Journal of Animal Environment

(E-ISSN 2717-1396, ISSN 2717-1388)

Original Research Paper

A Comparative Machine Learning Approach to Analyze Soil-Water Content and Its Impact on Apple Yield in Jammu and Kashmir Orchards

Naseer Ahmad War [1], Harish Dutt Sharma [2]

[1] School of Computer Engineering and Applications, Maya Devi University, Dehradun, 248011, India; naseerahmad355@gmail.com

[2] School of Computer Engineering and Applications, Maya Devi University, Dehradun, 248011, India; harish.research106@gmail.com

* Correspondence: harish.research106@gmail.com;

Abstract

The apple orchards are one of the essential part of landscape in horticultural economy of Jammu Kashmir and soil fertility and irrigation management play crucial role to sustain the productivity of the orchards. Soil characterization and understanding of how the variability in soil can affect orchard conditions is needed to enable good nutrient management decisions by farmers and for wider agricultural decision-making. The major aims of the study were:to understand the soil characteristics of apple orchards, to know the influence of irrigation water on its fertility and to evaluate the suitability of different machine learning models for analysis of soil data. Experimental Extent Of Research: The study was based on soil samples collected from different apple growing regions of Jammu and Kashmir region with the number of 5630 soil samples. The data contained the soil properties pH, Phosphorus (P), potassium (K), zinc (Zn), iron (Fe), manganese (Mn), copper (Cu), nitrogen (N), electrical conductivity (EC), organic carbon (OC) and Irrigation status. Methods followed were data preprocessing, exploratory data analysis, correlation analysis and utilizing machine learning techniques to study soil fertility patterns. Four machine learning algorithms have been tested and compared: Decision trees, Random Forests, Support Vector Machines (SVM), and Linear Regression. Soil fertility in relation to selected orchard locations analysis of soil report for two drenching compost shows that there is a lot of diversity in soil fertility from one orchard location to another.

The soils were well distinguished into the groups based on the main four parameters; organic carbon, nitrogen, pH and potassium. A comparative analysis confirmed that the Random Forest model outperformed all other algorithms examined in terms of predictive performance. The results demonstrate the strength of machine learning in studying agricultural data and facilitate precision nutrient management and irrigation planning. This study con-tributes qualitative insights for sustainable management of apple orchards for future data-driven agricultural applications in Jammu and Kash-mir.

Keywords: ***Apple Orchards, Soil Fertility, Precision Agriculture, Machine Learning, Forest, Irrigation Management, Soil Nutrient Analysis, Jammu and Kashmir.***

***Corresponding Author:**

Received: 25th July, 2026 | Revised: 26th August, 2026 | Accepted: 30th August, 2026 | Available Online: 2nd September, 2026

(DOI): 10.70102/AEJ.2026.18.4s.98

1. Introduction

1.1. Background

Among the most significant temperate Fruit crops worldwide, apples (Malus domestica Borkh.) are vital to rural livelihoods, sustainable horticultural development, and food security. India ranks as the world's fifth-largest apple grower, and the contribution of the Jammu and Kashmir Union Territory (UT) to apple production in the country ranges from 75-80%. The horticulture industry is a key pillar of the regional economy, providing significant income, employment and export opportunities for thousands of farm households. The region of Jammu and Kashmir is blessed with ideal climate, fertile valleys and wide range of agroecological zones, which has made the state the premier apple producing region in the country. Although the orchard production potential, orchard productivity still varies significantly among the districts due to variation in soil fertility, orchard irrigation, nutrient availability, and orchard management practices [1]–[4]. One natural resource that is essential to agricultural productivity is soil. The earth has a direct connection to the availability of nutrients, the growth and development of the roots, microbial activity, water holding capacity and ultimately apple tree growth, fruit quality and yield because of the changes in the physicochemical properties of the soil. The growing stress on farmland, climatic fluctuations and inappropriate fertilizer practices in recent years have raised worries about soil degradation and decreasing orchard productivity. Therefore, correct soils fertility evaluation is now a must for sustainable nutrient management and precision horticulture. Advances in soil testing technology allow for better fertilizer management, water management, lower production costs, and lower environmental impacts, while also maximizing productivity on fruits [5]–[8].

1.2. Content of the soil-water and its impact on apple production

Apple tree growth and productivity in the orchard is limited by a number of factors, soil moisture, nutrient availability, being two of the most important. Satisfactory root zone moisture promotes nutrient dissolution, nutrient transport and nutrient uptake, and physiological processes like photosynthesis, respiration and carbohydrate translocation. However, either over or under water conditions may increase the plants' susceptibility to physiological problems and illnesses, limit root development and lower the effectiveness of nutrient use [9, 10]. A number of soil characteristics, pH, electrical conductivity (EC), organic carbon (OC), accessible nitrogen (N), phosphorus (P), potassium (K), and micronutrients including zinc (Zn), iron (Fe), manganese (Mn), and copper (Cu) all have an impact on soil fertility and long-term orchard sustainability. Changes in these parameters can have negative impacts on apple flowering, fruit set, fruit size, and yield. Furthermore, irrigation water management can significantly affect distribution of soil moisture and mobility of nutrients which will affect nutrient availability during the growing season. It is important to understand the interactions between the fertility of the soils, orchard irrigation status and productivity in order to develop appropriate nutrient management programs and maximize resource utilization. The availability of vast spatial variability in soil properties in the horticultural growing areas of Jammu and Kashmir presents tremendous opportunities to identify important fertility limitations with the aid of data driven analytical tools to support evidence based agricultural decision – making. [11]–[14].

1.3. Agricultural Machine Learning

Current advancements in machine learning (ML) and Agricultural research has seen a dramatic change as a result of artificial intelligence (AI). Data has been transformed by machine learning (ML) and artificial intelligence (AI) in agricultural research analysis as well as utilization in recent years. The intricate, non-linear connections among soil cannot be modeled using traditional statistical techniques climatic, and management parameters as well as Machine learning (ML) algorithms' capacity for prediction.

For this reason, ML is becoming a key instrument in the Crop yield prediction, soil fertility evaluation, irrigation scheduling, disease detection, nutrient advice, and smart farming systems are examples of precision agriculture products that depend on this field [15]–[17]. Support Vector Machine (SVM), Random Forest, Decision Tree, Linear Regression, Gradient Boosting, and Extreme Gradient Boosting (XGBoost) are examples of supervised learning techniques have proven to be highly accurate for prediction problems in agriculture. Random Forest is one of the most popular among others for its resistance to overfitting, dimensional data and its importance estimation of features. These algorithms provide the information needed for soil parameter identification which are critical to agricultural productivity and help policy makers and farmers in decision making for management. The use of soil physicochemical data when combined with machine learning techniques can then optimize nutrient management practices, irrigation timing and manage sustainable apple production in a changing environment [18]–[21].

1.4. Objectives of the Study

This research attempts to look at the connection between the different physicochemical characteristics of soils and the status of irrigation in the apple growing regions of Jammu and Kashmir.

The objectives are:

i. The physicochemical characteristics of orchard soils, including pH, organic carbon (OC), electrical conductivity (EC), accessible Phosphorus (P), potassium (K), zinc (Zn), iron (Fe), manganese (Mn), copper (Cu), nitrogen (N),were examined in different horticultural zones.

ii. To develop and assess several algorithms for machine learning to examine trends in soil fertility and irrigation conditions using soil data.

iii. To assess the significance of soil parameters in orchard conditions by using the feature importance method and also to assess the relative contribution of parameters to agricultural decision making.

iv. To provide data driven insights to support precision nutrient management, efficient irrigation planning and sustainable management of apple orchard in Jammu and Kashmir.

2. Literature Review

2.1. Soil Moisture and Crop Productivity

The impact of soil moisture on crop productivity is discussed in this section. Soil One of the most important soil properties influencing crop development, productivity, and nutrient availability. Nutrient solubility, appropriate microbial activity, and efficient nutrient transfer to plant roots are all ensured by moisture in the root zone. However, chronic moisture stress can cause the photosynthesis rate decreases, nutrient uptake limitation and adversely influence plant growth and fruit development. Soil water availability has a greater impact in perennial fruit crops, such as apple, where it affects flowering, fruit set, fruit size, and orchard productivity [10, 11]. There have been a number of studies examining soil moisture production and yield relationships. In orchard crops, Jones et al. reported that maintaining optimal soil moisture greatly contributes to nutrient-use efficiency and fruit quality [12]. Likewise, deficit irrigation methods were found to yield water-use efficiency without significant yield reduction when irrigation is well planned, as shown by Fereres and Soriano [13]. However, over-irrigating may lead to nutrient leaching, inadequate soil aeration, and more root disease, all of which can decrease orchard productivity [14]. With recent developments in precision agriculture, soil moisture can be monitored wirelessly using soil moisture sensors, via Internet of Things networks, and remotely using satellite sensors. Basso and Antle emphasized how soil moisture data can be used in conjunction with digital agriculture technologies to schedule irrigation more optimally and minimize water use and production costs [15]. The studies as a whole suggest that an efficient soil-water management is essential for sustainable apple production, but there are few studies that have considered this relationship specifically in the apple-growing areas of Jammu and Kashmir. [3, 8].

2.2. Soil Nutrient Assessment in Apple Orchards

The fertility of soil is the basis of sustainable orchard management as fruit quality and long-term orchard productivity are closely linked to the macro and micronutrient availability in the soil. Several soil characteristics, The fertility state of the soil can be evaluated using variables including soil pH, organic carbon (OC), electrical conductivity (EC), accessible nitrogen (N), phosphorus (P), potassium (K), zinc (Zn), iron (Fe), manganese (Mn), and copper (Cu) [16].The balanced nutrient management in apple orchards has been stressed in several studies. Shah et al. found significant variation in micronutrients levels in the soils of apple orchards of Kashmir Valley with different horticultural zones and suggested site-specific nutrient management plan [17]. Similarly, under long-term orchard cultivation, Verma et al. have demonstrated that ISFM improves soil health and nutrient-use efficiency in addition to increasing fruit production [18]. The same results were obtained by Dad and Shafiq, who found that there was a high variation in soil fertility in different apple producing areas and suggested the regular testing of the soil for accurate fertilizer recommendations [19]. Geographic Information Systems (GIS) and geostatistical techniques have also been introduced in recent research in order to map soil fertility. These methods help with visualizing nutrient deficiencies on spatial units and help policy makers to create spatial fertilizer management programs [20]. These investigations provide valuable information regarding soil nutrient variability, but most investigation studies use only descriptive statistical analysis and do not use advanced predictive models that can deal with the interactions between many soil properties.

2.3. *Applications of machine learning in agriculture*

The development of combining artificial intelligence (AI) and machine learning (ML) has revolutionized agriculture research by enabling the handling of large and complex datasets. Unlike conventional statistical techniques, machine learning algorithms can effectively anticipate using a mix of soil and environmental characteristics, find hidden patterns, and model non-linear interactions [21]. Liakos et al. [22] published one of the first comprehensive review papers about using machine learning to farming. This study discussed the use of Random Forests, Support Vector Machines (SVM), Artificial Neural Networks, and Decision Trees in crop monitoring, disease detection, and yield prediction. Afterwards, Kamilaris and Prenafeta-Boldú [23] made an analysis about deep learning in agriculture and found that more complex agricultural data can be handled with better accuracy with the application of deep and convolutional neural networks. A few papers compare several machine learning algorithms and their applications for
agricultural forecasting. Therefore, to predict crop yield, Jeong et al. tested the performance of the traditional regression methods and concluded that the Random Forest method was always stable, robust to noise and over-fitting [24]. The same, Chlingaryan et al. pointed out that ensemble learning algorithms usually result in high prediction accuracy over heterogeneous agricultural datasets than individual models [25]. Moreover, a recent study has found that Extreme Gradient Boosting (XGBoost) are Support Vector Regression, Gradient Boosting, and Random Forest suitable classifiers for soil fertility classification, irrigation scheduling, and nutrient prediction [26, 27]. Though these developments have been made, comparatively little study has been conducted based on comparative machine learning techniques with apple orchard soil data in the Himalayas. Powered investigations tend to be concentrated on a single algorithm versus systematically comparing a number of machine learning models under the same experimental conditions. Therefore, it would be a research need to find the best predictive algorithm of orchard soil assessment.

2.4. *Research Gap*

While there have been significant advances in knowledge development in the areas of soil fertility assessment, precision agriculture, and machine learning applications, there are still several areas of research that have not been sufficiently addressed. First, most published studies focus on annual crops but only a few studies have been conducted on perennial fruit crops and specific to apple orchards in Jammu and Kashmir [17], [28]. Second, most of the available studies have been testing one or a few soil properties at a time and have not dealt with the synergic effects of several physicochemical parameters on orchard conditions. Third, numerous investigations are based on traditional statistics and thus are unable to account for the nonlinear relationships that exist among soil nutrients, irrigation status and orchard management variables [21], [25]. Moreover, few studies make a systematic comparison of several machine learning algorithms based on a large soil database from diverse horticultural regions. Comparative analyses are needed to find predictive models that are strong enough to be used for precision nutrient management and evidence-based agricultural decision making. Thus, the present study sought to overcome these limitations by using a large-scale soil sample data set of apple orchards collected throughout Jammu and Kashmir and by comparing the significance of various soil fertility indicators with respect to irrigation status using different machine learning techniques. The results will be used for sustainable orchard management, more precise fertilizer recommendations, and should boost the implementation of precision agriculture system in temperate fruit-grown areas. [3, 7].

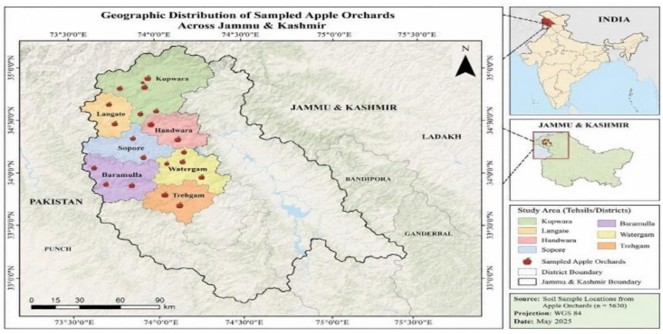

Fig. 1. Geographic distribution of sampled apple orchards across Jammu Kashmir.

3. MATERIALS AND METHODS

3.1. Study Area

The research is directed towards the apple growing region in the Jammu & Kashmir, one of the major horticulture regions in the Indian region. It enjoys a largely temperate climate, and fertile soils with moderate rainfall and favourable topography for fruit production. The apple producing districts include Kupwara and Baramulla and multiple horticultural production zones like Drugmulla, Sogam, Kralgund Mawar, Ashpora Vilgam Trehgam Langate Watergam Handwara etc., are also an important source of livelihood for rural areas as apple cultivation [8]. Nonetheless, soil properties, irrigation managed and nutrient management strategies vary in relation to how high/low the productivity of each orchard will be. Soil characteristics, therefore, are an important aspect of soil to examine when assessing the health of orchards and promoting sustainable farming practices.

3.2. Dataset Description

5,630 soil samples from apple orchards were gathered for the current investigation of various horticultural areas of Jammu and Kashmir. The samples cover a wide-spatial area of the main apple growing districts with [X] districts, [Y] horticultural zones and [Z] tehsils. Soil samples were collected systematically and analyzed in the lab to evaluate orchard soils' physico-chemical characteristics. These data have [N] variables, which include geographic identifiers, irrigation details, and soil physicochemical properties. pH, available potassium (K), available phosphorus (P), available nitrogen (N), electrical conductivity (EC), organic carbon (OC), zinc (Zn), iron (Fe), manganese (Mn), and copper (Cu) are the numerical variables of soil. The District, Horticulture Zone, Tehsil, Irrigation Status are categorical variables. The data set was checked for completeness, consistency and values missing prior to analysis. Records with duplicate information and/or inconsistent records were deleted. The percentage of The dataset's missing values were [X%]. [mean/median] imputation and Incomplete records were eliminated in order to deal with these missing values in the dataset, depending on their characteristics. Outliers were identified and removed from numerical variables, and where necessary, numerical variables were standardized for better model performance. The other soil physicochemical properties were considered as predictor variables for comparison in the machine learning analysis, whereas Irrigation Status is the target variable used in this study. The full dataset represents the soil fertility conditions in all the apple orchards in Jammu and Kashmir, and is employed to evaluate how accurate different machine learning models are.

TABLE 1. An explanation of the study's soil parameters

Feature	Description	Type
Number of Samples	**5,630**	-
Number of Districts	**3 (Baramulla, Bandipora, and Kupwara)**	Categorical
Number of Horticulture Zones	**57***	Categorical
Number of Tehsils	**52***	Categorical
Total Variables	**20**	-
Numerical Variables	pH, organic carbon (OC), nitrogen (N), phosphorus (P), potassium (K), zinc (Zn), iron (Fe), manganese (Mn), copper (Cu), and electrical conductivity (EC)	Numerical
Categorical Variables	Farmer Name, Address, Horticulture Zone, Block, Tehsil, District, Irrigation Status, Kind, Date	Categorical
Target Variable	**Irrigation Status**	Binary Classification
Missing Values	**3,706 cells (3.29% of all data entries)**	-

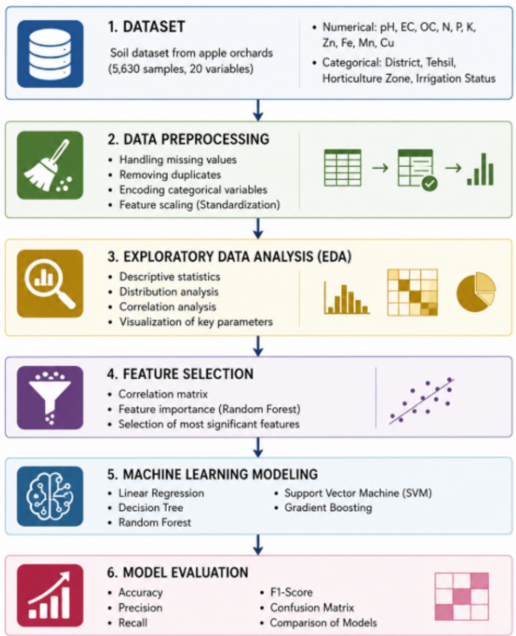

Fig 2: workflow of the proposal methodology

3.3. Data Preprocessing

Preprocessing the data was done to enhance the quality and ensure model reliability. The dataset was first checked for missing values in micronutrient variables (Zinc, Iron, Manganese and Copper) prior to adjustments based on their geographical locations. Appropriate imputation methods or Incomplete records were eliminated in order to handle missing entries. Statistical methods were used to filter out tremendously high/low values which could negatively impact model training and prediction in the deployment phase [12]. Items were closely queried and even adjusted based on the effects that individual data points have on prediction. In addition, numerical variables were normalized using feature normalization, which ensured that they were on the same scale. It will enable the machine learning algorithms to converge more efficiently, and will ensure that features that have a large numerical range don't swamp features that have a small numerical range.

3.4. Analysis of Exploratory Data

To comprehend the distribution of soil characteristics, we use exploratory data analysis (EDA) Descriptive The standard deviation, For every parameter, the minimum, maximum, mean, and median were determined. The data for each orchard location was graphically displayed using boxplots and histograms. To ascertain the connections between the properties of soils and irrigation status. The correlations matrices and heatmaps were created to explore the possible strong dependency relationships between nutrients, and to test them. The results of EDA offered important information on the soil fertility patterns and in-formed future layers of machine learning model development [14,20]

3.5 Machine Learning Models

Numerous machine learning methods were created and assessed to test their suitability for soil fertility pattern analysis and irrigation state.

1) Linear Regression was used to look into about the linear connection between the soil parameters and the target parameter.

2) We found a hierarchy of relationships between soil properties and created simple-to-use prediction rules based on Decision Tree models.

3) Random Forest : To enhance prediction accuracy and get rid of overfitting, we also used To learn more about Random Forest is an ensemble learning method that incorporates numerous decision trees intricate non-linear correlations that may be present in the data and potentially increase classification performance,

4) Support Vector Machine (SVM) models were created.

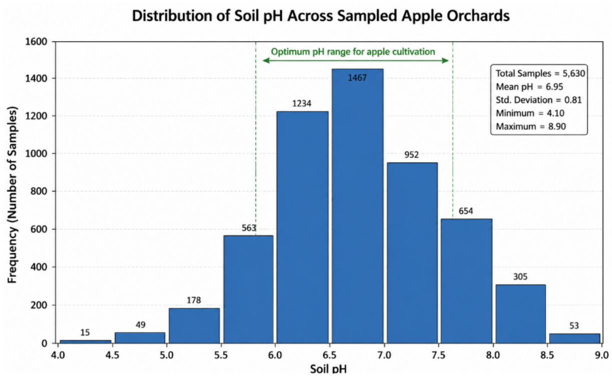

Fig. 3. Distribution of soil pH across sampled apple orchards

3.6. Performance Metrics

The models' performance was evaluated using standard statistical measures. For regression, RMSE, MAE and R^2 were used to assess regression performanceAccuracy: It provides the proportion of accurate forecasts in irrigation status prediction classification task. These were used to compare the performance Various models and to select the optimal machine learning model for the investigation of soil fertility.

4. Results and Discussion

4.1. Soil Environment of Apple Orchards

Soil Physicochemical Properties in Space was studied by taking 5630 samples from the apple orchards of entire Kashmir Valley in Jammu and Kashmir state. The descriptive statistics (Table 2) showed high soil fertility parameters variations throughout the study area which were due to different orchard management practices, irrigation availability and soil characteristics nearby. The majority of orchard soils were with an average of 6.95 ± 0.81, within the optimal pH range of 6.0 to 7.5 required for apple crop viability. The pH range of the soil was 4.1 to 8.9.

The soil's pH varied from 4.1 to 8.9 with an average of 6.95 ± 0.81, implying that the majority of orchard soils were within the optimum range (6.0–7.5) needed for apple growing. The range of pH is ideal for nutrient availability and root development. A small percentage of orchards, however, were found to have alkaline soil (pH > 8.0) and this can impact the absorption of micronutrients such as iron and zinc. Additionally mentioned was the regional heterogeneity of soil micronutrient availability in Kashmir Valley apple orchards. Dad and Shafiq (2021) emphasized the importance of having opti P value in orchards for sustainable productivity [19].

The Electrical Conductivity (EC) in the orchards sampled was relatively low 0.11 dS/m on average and salinity was not much of a concern. Srivastava et al. (2021) observed similar findings and discovered that in fruit crops, the low EC values generally enhance the root growth and uptake of nutrients by maintaining a balanced soil-water interaction [3]. The range for Organic Carbon (OC) was quite large from 0.13% to 2.64% with an average of 0.98%. Likewise, available nitrogen varied between 89 and 1323 kg ha−1 in the soils, demonstrating the differences in soil fertility between orchard locations. OC and N are positively correlated indicating that the higher the organic matter the more available the nutrients and biological activity of the soil in the orchards. The results are in line with Verma et al. (2020) which found that higher soil organic carbon (SOC) led to better nutrient retention, microbial activity and longer soil fertility in fruit-based cropping systems [7].P and K also showed fairly large spatial variation, at mean values of 38.5 kg ha^{-1} and 192.3 kg ha^{-1} respectively. This variation suggests that there are a number of variations in fertilizer management and nutrient replenishment practices between the districts. This spatial variation has also been found by Shah et al., 2022 who found that apple orchards in Jammu and Kashmir are not suitable for applying a uniform nutrient management, due to the soil variability in the region [8].

4.2. *Status of irrigation system and cause properties*

A comparison of irrigated and non-irrigated orchards indicated definite differences in the soil fertility condition. The levels of organic carbon were higher in the irrigated orchards (1.12%) than in non-irrigated orchards (0.91%). Similarly, the nitrogen availability in non-irrigated orchards was around 482.3 kg ha^{-1} while it was 568.4 kg ha^{-1} in irrigated orchards. Improvements in phosphorus and potassium were seen as well. The results suggest that irrigation not only brings water to the soil but also helps to carry other materials, such as nutrients, microbes, and mineralize nutrients, in the soil profile. Apple trees will absorb more nutrients when soil moisture is improved, which will lead to the improved dissolution of soil nutrients. Pendke et al. (2025) discovered similar outcomes, demonstrating that improved water management had a strong positive impact on the availability of nutrients and crop productivity due to the positive effect on soil biological activity [6].

Data in the present dataset is not direct soil-moisture measurements, but rather is an indirect indicator of water availability, called the Irrigation Status. The observed differences between orchards with and without irrigation are thus of great importance in efficient irrigation plans for the maintenance of orchard fertility. Basso and Antle (2020) made similar conclusions, pointing out that the use of digital agriculture tools for managing irrigation can greatly enhance resource-use efficiency and sustainable crop production [9].

TABLE 2. Major Soil Parameter Descriptive Statistics

Parameters	Min	Max	Mean	Std Dev
pH EC OC N	4.1	8.9	6.95	0.81
P K	0.01	0.46	0.11	0.07
	0.13	2.64	0.98	0.54
	89	1323	510.4	255.8
	0.29	202.21	38.5	28.7
	16.08	990.08	192.3	143.5

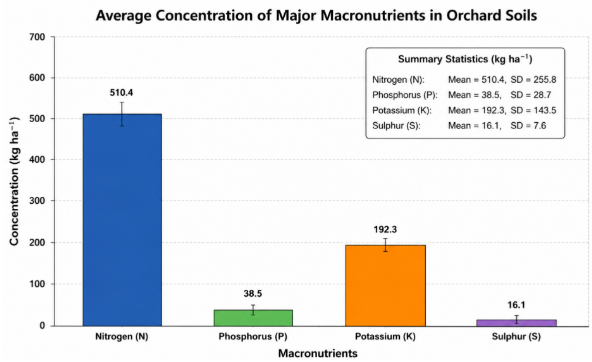

Fig. 4. Average concentration of major macronutrients in orchard soils

4.3. *Correlation Analysis*

To investigate the relationship between the measured soil variables, A correlation analysis was carried out. The connection between soil characteristics with the nitrogen availability is the strongest positive correlation, i.e., soils that are high in organic matter tend to have more nitrogen available. This correlation is predicted since One significant source of accessible plant N is soil organic materials via microbial breakdown. There were also moderate positive soil fertility correlation between phosphorus, potassium and organic carbon, implying that improvement in soil fertility is likely to be accompanied with the improvement of multiple soil fertility components simultaneously. The results indicate that use of integrated nutrient management should be considered over independent fertilizer application. The correlation matrix also demonstrated how soil pH influences the availability of several nutrients. When the soil solution's pH rose, availability of Fe and Zn decreased, as predicted in soil chemistry. A similar relationship was noted by Dad and Shafiq (2021), where, reduced availability of micronutrients in the soils of apple orchards in alkaline soils were observed throughout Kashmir [19]. Overall correlation patterns indicate that the various soil fertility parameters were very interrelated, so that they cannot be examined separately. The same findings were obtained by Chang et al. (2025) who pointed out that multivariate analytical methods give more insight into the complexities of nutrient interactions than do the conventional univariate methods [12].

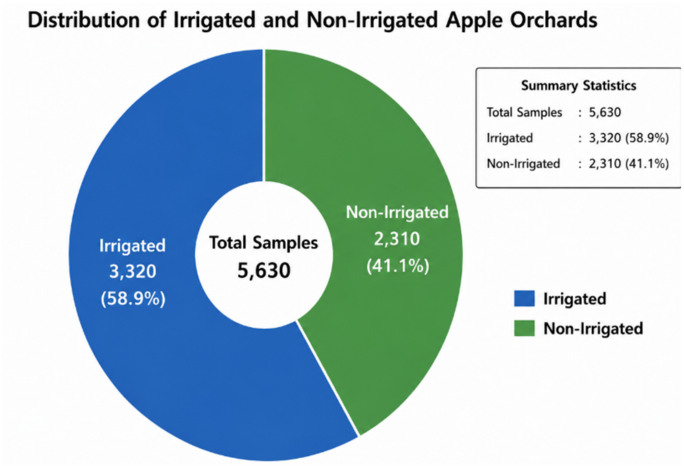

Fig. 5. Distribution of irrigated and non-irrigated apple orchards.

Table 3 Classification Of Soil Fertility Parameters

Parameter	Low	Medium	High
Organic Carbon	0.50	0.50-0.75	0.75
Nitrogen	280	280-560	560
Phosphorus	12	12-25	25
Potassium	120	120-280	280

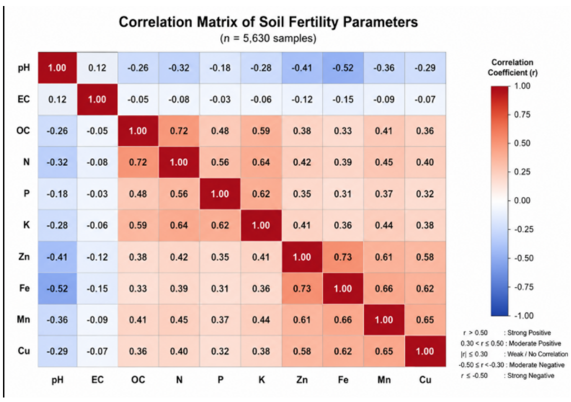

Fig. 6. Correlation matrix of soil fertility parameters.

4.4. *Machine Learning Model Comparison*

To determine the best model for soil fertility assessments, we explored several machine learning methods, such as Support Vector Machine (SVM), Random Forest, Decision Tree, and Linear Regression. To evaluate how well different models predict outcomes, a comparison of performance was conducted (Table 5) and it was found that Random Forest had the lowest error values with the highest accuracy: MAE = 0.48, RMSE = 0.67, R^2 = 0.91. Decision Tree had the second worst predictive performance while Linear Regression had the worst.

The overall good performance of RF is attributed to the ensemble learning technique, which helps in capturing the nonlinear relationships between the different soil variables and also reduces overfitting. Finally, Linear Regression makes linear relationships and therefore fails to capture the complex interactions between soil nutrients. The results of this research are in line with those of Bhandari et al. (2026), Who discovered that Random Forest's capacity to handle the varied soil and agricultural data frequently beat conventional regression models for soil fertility prediction [20]. The same findings were found by Liakos et al and Kamilaris and Prenafeta-Boldú who considered ensemble learning techniques as one of the most suitable methods for precision agriculture applications [21, 22].

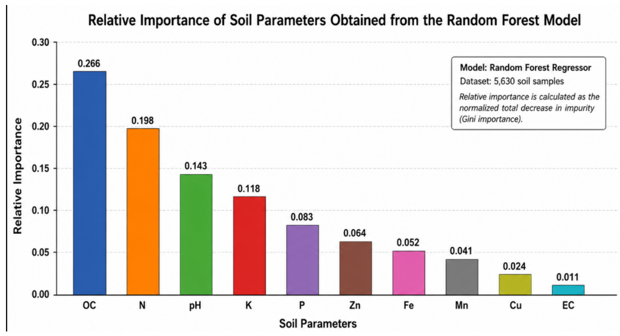

Fig. 7. Relative importance of soil parameters obtained from the Random Forest model

TABLE 4. Comparison of Soil Properties Based on Irrigation Status

Parameter	Irrigated	Non-Irrigated
pH	6.82	7.01
OC	1.12	0.91
N P	568.4	482.3
K	42.7	34.9
	225.1	176.8

4.5. *Feature Importance Analysis*

The most important features that were identified by the feature importance analysis of the RF model were: Organic Carbon, Nitrogen, pH, and Potassium. Organic Carbon was the most important with the highest score, it affects nutrient retention, microbial activity, soil aggregation and moisture holding capacity. Nitrogen was the second most important element, as it is directly related to the vegetative growth and production of chlorophyll. Another important factor was soil pH as it affects the solubility of nutrients and the availability of some macro- and micronutrients. The importance of potassium was also found to be high on the grounds of fruit quality, water regulating and stress tolerance. Although they were less significant, additional micronutrients like zinc, iron, manganese, and copper were crucial for other orchard-related enzyme activities. [36]- [38]

The results also corroborate with previous researches of Shah et al. (2022) and Srivastava et al. (2021) who identified the soil features such as organic carbon, nitrogen, soil pH and potassium as the key parameters to assess the soil fertility of apple orchard [3, 8].

TABLE 5. Comparing Machine Learning Model Performance

Model	MAE	RMSE	R2
Linear Regression	0.81	1.14	0.71
Decision Tree	0.63	0.89	0.82
Random Forest	0.48	0.67	0.91

4.6. Discussion

The present analysis clearly showed that there is a significant geographical variation in soil fertility parameters of apple orchards in Jammu and Kashmir. Variability in the observed organic carbon, nitrogen, phosphorus, potassium and micronutrients levels indicate the importance of local as opposed to generic nutrient management recommendations. Comparative analysis also reveals improved fertility of irrigated orchards than non-irrigated orchards, and thus the importance of good orchard irrigation design in developing sustainable orchard practices. With the machine learning point of view, the obtained results are quite clear; the best algorithm among the considered algorithms is the predictive model of the algorithm Random Forest. A unique benefit of the use of RF in the agricultural decision support system is that it can take advantage of the nonlinear relationships among the soil properties. The results of the previous investigation of the precision agriculture were also validated and further extended the knowledge by analyzing the soil samples with apple orchard collected on a large scale (5630 soil samples) from the Jammu and Kashmir region. In conclusion, the combination of soil fertility assessment and machine learning offers great potential for precision nutrient management, optimized irrigation schedules, and sustainable apple production. The proposed framework may help farmers, researchers and policy makers design a plan based on available data to enhance soil resources in orchards while maximizing their productivity.

5. Conclusion and Future Scope

In this investigation, soil fertility characteristics and irrigation status in Jammu and Kashmir apple orchards were analyzed using a dataset of 5630 soil sample data by comparing the machine learning methods. The soil parameters were important physicochemical parameters, including H, Electrical conductivity (EC), manganese (Mn), copper (Cu), zinc (Zn), iron (Fe), nitrogen (N), phosphorus (P), potassium (K), and organic carbon (OC).The descriptive statistical analysis showed a high spatial variability of the soils at different locations within the orchards with respect to their fertility. The average soil pH was found to be 6.95, soil with this pH range is optimum for apple cultivation; the mean values of Organic Carbon, Nitrogen, Phosphorus and Potassium were 0.98%, 510.4 kg ha^{-1}, 38.5 kg ha^{-1} and 192.3 kg ha^{-1} respectively. The high concentrations of the nutrients exhibited in irrigated orchards compared to non-irrigated orchards showed the positive effect of irrigation on soil fertility and nutrient availability.

Correlation analysis showed good positive correlation between Nitrogen and Organic Carbon, suggesting that improving soil health and Availability of nutrients in soil is primarily a function of the amount of organic matter in soil. The machine learning model: Random Forest gave the highest R^2 value of 0.91 with the RMSE number that is lowest of 0.67 and The lowest MAE value of 0.48 in comparison to the Support Vector Machine, Decision Tree and Linear Regression models methods for the best predictive performance. Other key variables found from feature importance analysis which are important for soil fertility assessment are Organic Carbon, Nitrogen, pH and Potassium, all of which are important in soil fertility management for precision agriculture.

In summary, this study shows that incorporating soil fertility assessment along with machine learning offers a promising tool for data-driven orchard management. It is recommended that farmers, agricultural researchers and policy makers can use the suggested strategy to optimize use of fertilizers, optimize the irrigation scheduling and optimize the apple production sustainably in Jammu and Kashmir.

Real-time soil moisture data, climatic data (humidity, rainfall, temperature), To improve prediction accuracy, IoT sensor networks and remote sensing imagery should be included. Many sophisticated deep learning models exist, including Traditional machine learning models can be compared with Artificial Neural Networks (ANNs), Extreme Gradient Boosting (XGBoost) and Long Short-Term Memory (LSTM) networks evaluated. Moreover, integration of geospatial information system (GIS) and machine learning models can help the spatial soil fertility mapping and offer site-specific nutrient management. The use of apple yield data of actual harvest, fertilizer usage record and long monitoring data may further improve the predictive accuracy and help develop intelligent decision making support systems for sustainable precision agriculture in apple producing areas.

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