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Mountain-Specific AI System for Optimized Crop Planning and Fertilizer use

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***Abstract*— A number of studies address the application of machine learning (ML) methods for assessing soil fertility and crop yield in fragile mountain ecosystems like Yunnan Province, the Indian Himalayas, and the European Alps. ML methods including Random Forest (RF), Support Vector Regression (SVR), and ensemble models have been used to predict soil depth, spatial distributions of soil organic carbon, nitrogen, phosphorus, and potassium, as well as their associations with environmental covariates (e.g., elevation, precipitation, temperature, and terrain). The models have generally demonstrated strong predictive performance (R^2 of 0.85–0.98), producing fine-resolution digital soil mapping (DSM) and reliable crop yield forecasts.**

***Index Terms*— Machine Learning, Soil Fertility, Crop Yield Prediction, Digital Soil Mapping, Mountain Ecosystems.**

I. Introduction

The conventional approach of crop planning or choosing when to plant according to the specific location of my farm adopts a linear and static approach that fails to represent the dynamic conditions of mountain farming, and instead farmers likely would have adopted an experienced-based approach that did not capture the depth of variability including soils (heterogeneity), microclimates, and market variations [1].An AI system specially designed for mountains may come with a long list of a great variety of possible benefits, for example, to the farmers it would give them tailored recommendations for the specific location of their farm and the conditions of the soil that can be used for selecting the crop and fertilizing it in a way that the production will be doubled and the profits will be increased, in this way, a piece of land that was considered unproductive can become the best place to grow a new kind of crop. The specific goals are: · To review adaptive optimization strategies, including a Hybrid Simulated Annealing Genetic Algorithm (H-SAGA), for re/allocation of responsive crops [2]. To review machine learning models for mapping soil fertility and forecasting key parameters (SOC, N, P, K, soil depth) in mountainous contexts [3]. · To review crop yield forecasting models that combined soil, climatic, and remote sensing datasets [4]. To explore fertilizer recommendation systems based on AI approaches including but not limited to ensemble learning, IoT based mapping, and neuro-fuzzy models [5].

II. Methodology

Random Forest is currently one of the most reliably used algorithms used in agriculture. The framework of ensambling of Random Forest allows for multiple modeling tools to deal with larger complex datasets that could represent more than one-dependent variable and attempt to avoid potentially problematic model overfitting.

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Random Forest has been used in research studies to predict crop yield, classify soil nutrients, and map the distribution of soil organic carbon (SOC). The literature recommends applying different types of AI and ML models to analyze agricultural datasets, including basic regression models to complicated deep networks. The use of artificial neural networks (ANN) and deep learning networks has become prominent for tasks requiring pattern recognition [6]. For example, convolutional neural networks (CNN) have shown to be highly effective for crop disease prediction using image datasets [7]. Long short-term memory (LSTM) networks are particularly helpful for analyzing time-series data (e.g., yield history, weather data) because they are capable of recognizing long-term dependencies better than more traditional methods [8]. Models that rely on gradient boosting methods such as XGBoost and Adaboost are also commonly used, as they tend to have good prediction power by combining multiple weak learners [9].

III. Inclusion and Exclusion Criteria

Inclusion and exclusion principles provide a rigorous filtering system to determine if studies or datasets have been done reliably, accurately, and are aligned with research intents [10]. In agricultural modeling endeavors, often times inclusion principles focus on the presence of needed data variables, such as soil nutrients, crop type, data on weather conditions, and yield records [11]. For example, many studies may only include datasets that have consistent rainfall, temperature, humidity, and soil fertility data, in the form of time series data [12]. Likewise, precision agriculture research includes data collected by methods from credible, standardized techniques, such as soil sampling, spectrometer, or IoT sensors, while excluding data collected through non-standardized techniques or methods [13].

IV. Literature Review

Most of the past agriculture was based on farmer experience and trial and error, and static crop planning proposals that didn't combine the complexities of ecosystem and market variability [14]. Now, with the emergence of tools such as artificial intelligence (AI) and computational models, many of these strategies are conceptually adaptive and driven by data [15].

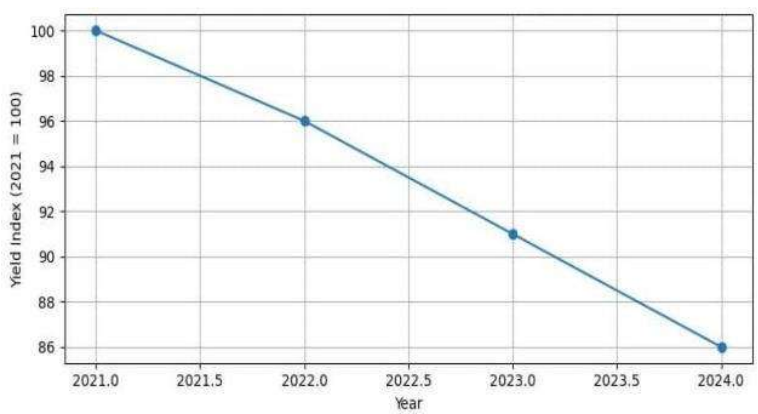

Fig 1: Recent Decline in Crop Yield

Researchers have developed frameworks that meaningfully integrate climate forecasts, and soil fertility data with crop growth models in order to improve agricultural productivity. For example, recently, we have developed dynamic crop planning strategies using hybrid optimization approaches that optimize the global search of combinations of crops and local search for yield prediction [16]. Such strategies will ensure that farmers selected crops that are appropriate to the soil type and climate resilient while maintaining profitability [17]. Another important strategy is precision agriculture, which focuses on tailoring agricultural practice to the specific features of each plot or zone in the field [18]. Farmers can now achieve a level of precision in their application of fertilizers, use of irrigation, or pest control inputs, rather than broadcasting treatments uniformly because of advances in remote sensing, satellite data, and digital soil maps [19]. Water, fertilizers, and energy are also being actively controlled and managed through real-time analytics [20]. In fact, to achieve optimal use of agricultural inputs, automated systems are being integrated for advanced irrigation scheduling, artificial intelligence - based weed management, and automated fertilizer recommendations [21].

TABLE I. RESEARCH PAPER SUMMARY

Author and Year Ref.	Purpose/ Objective	ML Model(s) Used	Issues/ Challenges	Key Analysis/ Findings
V. Goyal 2024	Using soil and environmental data to forecast agricultural yields for making better agricultural decisions.	Random Forest (RF), Multiple Linear Regression (MLR)	The existence of multicollinearity and nonlinear patterns lowers the accuracy of traditional regression methods	Researchers effectively dealt with nonlinearities using RF models, thus improving prediction accuracy
B. Su et al 2024	Determining the main soil characteristics of the mountain peak area for correct advisory in agriculture.	Random Forest (RF)	Uneven sampling and noisy remote sensing data from difficult terrains	RF shows the small soil changes that can be used for targeted management
J. G. Kalambukattu et al. 2025	Creating a soil organic carbon (SOC) map of the Himalayas to facilitate carbon storage.	Support Vector Machine (SVM), RF, XGBoost	Limited samples and complicated topography make mapping a challenging task	ML models played a vital role in the spatial prediction of SOC
Kalambukattu, J.G., Kumar, S., Das 2025	Helping soil depth variability estimations in the Himalaya to land use and conservation planning become more viable.	Cubist, Regression Trees	Sparse spatial data and steep gradients made the prediction more difficult	RF models gave reliable soil depth estimates with significant accuracy
S.Sow 2024	Use AI techniques for increasing the efficient use of agricultural inputs up to a maximum and for lowering the surplus.	Artificial Neural Network (ANN), MLR	The variety of datasets and the scalability for large farms	AI allowed the efficient use of fertilizer and water inputs, resulting in a higher yield
A. Sahoo 2023	Create AI models that gather IoT and satellite data to make the most of the farmland and keep a log of the crops.	Convolutional Neural Networks (CNN), RNN	Heterogeneous data fusion and missing data handling	The hybrid AI models extended the forecasting accuracy and the surveillance.
R. Zhu 2023	The web-based AI platform is designed to take local field-level data as input and output the best planting density for crops.	Artificial Neural Network (ANN), Genetic Algorithm (GA)	Changes in the environment and interface usability	The AI suggestions promoted higher yield up to 12-15%, which is a nice result for the farmers to put into practice.
M. Nautiyal 2025	Make a great change in crop management with the combination of ML and AI models that lead to more trustable decision-making.	Ensemble ML (Random Forest, GBM, Bagging)	The models integration with IoT and sensor data	The ensemble methods have improved the crop management by confidence and stability of the system.
S. Agaba, C. Ferré, M. Musetti, and R. Comolli 2024	Machine learning-based nutrient cycling analysis in alpine grasslands as a tool for the environment to comprehend the soil better.	Random Forest (RF)	Lack of spatial/temporal data	ML models are capable of capturing nutrient cycling patterns efficiently.
Y. Akkem, S. K. Biswas, and A. Varanasi 2023	Explore the use of machine learning for assessment of soil suitability in arid and semi-arid zones with the goal of supporting land management decisions.	Random Forest (RF), Support Vector Machine (SVM)	Soil quality degradation in dry climates and data variability	ML identified suitable agricultural zones accurately
Aijaz, N., Lan, H., Raza, T., Yaqub, M., & Raza, M. 2025	Soil fertility mapping supported by the Internet of Things and complemented by AI-generated fertilizer recommendations.	ANN, Random Forest (RF)	Real-time sensor calibration, data latency	AI models connected IoT data to accurate fertilizer dosing
Padhiary, M., & Sahoo, S. 2024	Globally, the aim is to increase the productivity of crops to a certain level and, besides that, maintain sustainability by the use of AI technologies.	Artificial Intelligence combining several ML methods (Random Forest, eXtreme Gradient Boosting, SVM)	The biggest challenge is data heterogeneity and model scalability	A higher accuracy as one of the main benefits of AI is better sustainable yield forecasting
Chetan Raju, Ashoka D.V., Ajay Prakash B.V. 2024	ML/AI implementation in precision farming with a focus on the range and depth of applications.	Ensemble ML (RF, XGBoost, LightGBM, CatBoost)	As the main issues with this research area are dataset imbalance and model integration	ML tools are found to be helpful in forecasting accuracy and farm resource optimization

Chetan Raju, Ashoka D.V., Ajay Prakash B.V 2024	The precise crop yield prediction with hybrid stacking ensemble was summed up in CropCast.	Stacking ensemble (Random Forest, Gradient (RF) Boosting, ANN)	Proper way of dealing with model complexity and at the same time avoid overfitting.	One of the most important results was that the ensemble outperformed the nonensemble methods in terms of prediction accuracy
Nimma, D., Dhanke, J.A., Murthy, G.S.N. 2025	Optimization of crop yields through big data analytics and AI-driven methods.	Data Analytics combined with RF, SVM, XGBoost	Experimenting with and integrating high-dimension datasets	AI with big data led to better sustainable yield optimization
K. Jhajharia 2023	Machine Learning and Deep Learning techniques for the prediction of agricultural yield incorporating temporal dynamics.	Random Forest (RF), ANN	The main challenges were overfitting and data transferability	The deep learning methods resulted in better temporal forecasting accuracy
S. Bai 2025	Assessment of the suitability of cropland with the help of machine learning techniques and environmental data.	Decision Tree (DT), Random Forest (RF),	The major issues were missing climatic inputs and inconsistencies in the data	Machine Learning (ML) techniques significantly helped in classifying cropland suitable for proper cropping decisions
M. Dutta 2023	Production optimization through ML-based pomological recommendation.	k-Nearest Neighbors (kNN), SVM	Sample bias and limited diversity	ML optimized fruit selection adapting to local environments
B. Basuki, R. Anggriawan, V. K. Sari, F. A. Rohman 2024	Soil classification and critical land prediction on steep slopes using ML.	Random Forest (RF), Support Vector Machine (SVM)	Unbalanced, noisy data with class imbalance	RF successfully classified degraded lands for reclamation planning
Suleymanov, A.R., Suleymanov, R.R. 2024	Machine learning identification of key drivers of soil organic carbon distribution.	Random Forest (RF)	Sparse terrain sampling	Elevation and land use were determined to be the main drivers for SOC spatial variation.
A.Suleymanov 2024	Mapping of soil properties digitally in polar regions with data sparsity.	Random Forest (RF)	The region is very different, and there is not enough data.	RF managed to make good predictions of soil properties with limited data.
Parashar, D., Kumar, A., Palni, S 2024	ML classification of land use/cover in the mountains by satellite images satellite imagery.	Random Forest (RF), Support Vector Machine (SVM)	Picture of the sky that had clouds and other small areas of the earth that had more than one kind of land	ML managed to correctly identify over 85% of the different kinds of LULC.
L. Feng 2022	Soil depth prediction using ML models and environmental correlations in complex areas.	Random Forest (RF)	Variability RF models	Generalized well providing precise soil depth maps
J. Liu 2023	Model crop–soil–climate interactions with ML and remote sensing data.	ML Regression (Linear, RF)	Handling multi-collinearities and dimensionality	ML helped quantify landscape-scale factors affecting cropping
Hegedus, P.B., Maxwell, B.D., Mieno 2023	Crop response empirical and machine learning modeling to variable fertilizer rates in field trials.	Regression, ANN	Field condition variability	ML improved fertilizer optimization in real farm conditions

V. Research Questions

RQ1. What trend is observed in AI-based agriculture research over recent years?
RA1. The increasing interest in precision and sustainable agriculture has led to a rapid exponential growth of research studies in the peripheral area since 2022 as a result of major advances in machine learning, higher accessibility of remote sensing data and increased research on AI Applications for agriculturists working in mountainous regions.
RQ2. Which machine learning models are most commonly used in crop and soil studies?
RA2. The most common ensemble models in academic literature are Random Forest and XGBoost, while the most popular Machine Learning classification algorithms are Support Vector Machines. The most common types of Deep Learning Methodologies used in Spatially and Temporally Dependent Data Analysis include Convolutional Neural Networks and Long Short-Term Memory Networks; however, there is an increasing trend toward the use of hybrid products/products utilizing complex optimization techniques.
RQ3. Why do most studies prefer ensemble or hybrid ML models?

RA3. Using ensemble techniques can limit overfitting and variability. Ensemble techniques also combine several models and therefore, model the effect of non-linear soil/climate interactions very well. Hybrid Techniques Improve the ability to optimize in complex terrain, thus, providing us with consistent results across multiple datasets, so they are usually considered to be the best option for agricultural applications in the real world.
RQ4. Why is soil property mapping important in mountainous agriculture?
RA4. Mountain areas have a large amount of soil variation due to soil depth, organic carbon, and nutrient levels; therefore; ML mapping allows us to capture this vast amount of information. With soil maps that accurately identify crop suitability, using them to make decisions about crop suitability can assist with developing sustainable land use.

VI. Conclusion

These methods may result in achieving some success under specific circumstances; nonetheless, they are incapable of addressing the increasingly complex issues caused by climate variability, soil degradation, and market volatility. AI and ML are the computational brains which can handle operations on large, multidimensional datasets such as soil chemistry, topography, weather dynamics, and crop genetics. The Hybrid Simulated Annealing–Genetic Algorithm (H-SAGA) is an example which depicts the scenario of adaptive intelligence by combining optimization and forecasting for new, adaptable, context-specific crop plans in an unexpected way. These models can map Soil Organic Carbon (SOC), nutrient balance, and water retention with unprecedented precision. Furthermore, integration with deep learning architectures such as CNNs and LSTMs allows continuous monitoring of soil dynamics and yield variations, empowering farmers and policymakers to make evidence-based decisions. Farmers gain access to real-time insights into soil moisture, nutrient concentration, and disease outbreaks.

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