

PORTABLE SOIL SENSORS FOR AGRICULTURAL DIGITALIZATION AND CROP OPTIMIZATION FOR INDONESIAN FARMERS IN THAILAND

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ABSTRACT

Indonesian farmers working in the mountainous agricultural area of Chiang Mai Province, Thailand, still depend largely on visual observation, hand-feel assessment, manual thermometers, and accumulated experience when determining soil condition, fertilizer dosage, irrigation timing, and crop suitability. This situation limits access to comparable field data and may lead to inefficient input allocation and avoidable operational expenditure. This community service activity aimed to implement a portable precision soil sensor as an appropriate technology for agricultural digitalization, while strengthening farmers' capacity to convert soil information into practical cultivation decisions. The activity used a Participatory Action Research approach through needs assessment, joint problem mapping, technology preparation, field deployment, demonstration, assisted practice, observation, and reflection with members of the Indonesian Farmers Union in Thailand. The sensor was used to provide real-time readings of soil moisture, pH, nutrient status, and water requirements. The readings were then interpreted for irrigation prioritization, fertilizer allocation, crop selection, and repeated monitoring of different land plots. The implementation produced an initial transition from experience-only assessment toward decisions supported by measurable field evidence. Farmers became able to operate the device, compare readings among sampling points, discuss the meaning of each parameter, and relate the information to routine land management. Program observations indicated potential fertilizer-use efficiency of 15–25% and potential overall production and operational-cost efficiency of 20–30%; however, these values remain preliminary projections because controlled multi-season yield and financial data were not available. The activity demonstrates that a portable soil sensor can function simultaneously as a measurement instrument, a farmer-learning medium, and a basis for more efficient and sustainable agricultural management. The program also supports SDGs 2, 9, and 17 through food-production optimization, practical innovation, and cross-country institutional partnership.

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INTRODUCTION

Agriculture remains a strategic sector in Southeast Asia because it supports food availability, rural livelihoods, employment, and long-term economic resilience (Napathorn & Kuruvilla, 2017; Nurmalasari et al., 2023). Thailand has extensive agricultural resources and a long history of irrigated cultivation, although the performance of agricultural systems differs according to location, infrastructure, and farmer access to knowledge and technology (Floch & Molle, 2013; Kumnerdpet & Sinclair, 2011; Rieser et al., n.d.). Within this context, Indonesian citizens living in Thailand have also developed agricultural livelihoods and are organized through the Indonesian Farmers Union in Thailand. The land managed by this farmer community is located in the mountainous area of Chiang Mai Province, as shown in **Figure 1**.

The physical setting illustrated in Figure 1 creates both production opportunities and management challenges. Mountainous agricultural land may contain substantial variation in slope position, drainage, soil depth, texture, moisture retention, and nutrient availability over relatively short distances (Bhakta et al., 2019). Consequently, a cultivation practice that is appropriate for one plot cannot automatically be applied

to another plot. Uniform irrigation or fertilizer application may be inefficient because each field section can respond differently to rainfall, water movement, nutrient loss, and crop demand.



Figure 1. Agricultural land managed by Indonesian farmers in the mountainous region of Chiang Mai, Thailand

Soil condition is a fundamental determinant of crop establishment, root development, nutrient uptake, plant health, and harvest quality (Kendall et al., 2021; Lajoie-O'Malley et al., 2020; Roychowdhury et al., 2005). Among the parameters that directly influence daily cultivation decisions are soil moisture, pH, nutrient status, and irrigation adequacy (Mainuddin et al., 1997; Nochaiwong et al., 2022; Shrestha et al., 2017). Moisture information is needed to identify water stress or excessive wetness; pH affects nutrient availability; and nitrogen, phosphorus, and potassium are associated with vegetative growth, root development, flowering, and overall crop performance. When these parameters are not measured, farmers must make decisions using indirect signs that may be difficult to compare among plots and cultivation periods.

Digital agriculture and precision farming have been developed to reduce this information gap by converting field conditions into measurable data that can support more timely and site-specific decisions (Basso & Antle, 2020; Shen et al., 2010). Nevertheless, the adoption of agricultural technology is not determined solely by the sophistication of the device. The technology must be affordable, portable, easy to operate, relevant to actual farmer problems, and accompanied by understandable training and follow-up assistance (Bhat & Huang, 2021; Muthumanickam et al., 2022; Pasupuleti, 2024). For small farmer groups, an appropriate technology should therefore strengthen existing knowledge rather than replace farmer experience with a rigid automated recommendation.

Initial observation and discussion with the Indonesian farmer community indicated that soil assessment was still carried out primarily through visual inspection, hand-feel assessment of soil texture and moisture, and the use of a manual soil thermometer. Crop selection, fertilizer dosage, irrigation frequency, and field inspection schedules were largely determined from previous cultivation experience. This knowledge remains valuable because it has been developed through repeated interaction with the land; however, it does not always provide standardized values that can be recorded, compared, or communicated consistently among farmers.

The absence of rapid and comparable soil information may result in repeated manual inspections, delayed responses to changes in soil moisture, generalized fertilizer application, excessive or insufficient irrigation, and uncertainty in estimating production costs (Klerkx et al., 2019). These problems reduce the efficiency required in modern agriculture, which increasingly emphasizes high productivity, efficient use of capital and labor, effective resource allocation, and accurate land management (Nurmalasari & Puspitasari, n.d.; Sinitsa et al., 2021). In mountainous land, the consequences may be greater because water

and nutrients can move differently across slope positions, making observation at only one point insufficient for representing an entire field.

The baseline practices are presented visually in Figures 2 and 3. Figure 2 illustrates the manual assessment of soil moisture and texture through direct physical contact, while Figure 3 shows the use of a manual thermometer to obtain a limited temperature reading. Both practices are simple and accessible, but they do not provide integrated information on moisture, pH, nutrient status, and water requirements. The figures therefore represent the main practical gap addressed by the community service program: farmers needed a portable instrument capable of expanding field observation from subjective signs toward multiple measurable soil parameters.

The program introduced a portable precision soil sensor as an appropriate technology for small-scale and community-based agricultural management. The tool was positioned not merely as hardware, but as part of a technology-transfer process that included problem identification, demonstration, guided operation, interpretation of readings, and reflection on management decisions. This approach is relevant to small producers because effective digitalization requires an accessible learning process and continuous adaptation to farmer capacity (Chandra & Collis, 2021; Hussein et al., 2024; Prabhakar et al., 2025).

The novelty of this activity lies in connecting four elements that are often separated in technology implementation: portable field measurement, direct participation of Indonesian farmers abroad, interpretation of data for routine cultivation decisions, and institutional collaboration between Indonesian and Malaysian universities and the Indonesian farmer community in Thailand. The activity did not treat digital agriculture as an abstract modernization agenda; instead, it translated soil measurements into practical questions faced by farmers, including which plots should be irrigated first, whether fertilizer should be applied uniformly, and whether soil conditions support the intended crop.

Accordingly, this activity aimed to identify the principal soil-management problems faced by Indonesian farmers in Chiang Mai, implement and demonstrate a portable precision soil sensor, strengthen farmers' ability to operate the device and interpret the displayed parameters, and evaluate the initial technical, learning, operational, and sustainability implications of its use. The expected contribution was an initial model of inclusive agricultural digitalization in which technology, farmer experience, and participatory mentoring are integrated within a practical community service program.



Figure 2. Conventional manual assessment of soil moisture and texture



Figure 3. Use of a manual soil thermometer during field assessment

Taken together, **Figures 2** and **3** confirm that the pre-program assessment system depended on separate manual observations rather than an integrated soil-information process. The intervention was therefore designed to retain the accessibility of field-based assessment while improving the breadth, comparability, and practical usefulness of the information available to farmers.

METHODS

The activity applied Participatory Action Research (PAR) because the main objective was not only to deliver a technological product, but also to involve farmers in diagnosing problems, testing the tool, interpreting the results, and reflecting on its usefulness. Indonesian farmers who were members of the Indonesian Farmers Union in Chiang Mai Province were positioned as program partners and users of the technology. Their experience was used to identify field constraints and to assess whether the proposed sensor could be incorporated into routine agricultural work.

The program was implemented on mountainous agricultural land managed by Indonesian farmers in Chiang Mai Province, Thailand. The location was characterized by differences among cultivated plots and by the continued use of manual soil-assessment practices. The initial condition was documented through direct observation of the land, visual documentation of existing practices, and interviews or focused discussions concerning soil-quality assessment, fertilizer use, irrigation, crop selection, field inspection, and operational expenditure.

The problem-mapping results were used to ensure that each intervention component responded to an actual farmer need. As summarized in **Table 1**, the program connected the identified baseline condition, its operational implication, and the corresponding response provided through the portable sensor and mentoring process.

Table 1. Relationship between identified problems and intervention responses

Identified condition	Operational implication	Intervention response
Soil condition assessed visually or by hand	Results are subjective and difficult to compare among plots	Portable readings are used as additional field evidence
Irrigation follows routine or experience	Risk of excessive or insufficient watering	Moisture information supports irrigation prioritization
Fertilizer dosage is generalized	Potential input waste and unequal nutrient supply	pH and nutrient readings support more selective allocation
Crop selection relies mainly on previous practice	Soil suitability may not be evaluated systematically	Sensor information is combined with farmer experience
Limited exposure to digital instruments	Technology may be underused or misunderstood	Demonstration, assisted practice, and group reflection are provided

The activity was organized into five connected stages: preparation and needs assessment, collaborative planning, technology deployment, observation and assisted use, and reflection or evaluation.

The sequence was iterative rather than strictly linear. Feedback obtained during demonstration and field use was used to adjust the explanation of parameters, the measurement procedure, and the way recommendations were communicated to farmers.

Table 2 presents the activities, partner roles, and evidence expected from each PAR stage. The table also shows that farmer participation was required throughout the program, beginning with the identification of problems and continuing through evaluation of whether the sensor was useful for actual cultivation decisions.

Table 2. Participatory Action Research stages and implementation evidence

Stage	Main activities	Farmer role	Output or evidence
Preparation and needs assessment	Observation, interviews, documentation, and problem mapping	Explain existing practices and priority constraints	Baseline condition and priority problems are documented
Collaborative planning	Define sensor functions, training focus, and field-use procedure	Confirm relevance and ease of use	Implementation plan is aligned with farmer needs
Technology deployment	Functional checking, demonstration, and measurements at field points	Observe and begin operating the device	Soil parameters can be displayed and recorded
Observation and assisted use	Guided practice, repeated measurements, and decision discussions	Operate, compare, and interpret readings	Initial ability to link values with management actions
Reflection and evaluation	Review benefits, difficulties, efficiency potential, and follow-up needs	Provide feedback and propose improvements	Technical, learning, and sustainability findings are identified

The portable precision soil sensor was prepared to display soil moisture, pH, nutrient status represented by nitrogen, phosphorus, and potassium, and information related to water requirements. Before field use, the hardware and software functions were checked to ensure that the required parameters could be displayed. The sensor was then introduced as a decision-support instrument rather than a substitute for farmer judgment or laboratory analysis. The measurement procedure emphasized correct probe placement, sufficient contact with the soil, waiting for a stable value, avoiding measurements at unrepresentative points, and comparing more than one sampling point when land conditions varied.

The use of sensors in digital agriculture can improve the speed and coverage of field observation, but the usefulness of the result depends on measurement quality, interpretation, and integration with crop-management knowledge (Queiroz et al., 2020; Weltzien, 2016). Therefore, the program did not present sensor values as automatic prescriptions. Farmers were encouraged to use the readings as evidence that should be considered together with crop type, plant growth stage, recent weather, drainage condition, and cultivation history.

The function of each displayed parameter and its intended use during mentoring are summarized in **Table 3**. Referring to **Table 3**, the training process focused on converting every measurement into a limited and understandable decision question, so farmers could avoid treating numerical values as information without practical meaning.

Table 3. Soil parameters, interpretation focus, and intended management use

Parameter	Interpretation focus	Intended management use	Implementation caution
Soil moisture	Relative wetness or dryness at the sampling point	Prioritize irrigation and avoid excessive watering	Compare several points and consider recent rainfall
Soil pH	General acidity or alkalinity condition	Assess suitability and support nutrient-management discussion	Use crop-specific requirements and periodic verification
Nitrogen (N)	Indication related to vegetative nutrient status	Support selective fertilizer allocation	Do not interpret without crop stage and field history
Phosphorus (P)	Indication related to root and reproductive support	Identify areas requiring further nutrient attention	Confirm unusual values through repeated measurement
Potassium (K)	Indication related to plant vigor and stress response	Support balanced nutrient planning	Avoid uniform recommendations across heterogeneous plots
Water requirement	Combined indication for irrigation attention	Organize irrigation priority and frequency	Treat as decision support, not an automatic command

Technology transfer was carried out through explanation, live demonstration, guided operation, repeated field practice, and discussion of example decisions. Farmers learned how to insert or position the sensor, wait until the reading stabilized, identify values that appeared inconsistent, repeat measurements, record results, and compare different sampling points. Mentoring also addressed how to communicate results within the farmer group so that the device could support collective learning rather than remain dependent on one operator.

Evaluation covered four dimensions. Process evaluation examined participation and completion of the planned stages. Technical evaluation examined whether the device could display the intended parameters and be operated at field points. Learning evaluation examined farmers' ability to explain the meaning of the readings and relate them to irrigation, fertilization, and crop selection. Initial outcome evaluation examined changes in work practices, potential input efficiency, and the feasibility of continued use. Because the source data did not include controlled multi-season yield records, laboratory comparisons, or audited farm budgets, the evaluation was interpreted descriptively and the reported efficiency values were treated as preliminary program projections.

Observation notes, interview information, training responses, and field-use evidence were organized according to the initial problems, implementation process, changes in farmer practice, and potential operational implications. The analysis compared conditions before and after technology introduction at the level of work process and decision support. No inferential statistical analysis was applied because the activity did not provide a defined experimental sample or repeated quantitative outcome dataset.

RESULTS

The initial field assessment confirmed that soil-management decisions were dominated by direct visual observation, hand-feel assessment, a manual thermometer, and accumulated farming experience. These practices were easy to perform, but they generated fragmented information. Farmers could identify whether the soil appeared wet or dry and could obtain a temperature reading, yet they did not simultaneously obtain pH, nutrient, and water-requirement information. As a result, comparisons among different plots were limited and decisions were often generalized across land with potentially different characteristics.

After the portable sensor was introduced, farmers could obtain several soil parameters directly at the field location. The principal change was not only the replacement of a manual tool with a digital display, but the expansion of the evidence available for decision-making. Moisture, pH, and nutrient readings could be observed at multiple points and discussed immediately. This made it possible to distinguish plots that required different levels of attention rather than assuming that an entire field had the same condition.

During assisted practice, farmers progressed from observing the demonstration to performing measurements and discussing the displayed values. They learned that a stable and representative reading required appropriate probe placement, adequate soil contact, and repetition when values appeared implausible. The activity also showed that farmer confidence increased when instructions were related to familiar cultivation problems. Instead of learning sensor menus as isolated technical features, farmers learned through questions such as whether a plot required immediate irrigation or whether fertilizer application should be reconsidered.

The availability of current field information supported a shift from uniform treatment toward more plot-specific irrigation and fertilizer decisions (Boutraa, 2010; Kavitha & Gitanjali, 2023; Soussi et al., 2024). Farmers could prioritize plots with lower moisture readings, avoid watering areas that remained sufficiently wet, and discuss whether nutrient inputs should be allocated equally. The technology also became a group-learning instrument because readings could be compared and used to justify a proposed action. This social dimension is important because adoption is influenced by farmer confidence, perceived usefulness, and the opportunity to integrate new tools into existing work routines (Ozdogan et al., 2017; Soma & Nuckchady, 2021).

The observed transition in management practice is summarized in **Table 4**. The table demonstrates that the intervention did not eliminate farmer experience; rather, it added measurable evidence to activities that had previously depended almost entirely on routine and intuition. **Table 4** also indicates that the principal program output was a change in the basis of decisions, from generalized assumptions toward comparisons among field points.

Table 4. Changes in soil-management practices after sensor implementation

Management aspect	Before implementation	After implementation	Practical implication
Soil assessment	Visual inspection, hand-feel test, and separate thermometer	Integrated digital readings at field points	Conditions can be recorded and compared
Irrigation	Timing based mainly on routine and experience	Moisture data support plot prioritization	Potential reduction of unnecessary watering

Management aspect	Before implementation	After implementation	Practical implication
Fertilization	Dosage tends to be generalized	pH and nutrient information support selective discussion	Potential reduction of input waste
Crop selection	Previous cultivation experience is the main basis	Soil information complements local knowledge	Suitability can be considered more systematically
Field inspection	Repeated manual checks with limited documentation	Faster multi-parameter observation	Labor and inspection time may be used more efficiently
Farmer learning	Limited interaction with precision tools	Assisted operation and group interpretation	Digital confidence and peer learning are strengthened

The potential operational benefit was associated with more targeted use of fertilizer, water, irrigation-pump energy, and inspection time (Cavazza, 2020; Chandio et al., 2024; Kolady et al., 2020). Program observations indicated a possible 15–25% reduction in unnecessary fertilizer use and a possible 20–30% improvement in total production and operational-cost efficiency. These values should not be interpreted as verified savings or measured yield increases. They represent preliminary estimates based on changes in input-allocation and work processes, because the activity did not include audited expenditure records or a controlled comparison across several growing seasons.

A significant non-material result was the increased ability of farmers to discuss soil conditions using shared numerical information. Before implementation, explanations were often based on personal impressions of whether soil was dry, fertile, or appropriate for a crop. After implementation, the group could refer to displayed parameters, compare sampling points, and explain why a management response was proposed. This change strengthened communication and reduced the possibility that the tool would be used only by one person without transferring knowledge to other members.

The combined evidence from observation, assisted practice, and farmer feedback is summarized in **Table 5**. As shown in **Table 5**, the strongest outcomes were achieved at the level of access to information, basic operation, and interpretation for routine decisions. Evidence concerning long-term yield, soil improvement, and verified financial savings remains incomplete and requires continued monitoring.

Table 5. Initial evaluation of technical, learning, operational, and sustainability outcomes

Evaluation dimension	Indicator	Observed evidence	Interpretation
Technical function	Required parameters can be displayed at field points	Moisture, pH, nutrient, and water-related information became accessible	Initial technical objective achieved
Operational skill	Farmers can conduct basic measurements	Farmers practiced positioning, waiting for stable values, and repeating readings	Basic user capacity developed
Data interpretation	Readings are connected with management questions	Values were discussed for irrigation, fertilization, and crop suitability	Decision-support function began to be used
Work-process change	Field management becomes more targeted	Plots could be compared rather than treated uniformly	Initial transition toward precision practice
Input efficiency	Unnecessary water, fertilizer, energy, or labor may decline	Program estimates indicate potential efficiency	Requires financial and seasonal verification
Sustainability	The tool can continue to be used and maintained	Farmers showed interest, but calibration, records, and follow-up are still needed	Partially achieved; continued support required

The activity also identified requirements for sustained use. The sensor must remain physically available to the farmer group, users need a simple recording system, unusual readings should be repeated or verified, and periodic technical assistance is needed for calibration and troubleshooting. Without these supporting elements, the device may continue to function but its information may not be incorporated consistently into management decisions.

DISCUSSION

The results confirm that the value of a portable soil sensor is particularly relevant in mountainous agriculture, where spatial differences can make uniform management inefficient. Variation in slope, drainage, moisture retention, and soil characteristics means that one reading cannot represent every plot. Under the previous system, this variation was addressed primarily through experience and trial and error. Portable multi-parameter measurement provides a faster basis for comparing field points, although repeated sampling remains necessary because sensor readings are influenced by local soil conditions (Astakhova et al., 2019; Ayers & Westcot, 1985; Xie, 2025).

The main contribution of the intervention was not automation, but reduction of uncertainty. The sensor translated soil properties that were difficult to estimate consistently into values that could be

observed and discussed. Even so, the device should not be treated as an independent authority. A farmer must still consider crop type, growth stage, weather, field history, drainage, and the possibility of measurement error. The most responsible use is therefore a combination of sensor evidence and local agricultural knowledge.

The results also demonstrate that technology transfer cannot be reduced to equipment delivery. Farmers need opportunities to practice, make mistakes, repeat measurements, ask questions, and interpret values in relation to actual work. PAR supported this process because farmer feedback influenced the content of mentoring and the emphasis placed on practical decisions. Participation also increased ownership: the technology was presented as a shared instrument for solving farmer-identified problems rather than an external device imposed through a one-directional program.

From an agronomic perspective, moisture and nutrient information can support more precise irrigation and input allocation when readings are interpreted within crop and field context (Fountas et al., 2020; Ray & Majumder, 2024). Avoiding unnecessary watering is relevant in mountainous fields because excess moisture may reduce root aeration, contribute to root problems, and increase nutrient movement. More selective fertilizer application can reduce material waste and lower the risk of applying nutrients to areas that do not require the same dosage. These practices are consistent with the broader objective of agricultural sustainability, which seeks to maintain productivity while protecting soil and water resources (Pretty, 2007; Tang et al., 2002).

Potential cost efficiency arises through several connected mechanisms: fewer unnecessary fertilizer purchases, reduced irrigation-pump operation, shorter inspection time, and lower risk of corrective action after inappropriate management. The projected 20–30% efficiency should nevertheless be interpreted cautiously. Actual savings depend on crop type, input prices, cultivated area, frequency of sensor use, and whether recommendations are followed. A future economic evaluation should compare documented expenditure and yield before and after implementation for at least one complete production cycle.

Agricultural digitalization also introduces responsibilities related to data quality and recommendation accuracy. Sensor values may vary because of calibration condition, probe depth, soil contact, recent rainfall, sampling location, or device maintenance. Farmers should therefore avoid making major decisions from a single unusual reading. Repeated measurement, simple field records, periodic calibration, and occasional laboratory confirmation are needed to reduce the risk of false precision. Responsible digital agriculture requires transparency about what the device can and cannot determine (Dara et al., 2022; Mohammed et al., 2025; Monchusi et al., 2024).

At the institutional level, the program demonstrates how university expertise and farmer experience can be connected through an international community service partnership. The contribution to SDG 2 is represented by efforts to improve productive and efficient cultivation; the contribution to SDG 9 lies in the practical application of portable digital innovation; and the contribution to SDG 17 is reflected in collaboration among Universitas Negeri Malang, Universiti Teknologi MARA, and the Indonesian farmer community in Thailand (Dhal et al., 2024; Quí et al., 2022). The partnership is especially relevant because it directs academic technology toward the needs of Indonesian citizens working abroad and creates a channel for continued training and adaptation.

Several limitations affect the interpretation of the results. The source document does not specify the number of participating farmers, the number and distribution of sampling points, sensor calibration results, laboratory validation, crop-specific thresholds, or the duration of post-implementation monitoring. The activity also did not provide a controlled comparison of yield, input expenditure, soil condition, or farmer knowledge scores before and after the program. Therefore, the findings are strongest as evidence of implementation feasibility, access to soil information, and initial work-process change, but they are not sufficient to prove a quantified increase in harvest productivity or verified financial savings.

A subsequent program should establish a standardized measurement protocol, record the coordinates or identity of each sampling plot, repeat readings at comparable soil depth, document crop stage and recent weather, and create a simple digital or printed logbook. Sensor readings should periodically be compared with laboratory analysis. Evaluation should include pre-test and post-test measures of farmer knowledge, documented fertilizer and irrigation use, labor time, production expenditure, crop yield, and product quality. A complete seasonal dataset would allow the current projections to be tested and would strengthen the academic evidence for wider replication.

CONCLUSION

The community service activity implemented a portable precision soil sensor as an initial solution to limited access to integrated soil information among Indonesian farmers in Chiang Mai Province, Thailand. Through Participatory Action Research, farmers were involved in identifying problems, observing the technology, operating the sensor, interpreting moisture, pH, nutrient, and water-related information, and discussing its relevance to cultivation decisions. The activity shifted the basis of field assessment from separate manual observations toward a more measurable and comparable process without eliminating the role of farmer experience.

The principal outcomes were improved access to real-time soil information, development of basic operational and interpretive skills, and an initial movement toward plot-specific irrigation and fertilizer allocation. Program observations indicated potential fertilizer-use efficiency of 15–25% and potential overall production and operational-cost efficiency of 20–30%. These percentages remain preliminary because the available evidence did not include controlled multi-season measurements, laboratory validation, or audited economic records. They should therefore be used as targets for further evaluation rather than as definitive proof of impact.

Long-term effectiveness will depend on regular calibration, repeated sampling, standardized data recording, crop-specific interpretation, farmer-group management of the device, and follow-up mentoring. Future implementation should measure yield, expenditure, input use, labor time, and soil condition across complete cultivation cycles. Under these conditions, the portable sensor has the potential to become a practical foundation for inclusive agricultural digitalization, more efficient resource use, stronger competitiveness of Indonesian farmers abroad, and sustained collaboration in support of SDGs 2, 9, and 17.

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