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From Leaf Spectra to Plantation Productivity: A Review of Near-Infrared Spectroscopy for Precision Management in Oil Palm Plantation

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ABSTRACT

Improving oil palm productivity without proportionally increasing land and agricultural inputs requires better information for timely and spatially differentiated management. Near-infrared (NIR) spectroscopy has emerged as a promising analytical technology because it can rapidly characterize plant and product properties while reducing reliance on slow, destructive, and chemically intensive laboratory procedures. This qualitative literature review synthesizes peer-reviewed evidence published primarily from 2020 to August 2026 concerning NIR, visible–near-infrared (Vis–NIR), hyperspectral sensing, and related spectral technologies relevant to oil-palm management. The review integrates direct oil-palm evidence with transferable findings from crop spectroscopy, oil-palm nutrition research, precision agriculture, and technology-adoption literature. The evidence indicates that the strongest plantation-level case for NIR currently lies in rapid foliar nutrient diagnosis, complemented by applications in fruit maturity and quality assessment, disease detection, and multi-scale remote sensing. However, predictive accuracy does not automatically translate into higher fresh-fruit-bunch yield. Productivity effects depend on a longer causal chain connecting reliable spectral measurement with agronomic interpretation, fertilizer prescription, timely field intervention, and subsequent learning. Calibration transfer, environmental variability, genotype and frond effects, external validation, skills, investment costs, input availability, and smallholder accessibility remain important constraints. A closed-loop measure–diagnose–prescribe–act–learn framework and a tiered sensing architecture are proposed. Policy priorities include shared calibration libraries, standardized protocols, independent validation, reference laboratories, shared-service models, workforce development, and multi-estate field trials measuring agronomic and economic outcomes.

Keywords

Near-infrared spectroscopy, Oil palm, Precision agriculture, Foliar nutrition, Fertilizer management, Hyperspectral sensing, Chemometrics, Digital agriculture, Productivity, Technology adoption.

JEL Classification: Q12; Q16; Q18; O33; Q15.

Introduction

Productivity, intensification, and the information problem in oil-palm management

Oil palm (*Elaeis guineensis* Jacq.) is an unusually productive perennial oil crop, yet substantial yield gaps remain between attainable production and actual output in many plantation systems. Closing these gaps is increasingly important because productivity improvement on existing agricultural land can potentially reduce the pressure to meet additional output through further expansion. Research examining Indonesian oil-palm systems has estimated substantial differences between attainable and realized yields in both large plantations and smallholder fields, while showing that improved management has considerable potential to raise output from established production areas [1].

The challenge, therefore, is not simply to use more inputs. It is to improve the quality and timing of management decisions so that water, fertilizer, labor, machinery, and biological resources are deployed where they generate the greatest agronomic response. Plant nutrition is particularly important because nutrient shortages may constrain bunch formation, leaf area development, photosynthetic performance, and long-term palm productivity. Field evidence from Sumatra demonstrates that fertilizer responses can be highly site-specific: potassium application increased fresh-fruit-bunch (FFB) yield substantially at several experimental sites, while magnesium responses were concentrated at fewer locations [2]. Such spatial variation illustrates why uniform prescriptions may be inefficient.

This issue is especially consequential among smallholders. Studies of Indonesian smallholder systems indicate that nutrient supply is frequently inadequate or unbalanced and that farmers' fertilizer decisions are affected not only by agronomic requirements but also by access, price, knowledge, credit, and logistics [3,4]. Independent research covering hundreds of smallholder fields has further identified widespread nutrient deficiencies and an important association between adequate nutrient status and higher yield [5]. These findings make nutrient diagnosis both an agronomic and an information-management problem.

The literature reviewed as the starting point for this review identifies a similar operational concern. The literature describes high fertilizer expenditure, difficulty in determining crop nutrient status rapidly, and delays associated with conventional laboratory analysis as plantation-management challenges. It subsequently presents a workflow in which a leaf sample is analyzed using FT-NIR, followed by nutrient prediction, interpretation, and fertilizer recommendation. These statements are useful for understanding the practical problem perceived by technology providers and plantation managers; however, its performance and productivity claims are treated in this article as contextual industry propositions rather than independent validation.

The core management problem can consequently be framed as an **information latency problem.** Conventional nutrient assessment normally requires representative leaf sampling, sample handling and preparation, laboratory analysis, data reporting, agronomic interpretation, and subsequent fertilizer decisions. Although reference laboratory chemistry remains indispensable for accurate calibration and periodic validation, the time and marginal cost associated with conventional analysis can limit how frequently and intensively plantation blocks are sampled. A technique that increases measurement frequency and reduces turnaround time may therefore improve the informational basis of fertilizer management even before considering any direct reduction in analytical cost.

Near-infrared spectroscopy is attractive in this context because it offers rapid spectral measurements that can be related, through calibration models, to physical or chemical characteristics of biological materials. Modern agricultural applications range from benchtop Fourier-transform NIR (FT-NIR) instruments to portable spectrometers, multispectral cameras, hyperspectral sensors, UAV platforms, and combinations of spectroscopy with machine learning [6,7].

Direct oil-palm research has already demonstrated the feasibility of using spectral data to classify or estimate macronutrient status. Amirruddin et al. [8], for example, investigated N, P, K, Mg, and Ca using hyperspectral information from mature oil palms and showed that predictive performance differed according to nutrient, modelling strategy, and frond position. Other studies have extended spectral nutrient assessment to multispectral proximal imagery, satellite imagery, handheld spectroscopy, and nursery-stage Vis–NIR sensing [9-13].

Yet an important conceptual distinction is frequently overlooked. **A model capable of predicting nutrient concentration is not itself a technology that directly increases yield.** Yield improvement requires the spectral prediction to change a management decision, the decision to result in an appropriate intervention, and that intervention to generate a positive plant response under the relevant field conditions. This distinction motivates the present review.

Purpose and research questions

The purpose of this article is to critically synthesize recent literature on the development, utilization, limitations, and prospects of NIR spectroscopy for improving oil-palm plantation productivity. The review gives particular attention to nutrient diagnosis because it provides the clearest pathway between spectral information and plantation-level input management, while also considering complementary applications in crop health, fruit quality, and remote sensing.

The analysis is guided by four questions. First, how has NIR-based sensing for oil palm developed since 2020, and which plantation applications currently have the strongest empirical support? Second, through what agronomic and managerial pathways can NIR-derived information contribute to productivity and resource-use efficiency? Third, what technical, agronomic, economic, organizational, and institutional constraints limit adoption? Fourth, what technological, managerial, research, and policy interventions are necessary to make NIR-supported management reliable and scalable?

The central proposition developed in this article is that **NIR spectroscopy is best conceptualized as an enabling information and decision-support technology rather than an independent yield-enhancing input**. Its contribution to productivity is mediated by a chain of activities linking measurement, validated diagnosis, agronomic interpretation, prescription, field action, and organizational learning.

Literature Review

Scientific foundations of near-infrared spectroscopy

NIR spectroscopy forms part of vibrational spectroscopy and utilizes information contained in the interaction between electromagnetic radiation and matter. In plant materials, the NIR region contains broad and overlapping absorption features associated mainly with overtones and combinations of molecular vibrations involving bonds such as O–H, C–H, and N–H. Because water, carbohydrates, proteins, oils, structural compounds, and other constituents contain these molecular groups, their variations can influence spectral responses [6,14].

The source used for this article describes an operational NIR region of approximately 780–2526 nm and similarly highlights C–H, O–H, N–H, and related molecular bonds as relevant spectral features. The exact usable wavelength range differs across instruments and applications, however. Compact devices may cover only part of the NIR or Vis–NIR region, while research-grade hyperspectral instruments can extend from visible wavelengths through the short-wave infrared region.

This distinction is important because the technological category "NIR" encompasses several analytical configurations. FT-NIR instruments are commonly associated with controlled laboratory environments and high spectral stability. Portable and handheld systems sacrifice some instrumental sophistication in exchange for lower cost and field mobility. Hyperspectral imaging adds spatial information to spectral information, enabling assessment of individual leaves, canopies, or image pixels. UAV and satellite platforms expand coverage still further, although increased spatial scale usually introduces additional atmospheric, illumination, canopy-structure, and mixed-pixel effects.

The attached industry material proposes the use of FT-NIR for laboratory analysis of oil-palm leaf samples and emphasizes faster analysis, automation, and the possibility of predicting macro- and micronutrient information. Scientifically, however, spectral predictions should always be interpreted in relation to the calibration dataset and reference analytical method used to construct the model.

From spectrum to agronomic information: chemometrics and machine learning

Raw spectra rarely translate directly into agronomic recommendations. A typical NIR analytical workflow begins with representative sampling and a reference measurement of the property of interest. Spectral preprocessing may then be applied to reduce baseline variation, scattering, noise, or other undesirable effects. Common approaches include standard normal variate transformation, multiplicative scatter correction, smoothing, derivatives, normalization, or combinations of these procedures.

Dimensionality reduction and calibration follow. Partial least-squares regression remains widely used because spectral datasets contain large numbers of highly correlated wavelength variables. Principal component methods, support-vector machines, random forests, artificial neural networks, ensemble methods, and deep-learning models have increasingly supplemented traditional chemometric approaches [15-17].

Studies in crops other than oil palm illustrate both the opportunity and the limitations. NIR approaches have been used to estimate nutrient concentrations in cotton, maize, strawberries, orchids, wheat, citrus, lettuce, and woody plants [18-21]. These studies show that rapid nutrient assessment is technically plausible across diverse crop matrices, but they also illustrate that model performance is conditional on sampling design, nutrient range, plant stage, water status, measurement configuration, and validation strategy.

An additional issue is the interpretation of mineral nutrient prediction. Elements such as N, P, K, Mg, and Ca do not necessarily produce isolated, directly identifiable NIR absorption peaks in the same way as major organic compounds. Their concentrations can nevertheless be estimated because nutrient status changes plant biochemical composition, water relations, pigments, tissue structure, or associated organic compounds. Consequently, statistical relationships between spectra and laboratory nutrient concentrations may be strong even when the causal spectral mechanism is indirect. This makes external validation especially important.

Validation, transferability, and model robustness

Calibration accuracy measured on samples similar to those used for model construction is not sufficient evidence of robust plantation performance. Operational deployment exposes models to changes in instrument, temperature, humidity, operator, sample preparation, palm age, genotype, soil type, season, leaf water status, disease, and management history.

Calibration transfer is therefore a central problem in practical NIR systems. Studies have shown that spectra acquired using different instruments can deviate sufficiently to degrade predictions unless transfer, standardization, or updating methods are applied [22-24]. A model developed for one estate, instrument, or season should not automatically be assumed to remain valid elsewhere.

This problem becomes more important as spectroscopy moves from dried and ground laboratory samples to fresh field leaves. Field measurements are operationally attractive because they reduce preparation, but water content, surface condition, orientation, illumination, and leaf morphology introduce additional variation. Similar trade-offs have been documented in portable plant spectroscopy and other agricultural NIR applications [25-27].

Model robustness therefore depends on more than a high coefficient of determination. Relevant performance criteria include prediction error, bias, repeatability, robustness across independent sites, classification sensitivity, uncertainty around agronomic thresholds, and stability over time. For plantation management, an apparently modest reduction in prediction accuracy may be acceptable if the method is sufficiently rapid and inexpensive to permit much greater sampling intensity; conversely, an extremely accurate calibration may have limited value if its performance collapses when transferred to another estate.

Oil-palm nutrition as the agronomic bridge to productivity

Foliar analysis has long been integrated into commercial oil-palm nutrition management because leaf nutrient status reflects the interaction between nutrient supply, soil conditions, plant demand, environmental factors, and previous management. Recent research continues to refine critical concentrations and nutrient-limitation diagnostics for precise fertilizer recommendations [28].

Nutrient interpretation is complicated by interactions among nutrients and by variation among planting materials. Dassou et al. [29] showed that high-yielding oil-palm progenies may differ in leaflet mineral concentrations, including K and Mg, demonstrating that a universal spectral calibration or a universal diagnostic threshold cannot be assumed to work equally well across genetic materials.

Field response studies reinforce this point. Prabowo, Foster and Nelson [2] reported substantial yield responses to potassium at several contrasting sites but much less uniform responses to magnesium. The agronomic value of an NIR measurement therefore depends on whether its predicted nutrient concentration can be interpreted relative to an appropriate threshold and linked to a fertilizer recommendation whose likely response is known under the relevant soil, climate, and management conditions.

The conceptual bridge from spectroscopy to productivity can thus be represented as:
spectral measurement → nutrient diagnosis → agronomic interpretation → fertilizer prescription → field intervention → physiological response → FFB and oil yield.

Every arrow in this sequence is potentially a point of failure. NIR can shorten the first part of the chain, but it cannot substitute for valid agronomy in the remaining stages.

Oil-palm applications beyond leaf nutrient diagnosis

The NIR-related literature on oil palm is broader than nutrition. Spectroscopy and hyperspectral imaging have been studied for detecting *Ganoderma boninense* and basal stem rot, including asymptomatic or early-stage disease detection using machine learning and UAV-based hyperspectral imagery [30-32]. Early detection may protect productive stands by allowing interventions before severe symptoms become visible, although operational performance under heterogeneous commercial conditions requires continuing validation.

NIR has also been studied for oil-palm fruit properties. Novianty et al. [33] combined NIR spectra with signal decomposition and neural-network modelling to estimate palm-fruit oil content, while Budiastra et al. [34] investigated non-destructive prediction of oil and free fatty acid characteristics. More recent work has applied NIR and chemometric methods to palm mesocarp quality [35].

These applications could contribute indirectly to plantation and value-chain productivity through improved harvest decisions, grading, extraction efficiency, and quality control. Nevertheless, the present review gives primary analytical attention to foliar nutrient diagnosis because that application has the most direct connection with plantation input management.

Method

Review design

This study uses a qualitative literature review rather than a Systematic Literature Review (SLR). The objective is interpretive and explanatory: to integrate heterogeneous evidence and develop a coherent conceptual account of how NIR technology may contribute to oil-palm productivity, the conditions under which that contribution can occur, and the barriers that can prevent it.

Qualitative reviewing permits iterative interpretation of literature, explicit comparison of contexts, and development of themes and conceptual propositions rather than requiring exhaustive enumeration of all records matching a predetermined protocol. This orientation is consistent with methodological guidance emphasizing interpretation, reflexivity, and coherent synthesis in qualitative literature reviewing [36-38].

Accordingly, this review does not claim exhaustive coverage of the global literature, does not employ a PRISMA flow diagram, does not calculate pooled effect sizes, and does not conduct formal meta-analysis or systematic risk-of-bias scoring. These omissions are intentional and reflect the research design rather than procedural deficiencies.

Identification and organization of literature

Peer-reviewed studies published primarily between January 2020 and August 2026 were purposively and iteratively identified around combinations of concepts including "near-infrared spectroscopy," "oil palm", "leaf nutrient", "hyperspectral," "Vis–NIR", "precision fertilization", "calibration transfer", "oil palm nutrient deficiency", "oil palm productivity", and "precision agriculture adoption".

Sources were organized into five interconnected evidence domains. The first consisted of studies directly examining spectral analysis in oil palm. The second contained oil-palm agronomy and nutrient-response studies needed to establish the relationship between diagnosis and productivity. The third comprised transferable evidence from NIR and hyperspectral nutrient analysis in other crops. The fourth covered chemometrics, portable spectroscopy, model transfer, and related methodological issues. The fifth covered precision-agriculture adoption, digital agricultural services, economics, and institutional conditions.

Thematic synthesis

The literature was interpreted iteratively using themes rather than transformed into a quantitative evidence table for meta-analysis. Initial codes included technological development, nutrient diagnosis, model performance, sampling conditions, productivity pathway, field scalability, calibration transfer, economic constraints, organizational capacity, and policy requirements. These categories were subsequently consolidated into six themes presented in the Results section.

Particular attention was given to evidence proximity. Direct oil-palm observations were treated as the strongest evidence for claims about oil-palm applications. Findings from other crops were used to explain mechanisms, methodological possibilities, or likely implementation challenges, but they were not presented as proof of oil-palm performance. Similarly, evidence showing that fertilizer improves oil-palm yield was not interpreted as proof that

NIR itself improves yield.

This distinction was essential for avoiding a common technology-review error in which analytical accuracy, decision quality, and agronomic outcomes are treated as interchangeable outcomes.

Research rigor

Rigor was strengthened in four ways. First, key claims were triangulated across spectral, agronomic, and adoption literature. Second, claims based on the industry presentation were explicitly separated from peer-reviewed findings. Third, publications included in the final bibliography were restricted to recent journal literature for which a DOI or identifiable journal/publisher record could be located. Fourth, conflicting or context-dependent results were retained rather than harmonized artificially.

The review therefore seeks analytical credibility through transparency and triangulation while preserving the interpretive character of qualitative literature synthesis.

Results

Theme 1: NIR technology is evolving from laboratory analysis toward multi-scale plantation sensing

The first major finding is a progressive technological movement from centralized spectral analysis toward more distributed sensing. At one end of the spectrum, FT-NIR laboratory instruments can support controlled and repeatable analysis of prepared plant samples. At the other end, portable spectrometers, proximal imaging systems, UAVs, and satellites can potentially provide progressively greater spatial coverage.

This transition is visible in oil-palm research. Yadegari et al. [9] evaluated satellite information for nitrogen management, while Kok et al. [10] applied Landsat-8 imagery and machine learning to classify macronutrient levels. Munir et al. [39] subsequently used Sentinel-1-derived information and random-forest regression to estimate leaf nitrogen across a dataset spanning major Indonesian production regions. Such studies demonstrate the wider movement from laboratory measurement toward geospatially explicit crop monitoring.

At the proximal scale, multispectral and hyperspectral approaches can capture information that is more detailed than conventional broad-band remote sensing. Chungcharoen et al. [11] investigated proximal multispectral imagery for predicting nutritional status in oil-palm leaves, whereas Amirruddin et al. [8] examined hyperspectral classification of multiple macronutrients in mature palms.

Portable NIR offers another pathway. Handheld instruments reduce the physical distance between measurement and management, potentially allowing field personnel to analyze more samples before deciding which subset should undergo laboratory confirmation. The usefulness of such instruments has been demonstrated across several plant species, though portable models must generally address wider environmental variation than laboratory instruments, [18,23].

The technological prospect is therefore not that one platform will replace all others. The literature instead points toward a **nested sensing ecosystem** in which laboratory reference measurements, field NIR, UAV sensing, and satellite observations perform different but complementary roles.

Theme 2: Rapid leaf-nutrient diagnosis is the strongest plantation-level NIR use case

Among plantation applications, nutrient assessment provides the clearest pathway from NIR measurement to agronomic management. Amirruddin et al. [8] showed that hyperspectral data from oil-palm fronds could be used to classify N, P, K, Mg, and Ca status, with performance varying among nutrients and between frond positions. This is a critical result because commercial foliar sampling protocols are sensitive to leaf position; spectral models must therefore be aligned with standardized sampling rules rather than treated as independent of agronomic protocol.

Multispectral approaches provide complementary evidence. Chungcharoen et al. [11] demonstrated the feasibility of machine-learning prediction of oil-palm nutritional status using proximal multispectral images, illustrating that useful diagnostic signals need not always require full laboratory-range hyperspectral instrumentation.

Satellite approaches show both potential and limitations. Kok et al. [10] reported stronger classification performance for some nutrients, including N and K, than for others when applying Landsat imagery and machine learning to oil-palm plots. This variation is scientifically plausible because canopy-scale signals integrate pigment status, architecture, shadows, soil background, moisture, and multiple nutrient interactions. Remote detection should therefore be regarded as a screening or spatial-prioritization mechanism unless supported by local calibration.

The emerging handheld literature is strategically important because field-portable instruments may offer the best compromise between analytical specificity and operational accessibility. Hariadi et al. [12] examined handheld spectrometer prediction of N, P, and K in oil-palm leaves. Nursery-stage research has also shown that different NPK fertilizer treatments can produce distinguishable Vis–NIR spectral responses, particularly around physiologically informative spectral regions [13].

Evidence from other crops strengthens the plausibility of this trajectory. Rapid NIR nutrient analysis has been investigated in cotton leaves, maize, strawberry leaves, orchids, wheat, citrus, lettuce, and other plant materials [18-21,40]. The transfer lesson is not that an oil-palm calibration can be borrowed from another crop, but that field and laboratory spectroscopy can support nutrient-screening systems when calibration design reflects biological variability.

Theme 3: The productivity benefit depends on translating diagnosis into better fertilizer decisions

The third theme is the most important for evaluating claims about productivity. Oil-palm agronomic research independently demonstrates that nutrient shortages and fertilizer management can materially influence yield. Prabowo, Foster and Nelson [2] reported potassium-induced yield increases at most of their contrasting Sumatran sites, while response patterns differed for magnesium. Studies of smallholder systems likewise identify nutrient insufficiency and imbalance as widespread constraints [3,5].

This evidence creates a logically plausible productivity pathway for NIR. If conventional analysis is too slow or expensive to support sufficiently dense sampling, rapid spectroscopy could increase the frequency or spatial resolution of nutrient observations. Better observations could allow managers to differentiate deficient and sufficient blocks, prioritize expensive fertilizers, verify treatment effects, and identify emerging deficiencies before substantial yield losses accumulate.

Yet the relationship is conditional. Consider two contrasting scenarios. In the first, an NIR model detects low potassium accurately, the agronomist interprets the result correctly, fertilizer is available, the site is responsive to potassium, application occurs at the appropriate rate and time, and subsequent measurements confirm correction. Under those circumstances NIR contributes meaningful information to a productive intervention.

In the second scenario, the same prediction is produced, but fertilizer is unavailable, the diagnostic threshold is inappropriate for that genetic material, or the observed concentration reflects another physiological constraint. The measurement has then created information without creating productivity.

The possibility of connecting diagnosis to spatially differentiated action is strengthened by developments in application technology. Yamin et al. [41] investigated design requirements for variable-rate liquid fertilizer application in mature oil palms, showing that site-specific fertilizer delivery can in principle be integrated with information-rich management. The technology pathway therefore extends beyond spectroscopy itself toward an emerging precision-management system.

This leads to the first major synthesis proposition of the review:
The productivity value of NIR is proportional not simply to predictive accuracy, but to the extent to which additional spectral information changes an agronomically correct and economically consequential management decision.

Theme 4: NIR can protect productivity through fruit-quality and disease-management pathways

Nutrient management is not the only contribution. NIR spectroscopy can potentially influence realized productivity and profitability through the harvest and processing interface. Oil-palm fruit composition changes during ripening, and oil content and free fatty acid status are commercially significant properties.

Novianty et al. [33] combined NIR signals with empirical-mode decomposition and neural-network modelling for non-destructive prediction of palm-fruit oil content, reporting encouraging predictive performance. Budiastra et al. [34] similarly investigated NIR-based prediction of oil and free fatty acids, while Simeone et al. [35] evaluated palm mesocarp quality using NIR and chemometrics.

These applications create a second productivity pathway. Better fruit characterization may support harvest scheduling, grading, quality segregation, and mill-process management. The literature review extends this industrial vision further by proposing online NIR monitoring for CPO, crude oil, and final effluent and by connecting real-time measurement to faster corrective actions. These applications are operationally relevant but should be independently validated for each process stream before performance or financial benefits are generalized.

Disease detection constitutes a third pathway. Basal stem rot caused by *Ganoderma boninense* is an important threat to stand productivity, and remote or proximal spectral systems have been explored for pre-symptomatic and early detection. Studies using hyperspectral information with support-vector machines and UAV-based sensing demonstrate that disease-related physiological changes may become spectrally detectable before conventional visual diagnosis is fully reliable [30-32].

The overall implication is that NIR should not be restricted conceptually to fertilizer management. It forms part of a broader spectral-monitoring capability that can potentially support crop nutrition, plant health, harvest quality, and processing efficiency.

Theme 5: Model robustness is the dominant technical barrier to scaling

Technical feasibility at research scale does not guarantee robust performance across commercial plantations. The literature consistently identifies calibration as both the strength and the vulnerability of NIR. Spectral analysis is fast after a reliable model exists, but the model itself depends on expensive and careful reference measurements.

For oil palm, representativeness is particularly challenging. Commercial landscapes encompass contrasting soils, palm ages, planting materials, weather patterns, management histories, nutritional interactions, and disease conditions. A calibration dominated by a narrow concentration range or one estate may produce excellent internal statistics but weak extrapolation elsewhere.

Frond position is a concrete example. Amirruddin et al. [8] found that nutrient classification performance differed between frond 9 and frond 17. This means a plantation cannot regard sampling protocol as a trivial preprocessing issue. An algorithm calibrated on one frond position should not be applied casually to another.

Genetic variation creates an additional source of domain shift. Differences in mineral nutrition among high-yielding oil-palm progenies have been documented, suggesting that relationships between spectral properties, tissue concentration, and agronomic sufficiency may vary across planting materials [29]. Similarly, water status can dominate portions of the NIR signal because O–H absorption is strong, potentially masking more subtle nutrient-related responses.

Instrument transfer also matters. Calibration-transfer research demonstrates that changing spectrometers can alter spectral response sufficiently to require standardization, transfer learning, feature-selection methods, or recalibration [22-24]. This is particularly important for a long-lived perennial sector in which instruments may be replaced over a 20–25-year plantation cycle.

External validation therefore deserves greater attention than marginal improvements in internal cross-validation statistics. A commercially meaningful study should ideally test a model on palms, estates, seasons, and potentially instruments that were absent from model construction. Prediction uncertainty should also be reported near agronomic decision thresholds. Misclassifying a clearly sufficient palm as marginal may merely cause an additional confirmatory test; misclassifying a severely deficient block as sufficient can have much larger consequences.

Theme 6: Adoption is constrained by economics, skills, institutions, and input availability

Precision agriculture is frequently discussed as though adoption depended mainly on purchasing hardware. The broader technology-adoption literature demonstrates otherwise. Adoption depends on farm scale, complementary skills, expected profitability, risk, finance, information networks, infrastructure, and whether the technology integrates with existing workflows [42,43].

The contrast between large estates and smallholders is particularly important for NIR. A large plantation company may be able to maintain a reference laboratory, employ chemometric and agronomic specialists, distribute instruments across estates, standardize sampling protocols, and internalize the value of improved fertilizer decisions. An individual smallholder may manage only a small number of palms and have no economic reason to purchase a sophisticated spectrometer.

Digital agricultural services research suggests that service models and information intermediaries can be important when individual ownership is unrealistic. Personalized extension and digital information have been associated with changes in agricultural decision-making, while technology-adoption studies emphasize heterogeneity in farmers' ability to capture benefits [44-46]. Social and extension networks also affect diffusion, meaning that a technically valuable technology can spread slowly without trusted demonstration and peer learning [47].

Oil-palm-specific evidence makes this institutional problem especially clear. Indonesian smallholders may face fertilizer-price, availability, knowledge, and financing constraints [3,4]. Under these conditions, identifying a nutrient deficiency does not guarantee that the recommended nutrient can be purchased and applied.

Consequently, widespread NIR deployment requires attention to **service architecture** rather than instrument sales alone.

Discussion and Analysis

NIR should be understood as an information technology

The combined evidence suggests that the most useful conceptual reframing is to treat NIR spectroscopy as **measurement infrastructure embedded in a management system**. A spectrometer does not create additional biomass in the same way that nutrients, water, radiation, or improved genetic material do. Instead, it reduces uncertainty about crop or product status.

This distinction has major implications for evaluating performance. The relevant economic question is not simply whether NIR agrees with a laboratory value. It is whether faster or denser information changes decisions enough to create benefits exceeding the cost of obtaining and acting on that information.

Four characteristics potentially generate value.
First is **speed**. Faster measurement shortens the interval between detecting a condition and responding to it.

Second is **frequency**. Lower marginal analytical cost may permit more frequent monitoring.

Third is **spatial resolution**. More observations may reveal within-estate variation hidden by sparse composite sampling.

Fourth is **feedback**. Repeated measurements can show whether a fertilizer or other intervention corrected the diagnosed condition.

For this reason, the application concept of moving from rapid nutrient monitoring to targeted fertilization and subsequently to productivity improvement is directionally plausible, but the final causal step requires independent field evidence. Peer-reviewed agronomic research establishes that nutrients affect oil-palm productivity, while spectral studies establish that nutrient status can sometimes be predicted; substantially fewer studies directly compare NIR-guided fertilizer management versus conventional recommendation systems using subsequent FFB yield and economic return as endpoints. That gap should remain explicit.

The evidence asymmetry: analytical validation is stronger than causal productivity evidence

The literature displays an important asymmetry. Evidence is increasingly strong at the left-hand side of the causal chain—spectral measurement, classification, and nutrient prediction. Evidence becomes progressively thinner as one moves toward fertilizer prescription, changed management, long-term nutrient-use efficiency, FFB response, oil yield, and return on investment.

This is not an argument against NIR. It indicates where research investment should shift.

A new study showing a small improvement in cross-validated R^2 may contribute less to plantation decision-making than a multi-estate trial testing whether an already adequate calibration changes fertilizer allocation, cost per hectare, nutrient sufficiency, FFB yield, and gross margin. Researchers should therefore move beyond a primarily **prediction-centered research paradigm** toward an **outcome-centered implementation paradigm**.

The central causal argument of this review is summarized in Figure 1. The figure intentionally separates **analytical performance** from **agronomic performance** and **economic performance**. NIR affects productivity only when information passes successfully through every stage of the decision chain.

Figure 1 demonstrates why an accurate spectrum-to-nutrient model is necessary but insufficient. A weak calibration compromises diagnosis; an inappropriate sufficiency threshold compromises interpretation; fertilizer scarcity prevents action; and adverse environmental conditions can modify crop response. The productivity contribution of NIR is thus systemic and mediated, rather than automatic.

A closed-loop model: measure–diagnose–prescribe–act–learn

The evidence supports a five-stage management model.

Measure refers to acquiring spectral observations under standardized conditions. At this stage, the principal concerns are representative sampling, instrument stability, wavelength range, moisture, and metadata.

Diagnose converts spectra into meaningful estimates or classes using validated calibration models. Reference chemistry remains essential because NIR predictions ultimately depend on trustworthy ground truth.

Prescribe translates predicted plant status into an agronomic recommendation. This step requires nutrient sufficiency standards, information on soil and crop history, fertilizer-response knowledge, prices, and practical constraints.

Act implements the recommendation, whether through conventional block-level fertilizer application, site-specific application, additional sampling, disease inspection, or harvest intervention.

Learn compares subsequent measurements and outcomes against the original prediction. This stage allows calibration updating, assessment of recommendation effectiveness, detection of model drift, and improvement of the decision system.

The last stage is often neglected. A digital plantation capable of collecting large quantities of spectral data but unable to connect predictions with fertilizer records and subsequent yield data forfeits

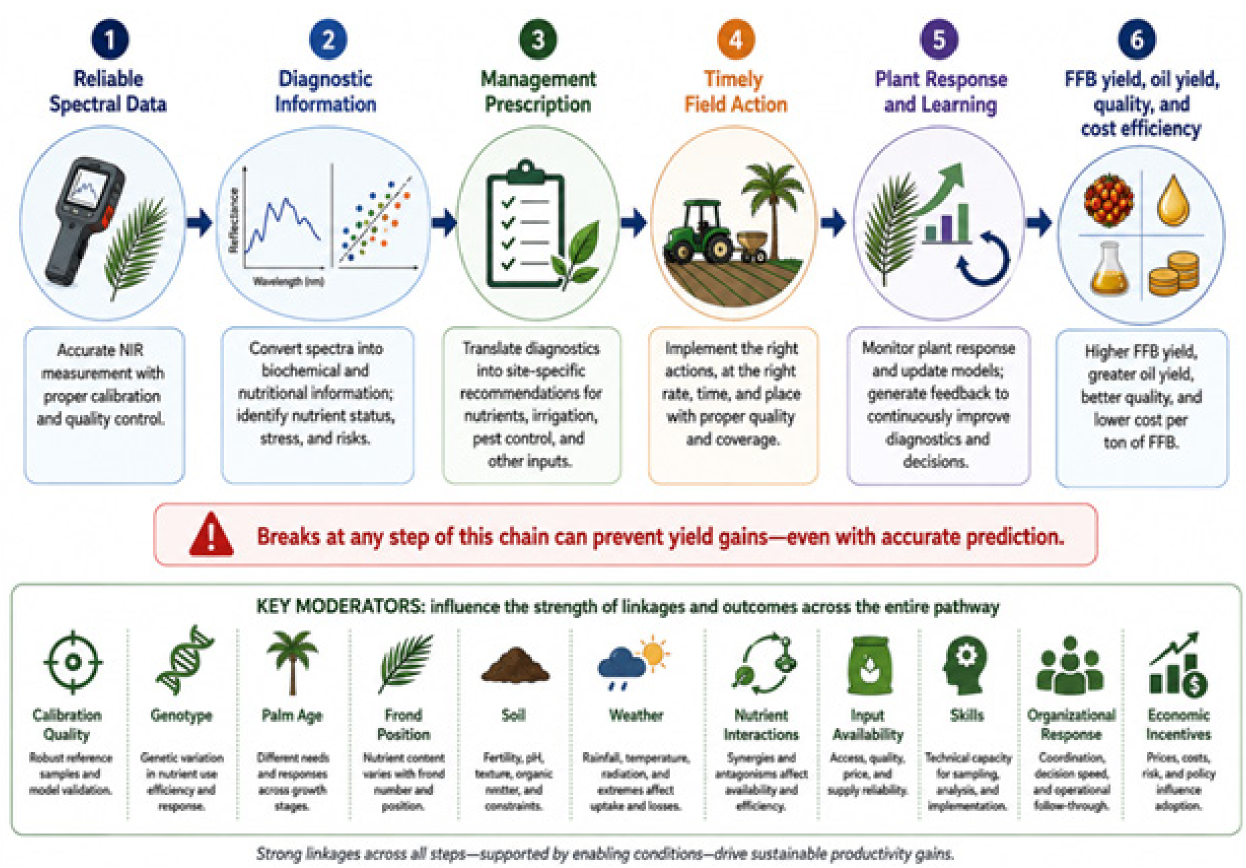

Figure 1: The NIR-to-Productivity Causal Pathway in Oil-Palm Plantations.

an important opportunity. Long-term value will increasingly come from linking the spectroscopy database to georeferenced agronomic history.

A tiered sensing architecture is more realistic than a single universal device

The literature does not support a simple choice between "laboratory NIR" and "field NIR." Different measurement platforms solve different problems. The appropriate architecture is hierarchical.

At the foundation, a reference laboratory provides wet-chemistry values and high-quality FT-NIR spectra. Above this, portable instruments permit dense field sampling. UAV or proximal hyperspectral sensing maps variability within blocks. Satellite data can prioritize broad areas for closer investigation. These data can then be combined within a GIS or plantation-management system.

Figure 2 translates this interpretation into a tiered architecture. The key concept is **calibration anchoring**: higher-throughput field and remote sensors should remain linked to a smaller but high-quality stream of reference observations.

This architecture avoids two extremes: requiring every decision to wait for slow reference analysis, and trusting an unanchored portable or remote model indefinitely. Reference laboratory measurements remain fewer but authoritative; proximal and remote observations provide scale.

Economic value must be evaluated at the decision-system level

An appropriate techno-economic assessment should compare management systems, not merely analytical costs per sample. Relevant benefits may include reduced laboratory expenditure, reduced sample transport and processing, more frequent monitoring, fewer unnecessary fertilizer applications, earlier correction of nutrient deficiencies, better targeting of expensive nutrients, improved quality, and reduced production losses.

Relevant costs include instrument acquisition, calibration development, reference chemistry, maintenance, instrument replacement, software, data infrastructure, personnel training, model updating, quality assurance, and the opportunity cost of organizational change.

The optimum model may differ sharply between large plantations and smallholders. A plantation group processing thousands of samples per year can spread fixed calibration costs over a large analytical volume. Smallholders may benefit more from a shared-service model in which a cooperative, extension service, mill, research institution, or commercial laboratory owns the instruments and delivers diagnostic information as a service.

Such arrangements parallel broader findings from agricultural technology adoption: returns and adoption rates depend on farm structure and complementary resources, meaning that efficiency gains demonstrated for one producer category should not automatically be extrapolated to another [42,46].

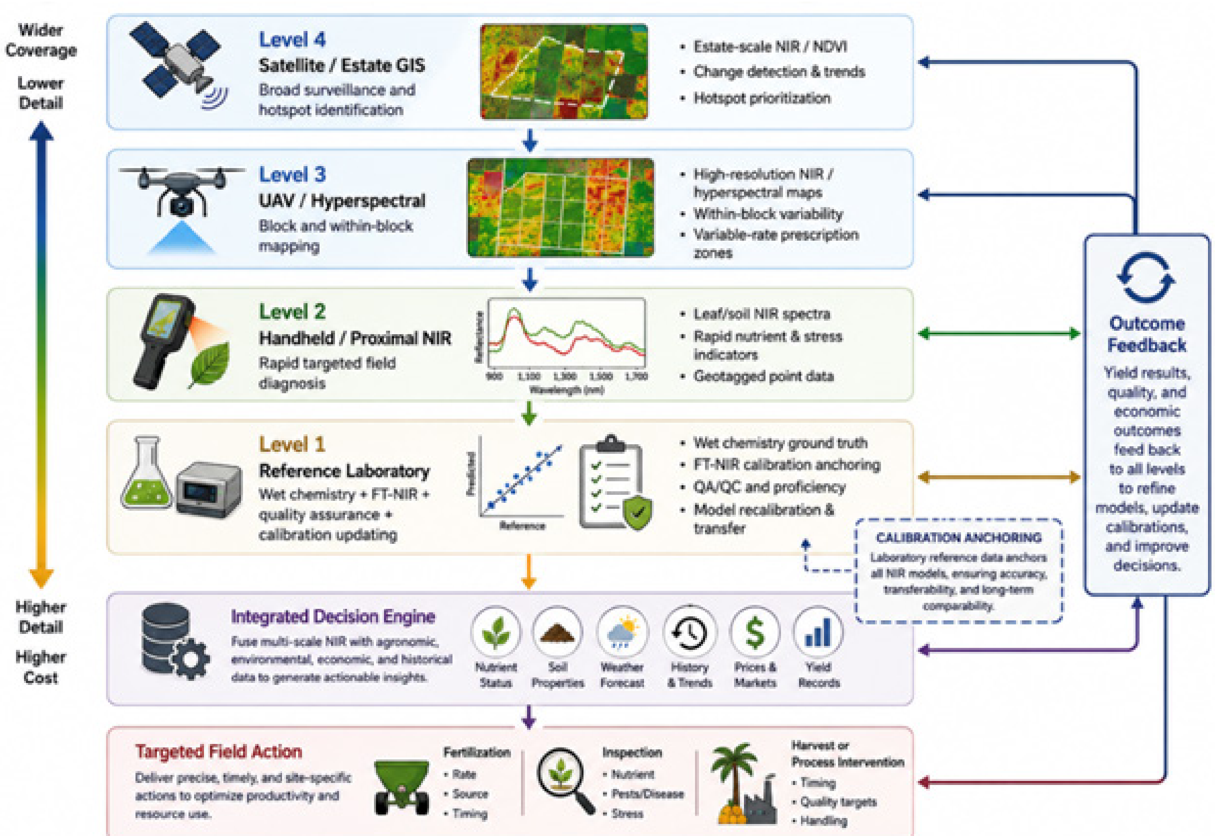

Figure 2: Proposed Multi-Scale NIR-Enabled Precision-Management Architecture.

Inclusive deployment requires solving the "diagnosis without remedy" problem

One of the most important institutional risks is the creation of technically sophisticated diagnosis in contexts where users cannot act on it. If a smallholder is informed that a field is potassium-deficient but appropriate fertilizer is unavailable or unaffordable, diagnostic accuracy has limited immediate value.

Recent research on Indonesian smallholders documents precisely these complementary constraints, including fertilizer availability, economic considerations, knowledge, and access to services [3,4].

Policy should therefore avoid isolated instrument-subsidy programs. NIR deployment should be combined with fertilizer-access strategies, agronomic extension, trusted interpretation services, credit where appropriate, and mechanisms that convert spectral results into actionable recommendations.

A particularly promising institutional model is an analytical hub-and-spoke system. A central laboratory or regional service hub could maintain reference calibrations and quality assurance. Field agents, cooperatives, or plantation extension teams could operate portable instruments. Samples producing predictions outside the calibration domain or close to decision thresholds could automatically be referred for laboratory confirmation.
Such a design would make expensive reference analysis strategic rather than obsolete.

Policy recommendations

A comprehensive NIR strategy for the oil-palm sector should address five interconnected policy domains.
The first is measurement standardization. Sampling protocols should specify frond position, leaflet location, timing, sample condition, instrument configuration, metadata, and quality-control criteria. Standardization is especially important because direct oil-palm research has demonstrated that frond selection affects spectral classification performance.

The second is calibration infrastructure. Universities, plantation companies, public laboratories, producer organizations, and technology providers should consider creating shared, diverse calibration libraries incorporating multiple production regions, soils, seasons, ages, and planting materials. Commercially sensitive farm data can remain protected while standardized reference spectra and validation samples are shared under appropriate governance.

The third is independent validation and proficiency testing. Technology procurement should not rely solely on manufacturer calibration statistics. Instruments and models should be evaluated against blind samples and external estates. Prediction uncertainty and calibration-domain warnings should become normal components of analytical reporting.

The fourth is human capacity. Plantation agronomists need not become spectroscopy specialists, but organizations require personnel capable of understanding calibration limits, identifying anomalous predictions, evaluating model drift, and linking predictions to fertilizer prescriptions.

The fifth is inclusive service delivery. Smallholder access should emphasize cooperatives, regional analytical hubs, mobile services, mill-linked diagnostic schemes, and extension networks rather than assuming household-level instrument ownership.

Research agenda

Future research should prioritize outcomes beyond analytical accuracy.
The first priority is a multi-estate, multi-season fertilizer-management trial comparing conventional recommendations with NIR-supported recommendations. Treatments should be evaluated using FFB yield, oil yield, nutrient-use efficiency, fertilizer expenditure, gross margin, labor requirements, and analytical turnaround time.

The second priority is external model validation across major ecological and production zones. A strong model should be challenged using different palm ages, planting materials, soil groups, rainfall regimes, seasons, and operators.

The third priority is calibration-transfer research. Model portability between benchtop and handheld instruments, or among multiple handheld units, should be quantified before large-scale procurement.

The fourth priority is decision uncertainty. Future systems should report whether a prediction lies safely within a calibrated domain and how close the result is to an agronomic intervention threshold.

The fifth priority is multi-sensor integration. Combining NIR with UAV, satellite, soil, weather, terrain, and historical-yield information may be more powerful than seeking a single universal spectral model.

The sixth priority is implementation economics. Researchers should identify the annual sample volume and decision value required for FT-NIR, portable NIR, UAV, or shared-service systems to become financially attractive under contrasting estate and smallholder structures.

The literature indicates that scaling will require sequential capability development rather than immediate full digitalization. Figure 3 proposes a phased roadmap linking major barriers with corresponding institutional responses.

The roadmap emphasizes that the first policy objective should not be the maximum possible number of deployed instruments. It should be the establishment of trustworthy measurement and calibration infrastructure. Scale without quality assurance can amplify diagnostic error rather than reduce it

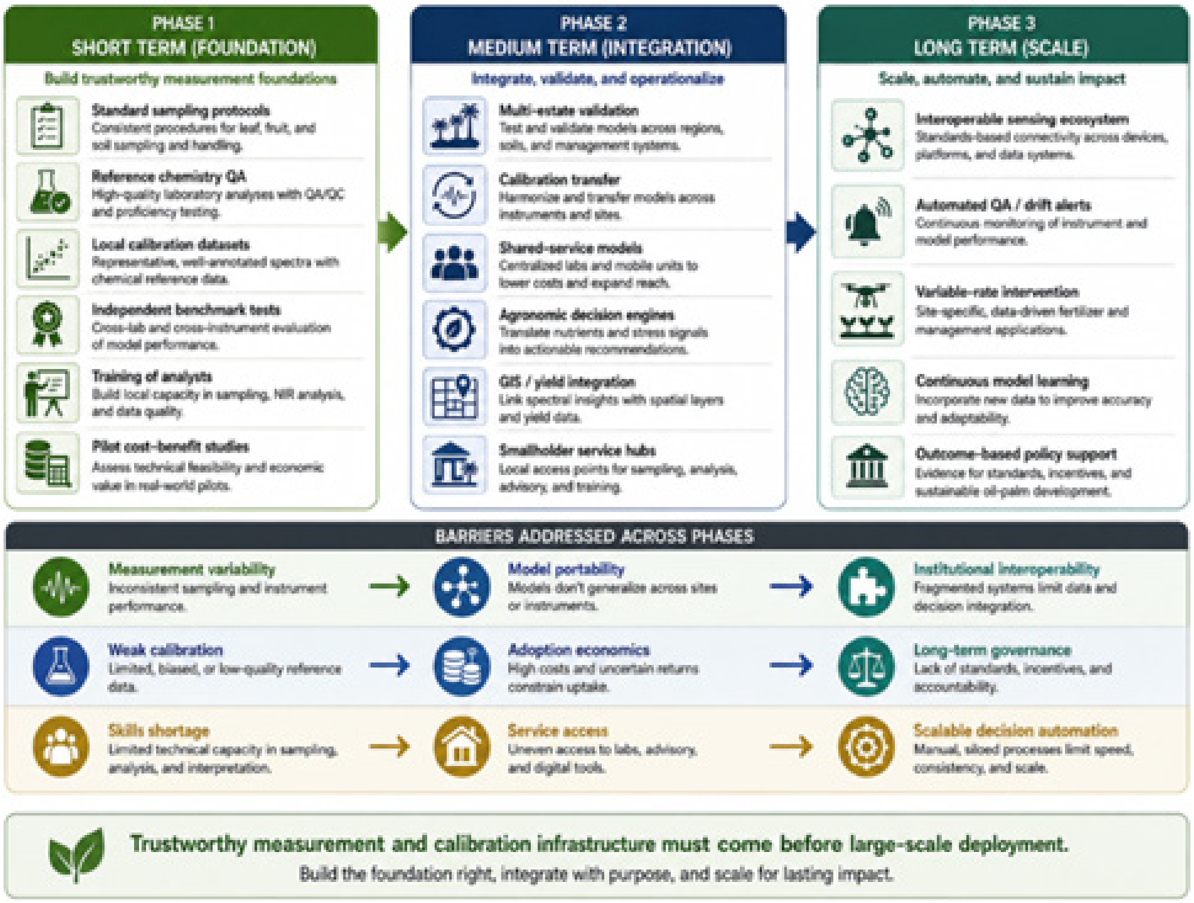

Figure 3: Phased Roadmap for Scaling NIR in Oil-Palm Management.

Conclusion

Near-infrared spectroscopy has moved beyond being solely a laboratory analytical technique and is increasingly part of a broader agricultural sensing ecosystem involving portable instruments, imaging systems, UAVs, satellites, machine learning, and digital decision-support tools. Recent oil-palm research provides credible evidence that spectral information can identify or estimate important aspects of plant nutrient status, with particularly promising results for N and selected macronutrients under appropriate calibration conditions.

The principal conclusion of this qualitative review, however, is that NIR should not be represented as a technology that automatically increases oil-palm yield. Its principal function is to reduce information constraints. Productivity effects occur only when reliable spectral measurements are converted into agronomically valid diagnoses, when those diagnoses alter fertilizer or other management decisions, and when the resulting interventions are feasible and effective.

This interpretation reconciles three bodies of evidence. Spectroscopy research demonstrates increasing analytical capability. Oil-palm agronomy demonstrates that nutrient deficiencies and fertilizer responses can materially affect yield. Agricultural-technology research demonstrates that adoption and impact depend on complementary skills, services, incentives, and access to inputs. Taken together, they support a mediated rather than deterministic relationship between NIR and productivity.

For plantation companies, the immediate priority should be locally validated calibration, standardized sampling, integration of spectral information with agronomic and yield databases, and rigorous calculation of return on investment. For smallholders, shared diagnostic services are likely to be more appropriate than individual instrument ownership. For research institutions, priority should shift toward multi-estate external validation and field experiments comparing NIR-guided management with conventional fertilizer recommendation systems. For governments and industry associations, useful interventions include reference laboratories, calibration-sharing standards, independent proficiency testing, extension and technical training, interoperability standards, and financing mechanisms for shared analytical infrastructure.

A particularly promising future model is a tiered system in which wet chemistry and FT-NIR provide reference-quality information, portable NIR increases field sampling density, UAV sensing maps within-estate variation, and satellite data support regional surveillance. All levels should feed a common decision platform and be linked to outcome data.

The most important research frontier is therefore no longer simply whether a spectrometer can predict a nutrient concentration. The more consequential question is whether NIR-enabled information can repeatedly produce better decisions, better-targeted inputs, higher nutrient-use efficiency, measurable improvements in FFB and oil yield, and superior economic performance across heterogeneous commercial plantations.

The technology's long-term contribution will depend on moving from spectral prediction to agronomic prescription, from isolated instruments to integrated decision systems, and from demonstrated analytical accuracy to independently verified productivity outcomes.

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