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Fuzzy logic driven real time fertiliser recommendation system with internet of things-integrated soil and environmental sensor suite

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Abstract

Precision nutrient management is essential for improving crop productivity while minimising fertiliser misuse, production costs and environmental impacts. This paper presents a low-cost, portable and real-time fertiliser recommendation system that integrates an Internet of Things (IoT)-based soil and environmental sensor suite with a fuzzy logic inference engine. The proposed system acquires key soil parameters, including nitrogen (N), phosphorus (P), potassium (K), pH and electrical conductivity (EC), along with environmental data and geolocation information. Sensor readings are calibrated and processed to estimate nutrient deficiencies and soil conditions. A fuzzy inference system utilises crop type, crop growth stage and nutrient deficiency percentages as inputs to generate crop-specific fertiliser recommendations for urea, diammonium phosphate (DAP), single super phosphate (SSP) and muriate of potash (MOP). An additional pH reclamation module recommends suitable amendments such as lime or gypsum. To enhance usability, a mobile application and Python-based dashboard were developed, enabling users with no prior agricultural expertise to select the crop and growth stage, deploy the sensor in the field and receive actionable recommendations, including fertiliser quantities, estimated costs and labour requirements. The system was validated using 100 soil samples collected from Southern India. The fuzzy logic output was tested across more than 40 crops and all four growth stages; however, the fuzzy-versus-conventional mathematical comparison is presented for 10 representative soil samples using sugarcane at the basal stage to provide a uniform comparison. Experimental results showed that the fuzzy recommendations followed the same recommendation trend as conventional mathematical calculations, with quantitative differences varying by fertiliser and sample. The proposed framework demonstrates a practical and scalable solution for real-time, in-field nutrient management and informed agricultural decision-making.

Keywords: fertiliser recommendation system; fuzzy logic inference system; internet of things-based soil sensing; precision agriculture; soil nutrient management

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Introduction

The agricultural industry plays a major role in the growth of a country's economy, influenced by various factors such as population growth, food security and increased productivity demands (1–7). To meet the increasing demand for food production, several modern agricultural technologies such as internet of things (IoT)-based sensors, soil testing and fertiliser recommendation tools have been developed. Plants require macronutrients for their growth and development, namely nitrogen (N), phosphorus (P) and potassium (K). Apart from these nutrients, an appropriate soil pH range is required for efficient nutrient uptake by the majority of crops. Soil having optimum nutrient quality provides optimum yield and maintains soil health (8–14). Traditional methods of soil amendment did not have a regulated amount of application and the application was often performed based on experience, peer recommendations, or word of mouth, leading to an unscientific approach to fertiliser application. This resulted in inefficient nutrient supply or excessive application of fertilisers, which can lead to toxicity, surface and groundwater contamination, leaching and runoff and changes in the physical, chemical and biological properties of soil (14–17).

Conventional soil testing is laboratory-based and requires expensive equipment and trained professionals.

The process involves soil sampling, transportation of samples and chemical testing, making it tedious and cost-inefficient, while also being prone to manual errors and sample mix-ups at different stages. In addition, accessibility to soil testing laboratories is limited in some regions and conventional soil testing does not directly provide crop- and growth-stage-specific fertiliser recommendations (18–20). With the current rise in IoT and precision agriculture, advancements in sensor technologies, wireless monitoring and decision-making systems have enabled real-time monitoring and data-driven approaches in modern farming (19, 21–23).

Research in this field has demonstrated multiple approaches for agricultural decision-making and nutrient management. Machine-learning approaches based on random forest (RF) and hybrid long short-term memory (LSTM) + RF have demonstrated reliable decision-making by simulating different environmental situations and improving prediction capacity for efficient nutrient use; however, their application was limited to rice (24). Stage-specific real-time decision support systems have also been developed using NPK, temperature, humidity and rainfall parameters, although the recommendations were focused on crop selection rather than fertiliser dosage (25). Fertiliser recommendation systems based on NPK values have also been developed with integrated purchasing portals, but without incorporating other relevant farm and environmental parameters (26). Neural-network-based approaches have demonstrated the prediction of soil parameters by integrating NPK sensors with MAX485 TTL to RS485 converter modules (27). The IoT-based nutrient monitoring has also been investigated in citrus plants, where differences in nutrient readings were observed between wet and dry soil conditions (28). Agricultural systems integrating artificial intelligence and wireless communication technologies have further demonstrated the potential for sustainable agricultural management (29). Mamdani-based crop yield prediction has also been investigated using environmental parameters such as temperature, humidity and rainfall, but without incorporating soil nutrient parameters (30). Reviews of IoT-based soil nutrition monitoring and management technologies have further highlighted the development of soil nutrient monitoring and management systems and the need for large-scale field experiments under a variety of actual environmental and crop conditions (19).

Although these studies demonstrate the potential of IoT, artificial intelligence, machine learning and sensor-based approaches in agriculture, a gap remains in integrating real-time multi-parameter soil sensing with a crop- and growth-stage-specific fertiliser recommendation mechanism. Existing approaches have primarily focused on individual aspects such as soil nutrient monitoring, crop recommendation, environmental prediction, crop yield prediction or fertiliser recommendation based on limited parameters. Furthermore, the simultaneous consideration of soil N, P, K, pH and electrical conductivity (EC) conditions along with crop type and growth stage for generating fertiliser recommendations remain comparatively limited. There is therefore a need for an integrated, portable and low-cost system capable of processing real-time soil information and converting it into practical fertiliser recommendations while reducing dependence on manual calculations and laboratory-based decision-making.

The present study proposes a precision agricultural system that integrates an IoT-based soil sensor and fuzzy inference system to generate fertiliser recommendation outputs in real time. The system is designed to provide a low-cost and portable approach for soil nutrient assessment and fertiliser recommendation while considering crop type, growth stage and soil nutrient status. The system further aims to support sustainable fertiliser application by reducing excessive or insufficient nutrient application, thereby saving farmers' time and resources and improving the efficiency of nutrient management.

The hypothesis of the present study is that integrating real-time multi-parameter soil sensing with a crop- and growth-stage-based fuzzy inference system can generate fertiliser recommendations that provide comparable nutrient-based outputs to conventional mathematical fertiliser calculations while reducing the need for manual computation and enabling rapid, field-level decision-making.

The objectives of the present study are to (i) develop and calibrate an IoT-integrated soil sensing system for real-time measurement of soil N, P, K, pH, EC and other relevant soil and environmental parameters; (ii) develop a fuzzy inference system incorporating crop type, growth stage and nutrient deficiency conditions for fertiliser recommendation; (iii) integrate the sensing, fuzzy inference and recommendation components into a portable software-based decision support system; and (iv) evaluate the fertiliser recommendations generated by the fuzzy inference system against conventional mathematical fertiliser calculations across representative soil samples, crops and growth stages.

Materials and Methods

Hardware design-sensor architecture

The hardware architecture of the proposed system has been developed using an ESP32 microcontroller, which has been integrated with a multi-parameter NPK sensor, digital humidity and temperature 11 (DHT 11), global positioning system (GPS) module and recommended standard 485 (RS485) to MAX485 bidirectional transistor-transistor logic (TTL) communication interface. The NPK sensor measured soil NPK concentration, pH, EC, temperature and humidity of the fertile top layer or up to a depth of 15 cm. Surface environmental parameters were monitored through DHT 11 and GPS acquired Geocoordinates. The detailed sensor architecture is shown in Fig. 1.

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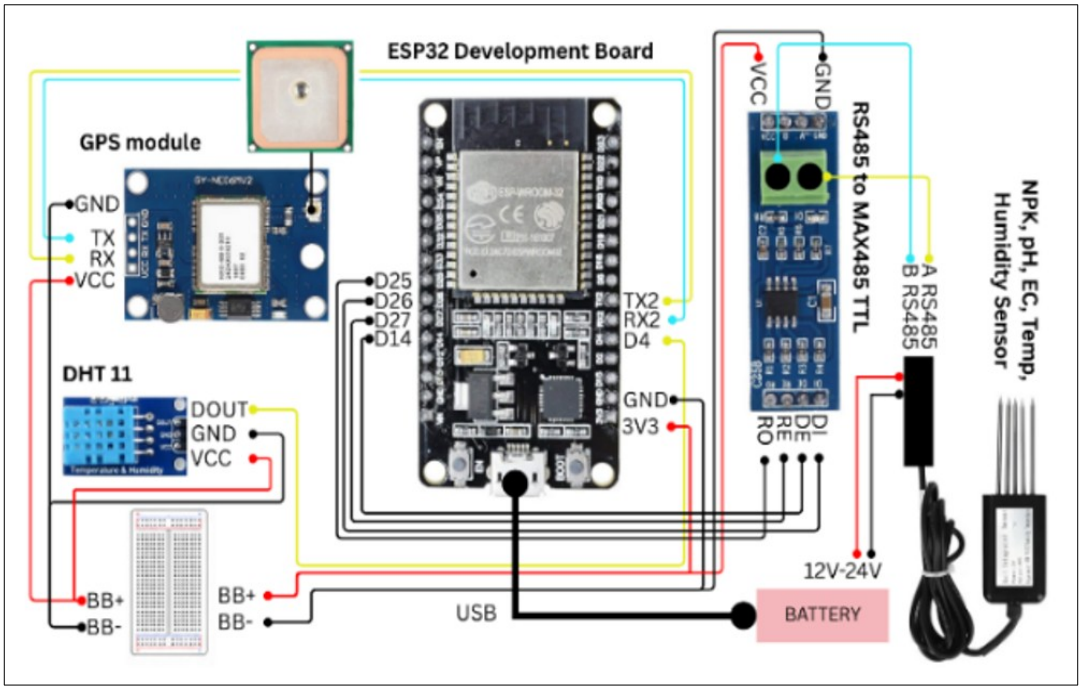


Fig. 1. Sensor architecture, comprising the wiring of all electronic components, sensor modules and microcontroller unit with detailed pin-to-pin connections.

Sensor calibration

For calibration, randomly selected 10 samples from the total, performed chemical analysis and derived the final values (kg ha^{-1} and mg kg^{-1}). Then the sensor probe was inserted into each soil sample to see the values it generated. The raw sensor outputs were obtained from the NPK sensor and the values were subjected to parameter-specific calibration for N, P, K, pH, EC to improve the reliability of the sensor readings under various soil types. Calibration of temperature and humidity measure was not required as the NPK Sensor and DHT11, as the readings were comparable to laboratory and weather station data. The calibrations of sensor are mentioned below and may vary sensor to sensor.

Nitrogen calibration

Nitrogen calibration was performed using an EC-dependent slope correction.

$$N_C = N_r \times S_{EC} \qquad \text{Eq. 1}$$

Where,

$$S_{EC} = \begin{cases} 0.30, & EC_r < 300 \\ 0.195, & 300 \le EC_r < 1500 \\ 0.10, & EC_r \ge 1500 \end{cases}$$

Here,

N_C = Calibrated nitrogen value

N_r = Raw nitrogen sensor reading

S_{EC} = EC-dependent slope factor

E_{CR} = Raw EC reading

Phosphorus calibration

Phosphorus calibration was performed using EC and moisture compensation.

$$P_C = (0.754P_r + 4.11) \times \frac{F_{EC}}{F_M} \qquad \text{Eq. 2}$$

Where,

$$F_{EC} = \max(0.7, 1 - \frac{EC_r}{4000})$$

$$F_M = 1 + \frac{M_r}{800}$$

Here,

P_C = Calibrated phosphorus value

P_r = Raw phosphorus sensor reading

EC_r = Raw EC reading

M_r = Raw moisture reading

F_{EC} = EC correction factor

F_M = Moisture correction factor

Potassium calibration

Phosphorus calibration was performed using EC and moisture compensation.

$$K_C = (3.677K_r + 17.79) \times \frac{F_{EC}}{F_M} \qquad \text{Eq. 3}$$

Where,

$$F_{EC} = \max(0.7, 1 - \frac{EC_r}{5500})$$

$$F_M = 1 + \frac{M_r}{600}$$

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Here,

K_C= Calibrated potassium value

K_r = Raw potassium sensor reading

Ec_r = Raw EC reading

M_r = Raw moisture reading

F_{EC} = EC correction factor

F_M = Moisture correction factor

pH calibration

Raw pH values were corrected using an EC-dependent compensation factor.

$$PH_C = \frac{pH_r}{100} + \Delta \quad \text{Eq. 4}$$

Where,

$$\Delta = \begin{cases} +0.10, & EC_r < 300 \\ -0.10, & 300 < EC_r \leq 600 \\ -0.34, & 600 < EC_r \leq 1500 \\ -0.20, & EC_r > 1500 \end{cases}$$

Here,

PH_C = Calibrated pH value

PH_r = Raw pH sensor reading

EC_r = Raw EC reading

Δ = EC-based correction factor

Electrical conductivity calibration

Electrical conductivity was calibrated using range-specific scaling factors.

$$EC_C = \begin{cases} \frac{EC_r}{900}, & EC_r < 200 \\ \frac{EC_r}{2500}, & 200 \leq EC_r < 500 \\ \frac{EC_r}{4500}, & 500 \leq EC_r < 1500 \\ \frac{EC_r}{8000}, & EC_r \geq 1500 \end{cases} \quad \text{Eq. 5}$$

Here,

1. EC_C = Calibrated electrical conductivity
2. EC_r = Raw EC sensor reading

Internet of things architecture

The readings from all the sensors and the GPS module are sent to the ESP32 board, where the calibration factors and the codes have been programmed from this, it is transmitted to the user's device (Laptop). The readings are transmitted to the dashboard application, where it shows the live value in the Live Value Panel. The user manually selects or inputs data, such as the crop type, variety, growth stage and the area of land they want to be fertilised or pH reclaimed, based on the land metric (acre, hectare, etc.), for the total application across their entire field. Once Run Analysis is clicked, the system first calculates the nutrient deficiency by comparing the target nutrient requirement of the selected crop with the available soil nutrient levels. Then the calculated deficiency is allocated to the selected growth stage, as not all nutrient is required at every growth stage. Once the NPK nutrient deficiency percentage is generated, the fuzzy logic runs with some specific calculations and then it determines the application amount of fertiliser dose in kg ha^{-1} (Urea, diammonium phosphate (DAP), single super phosphate (SSP) and muriate of potash (MOP)). As for pH, based on the deficiency range, gypsum and lime amounts for soil pH reclamation are provided in t ha^{-1}.

The final Output is generated in the "Recommendation Preview" panel, giving the recommendation of how much fertiliser dose should be applied, as well as for pH reclamation. Apart from chemical recommendations for the field, the total cost of acquiring fertiliser is also provided based on the current market rate and total application time (based on average healthy individual), with various methods of application being considered as options, as well as the total weight they'll be carrying (avg. healthy individual). Giving the user all the factors for them to decide what suits them the best. The data can also be saved and printed and it stores the field trend data for reviewing the field health and performance over the time. The IoT architecture is shown in Fig. 2.

Software design: Fuzzy logic design

The fuzzy inference system was developed using four input variable: Growth stage (Day/ days after sowing (DAS)), nitrogen deficiency percentage (ND %), phosphorus deficiency percentage (PD %), potassium deficiency percentage (KD %). The output variables were urea, SSP, DAP and MOP as fertiliser recommendations. The growth stage input was represented using a trapezoidal membership function (Trapmf), to represent the progressive nature of crop growth. The nutrient deficiency inputs and fertiliser output are triangular membership functions (Trimf). However, the "Severe" in deficiency membership function (MF) and extreme pH classes ("Low" and "High") were trapezoidal membership function (Trapmf), this was done to accommodate boundary conditions and ensure appropriate system response at minimum and maximum limits of the input range. A scalable range generation system was also implemented, which adjusted the ranges automatically to different crops nutrient requirements (kg ha^{-1}), eliminating the need for fixed upper limits, enabling the system to accommodate a wide range of crops. Each of the four input variables consisted of four membership functions. Therefore, the complete combination of the four input variables resulted in 256 possible fuzzy (4 × 4 × 4 × 4 = 256). All the inputs and outputs with respective membership functions are given in Table 1 and Fig. 3 and 4 illustrate the trapezoidal and triangular membership functions. In addition to the 256 rule base, a separate set of pH-specific fuzzy rules was developed. These rules were maintained independently from the core 256 rules system, because soil pH reclamation is done before

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plant/seedling initiation. For this, one input is pH, having nine membership functions, ranging from strongly acidic to strongly alkaline, firing two outputs as gypsum and lime, having triangular membership functions, where values are in t ha^{-1}. In this, 9 rules were established, all inputs and mf are also given in Table 1. Therefore, leading to the 256 + 9 rule fuzzy logic design.

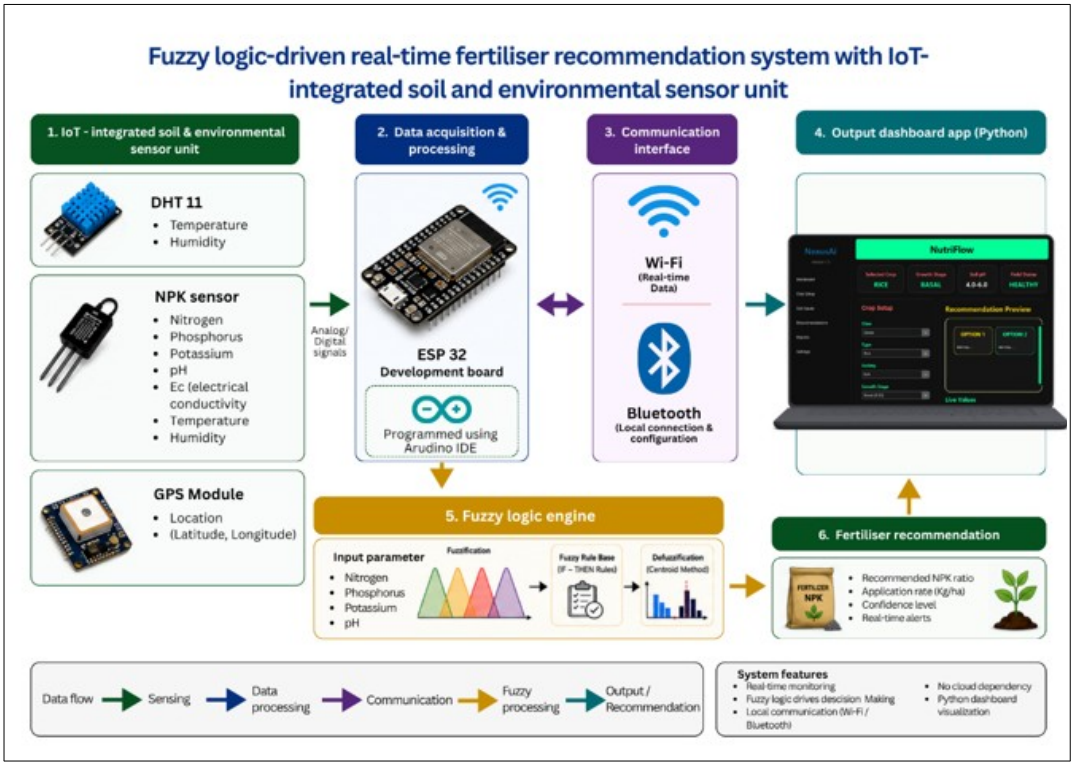


Fig. 2. Internet of things (IoT) architecture showing data flow from sensor to the dashboard, where fuzzy logic model generates fertiliser recommendation by processing the inputs in the background.

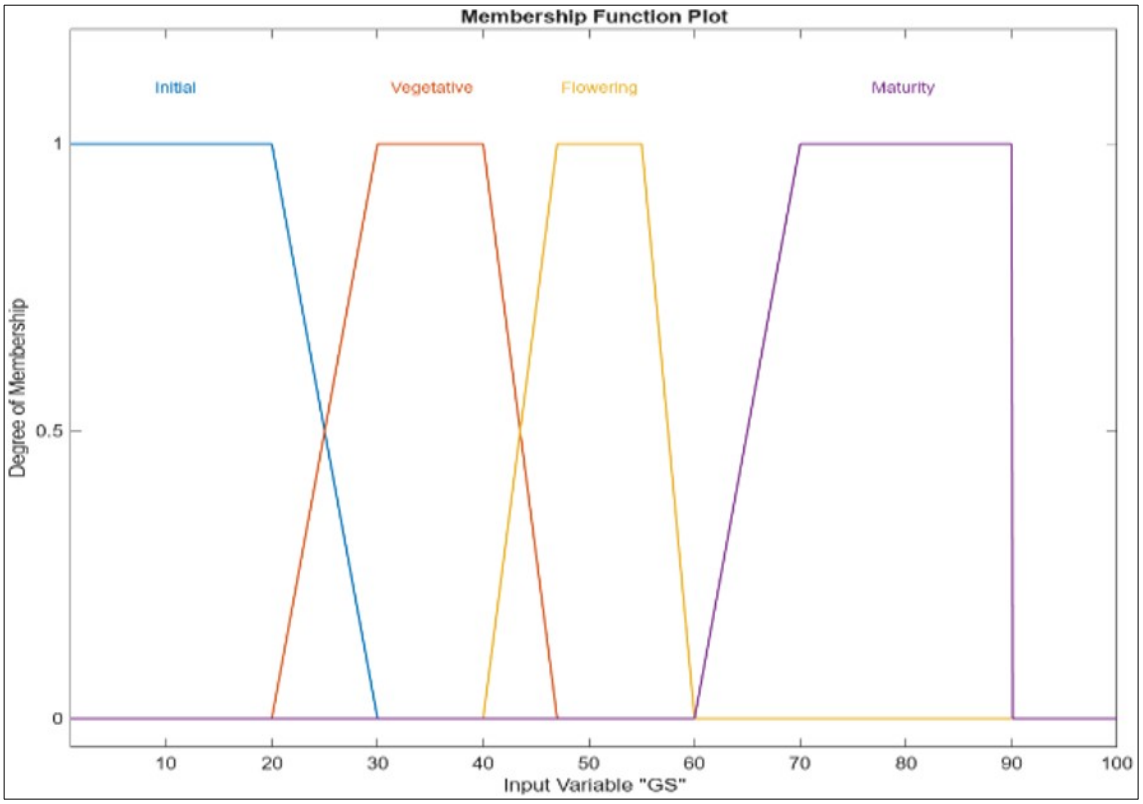


Fig. 3. Illustration of the trapezoidal membership function (trapmf).

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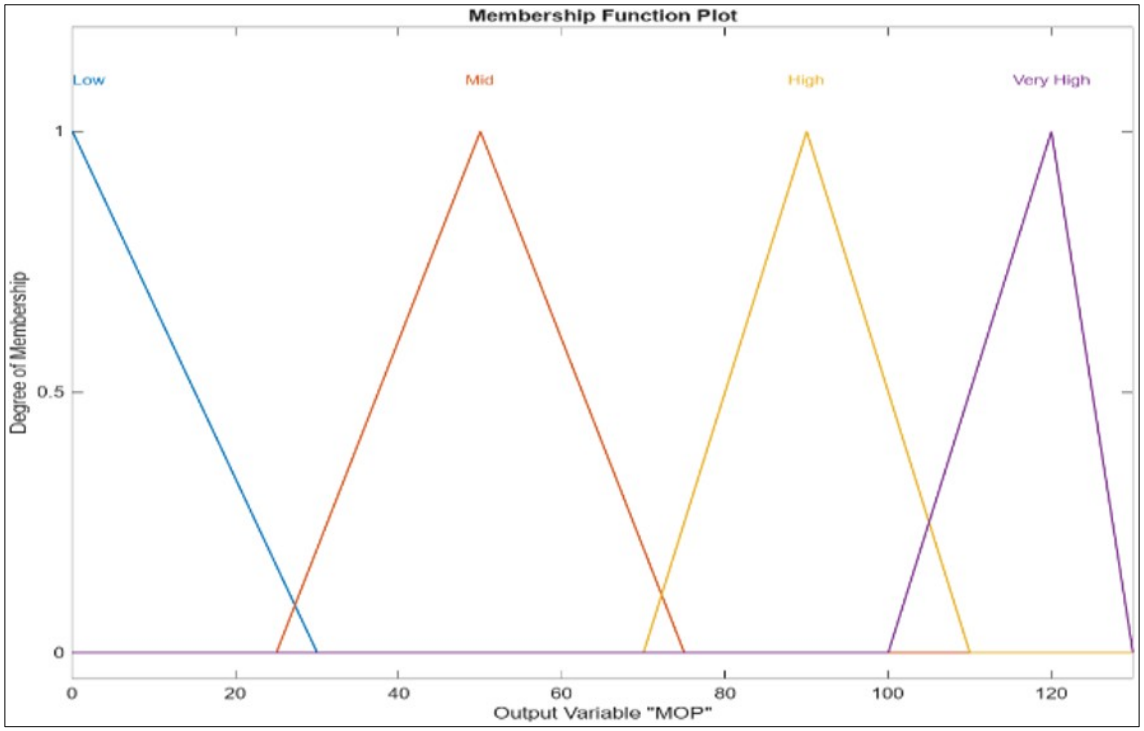


Fig. 4. Illustration of the triangular membership function (trimf).

Table 1. Inputs and output membership functions and their ranges

Input and output	Membership function	a	b	c	d
Growth stage	Basal	0	0	20	30
	vegetative	20	30	40	47
	Flowering	40	47	55	60
	Maturity	60	70	90	90
Nitrogen deficiency %	Low	0	0	20	
	Medium	15	30	45	
	High	40	60	75	
	Severe	70	85	100	100
Phosphorus deficiency %	Low	0	0	20	
	Medium	15	30	45	
	High	40	60	75	
	Severe	70	85	100	100
Potassium deficiency %	Low	0	0	20	
	Medium	15	30	45	
	High	40	60	75	
	Severe	70	85	100	100
pH	Very strongly acid	0	0	4.5	5
	Strongly acidic	4.8	5.2	5.5	
	Moderately acidic	5.5	5.7	6	
	Slightly acidic	6	6.3	6.6	
	Neutral	6.5	6.8	7.2	7.4
	Slightly alkaline	7.3	7.5	7.8	
	Moderately alkaline	7.8	8.1	8.4	
	Strongly alkaline	8.4	8.7	9	
	Very strongly alkaline	9	9.5	14	14
Fertilisers	Low	5	20	35	
	Medium	30	50	70	
	High	65	80	90	
	Very high	85	100	100	
	None	0	0	0.1	0.3
Gypsum	Low	0.8	1.5	2	
	Medium	2	2.3	2.6	
	High	2.6	2.8	3	3
	None	0	0	0.2	0.5
Lime	Low	0.5	2	3.5	
	Medium	3.5	4.5	5.5	
	High	5.5	6	7.5	7.5

Dashboard design and inference system

To run and view the analysis, a dashboard was developed using Python. This dashboard includes a crop setup where the user inputs the crop variety, selects the growth stage and then inputs the desired land area they want to supply nutrients to using a preferred unit such as acres, hectares, or other applicable metrics. The dashboard also provides a live monitoring panel displaying real-time sensor readings. The live monitoring panel displays real time measurements

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of surface and sub-surface temperature, humidity, pH, EC and soil nutrient level (NPK). Once the "RUN ANALYSIS" button is clicked, the algorithm runs and gives the fertiliser output in the recommendation window, where two options are given for farmers to choose from. Option A shows urea, SSP, MOP, whereas option B shows urea, DAP, MOP. This was done because the fuzzy system will run both SSP and DAP for PD %. Here, DAP is supplying N as well as P. Therefore, the urea output from the fuzzy combined with the N supplied from DAP will lead to excessive application of nitrogen. To address this issue, a N adjustment model was developed to account for N supplied through DAP and modify the recommended urea application rate. In addition to fertiliser recommendation the system also recommends the labour requirement in hours, considering average application time, total fertiliser quantity to be handled and estimates fertiliser purchase cost. These calculations were incorporated into the Python based recommendation algorithm being presented alongside the fertiliser recommendation as illustrated in Fig. 5.

The equations used for verification of Error percentage (Error %) and accuracy percentage (Accuracy %) are given in below:

$$\text{Error (\%)} = \frac{\text{Fuzzy - Mathematical}}{\text{Mathematical}} \times 100 \quad \text{Eq. (6)}$$

$$\text{Accuracy (\%)} = 100 - \text{Error (\%)} \quad \text{Eq. (7)}$$

Where, Fuzzy = fertiliser recommendation generated by fuzzy inference system (kg ha^{-1})

Mathematical = fertiliser recommendation generated by the conventional mathematical model (kg ha^{-1}).

Error (%) = percentage deviation of the fuzzy output from the mathematical output.

Accuracy (%) = agreement between fuzzy and mathematical recommendations.

Results and Discussion

To validate the proposed system, 100 soil samples were collected from predetermined locations in Southern India: Tamil Nadu, Kerala, Andhra Pradesh, Telangana and Pondicherry. The sampling locations were predetermined to obtain samples representing different environmental and agricultural conditions, including hill and cold areas, coastal areas, barren areas, fertilised fields, salt-affected areas, low and high altitudes, grassland, forest, marshy areas, plantations, near flowing and stagnant water bodies and varying crop fields at different preparation and growth stages, for a wide data set. One soil sample was collected from each selected location following proper field sampling procedures, avoiding field boundaries and other non-representative points. All the samples were air-dried, sieved through a < 2 mm sieve and then the chemical analysis was done. For N, the potassium permanganate method by B V Subbiah and G E Asija was used; the values were in mL. For P, Olsen and Bray methods were used according to soil condition, with spectrophotometric analysis and readings in absorbance (abs) (31–33). Potassium was analysed through a flame photometer; the readings were in ppm. Whereas pH and EC were read on their respective instruments. All instruments were calibrated before experimentation and a standard curve was also generated for P and K. Based on the standard curve; the final readings were obtained. The resulting standard curves are illustrated in Fig. 6. Then the noted values were calculated and converted into final kg ha^{-1} readings in Microsoft Excel, based on the NPK calculation formulas for the respective experiment, to reduce human error and generate large-volume data output, whereas pH and EC were the final readings in themselves. Illustrations from soil sampling to analysis are shown in Fig. 7 and the readings of select samples are provided in Table 2.

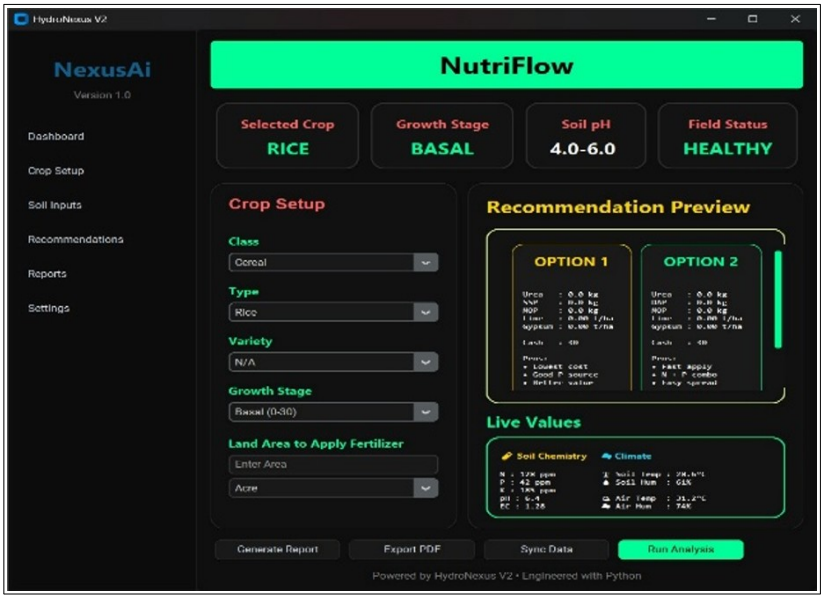


Fig. 5. Dashboard and inference system displaying fertiliser and pH recommendation along with economic and environmental factors to support users decision making.

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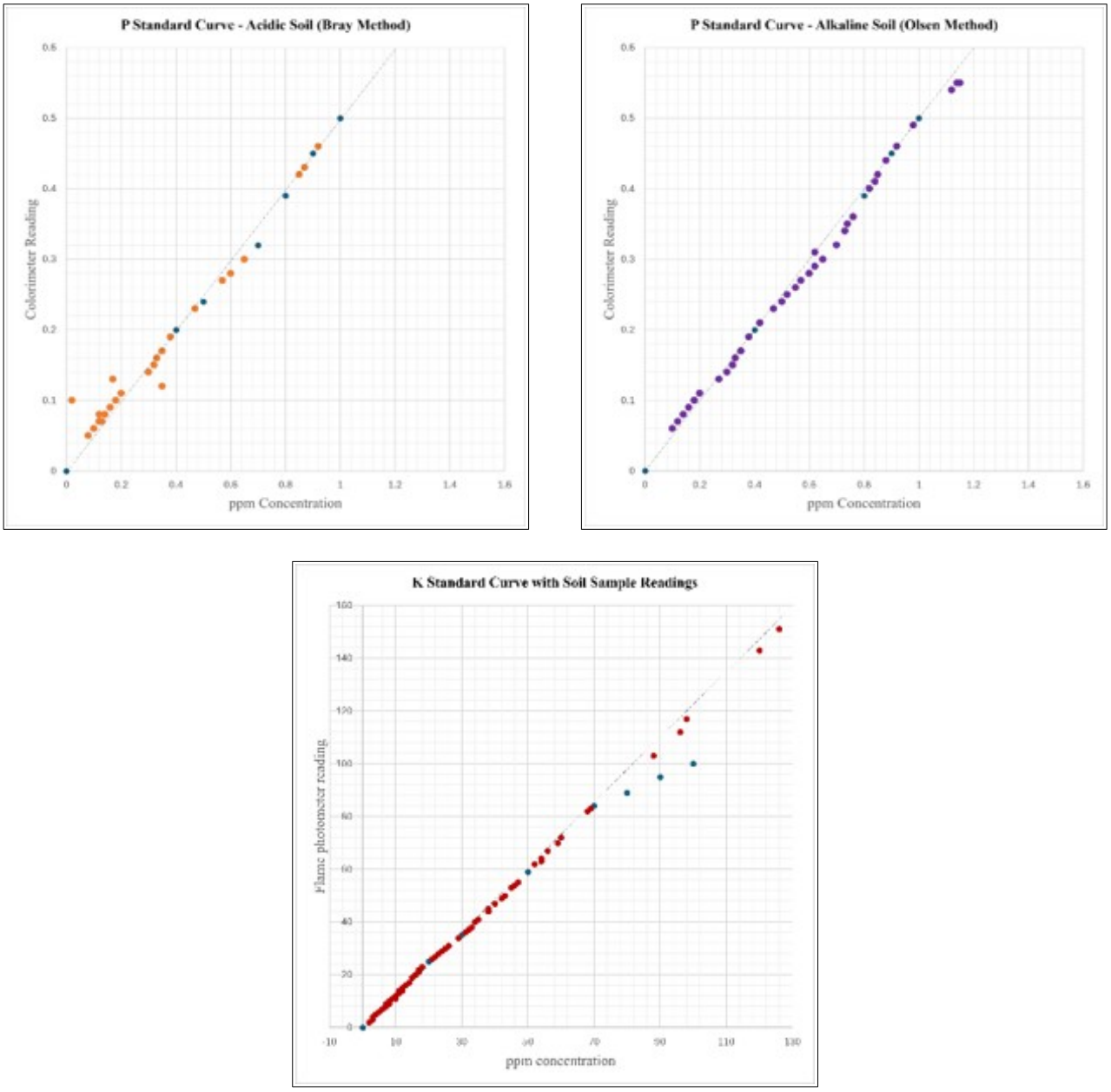


Fig. 6. Standard curves for phosphorus (P) and potassium (K).



Fig. 7. From sample collection to processing laboratory analysis.

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Table 2. Nutrient content in the collected soil sample

Sample No.	N (kg ha^{-1})	P (kg ha^{-1})	K (kg ha^{-1})	pH	EC (Dsm^{-1})
4	11.2	13	220	5.2	0.1
18	184.8	62	240	7.0	0.8
25	145.6	12	40	5.6	0.03
30	246.4	10	90	6.1	0.1
36	123.2	2	220	8.0	0.2
43	33.6	12	210	7.8	0.2
48	81.2	60	430	5.2	0.4
54	33.6	35	70	5.4	0.1
67	11.2	62	170	7.5	0.1
100	36.4	35	1200	8.1	0.3

N: nitrogen; P: phosphorus; K: potassium; EC: electrical conductivity.

The performance of the developed fuzzy logic system was evaluated by comparing the fertiliser recommendation generated by the fuzzy logic system with a conventional mathematical model. The conventional mathematical model was obtained by converting the agronomist/fertiliser recommendation calculation into formulae and coding the same calculations to reduce manual calculation error and enable quicker generation of multiple data results. The model calculated fertiliser requirement directly from nutrient deficits, whereas the fuzzy model generated recommendations based on membership functions and reasoning based on rules. The fuzzy logic output was tested across more than 40 crops, including rice, maize, banana, plantation crops, cereal crops and vegetable crops and all four growth stages were tested. However, for the presented fuzzy-versus-conventional comparison, 10 representative samples were selected using the same crop type and growth stage (sugarcane at the basal stage) to provide a uniform comparison across the different soil conditions. The basal stage was selected for the tabulated comparison because it is the stage at which the complete fertiliser requirement is considered, whereas later growth stages require selective nutrients depending on crop requirement and nutrient deficiency. For the other crops and stages, when the available soil nutrient content was satisfactory or above the crop requirement threshold, the system correctly generated no fertiliser dosage recommendation. The comparison included all recommendations (Urea, SSP, DAP, MOP, lime and gypsum) and the results of the representative samples are given in Table 3 for the fuzzy model and Table 4 for the mathematical model. The results indicated that the fuzzy logic recommendation closely matched that of the mathematical model.

Table 3. Fuzzy inference system fertiliser recommendation

Sample No.	Crop	Stage	Urea (kg ha^{-1})	SSP (kg ha^{-1})	MOP (kg ha^{-1})	DAP (kg ha^{-1})	Gypsum (t ha^{-1})	Lime (t ha^{-1})
4	Sugarcane	Basal	338.3	522	-	181.7	-	2
18	Sugarcane	Basal	-	118.7	-	41.3	-	1.9
25	Sugarcane	Basal	22.54	511.9	-	178	-	4.5
30	Sugarcane	Basal	0	534.3	-	185.8	-	2
36	Sugarcane	Basal	56.3	486	-	169	1.4	-
43	Sugarcane	Basal	291	520.8	-	181	1.1	-
48	Sugarcane	Basal	158.8	125	-	43.48	-	6.6
54	Sugarcane	Basal	290.7	317.6	-	110.4	-	6.5
67	Sugarcane	Basal	334.9	118.7	-	41.3	0.5	-
100	Sugarcane	Basal	284.6	317.5	-	110.4	1.4	-

SSP: single superphosphate; MOP: muriate of potash; DAP: diammonium phosphate.

Table 4. Mathematical model fertiliser recommendation

Sample. No.	Crop	Stage	Urea (kg ha^{-1})	SSP (kg ha^{-1})	MOP (kg ha^{-1})	DAP (kg ha^{-1})	Gypsum (t ha^{-1})	Lime (t ha^{-1})
4	Sugarcane	Basal	356	550	-	191.3	-	2
18	Sugarcane	Basal	-	237	-	82.6	-	2
25	Sugarcane	Basal	63.9	550	-	191.3	-	4.5
30	Sugarcane	Basal	-	562	-	195.6	-	2
36	Sugarcane	Basal	112.61	512	-	178.2	1.5	0
43	Sugarcane	Basal	307	550	-	191.3	0.5	0
48	Sugarcane	Basal	203	250	-	86	-	6.5
54	Sugarcane	Basal	307.3	406	-	141.3	-	6
67	Sugarcane	Basal	356	237.5	-	82.6	0.5	-
100	Sugarcane	Basal	301	406.25	-	141.3	1.5	-

SSP: single superphosphate; MOP: muriate of potash; DAP: diammonium phosphate.

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The developed fuzzy logic system generated fertiliser recommendations that were lower than those produced by the mathematical model. Depending on the nutrient under consideration, it was observed that the percentage of error ranged from 11–20 %. This reduction occurred because the fuzzy logic system provides recommendation ranges based on membership function and rule-based inference rather than attempting to meet the target nutrient requirement through direct mathematical calculations. This deviation is due to the nature of the fuzzy inference, occurring due to a gradual, smooth recommendation rather than a fixed one. The system prefers to give conservative dosages. This tendency is beneficial from an agricultural standpoint, as excessive fertiliser application raises the production cost and leads to nutrient losses through runoff, leaching and ultimately environmental contamination.

The results from Table 2 showed that both models followed similar recommendation trends. The comparison between fuzzy logic and mathematical fertiliser recommendation revealed that fuzzy logic followed the same conventional calculation method, while producing slightly lower fertiliser dosages. In some cases, the differences were most evident for SSP, whereas DAP, gypsum and lime recommendations were in agreement. Some values were not generated in both models because the available nutrients were in an excess range. The validation was presented using sugarcane because the available nutrient content of the selected soil samples, based on laboratory analysis, provided meaningful fertiliser-deficiency cases for comparison, whereas several other crop-soil combinations had satisfactory or above-threshold nutrient levels and therefore generated zero fertiliser recommendation. The fuzzy logic output was nevertheless tested across more than 40 crops and all four growth stages and the same logic operated across these combinations. Sugarcane at the basal stage was used in the presented comparison to maintain uniformity across the different soil types and avoid comparing cases in which only one nutrient or no nutrient required application. Although certain samples exhibited deviation from the mathematical model, the fuzzy recommendation remained within the calculated recommendation range and reflected the nutrient deficiency identified in the soil. These deviations arise from the fuzzy inference system, which evaluates nutrient requirements through overlapping membership functions and rule-based reasoning rather than having a fixed threshold. The differences are expected in the fuzzy system as it mimics an expert's agricultural decision-making under uncertain field conditions.

Overall, the fuzzy model demonstrates a strong agreement with the mathematical model, with a smooth and adaptive fertiliser recommendation. The final output is generated in the dashboard, showcasing the live sensor reading, fuzzy recommendation, with the cost of fertilisers and the time needed for applying them in the field based on various application methods. This allows the user to decide the best course of action according to their limitations. The present approach is consistent with previous fuzzy-logic-based fertiliser recommendation work, while extending the recommendation framework with real-time soil NPK, pH and EC sensing, crop and growth-stage inputs, pH reclamation and dashboard-based cost and labour estimates. The comparison presented in Tables 3 and 4 is a validation of agreement with a coded conventional mathematical recommendation model rather than direct validation against measured crop response. Therefore, the present results demonstrate computational agreement and system consistency, while field-level crop-response validation remains a limitation of the current study.

A limitation of the present validation is that the conventional mathematical model was used as the computational benchmark, while direct crop-response validation was not conducted for every crop and growth-stage combination. The 10-sample comparison was therefore used as a representative computational validation rather than as a claim of complete field validation across all crop-stage combinations. Future field experiments should evaluate yield response, nutrient-use efficiency, economic return and long-term soil response across multiple locations, crops and seasons.

Conclusion

The study developed a low-cost, portable precision agricultural system integrating an IoT sensor suite with a fuzzy inference system for real-time, crop- and growth-stage-specific fertilizer and pH reclamation recommendations. The system integrated calibrated nitrogen (N), phosphorus (P), potassium (K), pH and electrical conductivity (EC) sensing with a scalable fuzzy logic model and Python dashboard for real-time monitoring, fertiliser recommendations, cost and labour estimates. The fuzzy recommendations showed a conservative tendency, with an observed error range of 11–20 % compared with conventional mathematical calculations, while maintaining agronomically relevant recommendations. The integrated system demonstrated potential for real-time in-field nutrient management and reduced dependence on centralised laboratory-based decision-making. Future studies should focus on field validation across diverse crops, soil types and seasons, along with broader sensor calibration and agronomic and economic evaluation.

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Authors' contributions

ID carried out the drafting, sample collection, fuzzy logic and Python coding. SRR and RAS carried out soil sampling, location studies and soil laboratory analysis. RRP carried out AI-related testing, calibration, sensor assembly and design. KSK carried out the statistical analysis, model testing and code correction. All authors have read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest

Authors do not have any conflict of interests to declare.

Ethical issues

None

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