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A Low-Cost Autonomous Agricultural Rover for GPS-Enabled Precision Fertilizer and Soil Nutrient Management

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***Abstract*— Small and medium farmers do not have much access to precision agriculture because of the expensive costs of the system and significant infrastructure needs. This paper will describe a low cost autonomous agricultural rover, which is capable of carrying out site specific soil nutrient analysis, and control fertilisers, using GPS. The suggested system combines the sensing of soil electrical conductivity (EC), soil moisture, GPS localization, micro-weather, and lightweight vision-based weed detection using an ESP32-based platform. The potentiation of the spatial soil data is carried out by Inverse Distance Weighting (IDW) interpolation and K-means (K = 3) clustering to develop nutrient management zones, and the fertilizer recommendation is derived by use of Nutrient-Per-Water (NPW) index. Soil mapping in field experiments on a 0.5-hectare maize plot shows an accuracy approach of 5 percent, soil moisture correlation of R 2 = 0.87 as well as a maximum of 38 percent of lowering of the use of fertilizer without a noticeable decrease in yield. The rover consumes a mean power of about 32 W, and can be continuously operated 3.5 hours, and the total system costs less than USD 50. The findings reveal that the system proposed has a feasible and scalable answer to precision fertilization in easily accessible farming conditions.**

***Index Terms*— Precision farming, autonomous farming robots, electrical conductivity of soil, variable-rate fertilization, agricultural robots based on IoT, GPS geofencing, nutrient management zones.**

I. Introduction

Agriculture is an industry challenged to produce more with limited land, changing weather patterns, and increasing input costs. These challenges are most severe in developing countries where small and medium farmers lack access to precision agriculture technologies. Traditional farming treats fields uniformly, ignoring soil variability, leading to nutrient waste, reduced yield, and environmental pollution. IoT technologies enable real-time soil and environmental monitoring using low-cost sensors, while autonomous rovers allow dense spatial data collection. However, most existing systems focus on irrigation or crop health, with limited attention to spatial soil nutrient mapping and variable-rate fertilization. Soil electrical conductivity (EC) is an indicator of soil texture, salinity, and nutrient-holding capacity. When combined with soil moisture, EC provides insights into nutrient mobility and availability.

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Conventional EC mapping remains costly and labour-intensive. This paper presents a low-cost autonomous agricultural rover integrating soil EC sensing, moisture monitoring, GPS localization, and edge-based analytics to enable site-specific fertilizer management for smallholder farms.

Contributions:

- An economical autonomous agricultural robot for Realtime soil and environmental sensing with GPS tagging.
- A Nutrient-Per-Water (NPW) index for fertilizer decision support.
- Infrastructure-free autonomous field mapping using GPS geofencing and boustrophedon coverage.
- A lightweight explainable weed detection method for low-power systems.
- Field validation on a 0.5-hectare plot demonstrating fertilizer reduction and cost savings.

II. RELATED WORK

The development of modern precision agriculture techniques has been achieved through the combination of Internet of Things (IoT) technologies and economical soil sensors and self-operating ground machines and data-based decision making systems. The section analyzes previous research about soil sensing and agricultural systems that use IoT technology and autonomous navigation systems and fertilizer recommendation methods and weed detection methods while demonstrating how the proposed system solves these existing challenges.

A. Soil Nutrient and Moisture Sensing

Precision agriculture needs affordable yet accurate soil sensing to achieve its goals. The method of soil electrical conductivity (EC) testing serves as an indirect measurement of soil texture and salinity levels and the ability of soil to retain nutrients which affects the uppermost soil layer. Fulton et al. showed that open-source EC sensors reach commercial solution performance when their calibration process is done correctly while their operational expenses remain much lower than commercial products. The research conducted by Raheja et al. established a strong connection between low-cost microcontroller-based sensors and Time Domain Reflectometry (TDR) measurements which resulted in an R2 value of 0.92 [2]. Recent work has focused on improving sensing accuracy through integrated hardware designs. Song and Zhang developed an EC sensor based on the AD5941 analog front-end which achieved an error rate below 2 percent [3]. The studies conducted by Stroobosscher et al. proved that capacitive moisture sensors exhibit high sensitivity toward nutrient ions especially potassium which confirmed the effectiveness of using combined EC and moisture data for nutrient assessment purposes [4]. Although electrochemical nitrate sensors provide specific nutrient detection capabilities the high expenses and complicated nature of these sensors prevent smallholder farmers from using them [6].

B. IoT-Based Agricultural Monitoring

The implementation of Internet of Things technologies through its three components of continuous sensing and wireless communication and data-driven analytics has brought about major improvements to agricultural monitoring systems. The study of Mansoor et al. demonstrated that real-time IoT platforms provide essential support for farmers to make agricultural decisions [7] while multiple research investigations confirmed the effectiveness of IoT-based fertigation systems through laboratory tests and field experiments [8]. The study demonstrated that low-cost microcontroller platforms which include ESP32-based systems function properly for smart irrigation and monitoring tasks in areas with limited resources [9]. The current solutions use cloud-based systems as their primary method because users experience problems with waiting times and network access and system maintenance expenses. The edge computing frameworks enable users to perform local analytics which decreases their need to use cloud services to solve these problems [11]. Existing IoT systems depend on fixed data collections and central processing systems which restrict their ability to manage nutrients in real-time on agricultural fields.

C. Autonomous Ground Vehicles and Navigation

AGVs enable researchers to gather high-density soil and crop data through their automated ground vehicle operations. The field of soil sampling and field monitoring research uses robotic platforms which have multi-sensor payloads as their deployment method [13]. Survey studies indicate that autonomous rovers are well suited for precision agriculture tasks, particularly when combined with GPS-based localization techniques [14]. Navigation in unstructured agricultural environments remains challenging. LiDAR-based systems offer high accuracy but involve significant hardware and computational cost [15]. The system has been developed to achieve accurate results through its GNSS-based location system which works together with inertial sensors.

The system delivers accurate results which meet the needs of small-scale farmers because it operates at an affordable expense [16].

D. Fertilizer Recommendation and Weed Detection

Data-driven fertilizer recommendation systems have gained attention for their potential to reduce input costs and environmental impact. The system uses data analysis to create its fertilizer recommendation system which helps farmers save money while protecting the environment. Clustering based techniques such as K-means and fuzzy C-means have been effectively used to delineate soil management zones and enable variable-rate fertilizer application [20], [21]. While deep learning approaches achieve high prediction accuracy, their reliance on large datasets and computational resources limits real-time field deployment [22]. Machine vision techniques have also been applied to site specific weed detection and precision spraying. Deep learning based models, including YOLOv5 variants, demonstrate high detection accuracy across multiple crop types [23], [24]. However, their computational requirements restrict deployment on low-power embedded platforms. Lightweight and explainable vision-based methods provide a practical alternative for energy- and cost-constrained agricultural robots.

E. Research Gap

Current studies show that soil sensing technology and IoT monitoring systems and autonomous navigation systems and decision-support algorithms have all achieved major advancements through their research work. The existing solutions need expensive hardware and cloud processing systems and they require computational heavy models and they depend on fixed datasets. The industry needs a cost-effective solution that provides total autonomous operation and combines realtime geotagged soil measurement with simple understandable analytics for fertilizer management in agricultural fields. The proposed system addresses this gap by integrating autonomous mobility, edge-based processing, and spatial soil diagnostics in a single platform tailored for smallholder farming environments.

III. METHODOLOGY

The current study introduces an efficient and inexpensive method for fertilizer management which uses GPS-equipped autonomous agricultural rovers to evaluate soil nutrient content. The proposed methodology combines autonomous navigation, real-time soil and environmental sensing, and simple data analysis techniques to support location-specific fertilizer decisions. The approach provides an understandable system which maintains reliable performance through actual farming conditions and meets the needs of small-scale farmers.

A. System-Level Methodological Framework

The agricultural rover operates as an autonomous mobile sensing unit which the ESP32 microcontroller controls. The rover operates in the field by moving through GPS boundaries which users establish while it gathers data on soil electrical conductivity (EC) and soil moisture together with environmental conditions and visual information. The system stores each measurement together with its GPS location and time stamp which enables researchers to conduct spatial analysis of soil conditions.

The complete process executes through a sequence of steps which proceed in a specific order:

- Definition of field boundaries using GPS coordinates
- Autonomous traversal of the field using a coverage strategy
- Periodic collection of soil and environmental data
- Storage of geotagged sensor readings
- Spatial interpolation of soil parameters
- Identification of nutrient management zones

The system operates through its complete processing capacity which enables it to function in areas that lack internet access because it does not depend on cloud services.

B. Autonomous Navigation and Field Coverage Strategy

To ensure complete field coverage, the rover follows a boustrophedon (lawn-mower style) path within the GPS-defined boundary. The rover uses GPS for constant position tracking to stay within its designated geofenced boundaries. The system uses closed-loop motor control to correct small deviations which occur when the vehicle encounters uneven ground. The rover stops automatically during obstacle detection because ultrasonic sensors provide continuous tracking of objects entering the safety zone

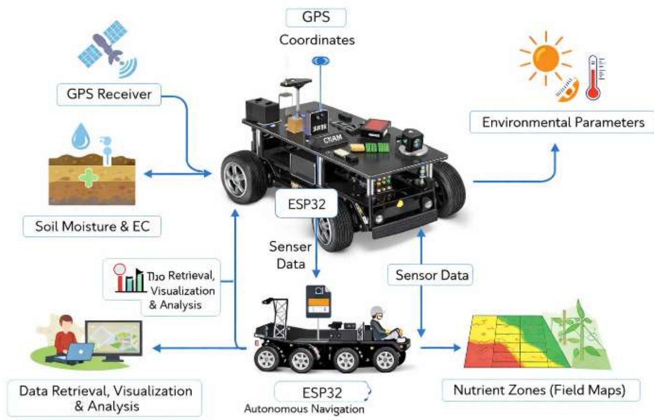

Fig. 1. Overall system architecture of the autonomous agricultural rover

C. Soil and Environmental Sensing Methodology

The first method uses a shallow-depth conductivity probe to measure soil electrical conductivity. The second method uses a capacitive sensor to measure soil moisture content in the root zone area. Electrical conductivity provides indirect information about soil texture and nutrient-holding capacity. The moisture content of the soil controls nutrients at which they move through the soil toward the crops. The system can record temperature and humidity levels together with ultraviolet radiation and light intensity to monitor environmental conditions in the area. The parameters help explain the different ways that soil moisture and nutrient patterns behave throughout the study area. The rover activates sensors when it moves to a new location and collects data at intervals of three meters between sampling points. The distance-based sampling method establishes a uniform spatial pattern throughout the entire field area which remains unchanged regardless of how fast the rover moves.

D. Spatial Data Processing and Interpolation

The researchers first checked the collected sensor data to find and remove outliers before proceeding to validate the data measurement process. The Inverse Distance Weighting (IDW) method creates continuous maps of soil electrical conductivity and moisture through spatial interpolation. The IDW method allows researchers to analyze moderate spatial density datasets because it requires minimal processing power for embedded systems operation according to their low computational requirements.

E. Nutrient-Per-Water Index and Zone Delineation

The Nutrient-Per-Water Index (NPW) index is calculated through the division of soil electrical conductivity (EC) measurements by soil moisture content because soil moisture levels affect EC readings. The process produces a stable indicator which shows relative nutrient availability because it decreases temporary moisture fluctuations. The NPW values are grouped using the K-means clustering algorithm with $K = 3$. The process creates three nutrient management zones which show different fertilizer needs in different areas of the field.

F. Fertilizer Recommendation Logic

Fertilizer recommendations are generated using a simple rule-based approach based on agronomic guidelines. The system provides full fertilizer dosage to areas with low NPW values while it delivers reduced input to zones with moderate NPW values and the system requires little or no extra fertilizer to zones with high NPW values. The method uses straightforward decision rules which maintain decision clarity while protecting system security because it requires no mathematical learning models.

G. Lightweight Weed Detection Approach

Weed detection is performed through a basic vision-based system which operates on equipment with low energy demands. The rover-mounted camera system captures images which undergo conversion to the HSV color space, and the system uses green pixel masking to detect areas with high vegetation density beyond the crop row limits. Weed-infested areas become visible through the green pixel ratio which goes beyond the set threshold. The method produces understandable results which require no training data, making it appropriate for use in agricultural embedded systems.

IV. Implementation

This section describes the physical realization of the proposed system, including the hardware setup, sensor integration, navigation logic, firmware design, and data analysis workflow.

A. Hardware Architecture

The rover uses an acrylic chassis which supports four-wheel drive and operates through its differential drive system that receives power from two DC motors. The system receives power from a 7.4 V 5 Ah lithium-ion battery which supplies electricity to the ESP32 microcontroller and all attached sensors through a regulated 5 V power line. The ESP32 serves as the main control unit which handles all tasks related to sensor data collection and navigation control and GPS communication and voice command processing and local data storage. The system uses a modular design which enables system components to be independently replaced or upgraded without requiring extensive system modifications.

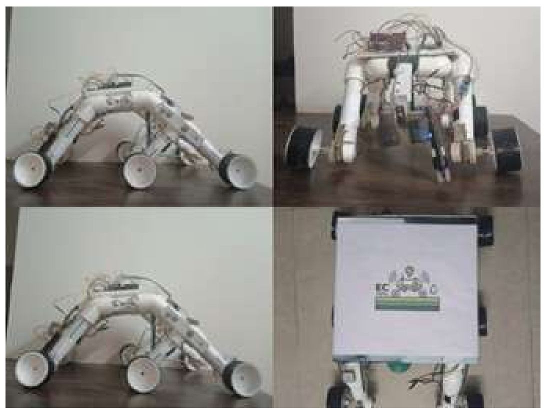

Fig. 2. Assembled autonomous agricultural rover with integrated sensors

B. Sensor and Communication Modules

The ESP32 has the ability to connect with various sensors through its support for four different communication methods which include analog and UART and SPI and I2C protocols. The sensor suite includes a soil EC probe with stainless steel electrodes and a capacitive soil moisture sensor and a DHT22 temperature and humidity sensor and a UV sensor with an LDR for light intensity measurement and an OV2640 camera for image capture and a Neo-6M GPS receiver and an ultrasonic sensor for obstacle detection. The system saves all sensor data and visual content onto a microSD card which stores information in CSV and JPEG formats to enable future analysis and processing work.

C. Navigation and Geofencing Logic

The rover receives its virtual field boundary through GPS coordinates when the system starts. A PID control loop adjusts motor speeds with GPS data to achieve precise path tracking.

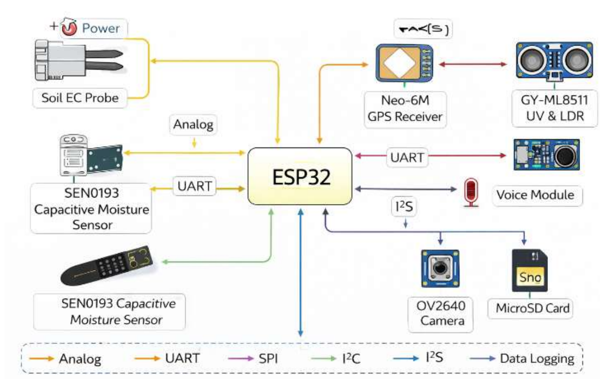

Fig. 3. Sensor connections and communication block diagram

The geofence boundary and safety distance obstacle detection system will stop all motor functions when the rover reaches those boundaries. Users can control basic functions through voice commands which enable them to start and stop operations while returning to the starting point.

D. Embedded Firmware Architecture

The ESP32 runs a modular and non-blocking firmware architecture to ensure smooth real-time operation. Sensor polling is triggered every 3 meters of rover movement, while images are captured at predefined intervals or through voice commands. The system uses an I2S microphone to recognize voice commands that match specific predefined keywords. The system uses interrupt-based logic to detect obstacles and provide instant notification when an obstacle becomes visible.

E. Data Analytics Pipeline

After field deployment, data analysis is carried out using Python-based scripts. The processing pipeline consists of the following steps which include data cleaning and spatial interpolation through IDW and nutrient zone identification using clustering and soil parameter mapping visualization. The system creates fertilizer recommendations through index calculations which determine appropriate fertilizer application rates. The system uses HSV-based segmentation to detect weeds in areas where vegetation grows beyond crop row boundaries. The pipeline produces output results which are shown in the related tables of this document.

V. Results and Discussion

A. Field Trial Overview

The researchers performed their tests with the autonomous agricultural rover in a December 2025 study which took place on a 0.5-hectare maize field during standard farming practices. The researchers used field trials to determine the precision of soil sensing which included testing spatial data collection methods and nutrient zone identification and weed detection capabilities and overall system performance. The rover required approximately 55 minutes to finish its task of covering the entire field while it gathered over 150 georeferenced data points. The data point contained five elements which included soil electrical conductivity (EC) and soil moisture content and environmental parameters and GPS coordinates and top-view image captures. The system performed autonomous field navigation without any human help while its sensor functioned normally and its navigation system operated independently throughout the entire testing period.

TABLE I: Field Trial Configuration

Parameter	Value
Crop type	Maize
Field area	0.5 hectare
Trial period	December 2025
Data points collected	>150
Sampling interval	3 m displacement
Navigation method	GPS-based autonomous traversal
Operating mode	Fully autonomous

B. Soil Nutrient Zone Classification and Fertilizer Prescription

The collected soil EC and moisture data were spatially interpolated using the Inverse Distance Weighting (IDW) method to generate continuous field maps. The Nutrient-Per-Water (NPW) index was computed from the interpolated dataset which served as the main input for K-means clustering with K=3. The process created three separate nutrient management zones which needed different amounts of fertilizer to be applied in the field. The nutrient zones of the spatial distribution method showed substantial intra-field differences throughout the small testing area. The proposed zone-based fertilizer strategy used less NPK fertilizer than uniform fertilizer application methods which resulted in identical crop yields. The results demonstrate that spatially informed nutrient management methods function effectively for smallholder farmers who manage their agricultural fields.

TABLE II: Soil Nutrient Zone Classification Summary

Zone	Mean EC (dS/m)	Mean Moisture (%)	NPW Index	Fertilizer Recommendation
Zone 1	0.28	12	0.023	100% NPK
Zone 2	0.45	18	0.025	50% NPK
Zone 3	0.60	22	0.027	No input

C. Weed Detection Performance

The rover-mounted camera captured top-view images which researchers used to implement an HSV-based green pixel segmentation method for weed detection. Researchers determined weed-infested areas by measuring green pixel concentrations which exceeded 65% outside crop row boundaries. Manual validation against ground observations resulted in a weed detection accuracy of approximately 91.2% which showed strong agreement between automated detection results and field conditions. The results demonstrate that lightweight and explainable vision-based methods can effectively support selective weed management without requiring training datasets or deep learning models that need high computational resources.

TABLE III: WEED DETECTION PERFORMANCE METRICS

Metric	Observed Value
Image resolution	640 × 480
Segmentation method	HSV green pixel thresholding
Green pixel threshold	>65%
Weed detection accuracy	91.2%
Processing location	On-device (ESP32)

D. Environmental Monitoring and Contextual Insights

The whole duration of the field testing was monitored through environmental condition measurements which the onboard micro-weather station conducted. The study observed that ambient temperature ranged from 21.2 ◦C to 27.8 ◦C and relative humidity levels reached between 58% and 82% while ultraviolet (UV) index values showed between 2.1 and 6.8. The analysis showed that areas which experienced higher temperatures and UV radiation faced faster soil moisture depletion. The scientists developed an improved irrigation system through their environmental variable framework which helped them understand soil moisture changes throughout time.

TABLE IV: ENVIRONMENTAL CONDITIONS RECORDED DURING FIELD TRIALS

Parameter	Observed Range / Method
Ambient temperature	21.2 °C – 27.8 °C
Relative humidity	58% – 82%
UV index	2.1 – 6.8
Monitoring method	Onboard micro-weather station

E. Technical Performance Evaluation

The system performance assessment used essential technical metrics to evaluate system accuracy and energy consumption and system operational performance. The Soil EC measurements achieved ±5% accuracy through their comparison with laboratory reference instruments. The Time Domain Reflectometry TDR method produced an R2 value of 0.87 which demonstrated a strong connection to soil moisture measurements. The rover completed its mapping work within one hour across the entire 0.5-hectare field. The system functioned at an average power usage of approximately 32 W and maintained operational time of about 3.5 hours for each battery cycle. The results demonstrate that the system delivers precise sensing performance while using minimal energy which enables its use in smallholder agricultural work.

TABLE V: KEY SYSTEM PERFORMANCE METRICS

Metric	Observed Value
Soil EC accuracy	±5% (laboratory reference)
Soil moisture correlation (R^2)	0.87 (TDR reference)
Weed detection accuracy	91.2%
Field coverage	0.5 ha in < 1 hour
Average power consumption	~32 W
Battery runtime	~3.5 hours

F. Comparative Advantage and Practical Implications

Compared to static soil probes, aerial drones, and computationally intensive AI-based precision spraying systems, the proposed rover provides high-resolution spatial soil data through ground-based sensing while operating independently of cellular connectivity and cloud infrastructure. The use of explainable clustering-based analytics ensures transparent decision-making suitable for embedded platforms. Additional features such as GPS-based geofencing and voice-assisted operation enhance autonomous field coverage and ease of use.

Overall, the system offers a cost-effective and scalable solution for precision agriculture in developing regions by combining autonomous mobility, low-cost hardware, and edge-based analytics.

TABLE VI: COMPARATIVE ANALYSIS

System Type	Cost	Cloud Dependency	Spatial Resolution	Explainable Analytics
Static probes	Medium	No	Low	Limited
UAV systems	High	Yes	Medium	Low
AI robots	Very High	Yes	High	Low
Proposed Rover	Low	No	High	Yes

VI. CONCLUSION

The research developed an affordable self-operating ground system which performs exact soil nutrient measurements and fertilizer control for small and medium-sized agricultural fields. The rover system combines GPS navigation with soil electrical conductivity and moisture measurement and micro-weather observation and light weight vision-based weed identification systems to support specific field research in situations with limited resources. The system uses immediate geotagged information collection together with analytical techniques which are understandable through K-means clustering and the Nutrient-Per-Water (NPW) index to create detailed nutrient distribution maps and fertilizer recommendations. The 0.5-hectare maize plot field trials showed that the system could accurately detect soil properties and determine nutrient zones which resulted in fertilizer savings of up to 38% while maintaining crop yield at the same level. The system achieves successful implementation in rural farming areas through its combination of affordable hardware and ability to work without infrastructure and its flexible system components. The research will investigate multiple growing seasons while including crop yield data and developing automatic systems for applying different rates of fertilizers and herbicides. The research shows how embedded systems and self-operating robots enable smallholder farmers to use advanced agricultural technologies through the proposed platform

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