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A Review of AI-Driven Methods for Soil Fertility Prediction and Management in Precision Agricultural Process Control

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Abstract—Soil fertility is among the main parameters that influence the productivity of agriculture, plant production and sustainable use of resources. The traditional approaches of soil fertility assessment are mostly labour-intensive, intricate and less effective for decision-making. With the advent of Artificial Intelligence (AI) and precision agriculture there is the potential for intelligent systems to predict soil fertility based on sensor data, environmental and soil data. This article aims to give students an extensive understanding of soil fertility, soil health management, ways of managing agricultural processes accurately and the impact of AI on farming. A few AIs are described and the application of these AIs in soil fertility prediction and agricultural decision making are explained. The review points out the advantages of predicting soil fertility, including fertilizer management, better crop production, use of fertilizers, and minimizing environmental impacts. The comparative study of the latest research materials revealed that there are issues with data availability, model generalization, computational complexity, and the lack of attention to various soil properties. The research underscores the significance of the convergence of AI-driven predictive models and precision agriculture technologies to maintain soil health and foster sustainable agriculture practices. Finally, some current gaps in soil fertility prediction and future perspectives are given with regards to the development of an intelligent, scalable and resilient system soil fertility prediction.

Keywords—Soil Fertility Prediction, Precision Agriculture, Soil Health Management, Smart Farming, Crop Yield Optimization, Artificial Intelligence (AI).

I. INTRODUCTION

Agriculture is a very important sector in many economies, particularly in less developed countries where it is a source of food security and livelihoods. Soil fertility is the capacity of soil to provide sufficient amounts of soil nutrients and is one of the factors determining agricultural production. Expert consultation and manual testing have been carried out to

determine the soil fertility [1]. The impact of soil moisture on agriculture, ecosystem functioning and hydrology is of a significant magnitude. It directly affects plant physiological processes such as germination, solubility of nutrients, root development and transpiration. Soil moisture measurement is thus a crucial need for the effective scheduling of irrigation, reduction of water losses, improved crop yields, and climate-smart farming. The advent of precision agriculture paradigm that assists in improved decision-making, resource utilization and environmental protection using technology is good development in view of global food demand and limited supply of fresh water resources [2]. Soil moisture estimate is one aspect of this paradigm that enables water-saving, adaptive crop management, and irrigation scheduling based on data.

Conventional techniques to measure soil moisture include time domain reflectometry (TDR) sensors, tensiometers, gravimetric sampling and neutron probes, which offer very accurate measurements for a small area, but are labour-intensive, expensive and limited regionally. Furthermore, there is a time lag between the time of the measurement and the time the data becomes available, and manual measurements are not easily made in large agricultural fields with a variable soil structure [3]. These have been dealt with to some extent, and large-scale observations have been made using remote sensing technology such as optical, microwave and thermal data from satellites. But the resolution of the remote sensing data may not be very high and also may suffer from different atmospheric conditions and temporal gaps between satellite passes [4]. Hence, using field data along with computational methods is now imperative for accurate, real-time, and large-scale soil moisture forecasting.

Crop output prediction and soil health monitoring enable farmers to use resources efficiently, minimise environmental impacts, and make informed decisions [5]. But in traditional

yield forecasting and soil health assessment approaches, manual methods are commonly adopted, which are labour-intensive, time-consuming and prone to errors. In recent years, AI and ML have been making major strides as a transformative technology for precision agriculture and soil fertility. Because machine learning can understand complicated and non-linear correlations between variables, it has completely transformed this discipline.

A. Paper Organization

Here is how the rest of the paper is structured. Section II discusses soil fertility concepts and precision agricultural process control, including the impacts. Section III presents the importance of soil health and management, along with key soil characteristics and the benefits. Section IV provides an overview of artificial intelligence technologies and their applications. Section V reviews recent studies on soil fertility prediction and precision agriculture, and identifies existing research gaps. Finally, the subsequent section VI conclusions of the study.

II. SOIL FERTILITY AND PRECISION AGRICULTURAL PROCESS CONTROL

The capacity of a region's soil to offer optimal chemical, physical, and biological conditions for plant development is referred to as "soil fertility." With the addition of more organic soil amendments, rich soil might help restore plants, which in turn could lead to the development of a carbon-neutral ecosystem [6][7]. Soil fertility is a key indicator of plant nutrition, and increasing crop yields throughout their development stages is possible with a steady supply of nutrients [8]. A soil's fertility may be defined as its capacity to provide plant nutrients, leading to optimal crop yields and healthy plant development. Some of the critical variables that affect soil fertility include;

- **Availability of Nutrients:** Availability of the macronutrients nitrogen, phosphorus, potassium, and micronutrients iron, manganese, and zinc.
- **Soil Texture:** It is the textural composition of soil particles, typically comprising higher percentages of sand, silt, and clay. Its typical characteristic includes retaining water and nutrients.
- **pH Levels:** Soil pH is quantified by a pH scale that ranges between 0 and 14. pH levels in soils alter microbial activity as well as solubility of nutrients.
- **Organic Matter:** Decomposed plant and animal material has vital contributions towards the supply of nutrients and structure to the soil in question [9].

Precision Agricultural Process Control (PAPC) is a cutting-edge farming technique that leverages sensors, data analysis, automation, and control systems to oversee and control farming processes with high accuracy. The main goal of PAPC is to maximise crop growth conditions, continuously sampling the field to determine the crop's real needs for water, fertilizers, and pesticides. Precision agricultural process

control is a closed-loop system consisting of sensing, data collection, data analysis, decision making and actuation. Soil sensors, weather stations, UAVs, satellite imagery [10], and other technologies continuously collect data from the field and feed it into a cloud or an edge platform. The data gathered is used by machine learning and AI algorithms to guide automated processes, such as variable rate fertilizer and irrigation. Precision agricultural process control is able to schedule soil nutrient, moisture, and crop health tests in real time to enhance soil fertility management. It optimises the use of resources, minimises input waste and environmental impacts, reduces production costs, and boosts productivity of the crops, and is a key element of modern sustainable agriculture.

Management of soil fertility and precision agriculture process control are closely interrelated. Soil fertility is an essential input for precision farming systems and process control technologies can offer the means to apply site-specific nutrient management strategies. Precision Agriculture allows continuous monitoring and automated decision-making, helping farmers to maintain the optimum level of soil nutrients, enhance crop performance, and contribute to the long-term health of soil. These technologies therefore an important contribution to Sustainable Agricultural Development, conservation of resources and food security.

A. Impacts Of Precision Agriculture

Sustainable development cannot be complete without precision agriculture (PA) due to its many benefits, including increased agricultural production, less environmental impact, and substantial financial savings. By improving agricultural yields and company performance, PA technologies help farmers decrease operational costs by maximising input utilisation and eliminating waste. Concurrently, PA reduces the environmental effect of farming by promoting soil health, lowering chemical runoff, and conserving water. In this section, we take a closer look at these two effects, backed by facts, case studies, and a review of the indirect effects on economic performance and society.

1) Economic Impacts

The most valuable monetary gain from PA is derived from the use of inputs. By enabling the site-specific delivery of water, herbicides, and fertilisers, technologies such as Variable Rate Technology (VRT) save costs and minimise abuse. For instance, research conducted in the United States Corn Belt has shown that VRT applications may reduce fertiliser costs by as much as 15–20%. This translates to an average annual savings of \$15–30 per hectare. Using inputs only when absolutely required helps farmers save money on costly chemicals and reduces labour expenses associated with blanket applications [11].

2) Social and Indirect Economic Impacts

There are substantial social and indirect monetary impacts of PA beyond the obvious monetary benefits. Improved resource utilisation and higher agricultural yield contribute to food security, especially in rural regions that are underdeveloped [12]. As a result of PA tools assisting small-scale farmers in improving land coordination, poverty risk is reduced and income is stabilised. By increasing demand for professional help, equipment maintenance, and instructional programs, technology-driven agricultural practices often stimulate regional employment development and improve rural economies.

3) Environmental Impacts

Precise farming techniques are crucial to lowering agriculture's environmental effect. Its efforts to reduce water use are among its most notable achievements. By using real-time soil moisture and meteorological data to precisely spray water where it is needed, precision irrigation systems reduce water waste and runoff [13]. The drought-prone San Joaquin Valley in California has seen a 30% drop in water consumption thanks to these devices, which has allowed farmers to save precious crops and water [14].

III. IMPORTANCE OF SOIL HEALTH AND MANAGEMENT

The long-term viability of farming systems and the efficient harvesting of crops depend on healthy soil. Soil biology is the study of soil and all the things it contains that affect its ability to be a living ecosystem, produce plants, and provide important services to other ecosystems (Fig. 1).

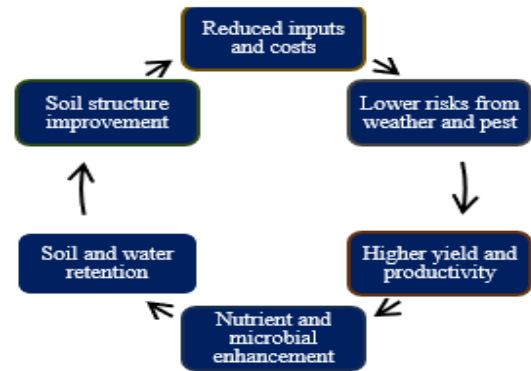


Fig. 1. Importance of soil health and management.

Soil health is essential for abundant crop yields because it improves nutrient availability, water retention, and root growth. Approximately 95% of the world's food supply comes from farms that rely on healthy soil [1]. Table I displays the results of recent developments in soil management techniques. Soil erosion, nutrient depletion, and pollution all contribute to soil health degradation, which in turn impacts agricultural production and food security. The United Nations reports that around 2 billion hectares of land are affected by degraded soils, which accounts for almost 33% of the world's total land area [15].

TABLE I. A COMPARATIVE STUDY OF ADVANCED METHODS FOR MANAGING SOIL.

Practice	Benefits	Challenges	Examples/Countries
Conservation Agriculture [16]	Improved soil health, water retention	Early expense and knowledge mismatch	USA, Brazil, Australia
Precision Agriculture [17]	Improved yield optimization and nutrient efficiency	Expensive high-tech infrastructure	USA, Netherlands, China
Organic Farming [18]	Conservation of biodiversity and soil fertility	Variability in yield and certification	India, Germany, USA
Integrated Nutrient Management [19]	A healthy diet and less pollution	Complex decision-making, cost-effectiveness	China, India, Canada
Agroecology [20]	Resilient ecosystems and sustainable land use	Knowledge-based, expanding	France, Costa Rica, Kenya
Biochar utilization [21]	Enhances water retention, increases soil fertility, and stores carbon.	High initial cost; requires particular circumstances to be successful	Brazil, Japan, USA
Cross-slope farming [22][23]	Reduces soil erosion, improves water infiltration, enhances crop yield	Labour-intensive, requiring careful preparation and upkeep	Philippines, Nepal, Ethiopia

A. Soil Characteristics and Properties

The physical, chemical, and biological components of soil influence its capacity to hold water, support plant growth, and carry out ecosystem functions. The features of the soil are depicted in Fig 2. The primary qualities of soil are as follows:



Fig. 2. Soil Properties [24]

- **Physical properties:** The physical qualities of soil include its density, texture, and structure. The texture of a material depends on the proportions of three types of particles: sand, clay, and silt. This soil's structure is dictated by these three particles. This has an impact on further effects on water retention and root penetration. The most important properties that affect plant growth are density, porosity, and aeration.
- **Chemical properties:** Chemical characteristics include nutrient concentration, pH, and CEC. Organic matter amount and soil pH are two major determinants of nutrient availability. The soil's capacity to hold and move ions, which are necessary for plant nourishment, is measured by the CEC value.
- **Biological Properties:** Soil microbes, fungi, earthworms, and bacteria influence soil biological characteristics. Bacteria play an important role in decomposing organic materials, cycling nutrients, and forming soils. Their activities are closely related to the fertility and health of soils.
- **Organic matter and pH:** A soil's pH is a useful indicator of its acidity or alkalinity, which in turn affects the abundance of microbes and nutrients in the soil. There is a correlation between the amount of organic matter in soil and its structure, water-holding capacity, and nutrient availability. Organic materials added improve erosion resistance and fertility. Soils with these properties are fertile, of good quality and productive, which promotes plant growth and ecosystem health.

B. Benefits Of Soil Fertility Prediction

Soil fertility prediction can be employed to provide a ballpark estimate of the amount of nutrients contained in a soil, and help the farmer make decisions on nutrient management and crop production practices. It is a true indicator of fertility and can help boost the productivity of

crops, reduce nutrient use, sustainable agriculture practices and reduce production costs. The following advantages are:

1) Crop Yield Optimization

Predictions of soil fertility help farmers to produce the maximum yield. The use of predictive models of soil fertility can assist in determining the most appropriate type and rate of fertiliser use for particular crops, to ensure the soil nutrients are readily available for best soil development and crop production. These figures enable farmers to make wise decisions on their fertilisation methods to enhance their treatment of the land and to accelerate their yield.

2) Nutrient Management

The analysis of soils may prove to be beneficial in fertiliser management in an eco-friendly approach. Crop nutrient supply plans based on soil nutrient estimates and nutrient availability could enable farmers to ensure that nutrients are supplied to the crop in rates that are more in line with the plants' requirements. This will provide the plant with the necessary nutrients for optimal growth without the danger of overfertilisation which can have a negative impact on the environment [25].

3) Environmental Impact Assessment

Models for predicting soil fertility may help in assessing the potential effects of agriculture on the environment. These models may predict the potential contamination of neighbouring bodies of water with nutrients by considering variables such as runoff and leaching. This information can enable land managers and policymakers to better reduce the impact on land.

4) Precision Agriculture

Precision agricultural techniques can be implemented by incorporating soil fertility prediction and other technologies, including remote sensing and GIS. Farmers can use site-specific fertilisers and map soil fertility types in a region to understand and apply the relevant amount of nutrients as farm-specific soil conditions change. This focused strategy may maximise the utilisation of beneficial resources, minimise fertiliser waste, and improve typical crop yield and health.

5) Land Use Planning and Decision Making

Soil fertility prediction models are fundamental for planned and executed land use. Soil fertility parameters can be used to assess the likely potential of soils for farming, forestry or urban development, to assist land managers in making informed decisions. Predictions of soil fertility can be used to identify soils that are low in fertility and require soil improvement or other land use for possible crop failure, but can also be used to maximise land productivity.

6) Soil Conservation

Soil conservation programs rely on accurate predictions of soil fertility. By identifying regions with soils that are prone to erosion, have poor fertility, or have an imbalance of nutrients, land managers may put appropriate soil

conservation measures in place. To improve soil structure, decrease erosion, and enrich nutrient content, these may also include terracing, contour ploughing, cover cropping, or targeted soil additions.

IV. OVERVIEW OF AI TECHNOLOGIES IN AGRICULTURE

Table II classifies the most common AI-based technologies and gives details on their uses in precision agriculture.

TABLE II. VARIOUS AI TECHNOLOGIES/METHODS/MODELS USED IN PRECISION AGRICULTURE

Category	Technology	Applications	Functions	Benefits
Machine Learning (ML)	Predictive Models	Crop yield prediction, resource optimization, disease detection	Agricultural input optimisation and crop performance forecasting via the analysis of real-time and historical data	Increased agricultural output, better decision-making accuracy, and efficient use of resources
Deep Learning (DL)	CNNs [26]	Disease detection	The use of image analysis to detect crop diseases by looking for indications like discolouration and lesions	Reduced crop loss, prompt action, and early diagnosis
Computer Vision[27]	Image Processing	Monitoring crop health, pest detection, weed identification	Crop monitoring, pest detection, and targeted herbicide application using satellite and drone image processing	Decreased use of chemicals, automated and accurate crop analysis
Robotics and Automation	Autonomous Farming Vehicles	Planting, spraying, harvesting	The use of autonomous machines and robots to do agricultural operations such as planting, pesticide spraying, and harvesting	Precision agricultural operations, less reliance on manpower, and increased efficiency
Natural Language Processing (NLP)	Advisory Systems	Real-time farming advice	The use of chatbots and virtual assistants to provide tailored agricultural advice	Enhanced productivity and decision-making
Drones and UAVs	Field Monitoring	Monitoring crop health, pest infestations, and water stress	Complete monitoring via the collection of high-resolution photos and analysis of field data	Improved crop management, prompt measures, and lower monitoring expenses
Reinforcement Learning	Autonomous Irrigation Systems	Optimizing water use	Optimising water use and crop productivity via precise regulation of irrigation systems	Significant water conservation and increased agricultural output
IoT and Sensor Networks	Real-time Data Collection	Monitoring weather, measuring soil moisture, and evaluating crop health	The use of IoT sensors to gather data for use in pest control, irrigation, and fertilisation planning	Less resource waste, better irrigation, and real-time insights
Supply Chain Optimization	Blockchain and GIS	Logistics optimization and post-harvest management	Ensuring product traceability, managing inventories, predicting demand, and optimising transportation routes	Improved market pricing, less food waste, and effective supply chain management
Vertical Farming	Growth Condition Optimization	Agriculture and Urban controlled [28]	Automating and keeping tabs on indoor agricultural environments' light, temperature, and humidity levels	Increased yields in constrained areas and resource-efficient farming
Soil Microbiome Analysis	AI-Driven Assessment	Improving crop-soil interaction	Soil microbiome analysis for improved soil health and nutrient availability	Improved soil fertility and environmentally friendly agricultural methods

V. LITERATURE REVIEW

Many papers have examined soil fertility by identifying soil constituents. The study in Zheng *et al.* (2026) introduces Swin-MBUNet, a novel system that uses the SwinTransformer encoder to extract hierarchical features from multivariate time series and a multi-branch UNet decoder to fuse features at different scales across different time periods. The model is able to provide predictions that are particular to a site and take field-level spatial variability into consideration by processing data from many sources, including 27 SoilMoisture channels from a 3×3 SpatialGrid at three depths. The model outperforms baseline designs in terms of accuracy, convergence stability, and uncertainty-aware prediction using data from winter wheat fields and meteorological and sensor sources [29].

Wanjale *et al.* (2025) show a Real-World Fertiliser RecommendationSystem Based on ML That Uses Environmental and Soil Conditions to Predict Which Fertiliser

Is Best for a Specific Crop. We have implemented various ML algorithms such as RF, NB, DT, SVM, and LR. An application for desktop fertiliser forecasting incorporates RF, the model with the highest accuracy. Reduced environmental impact, no more unnecessary fertiliser usage, and better decision-making for farmers are all outcomes of this realistic approach [30].

Shireshi and Raman (2024) suggest that agricultural operations can battle soil-borne diseases by using cloud-connected devices. The proposed system leverages IoT devices to effectively collect and store real-time data using cloud computing operations. Intelligent judgements are then made by a DL algorithm. The data on a cloud platform is analysed by a DL algorithm to provide useful insights. The DT algorithm incorporates the spatial and temporal patterns of diseases in the past, temperature and soil moisture in relation to soil-borne diseases. This study is relevant to smart agriculture as it proposes a scalable and effective soil-borne pathogen management approach. The IoT and DT algorithms not only provide the basis for data-driven farming and

precision agriculture but also enable proactive management of diseases [31].

Sunori *et al.* (2024) use ML algorithms to analyse and assess soil fertility, which is essential for sustainable agriculture. There are three different ensemble methods that are employed to build the models in MATLAB. The ensemble learning technique could be used to deal with complex datasets. Very precise predictions. The study is conducted using three parameters: pH, nitrogen content and concentration of phosphorus. This research could be useful to inform farmers and agricultural personnel of soil management options and give them a glimpse of how well ensemble techniques are performing in soil fertility classification [32].

Tanuja Toke *et al.* (2024) emphasis is on using ML to predict meteorological conditions and soil fertility, which can have significant effects on crop production. Our technology seeks to provide farmers with accurate weather predictions

and soil testing data, allowing them to make informed decisions regarding crop selection, irrigation scheduling, and pest management. We are a full-service precision ag provider with algorithms like NB for soil classification and LSTM for weather prediction. This approach both supports sustainable agriculture and boosts agricultural output by making better use of resources and reducing waste [33].

A *et al.* (2023) offer a comprehensive solution to multiple challenges in agriculture with machine learning. The proposed integrated method involves nine important abilities such as soil fertility prediction, total yield production, crop recommendation, species categorisation, soil classification, etc. It provides specific answers through ML to enable better decisions, and is a hub for agricultural workers and farmers [34].

TABLE III. SUMMARY OF RECENT STUDIES ON SOIL FERTILITY PREDICTION AND PRECISION AGRICULTURE

Author	Focus	Benefits	Challenges	Recommendations
Zheng et al. (2026)	Soil moisture prediction using Swin-MBUNet with multi-source sensor data and deep learning.	High prediction accuracy, improved convergence stability, uncertainty-aware predictions, and spatial variability consideration.	Requires extensive sensor infrastructure, large datasets, and high computational resources.	Investigate deployment in diverse agricultural environments and optimise computational efficiency for real-time applications.
Wanjale et al. (2025)	ML-based fertiliser recommendation system using soil and environmental parameters.	Accurate fertilizer recommendations, reduced fertilizer overuse, lower environmental impact, and improved farmer decision-making.	Dependent on data quality and limited validation under different soil and crop conditions.	Extend validation across multiple crops, soil types, and geographical regions.
Shireshi and Raman (2024)	Soil-borne disease prediction using IoT, cloud computing, and Decision Tree algorithms.	Real-time monitoring, proactive disease management, scalable architecture, and support for precision agriculture.	Reliance on continuous sensor connectivity and cloud infrastructure.	Integrate advanced machine learning models and expand disease prediction capabilities.
Sunori et al. (2024)	Soil fertility classification using ensemble machine learning methods.	Improved classification accuracy, effective handling of complex datasets, and support for soil management decisions.	Limited consideration of soil parameters (pH, nitrogen, phosphorus only).	Include additional soil properties and environmental variables for comprehensive fertility assessment.
Tanuja Toke et al. (2024)	Integration of soil fertility prediction and weather forecasting using Naïve Bayes and LSTM.	Better crop planning, optimized irrigation and fertilizer use, increased productivity, and sustainable resource management.	Accuracy depends on the availability and reliability of weather and soil data.	Incorporate more advanced predictive models and real-time data streams for enhanced performance.
A et al. (2023)	Unified ML platform for soil fertility prediction, crop recommendation, yield prediction, and soil classification.	Comprehensive agricultural decision support, multiple functionalities in a single system, and improved farming efficiency.	System complexity and potential scalability issues with large datasets and diverse agricultural conditions.	Conduct large-scale field validation and integrate real-time IoT-based monitoring capabilities.

Research Gap: Table III provides a summary of recent research on soil fertility prediction and precision agriculture, including the emphasis of the research, benefits, limitations, and identified gaps. It is seen from the review that most of the existing studies are dedicated to specific applications like soil moisture prediction, fertiliser recommendation, disease prediction or limited-parameter fertility classification. The approaches have some disadvantages such as diversity of the data, generalization of the models, calculation complexity and assessment of soil fertility over the entire soil. Thus, the need for a robust and scalable machine learning framework that can use variety of soil attributes and predict soil fertility with

accuracy and reliability across various agricultural environments still exists.

VI. CONCLUSION AND FUTURE WORK

High soil fertility can ensure agricultural production, ecological sustainability, and food security. Precision agriculture is changing the face of farming as we know it by allowing farmers to monitor and regulate soil and crop conditions in real-time using data. This review explored the significance of soil fertility, how AI is being applied to agriculture, soil health management and precision agricultural process control. The studies reviewed have shown that the use of ML and DL methods for the assessment of soil fertility,

determination of fertiliser needs, prediction of soil moisture and agricultural decision-making can be beneficial. More than that, although some great progress has been achieved, the existing approaches are primarily targeted at certain parameters or applications and have some restrictions in terms of data quality, scalability, computational requirements and model generalizability. The findings indicate that it is possible to improve the accuracy of predictions and achieve sustainable agriculture by utilizing the combination of different soil properties and advanced AI algorithms. Models are clearly needed that are powerful, easily interpretable, and scalable to accurately predict soil fertility in various types of agriculture.

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