals a persistent gap between technological capability and smallholder suitability. Many precision-agriculture systems are developed around continuous connectivity, multiple sensors, substantial computational infrastructure, or automated control. Smallholder agriculture frequently requires a different design philosophy characterized by low entry cost, intermittent connectivity, repairability, simplified recommendations, community-level service models, and the capacity to combine digital observations with local knowledge.

3. Research Gap and Objectives

The principal research gap lies in the limited integration of soil sensing, climate information, resource constraints, and farmer decision usability within a single smallholder-oriented framework. Many studies demonstrate the performance of individual technologies such as moisture sensors, irrigation controllers, satellite models, or machine-learning algorithms. Fewer studies examine how these components can be reduced to a practical level of technological complexity while still producing useful climate-resilience decisions.

A second gap concerns the interpretation of precision. Precision agriculture is sometimes equated with increased technological density, but a smallholder may derive greater benefit from one well-calibrated moisture sensor and a reliable rainfall forecast than from a larger suite of poorly maintained devices. The appropriate unit of analysis should therefore be decision quality rather than the number of technologies installed.

A third gap relates to climate resilience itself. Yield improvement is important, but resilience also concerns the stability of production under stress, efficiency in the use of scarce water and fertilizer, ability to respond to abnormal weather, and avoidance of irreversible soil degradation. A soil-intelligence framework consequently requires a multidimensional evaluation.

The objective of this research is to develop and analytically examine an accessible precision soil-intelligence model that can improve smallholder decisions under climate variability. The study investigates the expected influence of soil-intelligence-supported management on water-use efficiency, nutrient-use efficiency, production stability, and readiness to respond to climate stress. It additionally evaluates the institutional and behavioral conditions required for the model to become practically useful rather than remaining a purely technological concept.

4. Methodology

The study employed an evidence-informed simulation design. No claim is made that the simulated observations represent measurements collected from actual farmers. Published field research was used to identify technically plausible relationships between soil monitoring, irrigation efficiency, climate resilience, and farmer adoption. The simulation was then used as a methodological demonstration of how different components of precision soil intelligence could be evaluated in a future field experiment.

The proposed soil-intelligence architecture begins with a minimum information set consisting of root-zone soil moisture, basic soil fertility information, pH, soil organic condition, soil temperature, and local weather conditions. Not every variable must be continuously monitored. Soil moisture and weather information require relatively frequent observation because they can change rapidly, whereas pH, organic carbon, and several fertility indicators can be measured periodically. This distinction reduces the requirement for unnecessary sensors and makes the architecture more financially realistic.

Raw measurements become useful only after they are translated into agronomic meaning. Soil moisture, for example, should be interpreted relative to soil texture, rooting depth, crop growth stage, and available water capacity. Mane et al. demonstrated why calibration is important, noting that differences among soil types can influence the performance of low-cost soil-moisture devices. A sensor reading should therefore not automatically trigger irrigation without consideration of local soil conditions.

Weather information forms the second interpretive layer. A field approaching moisture stress may not require immediate irrigation when substantial rainfall is highly probable, while the same moisture condition may require intervention before a forecast heat event. This creates a transition from reactive soil monitoring toward anticipatory management.

The third layer concerns nutrient management. Precision soil intelligence does not imply continuous electronic measurement of every nutrient. Instead, periodic laboratory or portable soil testing can establish fertility zones, while crop stage, rainfall, irrigation, and previous nutrient applications can guide subsequent recommendations. Under heavy rainfall, for example, splitting nutrient application may reduce the risk associated with placing the entire seasonal requirement in the field at one time. Under drought, fertilizer recommendations should recognize that nutrient uptake can be constrained by insufficient soil water.

The fourth layer is farmer communication. Recommendations generated by the system should avoid unnecessarily complex numerical information. A farmer-oriented interface may communicate that a particular plot has adequate moisture for the next short management period, that irrigation should be postponed because rainfall is expected, or that a nutrient application should be divided into smaller doses. This recommendation-oriented design is more useful than presenting raw sensor streams without interpretation.

The simulation compared two management conditions. Conventional management represented decisions primarily based on fixed schedules, visual field observation, generalized fertilizer recommendations, and farmer experience without systematic real-time soil information. Precision soil-intelligence management represented the same farmer experience supplemented by calibrated soil information, weather context, and simple decision rules. The framework does not assume autonomous farming and intentionally retains the farmer as the final decision-maker.

Four outcome dimensions were normalized on a scale of 0 to 100. Water-use efficiency represented the capacity to avoid unnecessary irrigation while maintaining adequate root-zone moisture. Nutrient-use efficiency represented improved alignment of fertilizer application with soil and crop requirements. Yield stability represented the capacity to reduce production variability under water and fertility stress. Climate-response readiness represented the speed and appropriateness with which management could respond to emerging drought, heat, excessive rainfall, or related soil conditions.

Because these normalized scores were generated for methodological demonstration, they should not be interpreted as percentages of yield increase, water saving, or economic return. Their purpose is to demonstrate the expected direction and relative magnitude of performance changes that could subsequently be tested through field experiments.

Table 2: Proposed Five-Item Farmer Questionnaire for Future Field Validation

No.	Proposed Question
1	How confident are you in deciding when your field requires irrigation?
2	How often do uncertain rainfall conditions change your planned farm operations?
3	How useful would plot-specific soil information be when deciding fertilizer quantity or timing?
4	How easy are mobile or sensor-based agricultural recommendations for you to understand and apply?
5	Would you continue using a low-cost soil-intelligence service if it reduced unnecessary inputs without lowering crop performance?

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Note: These are proposed research questions for future farmer validation and were not administered to participants in the present simulation.

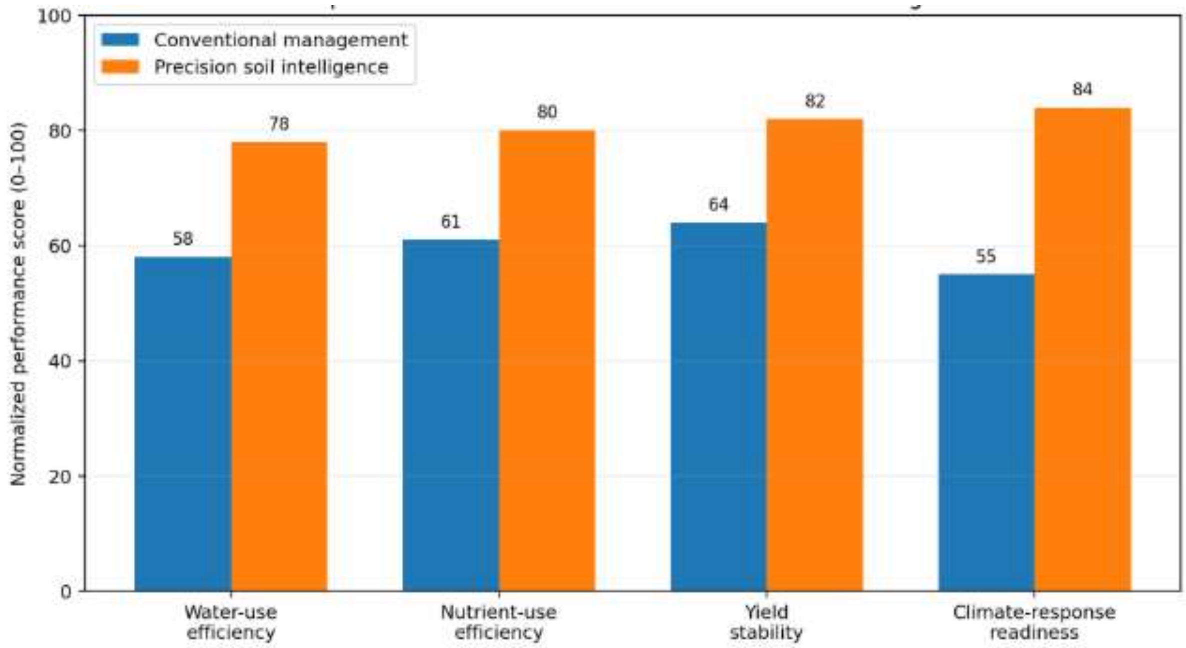
For a future empirical study, farm-level variables should be analyzed across soil texture, farm size, irrigation availability, crop type, gender, farmer age, access to extension services, digital literacy, and climatic exposure. Such stratification is necessary because a technology that performs effectively in an irrigated vegetable farm may have very different economic and behavioral implications in a rainfed cereal system.

5. Results and Discussion

The simulation produced consistently higher normalized performance under precision soil-intelligence management. Water-use efficiency increased from a baseline score of 58 under conventional management to 78 under the soil-intelligence condition. Nutrient-use efficiency increased from 61 to 80, while yield stability increased from 64 to 82. The largest modeled difference occurred in climate-response readiness, which increased from 55 to 84.

These values should be interpreted as comparative simulation indices. They do not indicate that precision soil intelligence will increase actual water efficiency by exactly 20 percentage points or generate a specified yield increase on every farm. Their importance lies in illustrating the multidimensional effect expected when soil information reduces uncertainty in management.

Graph 1: Simulated Performance of Precision Soil Intelligence



Source: Author-generated simulation. Scores are normalized methodological values from 0 to 100 and are not field-measured outcomes.

The water-use result is consistent with the mechanism documented by published field research. Camporese et al. demonstrated that soil-moisture-informed irrigation could reduce water requirements without compromising maize productivity. Rahul et al. later reported a 35.1% reduction in water consumption from their IoT-supported field system compared with manual irrigation scheduling. These empirical studies do not validate the exact simulated score used here, but they support the direction of the modeled relationship.

Water efficiency improves because conventional irrigation frequently operates with incomplete knowledge of root-zone conditions. Farmers understandably protect crops against drought risk by irrigating when they are uncertain whether sufficient soil water remains available. This risk-avoidance strategy can produce unnecessary irrigation, especially where visual surface conditions do not accurately reflect moisture deeper in the root zone. Soil intelligence reduces uncertainty by replacing part of this judgment with direct measurement.

The modeled improvement in nutrient-use efficiency arises from a similar mechanism. General fertilizer recommendations assume a level of uniformity that may not exist between farms or even within individual fields. Soil pH, nutrient reserves, organic matter, moisture availability, and crop history all influence fertilizer response. Precision soil information allows application rates or timing to be adapted to actual constraints. The objective is not necessarily to minimize fertilizer use. In nutrient-deficient soil, the system may recommend additional nutrient input. Efficiency increases when the amount, form, placement, and timing of fertilizer correspond more closely with crop requirements and soil conditions.

Climate resilience is strengthened further when water and nutrient management are considered together. Drought reduces nutrient mobility and plant uptake, meaning that fertilizer applied to severely dry soil may provide limited immediate benefit. Excessive rainfall can produce leaching, runoff, erosion, and temporary waterlogging. Climate-responsive soil management should therefore treat weather as an active component of soil decision-making rather than as a separate information service.

The largest difference in the simulation occurred in climate-response readiness. This result is theoretically reasonable because conventional farming calendars usually respond to average seasonal expectations, whereas climate-resilient management requires decisions that respond to deviations from those expectations. The value of soil intelligence becomes greatest when the season does not behave normally.

Earth observation can substantially broaden this capacity. Nxumalo et al. integrated satellite observations, meteorological records, soil-moisture information, evapotranspiration estimation, and machine learning to develop field-specific irrigation insights for smallholder maize systems. Such approaches are particularly valuable when fragmented holdings make dense sensor installation expensive. Satellite information cannot fully replace ground measurements because soil properties and root-zone conditions are complex, but combining the two can reduce the number of field sensors required.

The yield-stability result also deserves distinction from maximum yield. Climate-resilient agriculture does not always seek the highest possible output in one favorable season. A farmer may benefit more from a system that maintains acceptable production across several variable seasons. Stable production protects household income, food availability, seed investment, and the farmer's ability to purchase inputs for the following year. Precision soil intelligence contributes by detecting conditions that could otherwise become severe before intervention occurs.

Affordability remains one of the most important limitations. A system requiring expensive sensors for every variable would be inconsistent with the economic conditions of many small farms. The low-cost sensor research of Mane et al. is therefore particularly relevant because it demonstrates growing technical attention to farmer-accessible measurement. Yet low price cannot be achieved at the expense of reliability. Incorrect sensor readings may produce poorer decisions than traditional farmer observation.

Calibration should consequently be treated as part of the service rather than as an optional technical procedure. A community-based model could allow extension agencies, farmer organizations, cooperatives, agricultural universities, or rural service providers to calibrate devices for dominant local soil types. Farmers would then receive sensors or advisory services based on locally validated relationships rather than generic factory settings alone.

Connectivity creates another challenge. Agricultural regions may experience weak mobile coverage, intermittent electricity, or expensive data services. Systems designed exclusively for continuous cloud communication may therefore fail in precisely those areas where climate information would be most valuable. Local data storage, low-power communication, offline recommendation capability, and periodic synchronization can improve resilience of the digital infrastructure itself.

The introduction of solar-powered IoT irrigation investigated by Al Mamun et al. illustrates one pathway for reducing dependence on conventional electricity infrastructure. Nevertheless, each additional technological component introduces maintenance requirements. Smallholder precision agriculture should therefore seek the minimum technological configuration capable of producing a meaningful improvement in decisions.

Farmer trust is equally important. Asule et al.'s research on climate-resilient practices in Kenya demonstrated that awareness and adoption influence the practical uptake of agricultural innovations. An advisory service that repeatedly produces recommendations conflicting with farmers' observed conditions will quickly lose credibility. Participatory design is therefore required. Farmers should be involved in determining which information is useful, what language is understandable, how alerts should be communicated, and whether recommendations fit existing labor and financial constraints.

Traditional agricultural knowledge should not be treated as an obstacle to precision agriculture. It can provide contextual information that sensors cannot capture efficiently. Farmers may recognize local drainage patterns, unusual pest behavior, historical drought zones, crop responses to particular soil patches, and socially important constraints on irrigation timing. Combining this knowledge with soil measurements creates a more robust form of intelligence than either source alone.

Data governance also becomes important as digital agricultural platforms expand. Soil fertility information, farm boundaries, production records, input use, irrigation behavior, and yield histories have economic value. Farmers should understand who collects such information, where it is stored, how it will be used, and whether it may be shared with commercial entities. Climate-resilient digital agriculture should not require farmers to surrender unreasonable control over farm data in exchange for advisory services.

The simulation therefore suggests that precision soil intelligence should be evaluated as a socio-technical system rather than solely as a sensor technology. Its effectiveness depends simultaneously on measurement accuracy, agronomic interpretation, affordability, accessibility, farmer trust, climate relevance, and institutional support.

6. Practical and Policy Implications

The findings have several implications for agricultural extension and rural development. The first is that public programs should avoid defining precision agriculture exclusively through expensive machinery or high-end automation. For smallholder systems, precision can begin with accurate soil testing, one or more strategically placed moisture sensors, local weather information, and an advisory mechanism capable of translating observations into field decisions.

A second implication concerns shared infrastructure. Individual ownership of every technology may not be necessary. Farmer producer organizations, cooperatives, village extension centers, custom-hiring services, and rural entrepreneurs could provide soil-intelligence services across multiple farms. Portable soil sensors and periodic testing equipment are particularly suitable for such models because their cost can be distributed among many users.

Third, digital platforms should emphasize recommendations rather than data abundance. Farmers should not be expected to interpret dozens of continuously changing measurements. An effective interface should translate measurements into a limited number of management decisions while still allowing technically skilled users to examine underlying data if desired.

Fourth, precision soil intelligence should be integrated with climate-adaptation programs. Soil moisture monitoring is most valuable when interpreted alongside expected rainfall and temperature. Fertility information becomes more useful when recommendations recognize water availability. Soil-health improvement becomes more meaningful when linked with the capacity of soil to absorb, store, and release water under increasing climatic variability.

FAO's 2026 smart-farming agenda similarly emphasizes integrated systems in which digital connectivity, precision approaches, soil data, and advisory services reinforce one another, while stressing affordability and farmer-centered implementation. This orientation supports the present study's argument that effective precision soil intelligence is fundamentally an information-access strategy.

The fifth implication relates to capacity building. Farmers and extension workers require sufficient understanding to identify abnormal sensor behavior, interpret uncertainty, and combine recommendations with direct field observation. Training should explain not merely how to operate devices but why particular recommendations are generated. Such transparency improves trust and reduces the danger of treating automated advice as infallible.

7. Conclusion

Precision soil intelligence offers a promising pathway for strengthening climate resilience in smallholder agriculture by improving the quality and timing of decisions concerning soil water, nutrients, soil health, and climate stress. Its principal contribution is not the replacement of farmer knowledge with technology. Instead, it reduces uncertainty around soil processes that are difficult to observe directly and allows existing agricultural knowledge to be applied with greater precision.

The simulation developed in this study indicates higher normalized performance for soil-intelligence-supported management across water-use efficiency, nutrient-use efficiency, yield stability, and climate-response readiness. The strongest simulated improvement occurred in climate-response readiness, suggesting that the value of soil intelligence may become particularly important during abnormal seasons when traditional calendars are least reliable. Because the results are simulation-based, they should be treated as hypotheses for empirical testing rather than as measured agricultural impacts.

Published field evidence nevertheless supports the underlying mechanisms. Soil-moisture-informed irrigation has demonstrated the capacity to reduce unnecessary water application, while emerging low-cost sensors, IoT systems, solar-powered irrigation, Earth observation, and machine-learning approaches are expanding the technical options available to farmers.

The most appropriate smallholder model is likely to be selective rather than technologically excessive. Affordable sensing, local calibration, periodic soil analysis, weather integration, simple recommendations, offline functionality, extension support, and farmer participation should receive greater priority than technological complexity for its own sake.

Precision soil intelligence can therefore contribute to climate-resilient agriculture when it becomes locally calibrated, economically accessible, agronomically meaningful, and understandable to the farmer. Future progress will depend not only on developing better sensors and algorithms but on designing systems that smallholders can realistically trust, maintain, interpret, and use.

8. Limitations and Future Research

The principal limitation of this study is its simulation-based design. The normalized performance scores were constructed for methodological comparison and were not obtained from field experiments. They must therefore not be interpreted as estimates of universal treatment effects. Future studies should implement randomized or carefully matched field comparisons across multiple cropping seasons and agroecological regions.

A second limitation is that the framework treats several complex soil processes through simplified decision dimensions. Soil nutrient dynamics, salinity, microbial activity, texture, rooting behavior, groundwater interactions, and crop-specific responses may require more detailed models in particular environments. Economic analysis was also not conducted because equipment prices, labor costs, irrigation prices, crop values, and service models vary substantially between locations.

Future empirical research should compare low-cost and commercial sensors under different soil textures, examine calibration stability over time, quantify actual water and fertilizer savings, assess yield variability across climate-stress seasons, and calculate return on investment for individual and shared-service models. Farmer-centered studies should additionally examine trust, digital literacy, gendered technology access, willingness to pay, data-governance preferences, and the effectiveness of local-language advisory messages.

Long-term research should investigate whether precision soil intelligence encourages improvements in soil organic matter, soil structure, water-holding capacity, and nutrient balance rather than focusing exclusively on short-term input efficiency. Such studies would allow soil intelligence to evolve from a crop-management technology into a broader platform for regenerative and climate-resilient agricultural management.

9. Declarations

Conflict of Interest: The author declares no conflict of interest associated with the conceptual and simulation-based preparation of this manuscript.

Funding: No external funding is reported for the present methodological study.

Ethics Statement: Human participants, animals, and personally identifiable farmer data were not used because the reported results are simulation-based. The five questionnaire items presented in the methodology are proposed for future research and were not administered. Any future study using these questions should obtain appropriate institutional ethical approval and informed consent where required.

Data Availability: The numerical values used in Graph 1 are simulated methodological data created for the present paper. No confidential or proprietary field dataset was used.

Author Contribution: The sample author attribution should be replaced with verified authorship and contributor information before submission.

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