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Precision Nutrient Management Through AI-Integrated Sensors

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Abstract
Precision nutrient management optimizes fertilizer application to enhance crop productivity while minimizing environmental impacts. This study explores the integration of artificial intelligence (AI) with soil and plant sensors to monitor and manage nitrogen (N) and phosphorus (P) in temperate and semi-arid agricultural systems. Field experiments evaluated AI-driven sensors for real-time nutrient monitoring, coupled with machine learning models to predict crop nutrient needs. Results showed that AI-integrated systems improved nutrient use efficiency (NUE, PUE) by 15–25% and reduced fertilizer inputs by 20–30% compared to conventional methods. Soil microbial activity and crop yields were enhanced, particularly in temperate soils. These findings highlight the potential of AI-integrated sensors for sustainable agriculture, though challenges include high initial costs and data calibration needs.

Keywords: Precision Nutrient Management, Ai-Integrated Sensors, Nutrient Use Efficiency, Soil Sensors, Machine Learning, Sustainable Agriculture

Introduction

Precision nutrient management aims to deliver the right amount of nutrients to crops at the right time and place, improving yield and reducing environmental losses [1]. Traditional fertilization practices often lead to over-application, causing nutrient leaching, greenhouse gas emissions, and soil degradation [2]. Artificial intelligence (AI) integrated with sensors offers a transformative approach by enabling real-time monitoring of soil and plant nutrient status, optimizing fertilizer application through predictive modeling [3].

Soil sensors measure parameters like nitrate, phosphate, and moisture, while plant sensors assess nutrient uptake via spectral signatures [4]. AI algorithms, such as machine learning (ML) models, analyze sensor data to predict crop nutrient demands and guide application [5]. This study evaluates AI-integrated sensors for precision nutrient management in temperate and semi-arid agricultural systems. The objectives are to: (1) assess sensor accuracy in nutrient monitoring, (2) evaluate AI-driven fertilizer recommendations, and (3) analyze impacts on soil microbial functions and crop productivity.

Materials and Methods

Experimental Locations and System Design

Field experiments were conducted in temperate (Germany) and semi-arid (Morocco) agricultural regions in 2023. Temperate soils were loamy (20–30% clay), and semi-arid soils were sandy loam (10–15% clay), with low baseline nutrient levels (5–10 mg kg^{-1} Olsen P, 20–30 mg kg^{-1} mineral N) [6]. AI-integrated systems included soil sensors (nitrate, phosphate, moisture) and plant sensors (multispectral for leaf N and P). Sensors were linked to an AI platform using random forest and neural network models for nutrient prediction [7].

Field Setup and Sensor Deployment

Trials involved 60 plots per region (30 AI-managed, 30 conventional). AI plots used sensors to monitor soil nutrients and moisture every 6 hours, with data fed into ML models to recommend N and P application rates. Conventional plots followed standard fertilizer schedules (150 kg N ha^{-1}, 50 kg P ha^{-1}) [8]. Wheat (*Triticum aestivum*) was grown for 90 days. Sensors were calibrated using laboratory data (colorimetric analysis for N and P) [9].

Soil and Microbial Analyses

Soil samples were collected from the top 20 cm to measure nutrient levels (NH_4^+-N, NO_3^--N, Olsen P) via colorimetric methods [10]. Microbial biomass carbon (MBC) was quantified using the fumigation-extraction method, and enzyme activities (β-glucosidase, phosphatase) were measured using p-nitrophenyl substrates, expressed as µmol product g^{-1} soil h^{-1} [11]. Microbial community composition was assessed via 16S rRNA gene sequencing [12].

Crop and Nutrient Use Efficiency

Wheat yield, nutrient uptake (N, P), and nutrient use efficiency (NUE, PUE) were measured at harvest. NUE and PUE were calculated as the ratio of nutrient uptake to applied fertilizer [13]. Soil moisture and pH were monitored to assess environmental influences.

Statistical Analysis

ANOVA was used to compare nutrient levels, microbial parameters, and crop responses between AI and conventional systems, with Tukey's test for post-hoc comparisons ($p < 0.05$). Pearson's correlation coefficient (r) was calculated to evaluate relationships between sensor data and nutrient uptake [14]. ML model accuracy was assessed using R^2 and root mean square error (RMSE).

Results

Sensor Accuracy and Nutrient Monitoring

AI-integrated sensors accurately monitored soil nutrients, with R^2 values of 0.90 for NO_3^--N and 0.87 for Olsen P in temperate soils, and 0.85 and 0.82 in semi-arid soils (Table 1). RMSE values were 2.5 mg kg^{-1} for NO_3^--N and 1.8 mg kg^{-1} for Olsen P. AI systems reduced fertilizer inputs by 20–30% (N: 105–120 kg ha^{-1}; P: 35–40 kg ha^{-1}) compared to conventional systems [15].

Table 1: Sensor Accuracy for Nutrient Monitoring

Region	Nutrient	R^2	RMSE (mg kg^{-1})	AI Fertilizer Input (kg ha^{-1})	Conventional Input (kg ha^{-1})
Temperate	NO_3^--N	0.90	2.5	120	150
	Olsen P	0.87	1.8	40	50
Semi-arid	NO_3^--N	0.85	3.0	105	150
	Olsen P	0.82	2.0	35	50

Microbial Biomass and Enzyme Activity

AI-managed plots showed higher MBC (280–320 mg kg^{-1}) than conventional plots (220–250 mg kg^{-1}) in temperate soils, with a 10–15% increase in semi-arid soils (Table 2). β-glucosidase and phosphatase activities were 15–20% higher in AI plots in temperate soils, reflecting enhanced carbon and phosphorus cycling [16]. Semi-arid soils showed smaller increases (5–10%) due to moisture limitations [17].

Table 2: Microbial Biomass and Enzyme Activities

Region	System	MBC (mg kg^{-1})	β-Glucosidase (µmol g^{-1} h^{-1})	Phosphatase (µmol g^{-1} h^{-1})
Temperate	Conventional	240	50	35
	AI-Managed	300	60	42
Semi-arid	Conventional	200	40	30
	AI-Managed	220	44	33

Crop Responses and Nutrient Use Efficiency

AI-managed plots improved NUE and PUE by 15–25% in temperate soils (NUE: 70%; PUE: 65%) compared to conventional systems (NUE: 55%; PUE: 50%) (Table 3). Wheat yield increased by 10–12% in temperate AI plots (7.2 t ha^{-1} vs. 6.5 t ha^{-1}) but only 5% in semi-arid plots. Nutrient uptake was strongly correlated with sensor data ($r = 0.80$) for N, 0.75 for P, $p < 0.01$) [14].

Table 3: Crop Nutrient Uptake and Yield

Region	System	NUE (%)	PUE (%)	Wheat Yield (t ha^{-1})	N Uptake (kg ha^{-1})	P Uptake (kg ha^{-1})
Temperate	Conventional	55	50	6.5	82	25
	AI-Managed	70	65	7.2	84	26
Semi-arid	Conventional	50	45	5.5	75	22
	AI-Managed	58	52	5.8	77	23

Discussion

Sensor Accuracy and AI Performance

AI-integrated sensors provided high accuracy in nutrient monitoring, with R^2 values indicating robust predictions [15]. The random forest and neural network models effectively translated sensor data into fertilizer recommendations, reducing inputs by 20–30% while maintaining yields [7]. Lower accuracy in semi-arid soils may be due to variable soil moisture, which affects sensor performance [17]. These results align with studies on precision agriculture, highlighting AI's role in optimizing nutrient delivery [3].

Microbial Function Impacts

Higher MBC and enzyme activities in AI-managed plots reflect improved nutrient availability and reduced over-fertilization stress [16]. Enhanced β-glucosidase and phosphatase activities suggest that AI systems support carbon and phosphorus cycling by aligning fertilizer inputs with microbial demands [11]. Limited responses in semi-arid soils underscore the role of moisture in microbial activity, as water scarcity restricts nutrient diffusion.

Crop Productivity and Nutrient Efficiency

Improved NUE and PUE in AI-managed plots demonstrate the efficacy of real-time nutrient management [13]. The 10–12% yield increase in temperate soils reflects optimized nutrient timing and rates, while smaller gains in semi-arid soils indicate environmental constraints. Strong correlations between sensor data and nutrient uptake validate the use of AI-integrated sensors for precision agriculture [14].

Management Implications

AI-integrated sensors can reduce fertilizer waste and environmental impacts, making them ideal for sustainable agriculture [3]. In temperate systems, widespread adoption could enhance soil health and yields [15]. In semi-arid regions, combining sensors with irrigation management is critical to maximize benefits. Training farmers on AI tools and ensuring affordable sensor technologies are essential for scalability.

Limitations

High initial costs of AI-integrated sensors may limit adoption, particularly in resource-constrained regions [17]. Calibration requirements for diverse soil types and climates pose challenges [7]. Long-term impacts on microbial diversity and soil health need further investigation [14]. Future research should focus on cost-effective sensors and broader agroecological applications.

Conclusion

AI-integrated sensors enhance precision nutrient management by improving nutrient monitoring, reducing fertilizer inputs, and supporting soil microbial functions. Temperate soils benefit most, with higher microbial biomass, enzyme activities, and crop yields, while semi-arid soils require moisture management to maximize outcomes. These technologies offer a sustainable approach to agriculture but face challenges in cost and calibration. Further research is needed to optimize AI systems and ensure accessibility across diverse farming systems.

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