International Journal of Advances and Applications in Convergent Studies & Transdisciplinary (IJ-AACST)

Bridging Disciplines, Bridging Knowledge

Aligned with the Vision of NEP 2020 and UGC Guidelines

Website: https://aacstij.org || Email: journaleditor@aacstij.org

IoT- and ML-Based Fertilizer Recommendation for Sugarcane: A Focused Review

DOI: https://doi.org/ 10.5281/zenodo.24103563

Sushil R. Deokar[1]*, Dr. V. S Tondre[2]

*Corresponding Author: [1]Department of Computer Science & Application, Brijlal Biyani Science College, Amravati, Sant Gadge Baba Amravati University, Amravati, Maharashtra, India
sushil.deokar@gmail.com

[2]Department of Computer Science & Application, Brijlal Biyani Science College, Amravati, Sant Gadge Baba Amravati University, Amravati, Maharashtra, India
vstondre@gmail.com

ABSTRACT

Sugarcane is a long-duration crop that removes large quantities of nutrients from the soil, yet fertilizer is still commonly applied by uniform, calendar-based rules that ignore how soil supply and crop demand change across a field and across a season. This paper reviews how low-cost soil sensors, wireless connectivity and machine learning (ML) can be combined to make nutrient recommendations that are specific to a site and a growth stage. We discuss evidence on split and band-placed fertilizer application in plant and ratoon crops, ML-based nitrogen estimation from drone imagery, and the reliability of inexpensive NPK probes. Three themes emerge: stage-wise scheduling matters more for sugarcane than a single seasonal dose; imagery-based nitrogen models give moderate, variety-dependent accuracy; and commercial NPK probes have rarely been checked against laboratory analysis and, where they have, performed poorly. Building on these themes, we outline a conceptual five-layer architecture (AIFRF-SC) that treats growth stage and plant-versus-ratoon status as model inputs and that returns a dated application schedule with an explanation of the sensor readings behind it. The architecture is a proposal for future work and has not been field-tested.

KEYWORDS: sugarcane; fertilizer recommendation; precision agriculture; Internet of Things; machine learning; ratoon; site-specific nutrient management.

1. INTRODUCTION

Sugarcane (*Saccharum officinarum* L.) is an important agro-industrial crop in tropical and subtropical regions and contributes meaningfully to the Indian rural economy [1]. It stays in the field for most of a year, produces large biomass, and draws heavily on soil nitrogen (N) and potassium (K). Because of this, errors in fertilizer management are costly: under-application limits cane and sugar yield, whereas over-application raises input cost and increases nutrient loss to water and air [1].

Recommendations given to growers are usually written for an agro-climatic zone and expressed as a

© 2026 The Author(s). This article is published by the AACST in the IJ-AACST under the Creative Commons Attribution 4.0 International (CC BY 4.0) License. The authors retain copyright and grant AACST a non-exclusive license to publish, distribute, and archive the work.

fixed amount per hectare, sometimes divided into a few installments. Such rules are easy to circulate but cannot reflect differences in soil texture, moisture, organic matter or weather between neighboring plots. Site-specific nutrient management (SSNM) aims to close this gap by adjusting the type, amount and timing of fertilizer according to measurements taken in the field.

Two developments make SSNM more practical than before. Inexpensive microcontroller-based sensing nodes can now log soil and weather variables continuously, and ML methods can relate those records, together with imagery, to nutrient status. Surveys of IoT in agriculture describe these building blocks in general terms [6–8], but most published prototypes are crop-agnostic or demonstrated on small, single-season data. Sugarcane has distinctive requirements—a long cycle, repeated ratoon crops and several fertilizer installments—that a generic crop-recommendation tool does not address.

This paper therefore asks three questions. What does recent evidence say about how sugarcane should be fertilized in time and space? How well do sensing and ML methods currently estimate nutrient status in this crop? And what would a design look like that joins these pieces while avoiding the weaknesses found in existing work? The contribution is a structured synthesis and a conceptual architecture, not a new trained model.

2. SCOPE AND APPROACH

This is a focused narrative review rather than a formal PRISMA-style systematic review. We concentrated on three bodies of literature: field studies on fertilizer timing and placement in sugarcane; sensing and ML studies that estimate nitrogen or water status in sugarcane; and evaluations of low-cost soil nutrient sensors. Sources were located through keyword searches on sugarcane combined with nitrogen, UAV, multispectral, NPK sensor, ratoon and machine learning, and were read in full before being used. Quantitative figures quoted below are taken directly from the cited papers and are not pooled; because experimental designs, soils and varieties differ, the numbers show what each study found and should not be read as a benchmark ranking.

3. NUTRIENT DYNAMICS OF SUGARCANE

3.1 Long duration and uneven demand

Sugarcane is described in the agronomic literature as a long-duration, nutrient-exhaustive crop [1]. Uptake is not spread evenly over the season. It accelerates as tillers emerge, is largest during rapid stem elongation, and tapers as the crop matures and stores sucrose. Any recommendation system must therefore reason about crop stage and should output a schedule over time instead of a single figure.

3.2 Plant crop versus ratoon

After harvest, a ratoon crop regrows from the same root stock. Its establishment, root activity and nutrient uptake differ from those of the first (plant) crop, so a system that treats both crops identically will misestimate demand for one of them. Field work in the Indo-Gangetic plains has evaluated both cycles under the same treatments [1], which is the kind of evidence needed to calibrate separate model behavior for plant and ratoon fields.

3.3 Splitting and placing fertilizer

The strongest recent field evidence concerns how fertilizer is delivered. A two-year experiment on

calcareous soil in Bihar compared broadcast and band application, and different numbers of N and K splits, in plant and ratoon sugarcane [1]. Seven splits of N and K raised yield by 16.0% in the plant crop and 15.1% in the ratoon crop relative to a control with two N splits and no K split. Broadcasting, compared with banding, reduced millable cane number by 17.5% and 17.6%, cane yield by 14.8% and 17.1%, and sugar yield by 14.7% and 15.8% in plant and ratoon crops respectively. The authors concluded that band placement combined with seven N and K splits was the best protocol tested [1]. These results show that timing and placement are as important as total dose, which supports building the recommendation output around a stage-indexed schedule.

4. SENSING AND CONNECTIVITY

4.1 In-field soil and weather sensing

Most low-cost deployments pair a capacitive or resistive moisture sensor with a combined probe that reports NPK, pH and electrical conductivity, plus an air temperature and humidity sensor, all read by an ESP32- or Arduino-class board [6–9]. For a crop with deep roots such as sugarcane, a second moisture reading at greater depth is a sensible addition to a surface probe.

4.2 Reliability of low-cost NPK probes

The main uncertainty in this hardware concerns the NPK reading itself. A technical evaluation of three commercial low-cost probes compared sensor output with laboratory results and reported coefficients of determination between about 0 and 0.25, with results that depended strongly on soil moisture; the authors advised against relying on such probes for precision fertilizer decisions, although they may indicate trends [5]. Many IoT prototypes in the literature use the same class of probe without a comparable check [6–9]. In our view a recommendation system should treat probe nutrient values as weak evidence unless they have been calibrated on the target soil, and should lean more on moisture, EC, weather and periodic laboratory samples.

4.3 Remote sensing

UAV and satellite imagery offer an alternative route to nutrient status that avoids probe contact. A recent review of AI and remote sensing in sugarcane covers water stress, salinity and nitrogen estimation and concludes that these methods are promising for managing the crop [4]. Their cost, flight scheduling and need for ground-truth leaf sampling remain practical constraints for small farms.

4.4 Connectivity

Sugarcane fields are often large and far from reliable broadband. Wi-Fi with MQTT suits compact plots near infrastructure, while long-range low-power networks such as LoRaWAN suit large estates, trading data rate for range and battery life [6, 7]. Light pre-processing at a gateway (outlier removal and unit conversion) reduces the amount of data sent and the cleaning needed later.

5. MACHINE LEARNING FOR SUGARCANE NUTRIENT ESTIMATION

Tree-based ensembles, support vector methods and partial least squares (PLS) regression are commonly used when training sets are modest, whereas deep networks generally need more data [2]. Studies specific to sugarcane are summarized in Table 1.

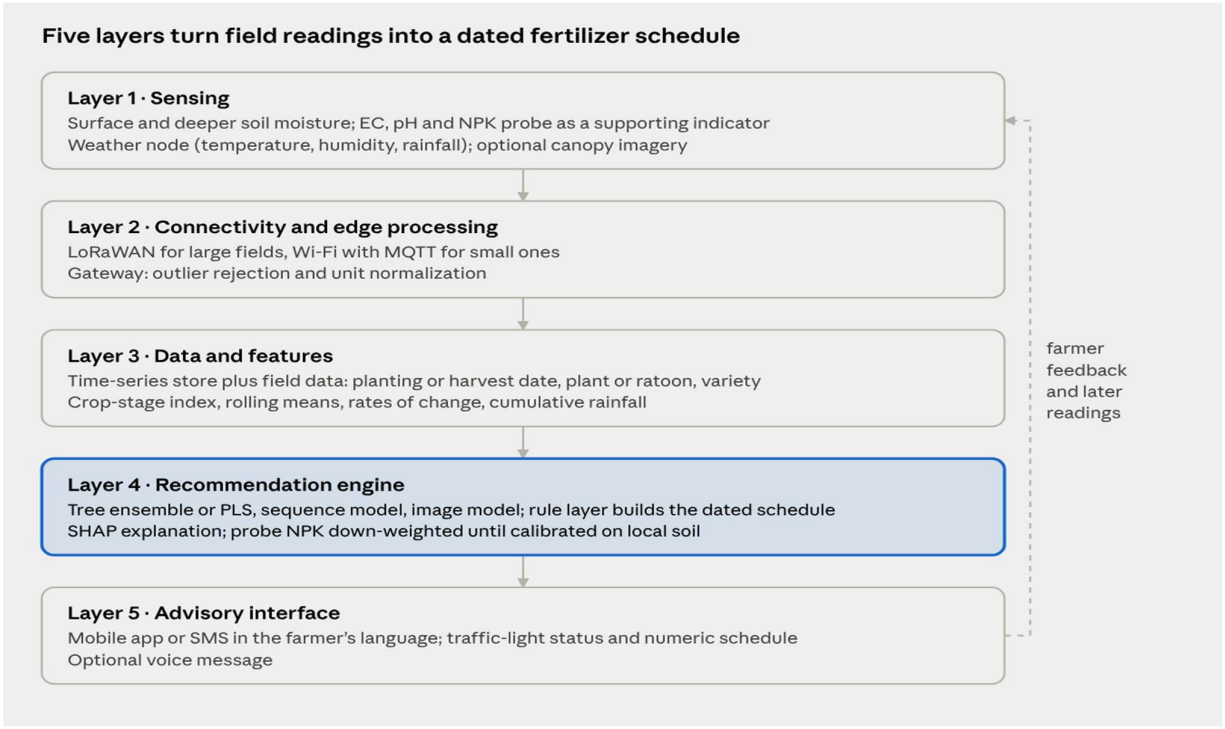
Table 1. Selected sugarcane-specific results quoted from the cited sources.

Study	Task	Data and methods	Reported result
Li et al. [2]	Canopy N and irrigation level	UAV multispectral images at elongation; three irrigation and five N levels; PLS, BPNN, ELM; SVM for irrigation	PLS best for N (Rv = 0.79, RMSE = 0.11); SVM classified irrigation level with 80.6% accuracy
Drone-imagery study [3]	Leaf N under organic fertilizer	UAV multispectral images of two varieties; ten vegetation indices; five ML models	PLSR and SVR best per variety (R^2 > 0.72, RMSE < 0.11); Random Forest best on pooled data (R^2 = 0.66, RMSE = 0.12)
Kumar et al. [1]	Application method and splits	Two-year plant–ratoon field trial, calcareous soil	Banding plus seven N/K splits gave the highest yield and uptake
Estrada et al. [5]	Low-cost NPK probe accuracy	Probe readings versus laboratory analysis	R^2 roughly 0–0.25; strong moisture dependence

Two observations follow. First, accuracy for nitrogen is moderate and falls when varieties are pooled [3], so models should be tuned or at least checked per variety. Second, the imagery studies were collected at a single growth stage [2, 3]; none of the cited work links such estimates to a full-season dosing decision. Predicting nutrient content is not the same as recommending an economically sensible dose, and the connection between the two remains largely unaddressed for sugarcane.

6. PROPOSED CONCEPTUAL ARCHITECTURE (AIFRF-SC)

We propose a five-layer design for sugarcane. It is a reference plan intended to guide implementation and trials; it has not been built or validated.



Layer 1 – Sensing

Surface and deeper soil moisture probes, a combined EC/pH/NPK probe used as a supporting indicator, a weather node (temperature, humidity, rainfall), and optional periodic canopy imagery from a fixed camera or UAV.

Layer 2 – Connectivity and edge processing

LoRaWAN for large fields and Wi-Fi/MQTT for small ones, with gateway-level outlier rejection and unit normalization.

Layer 3 – Data and features

A time-series store that also holds field metadata: planting or harvest date, plant versus ratoon, variety and irrigation method. Derived features include crop-stage index, rolling means and rates of change of moisture and EC, and cumulative rainfall.

Layer 4 – Recommendation engine

A tree-ensemble or PLS model estimates the current nutrient-sufficiency class; a sequence model forecasts short-term depletion where long logs exist; an image model corroborates deficiency when imagery is available. A rule layer built from agronomic guidance—for instance the split-and-band schedule evidence in [1]—combines the outputs into a dated list of applications with quantity, placement and source. An explainability component (for example SHAP attribution) lists the main readings behind each advice item so that a field officer can judge it. Because probe NPK values are unreliable [5], their weight is reduced unless a local calibration against laboratory data has been entered.

Layer 5 – Advisory interface

Delivery by mobile app or SMS in the farmer's language, using a simple traffic-light status together with the numeric schedule and an optional voice message. Farmer feedback and later sensor readings are stored to improve the models.

The design deliberately differs from generic crop-recommendation tools in three ways: crop stage and ratoon status are inputs rather than labels; the output is a schedule rather than a single dose; and sensor trust is modeled explicitly.

7. RESEARCH GAPS

Datasets - We found no widely used public dataset linking multi-season sugarcane soil and sensor records to measured yield and sugar outcomes. Much published modeling relies on tabular crop-recommendation data that were not collected in sugarcane fields.

Economic optimization - Evaluation is usually based on prediction error. A model with a low error can still recommend an uneconomic input rate, so assessment should include net return per hectare and nitrogen-use efficiency.

Sensor validation - Evidence on probe accuracy is limited and discouraging [5]. Soil-specific calibration studies are needed for the main sugarcane soils.

Field validation - The cited ML studies report error on measured samples from a single experiment [2, 3]; trials across seasons and locations that compare model advice with current practice are still missing.

Interoperability and trust - Sensor vendors use different data formats, and few systems explain their advice. Both issues limit reproducibility and adoption by growers**.**

8. FUTURE DIRECTIONS

First, shared, multi-season datasets covering plant and ratoon fields in several agro-climatic zones would give researchers common ground for benchmarking. Second, federated or transfer learning could allow estates and institutions to benefit from each other's data without pooling it. Third, joint modeling of nutrient status and economic outcome would move recommendations from agronomically plausible to financially defensible. Fourth, independent calibration of low-cost probes on regional soils should precede their use in decision systems. Finally, multi-season on-farm trials comparing the proposed schedule with the standard practice are the necessary step before any claim of benefit can be made.

9. CONCLUSION

Sugarcane differs from short-duration field crops in ways that matter for digital fertilizer advice: its cycle is long, its ratoon crops behave differently from the plant crop, and field evidence shows large yield effects from how fertilizer is split and placed [1]. Current sensing and ML work offers moderate nitrogen estimates from imagery [2, 3] but unreliable low-cost NPK probes [5], and little of it has been tested as a complete decision system. The AIFRF-SC architecture proposed here brings these findings together in a form that can be built and evaluated. Its value will depend on the dataset, calibration and field-trial work outlined above.

10. REFERENCES

[1] N. Kumar, L. Rana, A. K. Singh, B. Pramanick, A. Gaber, A. M. Alsuhaibani, M. Skalicky and A. Hossain, "Precise macronutrient application can improve cane yield and nutrient uptake in widely spaced plant–ratoon cycles in the Indo-Gangetic plains of India," *Frontiers in Sustainable Food Systems*, vol. 7, Art. 1223881, 2023. doi:10.3389/fsufs.2023.1223881

[2] X. Li, Y. Ba, M. Zhang, M. Nong, C. Yang and S. Zhang, "Sugarcane nitrogen concentration and irrigation level prediction based on UAV multispectral imagery," *Sensors*, vol. 22, no. 7, Art. 2711, 2022. doi:10.3390/s22072711

[3] "Use of drone imagery to predict leaf nitrogen content of sugarcane cultivated under organic fertilizer application," *Tropical Agricultural Research*, vol. 35, no. 1, pp. 11–23, 2024. doi:10.4038/tar.v35i1.8700 [ADD AUTHOR NAMES from the journal page]

[4] "Harnessing AI and remote sensing for precision sugarcane farming: Tackling water stress, salinity, and nitrogen challenges," *Frontiers in Agronomy*, vol. 7, Art. 1681294, 2025. doi:10.3389/fagro.2025.1681294 [ADD AUTHOR NAMES from the journal page]

[5] O. Estrada, G. Ramos, M. Lizarazo and D. Jimenez, "Technical report of the probe: Low-cost portable soil fertility sensors: Myth or reality?," Digital Transformation Accelerator, Alliance of Bioversity International and CIAT / CGIAR. [CONFIRM YEAR from the repository record]

[6] C. Prakash, L. P. Singh, A. Gupta and S. K. Lohan, "Advancements in smart farming: A comprehensive review of IoT, wireless communication, sensors, and hardware for agricultural automation," *Sensors and Actuators A: Physical*, vol. 362, Art. 114605, 2023. [VERIFY]

[7] H. Shahab, M. Iqbal, A. Sohaib, F. Ullah Khan and M. Waqas, "IoT-based agriculture management techniques for sustainable farming: A comprehensive review," *Computers and Electronics in Agriculture*, vol. 220, Art. 108851, 2024. [VERIFY]

[8] D. Huo, A. W. Malik, S. D. Ravana, A. U. Rahman and I. Ahmedy, "Mapping smart farming: Addressing agricultural challenges in a data-driven era," *Renewable and Sustainable Energy Reviews*, vol. 189, Art. 113858, 2024. [VERIFY]

[9] H. Singh et al., "Smart farming revolution: Portable and real-time soil nitrogen and phosphorus monitoring for sustainable agriculture," *Sensors*, vol. 23, no. 13, Art. 5914, 2023. [VERIFY].