

Sensor-Based Real-Time Soil Macronutrient Monitoring and Variable-Rate Fertilizer Application Machinery

Muhammad N. IBRAHIM^{1*}, Abubakar S. MOHAMMED², Iyanda M. ANIMASHAUN³, Shehu ABDULKADIR⁴

^{1*,2,3}Department of Agricultural and Bio-Resources Engineering, Federal University of Technology, Minna, Nigeria

⁴Department of Agricultural and Environmental Engineering, Bayero University, Kano, Nigeria

^{1*}nuhumimen2560@st.futminna.edu.ng, ²ask4sadeeq@futminna.edu.ng, ³ai.iyanda@futminna.edu.ng, ⁴ashechu.agc@buk.edu.ng

Abstract

Sustainable agriculture and increase in the yield of crop production are associated with efficient soil nutrient management. While conventional methods of testing soil in laboratories remain tedious, costly, time-consuming and poorly suited for site-specific decisions, the use of sensors and variable-rate technology (VRT) for site-specific need and effective resource use remains an alternative solution. This systematic review aims to synthesize recent research in real-time soil macronutrient sensing technologies and their integration with VRT systems, evaluate the agronomic, economic, and environmental impact and identify the gaps and future research priorities. Following systematic literature review framework, we analysed studies from Web of Science, Elicit, Consensus, IEEE, ScienceDirect, Scopus, SpringerLink and Peer-reviewed articles from Google Scholar published between 2015 and 2025 on electrochemical, optical and IoT-enabled sensing technologies. Findings reveal that sensor-based VRT achieves nitrogen savings between 19 – 45%, reduction in application errors below 5%, and high yield production maintained. Machine learning models such as Random Forest, XGBoost, and Support vector machines (SVMs) show strong predictive ($R^2 \approx 0.812-0.99$), though validation remains predominantly on generic datasets. Widespread adoption of sensor technology, particularly among smallholder farmers, remains constrained by high initial and maintenance costs, calibration demands, and cross-sensitivity issues. Crucially, performance varies substantially by sensor type, and field-scale validation remains limited under real-world agricultural conditions. Future research should focus more on the multi-sensor fusion, edge artificial intelligence, digital twin technologies, autonomous agricultural robots, and a closed-loop nutrient management systems to enhance the durability, reliability and scalability of precision fertilization technologies.

Keywords: Soil Macronutrient Sensing; NPK sensors; Variable-rate Technology; Precision Agriculture; Autonomous Machinery.

1.0 Introduction

The three most important macronutrient in the soil (Nitrogen, phosphorus, and potassium) contribute significantly to the yield of the crop, and often varies within the same field [1, 2]. The percentages of their presence in the soil varies with soil type, drainage, soil texture, past cropping patterns, and microtopography, sometimes over distances of a few meters [3]. A single composite soil sample sent to the laboratory to test these variations in soil nutrients may take days or even weeks and still cannot capture variation because it cannot be taken from the entire field area. As a result, most fertiliser is still applied at a uniform rate across the entire field, leading to either over-fertilization or under-fertilization [1, 2].

The economic and environmental costs of this mismatch are substantial. Unused fertilizer does not remain in place. Instead, it leaches as nitrate into groundwater and streams, volatilizes as ammonia, or converts to nitrous oxide, a potent greenhouse gas [1], [4], [5]. Reducing these losses while maintaining crop yields requires matching fertilizer application rates to the real-time nutrient needs of each field area. This approach replaces static application maps derived from months-old samples and fixed uniform rates [4].

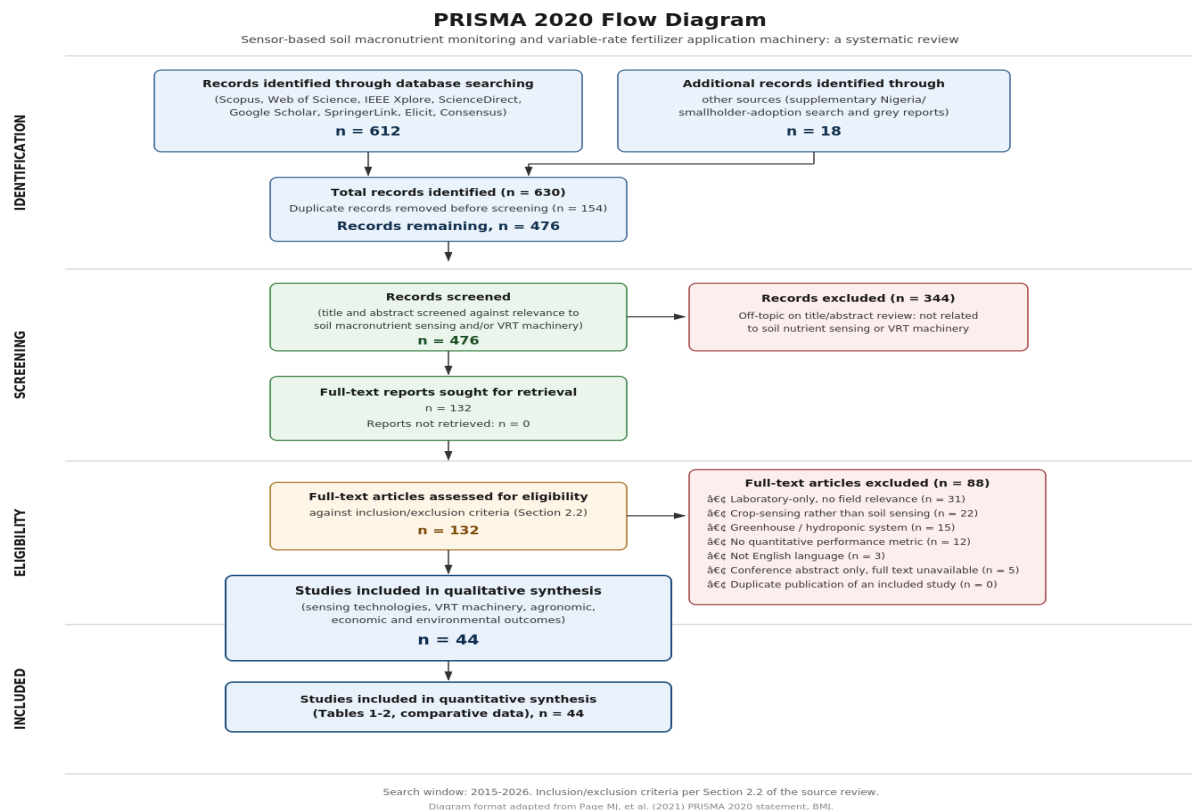
Two key developments make real-time management possible. First, direct field-based sensors measure soil nitrogen, phosphorus, and potassium without the multi-day delay of traditional laboratory testing [3], [6], [7]. Second, variable-rate technology (VRT) machinery enables real-time application adjustments. Modern fertilizer applicators integrate positioning systems, digital controllers, and mechanical actuators to alter rates dynamically as equipment moves across the field. Together, these technologies close the loop between measurement and application, transforming nutrient management from a seasonal decision into a meter-by-meter process [7].

This paper reviews real-time soil macronutrient sensing technologies and their integration with variable-rate fertilizer applicators, highlighting emerging developments in autonomous machinery, artificial intelligence, and digital twins. Additionally, it evaluates the empirical evidence on economic and environmental outcomes while identifying key limitations that restrict broader adoption.

2.0 Materials and Methods

This study employed a systematic literature review to synthesize current research on sensor-based real-time soil macronutrient monitoring and variable-rate fertilizer application machinery. The review process was structured following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines.

2.1 Search Strategy and Information Sources



3.0 Soil macronutrient sensing technologies

Four sensing approaches account for most of the reported work on real-time soil macronutrient detection: electrochemical and ion-selective sensors, optical and colorimetric sensors, spectroscopic sensors that use near-infrared or visible light, and multi-sensor systems that combine several signal types through a machine-learning model.

3.1 Electrochemical and ion-selective sensors

Ion-selective electrodes (ISEs) measure the activity of a specific ion—nitrate, potassium, ammonium—by generating a voltage across a membrane that responds selectively to that ion [8], [9], [10]. [11] built one of the first on-the-go systems using this approach, called direct soil measurement: a sampling mechanism pulled behind a vehicle brought a horizontal core of soil into contact with combination pH, potassium, and nitrate electrodes, logging each reading against a global positioning system (GPS) position. The method, since commercialized for pH mapping, produced weaker correlations for nitrate (R^2 of 0.41 – 0.51 against laboratory values) than for pH, a gap that later designs have tried to close [12].

One of the recent designs of ISE used screen-printed or solid-state membranes other than a glass bodies filled with liquid, which reduces the cost and improves durability and reliability in the field. [13] developed a screen-printed potassium electrodes and paired them with a strontium chloride extraction step, producing potassium readings consistent with inductively coupled plasma analysis. [14] also built a portable ISE-based reader for automated field testing of macronutrients, and [15] evaluated ISEs against standard Egner-Rhiem extraction for potassium determination. There are two weaknesses associated with Ion-selective sensing, one is the issue of electrode drift over time which reduces accuracy of the sensor unless it is recalibrated, and the second is the soil matrix itself moisture, texture and competing ions interferes with the target-ion signal in ways that are not yet fully corrected for under field condition and limit their accuracy in-field operation [3], [6], [8].

3.2 Optical and colorimetric sensors

Optical sensors estimate nutrient concentration from a color reaction, typically by mixing a soil extract with a reagent and reading the resulting color with a photodiode or a low-cost color sensor such as the TCS3200 [7], [16], [17]. [7], [18] used this approach in an Internet of Things-based system that reads soil nitrogen, phosphorus, potassium, and pH from a colorimetric sensor and transmits the results over a wireless link, reporting that the readings reduced total fertilizer applied by more than 45 percent relative to uniform application in field trials. These sensors are inexpensive and simple to deploy, but their accuracy depends on the extraction chemistry and lighting conditions, and they generally require a wet-chemistry step rather than a direct soil reading.

3.3 Spectroscopic sensors

Near-infrared (NIR) spectroscopy measures how soil reflects light across a range of wavelengths, then uses a calibration model most often partial least squares regression to relate the reflectance pattern to nutrient concentration [16], [19], [20]. Because a single spectrum carries information about several soil properties at once, spectroscopic sensors can, in principle, report nitrogen, organic carbon, and moisture from one scan. [9] built an in-situ detector using eight discrete NIR laser sources that reported total nitrogen and soil moisture together from a single scan, and a follow-up design by [19] extended this into an on-the-go detector calibrated with an extreme learning machine algorithm. A separate discrete-wavelength NIR device, calibrated at six selected wavelengths between 940 and 1550 nanometers using partial least squares regression, reported an R^2 of 0.867 in laboratory calibration and 0.812 in field validation for nitrogen [21].

Spectroscopic accuracy depends heavily on the size and soil diversity of the calibration set used to build the regression model [3], [16], [20]. This sensitivity to calibration conditions is the main reason spectroscopic sensors, despite decades of development, have not fully replaced laboratory testing for soil macronutrients.

3.4 Sensor fusion and machine-learning prediction

Because no single sensor measures nitrogen, phosphorus, and potassium with equal accuracy, several recent systems combine indirect signals electrical conductivity, pH, temperature, and moisture with a machine-learning model trained against laboratory reference values, rather than measuring each nutrient directly [3], [22]. These embedded systems run trained regression or classification models, most often random forest, gradient boosting, or support vector machine algorithms, directly on low-cost single-board computers, which produces a nutrient estimate without a round trip to a cloud server. This fusion approach trades direct chemical measurement for statistical prediction, which performs well within the soil conditions used for training and degrades when applied outside that range [3], [11], [12].

Table 1. Reported soil macronutrient sensing methods and their performance

Sensing Approach	Target Nutrient(s)	Response Time	Validation Level	Accuracy Metric(s)	Primary Limitation	Source
Direct Soil ISE	Nitrate (NO_3), Potassium (K^+), pH	Real-time (< 1 min)	Field-scale	R^2 0.41–0.51 for nitrate vs. laboratory reference	Sensor drift; soil-matrix interference	[12]
Screen-Printed Solid-State ISE	Potassium (K^+)	Rapid (< 5 mins)	Laboratory validation	Comparable to ICP-AES reference values	Requires chemical extraction step	[13]
Portable ISE Reader	Nitrogen (N), Phosphorus	Near real-time (< 10 mins)	In-field	Not quantitatively	Requires manual	[14]

Sensing Approach	Target Nutrient(s)	Response Time	Validation Level	Accuracy Metric(s)	Primary Limitation	Source
Colorimetric / Optical (TCS3200 + IoT)	horus (P), Potassium (K)		prototype	reported	sample preparation and handling	[7]
	N, P, K, pH	Near real-time (< 5 mins)	Field-scale prototype	> 70% reduction in applied fertilizer vs. uniform rate*	Dependent on extraction chemistry and ambient lighting	
	Total Nitrogen (TN)	Real-time (instantaneous)	Field-validated	$R^2 = 0.867$ (calib.), $R^2 = 0.812$ (val.)	High sensitivity to specific wavelength selection	
Discrete-Wavelength NIR Spectroscopy	Total Nitrogen (TN)	Real-time (instantaneous)	Field-validated	Not quantitatively reported (Simultaneous N & moisture output)	Requires stable optical alignment during field operation	[19], [20], [23]
Multi-Wavelength In-Situ NIR	Total Nitrogen (TN), Moisture	Real-time (instantaneous)	Field-validated			

***Note:** Refers to system-level agronomic efficiency rather than direct sensor measurement accuracy.

4.0 Data Acquisition and Connectivity System Architecture

This section presents a design-oriented architectural framework for real-time variable-rate technology (VRT) systems, supplemented by comparative performance benchmarks of communication protocols and processing architectures.

A soil sensor is only functional to an automated applicator if its signal reaches the rate controller fast enough to trigger action before the applicator moves past the target zone [1], [18]. The standard physical architecture consists of four sequential nodes: a sensor array, a signal-digitizing microcontroller, a wireless transmission link, and an in-cab terminal or cloud dashboard [3], [12], [24]. Wireless Sensor Networks (WSNs) expand this setup across field plots, utilizing distinct communication protocols depending on spatial scale and power limitations [3].

Table 2: Comparative Performance of Wireless Communication Protocols

Protocol	Operational Range	Data Bandwidth	Average Latency	Power Consumption	Primary VRT Role
LoRaWAN	High (5–15 km)	Low (0.3–50 kbps)	High (1,000 – 10,000 ms)	Ultra-Low	Static, low-frequency field telemetry nodes
ZigBee	Low (10–100 m)	Moderate (250 kbps)	Low (< 100 ms)	Low	Intra-machine node-to-node sensor arrays
Cellular IoT (NB-IoT/LTE-M)	High (10–30 km)	Moderate-High (20–1000 kbps)	Moderate (100–500 ms)	Moderate	Cloud synchronization and remote telemetry

Edge Computing vs. Cloud Processing Performance: Edge computing has increasingly replaced cloud-only architectures to satisfy latency requirements during active field passes [12], [22]. At typical operational speeds of 8 – 15 km/h (2.2 – 4.2 m/s), an applicator requiring 1 m spatial resolution must complete signal acquisition, processing, and actuator adjustment within a total control-loop latency of < 250 ms

Edge Architecture (On-Device Inference): Processing trained machine learning models locally on microcontrollers yields processing latencies of 10-50 ms, maintaining meter-level application precision [12], [22].

Cloud Architecture: Network round-trip delays, cellular handshakes, and backhaul transmission generate total latencies 500-3000 ms resulting in 1-12 ms spatial application delays and significant misapplication errors [3]. Positioning is provided by Global Navigation Satellite Systems (GNSS). Real-time kinematic (RTK) differential corrections supply sub-3 cm positioning accuracy, aligning live sensor streams, prescription maps, and individual boom section actuators in real time [1], [20], [22].

5.0 Variable-rate fertilizer application machinery

Variable-rate technology for fertilizer application divides into two control strategies: map-based application, where the rate follows a prescription map generated before the field pass, and sensor-based application, where the rate is calculated from a sensor reading in real time as the machine moves [25], [26]. A sensor-based VRT system typically includes a fertilizer tank, one or more sensors, a GNSS receiver, a microcontroller, and an actuator; a map-based system replaces the on-the-go sensor with a stored digital prescription file [1].

5.1 Map-based application

Map-based VRT uses a prescription map, built from grid soil sampling, yield history, or remote-sensing imagery, to set the application rate for each zone as the machine crosses it [1], [25], [26]. [20] developed and field-tested a map-based hydraulic system in which a GPS-fed microcontroller adjusted a proportional flow-control valve driving a hydraulic motor on the fertilizer applicator shaft, matching output flow against the target rate stored in the prescription file. Map-based systems remain the more widely used of the two approaches because they do not require an on-the-go sensor, but they cannot respond to conditions that were not captured when the map was built, such as a wet patch that changed nutrient availability after sampling [1], [18], [22], [25].

5.2 Sensor-based, on-the-go application

Sensor-based VRT closes the sensing-to-actuation loop within a single field pass [1], [18]: a nutrient sensor reads soil status ahead of or beneath the applicator, a microcontroller compares that reading against a target rate, and an actuator adjusts fertilizer flow before the machine leaves that section of the field [3]. Fewer sensor-based fertilizer systems have reached field validation than map-based ones, as a result of nutrient sensor accuracy and fast enough to trigger a rate change in the field. Also, it has as a less cost and engineering complexity beyond what a stored prescription map requires [1].

5.3 Control systems and actuation

VRT systems use for solid or granular fertilizer application generally uses three types of actuators: the hydraulic motors driving the metering mechanism, pneumatic cylinders or valves controlling gate or orifice size, and electric motors or solenoid valves under direct microcontroller control [1], [27]. [28] developed a pneumatic control actuator that adjusted the metering mechanism of a seed drill to vary granular fertilizer rate according to a prescription schedule. Across these designs, the delay between a rate-change command and the resulting change in output flow is a recurring performance measure: one reported system showed a significantly longer delay when switching from a low to a high discharge rate (0.22 seconds) than from a high to a low rate (0.15 seconds), a gap attributed to the mechanical inertia of the metering components. GNSS receivers also support section control, switching individual boom or spreader sections on and off at field boundaries and previously covered ground, which is now a standard feature on commercial applicators and reduces overlap-related over-application independently of nutrient sensing [1].

Table 3. Actuator types reported in variable-rate fertilizer application machinery

Actuator type	Control basis	Example system	Reported source
Hydraulic motor with proportional flow-control valve	Map-based, GPS-triggered	Fertilizer applicator with rotational-speed feedback on the drive shaft	[28]
Pneumatic cylinder/valve on seed-drill metering unit	Map-based, schedule-driven	Variable-rate granular fertilizer control for a seed drill	[27]
Electric/solenoid valve under microcontroller control	Sensor-based or map-based	General VRT control architecture (sensor, GNSS, microcontroller, actuator)	[1]
Pulse-width-modulated flow control for aerial spreader	Prescription map from NDVI/multispectral imagery	UAV-based granular fertilizer spreader	[20]

5.4 Aerial and Unmanned Aerial Vehicle (UAV-based) application

While UAVs primarily rely on canopy reflectance rather than direct soil sensing, they serve as crucial execution platforms for ground-derived soil macronutrient data. Ground-based soil sensor arrays generate high-resolution prescription maps that UAVs utilize for localized, targeted micro-dosing [20]. Unmanned aerial vehicles extend variable-rate application to granular and liquid fertilizer delivery, matching flow rate with flight speed to maintain uniform distribution across variable field terrain [20]. This approach accesses terrain impassable to heavy ground equipment and eliminates soil compaction. However, payload restrictions limit UAVs to targeted, in-season supplemental feeding rather than full-scale base fertilization.

6.0 Environmental, Economic outcomes, Limitations and adoption barriers

6.1 Environmental and Economic Outcomes

Variable-rate technology (VRT) offers two primary agronomic claims: it reduces total fertilizer applied without compromising yield, and it lowers downstream nutrient losses to water and air. Empirical evidence strongly supports input reduction and cost efficiency, whereas direct quantitative measurement of environmental gains remains less consistently documented across diverse climates and soil matrices.

To compare these empirical impacts across trial conditions, the reported agronomic, economic, and environmental outcomes are summarized below:

Table 4: Comparison of fertilizer savings, yield effects, and environmental outcomes across VRT system types and crops

Crop	System Type	Fertilizer Savings	Yield Effect	Environmental Outcome	Source
Maize	Proximal sensing + N-balance model	15–28% reduction	Neutral to slight increase (+2–5%)	Reduced post-harvest residual soil nitrate (NO_3^-)	[19], [20]
Maize	Autonomous robotic VRT + targeted seeding	10–20% reduction	Marginal, statistically non-significant gain	Reduced localized nutrient hot-spots	[8]
Wheat	High-resolution imagery & proximal N-sensing	12–25% reduction	Yield parity maintained	Decreased potential (N_2O) emission risks	[29], [30]
Mixed Crops / Grains	Real-time colorimetric sensor array	Up to 70% reduction*	Neutral yield impact	Reduced surface runoff and leaching potential	[7]

**Note: High percentage savings reflect experimental micro-dosing bench testing relative to uncalibrated uniform baseline rates.*

Economic Return and Spatial Heterogeneity

The profitability of VRT depends directly on intra-field spatial variability. Higher-resolution sensing technologies increase net margins primarily on fields characterized by high spatial heterogeneity and low spatial autocorrelation among soil types [29], [30]. On homogeneous fields, the return on investment for fine-resolution real-time sensing decreases sharply, making simpler static prescription maps equally cost-effective.

Environmental Dynamics

While nitrogen reduction logically decreases ammonia volatilization, nitrate leaching, and nitrous oxide (N_2O) emissions [4], [22], absolute environmental impact figures vary significantly across studies. Field-scale environmental losses are heavily governed by weather timing, soil moisture, and rainfall events, making real-time environmental mitigation difficult to quantify with a single global metric.

6.2 Limitations and adoption barriers

Real-time sensing VRT machinery have moved beyond research trials into larger commercial farms, but several technical and economic issues continue to limit their effectiveness. Sensor accuracy for phosphorus and potassium remains lower than for nitrogen and pH across most reported systems, since ISEs are harder to design for these ions and optical methods depend on extraction chemistry that varies with soil type [3], [6], [9], [31]. Frequent recalibration is required, because of the electrode fouling and drift, which increases the labor cost that offsets some of the savings from reduced fertilizer use [8].

Equipment cost is a separate barrier. Sensors, GNSS receivers, controllers, and actuators represent a substantial upfront investment, and small and medium farms often cannot justify that cost without subsidy or shared-equipment arrangements [12], [22], [32]. [29], [30] found that VRT profitability depends on field heterogeneity, which means the equipment cost is hardest to justify on the uniform fields where small farms are more likely to operate. Data management adds a further obstacle: combining soil maps, yield history, and sensor streams into a usable prescription requires software skills that not every operator has, and datasets from different sensors and platforms are not always compatible with one another [1].

Connectivity is a practical constraint as well in remote areas where many rural farming takes place, especially in areas with limited access to broadband internet and weak mobile coverage. Wireless sensor networks depend on a communication link reaching every node, and many agricultural fields sit outside reliable cellular or broadband coverage, which limits the real-time transmission that on-the-go systems depend on and pushes some deployments toward store-and-forward or edge-processing designs instead [3], [12], [17].

Table 5: Comparative Analysis: Map-Based vs. Sensor-Based (Real-Time) VRT

Evaluation Criterion	Map-Based VRT	Sensor-Based (Real-Time) VRT
Cost	Moderate: Lower initial hardware investment; costs driven by recurring laboratory soil sampling, grid mapping, and standard VRT controllers.	High: Significant upfront capital for onboard sensor arrays, high-speed controllers, and advanced actuators; high maintenance and calibration expenses.
Responsiveness	Static / Low: Weeks-to-months latency between soil sampling, prescription map rendering, and field application; unable to capture real-time changes.	Dynamic / Real-Time: Sub-second control loop latency (< 250 ms); application rates adjust dynamically on-the-go as the tractor moves meter-by-meter.
Sensing Requirements	Offline soil core sampling, laboratory chemical analysis, interpolated spatial grids, or satellite/drone vegetation indices.	Continuous onboard physical sensing (e.g., ISE, NIR spectroscopy, colorimetric arrays), active signal processing, and GNSS RTK integration.
Technology Maturity	High: Commercially mature and widely integrated into standard precision agriculture practices and machinery platforms.	Moderate / Emerging: Variable by nutrient; N and pH real-time systems are commercially available, while P and K sensors remain mostly experimental.
Primary Limitations	Misses short-term temporal/spatial dynamics; high interpolation errors between distant grid points; static maps age quickly.	Sensor drift and fouling; matrix interference; complex multi-source data compatibility; high operator skill barrier; connectivity limits.

While variable-rate technology (VRT) has traditionally relied on map-based systems, real-time sensor-based VRT offers a fundamentally different operational model. Map-based VRT uses pre-collected spatial data such as laboratory soil core tests, yield maps, or satellite imagery to construct static prescription files prior to application. This approach is commercially mature and requires lower onboard machinery costs, but it cannot account for rapid in-season changes in

Conversely, real-time sensor-based VRT eliminates the multi-day delay between sampling and application by measuring soil properties directly on-the-go. While this enables meter-by-meter precision, widespread uptake is constrained by higher capital costs, required technical proficiency, sensor drift, and technical limitations in measuring phosphorus and potassium relative to nitrogen.

7.0 Nigeria Perspective: Potential and adoption challenges

7.1 Review of Empirical Evidence and Adoption Landscape

While the global challenges of cost and connectivity are significant, in a country like Nigeria, they are even more pronounced. Here, the majority of the farmers are smallholders with fragmented lands, and rural infrastructure limitations in power, and internet are a primary barriers to adoption [33], [34]. Nevertheless, recent empirical studies demonstrate that precision agriculture is transitioning from theoretical concepts to practical field deployment within the country.

- i. **In-Situ IoT Innovations:** [35] and [36] evaluated an IoT-based soil testing prototype in Ogun State using an integrated sensor array (electrochemical NPK sensors, a Dallas temperature sensor, and a capacitive moisture sensor linked to an ESP8266 NodeMCU microcontroller). Across three field locations, the system successfully measured nitrogen (31 - 39 mg/kg), phosphorus (13 - 16 mg/kg), and potassium (14 mg/kg), transmitting real-time readings to a mobile app to guide localized fertilizer application [36].
- ii. **Field Scale & Decision Support Evidence:** A three-year randomized controlled trial (RCT) involving 792 smallholder farmers across Kaduna, Katsina, and Kano states evaluated site-specific nutrient management (SSNM) via the Nutrient Expert decision-support tool [37]. The intervention increased adoption of improved fertilizer management practices by up to 116%, yielding incremental gains of up to 18% in application rates, crop yields, and revenues while improving overall nutrient use efficiency and reducing greenhouse gas emission intensity [37].
- iii. **Economic Fit for Fragmented Plots:** Although high initial equipment costs remain a primary constraint [33], [38], spatial variability modeling demonstrates that VRT profitability increases with intra-field heterogeneity [29], [30]. Smallholder plots in Nigeria (frequently < 1 ha) exhibit high spatial micro-variability, making them strong technical candidates for site-specific management if hardware costs can be reduced.
- iv. Further reviews of opportunities and challenges of precision agriculture for sustainable food security in Nigeria, lack of digital infrastructure (internet and electricity), limited awareness and digital skills among farmers, and societal barriers as key constraints to adoption. These findings are consistent with reports from Sahel Consulting, which attributed low adoption rates to the high cost of precision farming technologies, which can be prohibitive for small-scale farmers, and poor awareness.

7.2 Recommendations: Proposed Low-Cost VRT Framework

To address the empirical adoption barriers identified above (specifically high capital cost, absent cellular infrastructure, and complex calibration requirements), the authors propose a tailored, low-cost VRT deployment framework optimized for Nigerian smallholders:

1. **Hardware Tier:** Deployment of modular, low-cost electrochemical sensors (e.g., solid-state ISE-based NPK probes integrated with open-source NodeMCU or Arduino microcontrollers) targeted at a total hardware price point of \$7 - \$20 (#10,000 - #28,580) per unit.
2. **Communication Tier:** Integration of low-power long-range (LoRa) communication modules capable of point-to-point transmission over 1 – 5 km, removing the requirement for active cellular data coverage in remote farming communities.
3. **Calibration & Execution Tier:** Implementation of pre-programmed, soil-type-specific calibration models tailored to common regional soil classes (loamy, clay, and sandy soils). This hardware configuration should be paired with established decision-support frameworks such as fertilizer microdosing and the Nutrient Expert platform to facilitate gradual, sustainable agricultural intensification [37], [39].

8.0 Emerging Technologies and Future Research Directions

While advanced computational and robotic tools offer promising concepts for next-generation nutrient management, these approaches remain primarily in the experimental and proof-of-concept stages. Significant hurdles in interoperability, real-world validation, and cost must be resolved before commercial deployment is viable.

8.1 Autonomous and robotic platforms

Autonomous field robotics represents an active area of research aiming to transition variable-rate application from driver-assisted machinery to unattended execution. Experimental platforms such as the AI-Enabled Robotic Nitrogen Management (AIR-N) system paired with the Flex-Ro robot [40], deep learning-driven electronic control units [41], [42], and high-capacity spreader concepts [31] demonstrate the technical feasibility of automated micro-dosing. Similarly, integrated platforms combining online visible/near-infrared (Vis-NIR) spectroscopy with real-time applicator controls have successfully demonstrated single-pass scanning and fertilizing in research trials [8]. However, these systems remain research-grade prototypes. Broad field deployment is currently constrained by extreme equipment costs, safety and regulatory uncertainties, and limited mechanical durability under harsh field conditions.

8.2 Artificial Intelligence and Edge Computing (Methodological Frontiers)

To bypass direct chemical sensing difficulties, researchers are exploring machine learning models (e.g., Random Forest, XGBoost, Support Vector Machines) to infer soil macronutrient levels from indirect proxy signals like pH, electrical conductivity, temperature, and moisture [3], [43], [44]. Embedded edge-computing architectures aim to run these trained regression models locally on microcontrollers, eliminating reliance on rural cloud connectivity and keeping control latency under sub-second thresholds. Furthermore, reinforcement learning (RL)

is being investigated in academic settings to dynamically adapt fertilizer rates based on continuous sensor feedback loops. Nevertheless, these computational frameworks remain highly sensitive to regional soil variability; without massive, standardized calibration datasets across diverse soil matrices, their predictive accuracy outside controlled test plots remains unverified.

8.3 Digital Twins and System Integration (Conceptual Frameworks)

Digital twins virtual field representations updated continually via sensor feeds, weather streams, and machinery telemetry are proposed as multi-system integration layers [5], [12], [23]. In theory, a digital twin reconciles real-time sensor data, historical yield maps, and machine positioning to dynamically update application rates during the growing season. In practice, digital twin architectures for soil macronutrient management exist almost exclusively as theoretical frameworks. Real-world implementation is strictly bottlenecked by data-standardization hurdles, proprietary software locks, and severe cross-platform interoperability gaps. Crucially, a digital twin's predictive value remains fundamentally limited by the accuracy and drift of the physical underlying sensors.

9.0 Conclusion

Precision nutrient management technologies have advanced substantially over the past two decades, yet commercial maturity varies widely across system components. A clear distinction must be made between commercially viable systems and experimental research concepts:

Commercially Mature Technologies: Map-based variable-rate application, static grid-based soil sampling, basic GNSS-guided boom section control, and canopy-reflectance optical sensing are established in commercial agriculture. These tools reliably reduce fertilizer waste on fields exhibiting high spatial variability.

Experimental & Developmental Technologies: Real-time in-situ soil macronutrient sensing particularly for phosphorus and potassium remains developmentally constrained by sensor drift, cross-sensitivity, electrode fouling, and complex soil extraction chemistry. Similarly, autonomous field robotics, edge-AI nutrient modeling, and digital twin integration represent promising future research directions rather than market-ready solutions.

Ultimately, variable-rate technology does not guarantee uniform economic or environmental returns; its efficacy depends heavily on intra-field soil heterogeneity. Transitioning real-time sensing from academic pilot studies to widespread commercial adoption particularly among smallholder farmers in regions like Nigeria or sub-Saharan Africa will not be driven by software complexity alone. It requires solving fundamental hardware challenges: developing low-cost, drift-resistant physical sensors, establishing robust local calibration models, and building simplified, modular equipment tailored to resource-constrained agricultural environments.

References

- [1] P. Pawase, P. M. Nalawade, G. A. W. Sachin Balasaheb Bhanage, A. B. Kadam, A. Pravin G Durgude, and M. R Patil, "Variable rate fertilizer application technology for nutrient management: A review," *Int. J. Agric. Biol. Eng.*, vol. 16, no. 4, pp. 11–19, 2023, doi: 10.25165/j.ijabe.20231604.7671.
- [2] S. Stamatiadis *et al.*, "Variable-rate nitrogen fertilization of winter wheat under high spatial resolution," *Precis. Agric.*, vol. 19, no. 3, pp. 570–587, 2018, doi: 10.1007/s11119-017-9540-7.
- [3] P. Musa, H. Sugeru, and E. P. Wibowo, "Wireless Sensor Networks for Precision Agriculture: A Review of NPK Sensor Implementations," *Sensors*, vol. 24, no. 1, pp. 1–14, 2023, doi: 10.3390/s24010051.
- [4] P. K. Dutta, "Fertilizer Optimization for Sustainable Agriculture: Needs, Current Strategies and Future," *Sustain.*, vol. 18, no. 11, 2026, doi: 10.3390/su18115639.
- [5] F. Howari, "AI-Remote Sensing for Soil Variability Mapping and Precision Agrochemical Management: A Comprehensive Review of Methods, Limitations, and Climate-Smart Applications," *Agrochemicals*, vol. 5, no. 1, p. 1, 2025, doi: 10.3390/agrochemicals5010001.
- [6] M. I. Hossain *et al.*, "Development of electrochemical sensors for quick detection of environmental (soil and water) NPK ions," *RSC Adv.*, vol. 14, no. 13, pp. 9137–9158, 2024, doi: 10.1039/d4ra00034j.
- [7] R. Adhikary, S. J. Choudhury, and T. Shankar, "Real-Time Soil Nutrient Monitoring Using NPK Sensors: Enhancing Precision Agriculture," *Int. J. Exp. Res. Rev.*, vol. 45, pp. 197–202, 2024, doi: 10.52756/ijerr.2024.v45spl.015.
- [8] M. A. Eldeeb, V. N. Dhamu, A. Paul, S. Muthukumar, and S. Prasad, "Espial: Electrochemical Soil pH Sensor for In Situ Real-Time Monitoring," *Micromachines*, vol. 14, no. 12, pp. 1–11, 2023, doi: 10.3390/mi14122188.
- [9] M. N. Reza *et al.*, "Trends of Soil and Solution Nutrient Sensing for Open Field and Hydroponic Cultivation in Facilitated Smart Agriculture," *Sensors*, vol. 25, no. 2, 2025, doi: 10.3390/s25020453.
- [10] S. K. Shin, Y.-E. Lee, S. J. Lee, and J. H. Park, "Evaluation of Sensor-Based Soil EC Responses to Nitrogen and Potassium Fertilization Under Laboratory and Field Conditions," *Agriculture*, vol. 16, no. 2, p. 137,

- 2026, doi: 10.3390/agriculture16020137.
- [11] D. M. Sobhy and A. Anandhi, "Soil Nutrient Monitoring Technologies for Sustainable Agriculture: A Systematic Review," *Sustain.*, vol. 17, no. 18, pp. 1–29, 2025, doi: 10.3390/su17188477.
 - [12] T. Miller, G. Mikiciuk, I. Durlik, M. Mikiciuk, A. Łobodzińska, and M. Śnieg, "The IoT and AI in Agriculture: The Time Is Now A Systematic Review of Smart Sensing Technologies," *Sensors*, vol. 25, no. 12, pp. 1–32, 2025, doi: 10.3390/s25123583.
 - [13] R. Rosenberg, S. B. J. Michael, B. Soumya, V. Chintan, K. Rohit, and J. A. Hart, "In-field determination of soil ion content using a handheld device and screen-printed solid-state ion-selective electrodes," *PLoS One*, vol. 13, no. 9, p. e0203862, 2018.
 - [14] K. Anubhuti, M. Preity, C. Swades Kumar, P. Girenda Mohan, and N. Md, "Estimation of soil nutrients and fertilizer dosage using ion-selective electrodes for efficient soil management," *Commun. Soil Sci. Plant Anal.*, vol. 55, no. 13, pp. 1920–1941, 2024.
 - [15] J. Ciesla, M. Ryzak, A. Bieganowski, P. Tkaczyk, and R. Walczak, "Simultaneous Analysis of Soil Macronutrients Using Ion-selective Electrodes," *Res. Agric. Eng.*, vol. 53, no. 1, pp. 29–33, 2018.
 - [16] R. P. Potdar, M. M. Shirolkar, A. J. Verma, P. S. More, and A. Kulkarni, "Determination of soil nutrients (NPK) using optical methods: a mini review," *J. Plant Nutr.*, vol. 44, no. 12, pp. 1826–1839, 2021, doi: 10.1080/01904167.2021.1884702.
 - [17] P. R. Tondhare and R. R. Raut, "Review on Npk Sensor Used on Soil," *Int. J. Agric. Sci.*, vol. 16, no. 01, pp. 38–46, 2025, doi: 10.53390/ijas.2025.16105.
 - [18] H. MirzakhaniNafchi, M. Singh, V. Bector, O. P. Gupta, and R. Singh, "Design and development of a variable rate applicator for real-time application of fertilizer," *Sustain.*, vol. 13, no. 16, 2021, doi: 10.3390/su13168694.
 - [19] P. Zhou *et al.*, "Variable-Rate Fertilization for Summer Maize Using Combined Proximal Sensing Technology and the Nitrogen Balance Principle," *Agric.*, vol. 14, no. 7, 2024, doi: 10.3390/agriculture14071180.
 - [20] C. Song *et al.*, "Variable-rate control system for UAV-based granular fertilizer spreader," *Comput. Electron. Agric.*, vol. 180, no. January, 2021, doi: 10.1016/j.compag.2020.105832.
 - [21] W. Isaac and N. Abdullah, "On-the-go soil nitrogen sensor based on near infrared spectroscopy," *Int. Conf. Inf. Technol. (InCITE)-The Next Gener. IT \summito Theme-Internet Things Connect Your Worlds*, pp. 312–315, 2016.
 - [22] A. Abdalla and A. Mirzakhani Nafchi, "Development and Evaluation of an Affordable Variable Rate Applicator Controller for Precision Agriculture," *AgriEngineering*, vol. 6, no. 4, pp. 4639–4657, 2024, doi: 10.3390/agriengineering6040265.
 - [23] C. Zhang, J. Song, X. Yin, J. Cai, Y. Liang, and J. Lu, "Digital twin-based approaches for agricultural machinery damage prediction and maintenance: A review," *J. Comput. Des. Eng.*, vol. 12, no. 10, pp. 87–117, 2025, doi: 10.1093/jcde/qwaf097.
 - [24] M. K. Senapaty, A. Ray, and N. Padhy, "IoT-Enabled Soil Nutrient Analysis and Crop Recommendation Model for Precision Agriculture," *Computers*, vol. 12, no. 3, 2023, doi: 10.3390/computers12030061.
 - [25] S. S. Mohan, "GPS and Sensor Based Technologies in Variable Rate Fertilizer Application," *Int. J. Agric. Environ. Biotechnol.*, vol. 14, no. 1, pp. 21–27, 2021, doi: 10.30954/0974-1712.01.2021.4.
 - [26] A. Guerrero, S. De Neve, and A. M. Mouazen, "Data fusion approach for map-based variable-rate nitrogen fertilization in barley and wheat," *Soil Tillage Res.*, vol. 205, no. January, 2021, doi: 10.1016/j.still.2020.104789.
 - [27] M. Yamin, W. I. Wan Ismail, M. S. Mohd Kassim, S. Abd Aziz, and R. Shamshiri, "VRT liquid fertilizer applicator for soil nutrient management," *J. Teknol.*, vol. 78, no. 1–2, pp. 73–78, 2016, doi: 10.11113/jt.v78.7262.
 - [28] J. F. Reyes, E. Wilson, C. Daniel, and O. Rodrigo, "Field testing of an automatic control system for variable rate fertilizer application," *Comput. Electron. Agric.*, vol. 113, no. 1, pp. 260–265, 2015.
 - [29] C. Schillaci, T. Tadiello, M. Acutis, and A. Perego, "Reducing topdressing N fertilization with variable rates does not reduce maize yield," *Sustain.*, vol. 13, no. 14, 2021, doi: 10.3390/su13148059.
 - [30] S. Marco, K. Ahmed, G. Steffano, C. Alessia, S. Luigi, and M. Francesco, "Economic comparison of satellite, plane and UAV-acquired NDVI images for site-specific nitrogen application: observation from Italy," *Agron.*, vol. 11, no. 11, p. 2098, 2021.
 - [31] N. Fathima, S. B. V. Kumar, and M. U. Bagali, "An Embedded IoT-Based System for Real-Time NPK Soil Quality Monitoring in Precision Agriculture," *Eng. Technol. Appl. Sci. Res.*, vol. 16, no. 2, pp. 33211–33217, 2026, doi: 10.48084/etasr.17091.
 - [32] S. Getahun, H. Kefale, and Y. Gelaye, "Application of Precision Agriculture Technologies for Sustainable Crop Production and Environmental Sustainability: A Systematic Review," *Sci. World J.*, vol. 2024, 2024, doi: 10.1155/2024/2126734.

- [33] K. . Bolaji, S. . Adisa, D. . Adesogan, D. . Adebayo, D. . Oke, and G. . Kabir, "Leveraging Precision Agriculture for Sustainable Food Security in Nigeria," in *Proceedings of the Second Faculty of Agriculture International Conference*, 2024, pp. 286–291.
- [34] E. J. U. Chidiebele, C. O. Edmund, and P. O. Azikiwe, "Sustainable engineering solutions for achieving resilient food security in Nigeria," in *Discover Agriculture*, 2026, p. 2653.
- [35] A. A. Raji, O. Joseph Folorunso, and E. Ibrahim Adewale, "Design and implementation of Internet of Things (IoT) based scheme for testing loamy soil," *Turkish J. Eng.*, vol. 9, no. 2, pp. 323–333, 2025.
- [36] J. Ajiboye *et al.*, "IoT-Based Intelligent System for Real-Time Soil Nutrient Monitoring and Decision Support in Farming: Potential for Deployment in Rice Farming in Nigeria," *Conflu. Univ. J. Sci. Technol.*, vol. 2, no. 1, p. 126, 2025, doi: 10.5455/cujostech.250415.
- [37] M. Miet, O. Oyakhilomen, A. Tahirou, and C. Jordan, "Sustainable maize intensification through site-specific nutrient management advice: Experimental evidence from Nigeria," *Food Policy*, vol. 121, p. 102546, 2023.
- [38] O. Damilola, "High cost limiting farmer's adoption of precision agriculture - Report," 2023.
- [39] V. N. F. Hotegni *et al.*, "Advances in Precision Agriculture in West and Central Africa," in *Precision Agriculture in Africa: Progress, Challenges and Opportunities*, 2026, pp. 79–93.
- [40] A. Kalra, "AI-Enabled Robotic Nitrogen Management," The University of Nebraska - Lincoln, 2025.
- [41] S. Sow *et al.*, "Artificial Intelligence for Maximizing Agricultural Input Use Efficiency: Exploring Nutrient, Water and Weed Management Strategies," *Phyton-International J. Exp. Bot.*, vol. 93, no. 7, pp. 1569–1598, 2024, doi: 10.32604/phyton.2024.052241.
- [42] Phanikant Chintamaneni, "Integrating Machine Learning and IoT Sensors for Enhanced Soil Nutrient Monitoring and Crop Recommendation Systems," *J. Inf. Syst. Eng. Manag.*, vol. 10, no. 44s, pp. 512–543, 2025, doi: 10.52783/jisem.v10i44s.8617.
- [43] L. Hagn, M. Mittermayer, A. Kern, S. Kimmelman, F. X. Maidl, and K. J. Hülsbergen, "Effects of Sensor-Based, Site-Specific Nitrogen Fertilizer Application on Crop Yield, Nitrogen Balance, and Nitrogen Efficiency," *Sensors*, vol. 25, no. 3, pp. 1–23, 2025, doi: 10.3390/s25030795.
- [44] S. V. Gaikwad, "Measurement of NPK, Temperature, Moisture, Humidity using WSN," *J. Eng. Res. Appl.*, vol. 5, no. 8, pp. 84–89, 2015, [Online]. Available: www.ijera.com