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Ai In Smart Agriculture: A Review Of Ai-Based Soil Analysis And Fertilizer Management For Precision Agriculture

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Abstract—Imbalanced fertilizer use is a major problem in Indian agriculture: excess nitrogen raises costs and pollutes water, while deficiencies of phosphorus, potassium and micronutrients limit yields. Effective fertilizer management requires knowing the nutrient status of each field, which conventional laboratory soil testing provides only slowly and at low spatial density. This paper reviews AI-based soil analysis and fertilizer management for precision agriculture. It examines soil sensing with in-field electrochemical NPK, pH and electrical-conductivity probes and with visible–near-infrared spectroscopy; machine learning models that classify soil fertility and predict nutrient levels from sensor and spectral data; digital soil mapping, which combines field samples with remote sensing and terrain covariates to map soil properties across landscapes; crop nitrogen status estimation; and recommendation engines that convert soil and crop information into site-specific fertilizer doses and variable-rate application. India's Soil Health Card programme is discussed as a data source and delivery channel. A five-layer architecture comprising soil sensing, data integration, AI analysis, fertilizer recommendation and farmer advisory layers is proposed, together with research gaps, objectives, a comparison of soil analysis methods and challenges such as sensor accuracy, sparse samples, model transferability, cost and farmer adoption. The review concludes that AI can make fertilizer use more efficient, profitable and environmentally sustainable.

Index Terms—Precision agriculture, soil nutrient prediction, fertilizer recommendation, NPK, digital soil mapping, Vis-NIR spectroscopy, machine learning, soil health card

I. INTRODUCTION

Fertilizer is one of the largest input costs for farmers, yet it is often applied by habit rather than need. When the same dose is used on every field, some plots receive too much nitrogen while others lack phosphorus or zinc. Gebbers and Adamchuk [1] argued that precision agriculture, which matches inputs to spatial variability within fields, is essential for food security and environmental protection.

Matching fertilizer to need requires soil information. Laboratory tests are accurate but slow, and a few samples per field cannot capture variation. India's Soil Health Card scheme [2] provides farmers with nutrient status and recommendations, but sampling density and turnaround remain limited. AI can combine sensors, spectroscopy, remote sensing and historical data to estimate soil properties quickly and recommend site-specific doses.

This paper reviews AI-based soil analysis and fertilizer management and proposes an integrated architecture.

II. RELATED WORK

Spectroscopy. Viscarra Rossel *et al.* [3] compared visible, near-infrared and mid-infrared reflectance spectroscopy for predicting many soil properties simultaneously and showed that spectroscopy is a rapid, low-cost alternative to wet chemistry for properties such as organic carbon, clay and pH.

Digital soil mapping. McBratney *et al.* [4] formalized digital soil mapping, which predicts soil properties from environmental covariates such as terrain, climate and imagery. Hengl *et al.* [5] produced SoilGrids, global soil maps at 250 m resolution using machine learning, and Padarian *et al.* [6] used convolutional networks that learn from the spatial context of covariates, improving prediction of soil organic carbon.

Nutrient classification and crop nitrogen. Suchithra and Pai [7] classified soil nutrient levels with optimized extreme learning machines, and Chlingaryan *et al.* [8]

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reviewed machine learning for crop yield prediction and nitrogen status estimation, identifying remote sensing combined with ML as a promising route to in-season nitrogen management.

Models. Random forests [9] and gradient boosting [10] are commonly used for soil property prediction, and Liakos *et al.* [11] reviewed ML for soil management among other agricultural tasks. Table I summarizes these works.

Ref.	Method	Key Findings	Limitations
[4]	Digital soil mapping	Formal DSM framework	Needs covariates
[3]	Vis-NIR / MIR spectroscopy	Rapid multi-property prediction	Calibration needed
[1]	Precision agriculture	Case for site-specific inputs	Perspective
[5]	SoilGrids ML mapping	Global 250 m soil maps	Coarse for farms
[8]	ML for yield and N status	Review of methods	Review only
[11]	ML in agriculture review	Soil management tasks	Review only
[6]	CNN digital soil mapping	Better SOC prediction	Regional data
[7]	ELM nutrient classification	Accurate fertility classes	Lab inputs

TABLE I Summary of Literature Survey

III. PRELIMINARIES

1. Soil Properties For Fertilizer Decisions

Fig. 1 groups soil properties into macronutrients (N, P, K), secondary and micronutrients, chemical properties (pH, EC, organic carbon) and physical properties (texture, moisture), along with methods for measuring them.

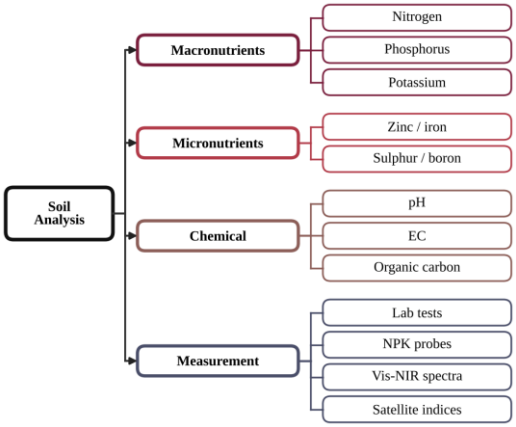


Fig. 1. Soil properties and measurement methods for fertilizer management.

2. Nutrient Balance

A basic fertilizer requirement can be expressed as the crop nutrient demand for a target yield minus the nutrient supplied by the soil, adjusted for fertilizer use efficiency.

IV. PROBLEM STATEMENT AND OBJECTIVES

1. Identified Research Gaps

- Low-cost NPK probes are less accurate than laboratory tests.
- Spectral and mapping models trained in one region transfer poorly to others.
- Soil samples are sparse relative to field variability.
- Recommendations rarely adapt in-season to crop nitrogen status.
- Advice often does not reach farmers in usable form.

2. Objectives Of The Review

- **O1:** To review soil sensing and spectroscopy for nutrient analysis.
- **O2:** To examine machine learning for soil fertility and nutrient prediction.
- **O3:** To study digital soil mapping and crop nitrogen estimation.
- **O4:** To propose a five-layer AI-based fertilizer management architecture.
- **O5:** To identify challenges and future directions.

3. Proposed Framework

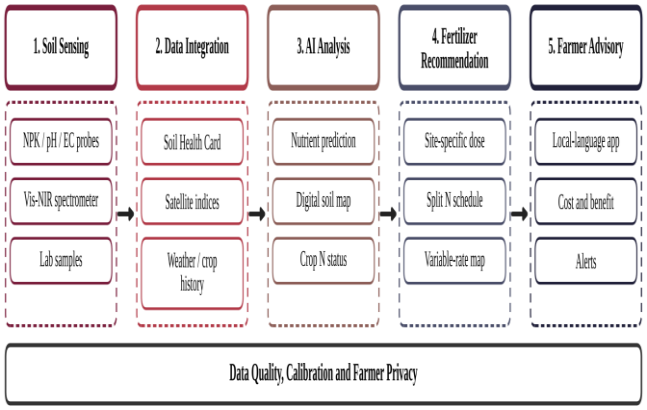


Fig. 2 shows the proposed architecture.

Fig. 2. Proposed five-layer AI-based soil and fertilizer management architecture.

4. Soil Sensing Layer

In-field NPK, pH, EC and moisture probes, a handheld Vis-NIR spectrometer and periodic laboratory samples collect soil data.

5. Data Integration Layer

Soil Health Card records, satellite vegetation indices, weather and crop history are combined with sensor readings using GPS locations.

6. Ai Analysis Layer

Calibrated models predict nutrient levels from spectra and probes; a digital soil mapping model interpolates properties across the field.

7. Fertilizer Recommendation Layer

A recommendation engine computes site-specific doses for the chosen crop and target yield, splits nitrogen across growth stages and generates variable-rate maps where equipment allows.

8. Farmer Advisory Layer

A mobile app in the farmer's language shows the soil status, recommended products and doses, cost and expected benefit.

V. WORKING METHODOLOGY

Fig. 3 describes the workflow. The fertilizer requirement for nutrient n is computed as

$$F_n = (Yield_target \cdot U_n - S_n) / E_n \quad (1)$$

where U_n is nutrient uptake per unit yield, S_n the soil supply estimated by AI and E_n the fertilizer use efficiency. Prediction accuracy is reported with R^2 and RMSE against laboratory values.

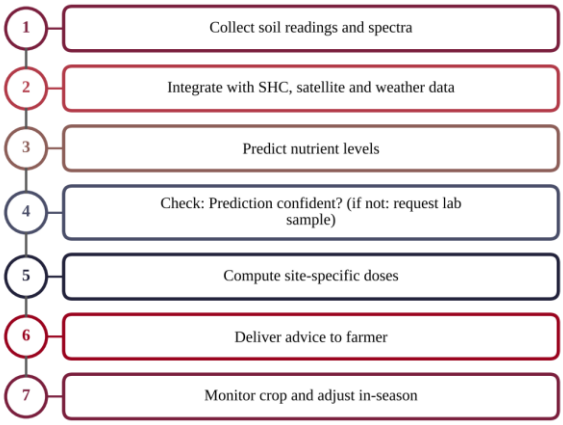


Fig. 3. AI-based fertilizer recommendation workflow.

VI. DISCUSSION

1. Comparison Of Approaches

Table II compares soil analysis methods. Laboratory analysis is the most accurate, spectroscopy offers speed at moderate cost, probes provide continuous data and digital soil mapping gives spatial coverage.

Method	Accuracy	Speed	Cost / Coverage
Laboratory analysis	High	Days–weeks	High / sparse
NPK / pH probes	Low–Medium	Real time	Low / point
Vis-NIR + ML	Medium–High	Minutes	Medium / point
Digital soil mapping	Medium	Fast once built	Low / field-wide
Satellite crop indices	Indirect	Weekly	Low / field-wide

TABLE II Comparison of Soil Analysis Methods

2. Open Challenges And Future Work

Table III summarizes challenges. Future directions include drone hyperspectral nitrogen sensing, national soil spectral libraries for India, federated learning across farms and integration of recommendations with fertilizer subsidy delivery.

Challenge	Mitigation
Probe accuracy	Calibration with lab samples
Model transferability	Local spectral libraries
Sparse samples	Digital soil mapping; smart sampling
Cost	Shared testing services; FPOs
Adoption	Local language; extension workers

TABLE III Challenges and Mitigation

VII. CONCLUSION AND FUTURE WORK

AI-based soil analysis and fertilizer management can move farmers from uniform, habit-based application to site-specific, need-based decisions. The reviewed literature shows that spectroscopy and machine learning estimate soil properties rapidly, digital soil mapping extends point measurements to whole fields and ML supports nitrogen management. Combined with programmes such as Soil Health Cards and farmer-friendly advice, these methods can reduce cost and pollution while improving yields.

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