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Precision agriculture for smallholder farmers: Maximizing economics productivity using a machine learning-based water recommendation system

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Abstract

This study explores how smallholder farmers in various communities can economically optimize productivity, connectivity, and efficiency using precision agricultural technologies, particularly and sensors. The study can empower many small scale farmers by demonstrating customized applications of precision agriculture tools, thus boosting their ability to maximize resource utilization, reducing risks, and increasing yields. Furthermore, this study developed a machine learning (ML) decision-making system to improve crop yield for smallholder farmers economically in rural South Africa. This system specifically optimises irrigation by detecting soil moisture anomalies and providing recommendations to maintain optimalsoil moisture levels. The optimal range was set for the range of 70 to 80%. The system was trained and modelled using several parameters of soil moisture humidity, atmospheric temperature, soil temperature, and soil moisture. A comparison was carried out using MLmodel and Logistic regression, XGBoost, CatBoost, Gradient Boosting and Support vector 13 machine (SVM). The metrics used were accuracy, F1 Score, Recall, and Precision. The results showed 4 that the XGBoost model performed better than the other four models5 with an accuracy of 0.73, an F1 Score of 0.64, and a recall of 0.73. The Gradient Boosting16 model had the 2nd best result with a precision of 0.79. The findings demonstrated that optimizing irrigation systems, enhanced crop yield could be achieved with better stability.

Keywords: Agricultural Economics, Irrigation systems, Learning, Precision Agriculture, Small Holder Farmer, Soil Moisture, South Africa.

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1. Introduction

Agriculture is the backbone of many developing economies, providing a lifeline to smallholder farmers' local food systems and livelihoods. These smallholder farmers, in most cases, operate on land sizes of less than two hectares and face serious challenges relating to poor access to resources, unsteady climatic conditions, and inefficiencies in traditional farming practices (Fishman et al., 2020). Precision agriculture (PA), using advanced technologies to boost productivity, connectivity, and efficiency, offers a transformative opportunity for smallholder farmers (Abiri, Rizan, Balasundram, Shahbazi, & Abdul-Hamid, 2023). Smallholder farmers in general face several obstacles that constrain their efforts to increase productivity and profitability. These obstacles include limited access to high-quality inputs, insufficient knowledge of modern farming practices, and high vulnerability to climate variability Lee, Strong, and Dooley (2021). N. Khan et al. (2021) stated the current farming systems are characterized by a typically uniform application of resources but do not consider the spatial variation in the agricultural fields or the progressive unpredictability that leads to low yields and inefficient resource use. PA integrates a suite of technologies, including Geographic Information Systems (GIS), GPS, remote sensing, Internet of Things (IoT), and data analytics, that target real-time insights and interventions (Mushi, Di Marzo Serugendo, & Burgi, 2022; Torky & Hassanein, 2020). GIS and remote sensing enable one to map and monitor field variability, while IoT devices such as soil moisture sensors and weather stations give continuous data on critical parameters. Data analytics and machine-learning-based algorithms combine these data to provide practical advice to farmers (Shaikh, Rasool, & Lone, 2022). Such technologies allow farmers to maximize key inputs such as water, fertilizers, and pesticides to ensure that their yields are optimized and that their environmental impact is minimized (Júnior et al., 2024). This will assist smallholder farmers working on rainfed and marginal lands with limited resources to become more resilient and profitable (Shaikh et al., 2022). PA offers numerous benefits to smallholder farmers; it increases productivity by providing the appropriate resources at the right time, leading to good yields and high quality produce (Abobatta, 2021; Aroba & Rudolph, 2024). It also encourages resource efficiency, reducing the environmental footprint of farming and lowering production costs. Ultimately, PA tools help farmers manage risks related to climate variability and pest infestations through early warning systems and predictive models (Abobatta, 2020). However, challenges exist in making advanced technologies affordable for smallholder farmers, especially given limited budgets and poor infrastructure in remote areas Gokool et al. (2023) and Mushi et al. (2022). Lee et al. (2021) also noted that the complexity of PA tools necessitates extensive training and capacity building. This research provides insights for both farmers and policymakers regarding the adoption of PA, its benefits, and the challenges that must be addressed to transform sustainable agricultural development and improve crop yield. Precision agriculture (PA), which uses cutting-edge technologies to maximize resource use and boost productivity, has become a revolutionary method of farming. Machine learning (ML) in water management methods offers prospective answers for Sub-Saharan African smallholder farmers, who frequently face obstacles such limited access to resources, climate variability, and inadequate infrastructure. This study of the literature looks at the approaches used to create machine learning (ML)-based water recommendation systems and evaluates how they are used in smallholder settings (M. U. Khan & Sarwar, 2023). The goal of precision agriculture (PA) is to use data-driven technologies to maximize agricultural inputs. In order to solve issues of sustainability and productivity, this strategy has gained traction recently, especially through machine learning (ML) applications. PA presents a chance to boost productivity for Sub-Saharan African smallholder farmers, who produce almost 80% of the region's agricultural output despite resource constraints. Efficient use of water, a crucial input whose scarcity and poor management can result in yield loss, economic suffering, and environmental degradation, is one of the most urgent issues in these areas (Adebayo et al., 2025; Zondo, Ndoro, & Mlambo, 2024).

This paper examines Precision Agriculture for Smallholder Farmers: Maximizing Economics Productivity using a Machine Learning-based Water Recommendation System, and determines how these technologies might improve economic agriculture, which is the nexus of financial sustainability and agricultural output.

2. Literature Review

2.1. Precision Agriculture

PA is an approach to farm management that employs information technology to quantify variations in crop or animal production. This technology is required to deliver optimum health and productivity (Abiri et al., 2023; Aroba & Rudolph, 2024; Mohamed et al., 2021). Although more common in large-scale operations, PA also offers significant benefits for smallholder farmers. This review discusses how PA can enhance productivity, connectivity, and efficiency for smallholder farmers by leveraging technological innovations (Pérez-Pons, Parra-Domínguez, Chamoso, Plaza, & Alonso, 2020). PA allows resources such as water, fertilizers, and pesticides to be applied more effectively in different field areas (Gawande et al., 2023). For example, Abobatta (2021) suggested that crop yields could be increased by 10% to 15% a critical improvement for enhancing food security and income levels among smallholders. Additionally, yield monitors attached to harvesters provide ongoing recordings of crop yield and moisture content, helping farmers identify high- and low-yield areas for targeted intervention (Kumar, Divya, Jayasudha, & Sudha, 2020). Similarly, high-quality data inputs are necessary for ML models to function well. Research has emphasized the utilization of Internet of Things (IoT) sensors to gather data on temperature, weather, and soil moisture in real time. For example, a system created in Uganda uses sensors based on Raspberry Pis to track environmental variables, sending data for analysis and facilitating prompt irrigation decisions (Wilberforce & Mwebaze, 2025). On the other hand, Blockchain technology is used in various systems to guarantee data transparency and integrity. These solutions increase stakeholder trust by preventing manipulation and storing sensor data on a decentralized ledger. It has been demonstrated that this integration increases the accuracy of crop forecasts and recommendations (Sizan, Layek, & Hasan, 2025). Furthermore, traditional farming methods frequently need to change in order to implement machine learning-based technologies. Uptake is further constrained by social factors including women's restricted decision-making authority or their fear of digital platforms, as they are frequently the main agricultural workers. The best irrigation schedules have been successfully predicted by machine learning models, particularly supervised learning algorithms like Random Forest, Gradient Boosting Machines, and Support Vector Machines. These models indicate when and how much to irrigate based on real-time and historical data. Additionally, farms with comparable water requirements have been grouped using unsupervised techniques like clustering, which has aided cooperatives and extension organizations in managing irrigation on a large scale. A number of precision farming projects are testing blockchain integration. It guarantees that sensor-generated data and algorithm-generated judgments are impenetrable, boosting (Mortazavizadeh et al., 2025; Sizan et al., 2025).

2.2. Pest and Disease Control

Early detection and management of pests and diseases are crucial for minimizing crop losses. The centralized hub system developed by the Centre for Ecological Intelligence (CEI) at the University of Johannesburg aids small-scale farmers (SCFs) by improving operations and resource optimization (Aroba & Rudolph, 2024). Remote sensors can monitor crop health and detect early symptoms of pest infestation (Fishman et al., 2020; Nhamo et al., 2020). In addition, high-resolution images analyzed by advanced algorithms can pinpoint stressed areas that may require targeted pesticide. applications, thereby reducing costs and environmental impacts (M. U. Khan & Sarwar, 2023). Remote sensing data can also be integrated with meteorological forecasts and pest life cycle information to facilitate timely interventions (Bayih, Morales, Assabie, & De By, 2022).

2.3. Collaborative Networks

PA fosters enhanced connectivity among farmers, researchers, and extension services. Digital platforms enable the sharing of knowledge and resources and provide forums, expert consultations, and training modules to help farmers learn from one another (Mushi et al., 2022). For example, Soussi, Zero, Sacile, Trinchero, and Fossa (2024) emphasize that Wireless Sensor Networks (WSNs) facilitate real-time monitoring of environmental conditions, thereby reducing labor costs and improving crop yields. Data transmitted to cloud-based platforms allows for further analysis and decision-making, benefiting the entire farming community.

2.4. Variable Rate Technology

Variable Rate Technology (VRT) enables inputs to be applied precisely according to site-specific data. By minimizing waste and reducing cost, VRT supports sustainable smallholder farming (Späti, Huber, & Finger, 2021). For example, soil sensors and yield monitors can be used to create prescription maps for fertilizer application, ensuring that each field section receives the right amount of nutrients. In addition, PA technologies improve the use of water, seeds, and other inputs, thereby enhancing crop performance and reducing environmental impacts (Mohamed et al., 2021). Mechanized systems like GPS-guided tractors and automated irrigation further reduce labor requirements (Kumar et al., 2020; Nhamo et al., 2020).

2.5. Precision Agriculture in Energy Conservation

PA also contributes to energy conservation. GPS-based guidance systems optimize field operations by reducing overlaps, thus lowering fuel consumption by up to 20% (Fishman et al., 2020; Nhamo et al., 2020). Automated machinery further reduces engine idling time, leading to additional energy savings. These energy-saving practices not only lower operational costs but also reduce carbon emissions, promoting environmental sustainability.By using machine learning technologies, precision agriculture (PA) improves financial resilience by using predictive analytics. Farmers can make appropriate plans by using machine learning (ML) models to predict future droughts or floods by comparing weather data with patterns of water consumption. This lowers the likelihood of crop failure and makes it easier to arrange for financing and insurance. innovative technologies to FinTech solutions that provide microloans and usage-based pricing are being integrated with a number of machine learning (ML)-powered precision agriculture systems. These strategies relate the cost of technology to crop outcomes, allowing farmers to "pay as they grow." This promotes economic agriculture by

coordinating the use of technology with revenue production. Economic agriculture is at the forefront of machine learning-based water recommendation systems, particularly for resources.
(Gebresenbet et al., 2023; Pérez-Pons et al., 2020).

3. Challenges and Opportunities

3.1. Barriers to the Adoption of Precision Agriculture

Despite its many benefits, PA adoption among smallholder farmers is hindered by several challenges. High initial equipment costs, limited technical expertise, and inadequate access to technology are major obstacles (N. Khan et al., 2021; Kumar et al., 2020). Many smallholder farmers work with tight budgets and cannot afford expensive PA tools. Furthermore, the lack of technical know-how and limited training opportunities contribute to the underuse or misuse of PA systems (Bayih et al., 2022; Singh, Berkvens, & Weyn, 2021). Rural infrastructure challenges, such as unreliable internet connectivity and electricity, further compound these issues (Kamal & Bablu, 2023).

3.2. Policy and Institutional Support of Precision Agriculture

Government policies and institutional support are critical for PA adoption. Funding mechanisms such as financial assistance, tax incentives, and grants can reduce the financial burden on farmers (Abiri et al., 2023). Policies that improve access to credit and insurance products further mitigate investment risks (Sudaryanto, Wahida, Rafani, & Andoko, 2022). Extension services and comprehensive training programs are essential to equip farmers with the necessary skills. Additionally, investments in rural infrastructure and public-private partnerships can promote the development of affordable and user-friendly PA tools (Gebresenbet et al., 2023; Späti et al., 2021). Recent technological innovations, including low-cost soil sensors, mobile applications, and solar-powered equipment show promise in overcoming many of these challenges (Bayih et al., 2022; N. Khan et al., 2021; Shaikh et al., 2022).

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Despite the clear potential of PA, its adoption among smallholder farmers has been hampered by several factors. The initial cost of advanced technology can be prohibitive, especially given the limited budgets and often poor infrastructure prevalent in remote areas (Gokool et al., 2023; Mushi et al., 2022). Moreover, the complexity of some PA tools necessitates extensive trainingand capacity building, which can be a significant barrier for farmers with limited access to education and support services (Aroba et al., 2025; Lee et al., 2021; Torky & Hassanein, 2020; Ugbedeojo, Adebiyi, Aroba, & Adebiyi, 2024). Therefore, the development of affordable, user-friendly, and context-specific PA solutions is pivotal for realizing its benefits among smallholder communities.

This research focuses on the development and evaluation of a machine learning-driven system for optimized irrigation scheduling. We leveraged readily available environmental data, collected through a network of sensors and accessible rainfall databases, coupled with machine learning models, to provide smallholder farmers with practical, real-time irrigation recommendations that improve water use efficiency and ultimately enhance crop yields.

3.4. Agricultural Economy of Precision Agriculture

Market access and supportive policy frameworks are critical for promoting the adoption of precision agriculture among smallholder farmers. Financial barriers, such as the high cost of technology, can be mitigated through government subsidies, grants, and affordable credit schemes. Policies that support rural infrastructure development, including internet connectivity and mobile network expansion, are essential for enabling access to PA technologies and services. Precision agriculture also enhances farmers' market competitiveness by improving produce quality and traceability, enabling participation in higher-value markets. Digital platforms and mobile applications, such as those developed by the GSMA, provide real-time market information, empowering farmers to make better marketing decisions and negotiate favorable prices. Strengthening these market linkages and policy support mechanisms is crucial for scaling precision agriculture adoption and ensuring its economic benefits reach smallholder communities.
To fully realize the economic potential of PA, targeted investments and supportive policies are essential. This includes:

- Infrastructure Development: Improving access to digital tools and internet connectivity in rural areas.
- Training and Capacity Building: Equipping farmers with the necessary skills to utilize PA technologies effectively.
- Financial Support: Providing subsidies or credit facilities to offset the initial costs of PA adoption.
- Such initiatives can enhance the economic viability of smallholder farming and contribute to broader agricultural development goals.

3.5. Agricultural Economics: Precision Agriculture for Smallholder Farmers

Smallholder farmers confront many obstacles in the changing agricultural landscape, such as restricted access to resources, erratic weather patterns, and financial limitations. For these farmers, precision agriculture offers a revolutionary way to increase productivity and financial viability, especially when combined with machine learning-based water recommendation systems. Smallholder farmers may find the upfront costs of deploying ML-based systems which include installing sensors and mobile devices to be unaffordable. Widespread adoption is still very difficult to achieve without funding or incentives. In order to guarantee inclusivity in precision agriculture, studies have emphasized the significance of reasonably priced technological solutions. The quality and accessibility of data determine how well machine learning models work. Limited sensor coverage and irregular data gathering can compromise model accuracy in many rural regions. Research has shown that the generalizability of machine learning models beyond geographical boundaries may be restricted by the absence of complete datasets. For wider use, it is crucial to guarantee these systems' scalability and adaptability. According to studies, system designs that are flexible and modular can make it easier to adapt to a variety of agricultural environments (AUDA-NEPAD, 2025; Mortazavizadeh et al., 2025; Reuters, 2025; Sharma, Prakash, Bhambota, & Kumar, 2025; Sizan et al., 2025; Zondo et al., 2024).

3.6. Economic Implications of Precision Agriculture

Precision agriculture uses cutting-edge technologies to track and control crop, soil, and water variability in the field. Adopting such technology can result in lower operating costs, higher yields, and optimized resource usage for smallholder farmers. When used in water management, machine learning algorithms can forecast the best times to irrigate crops, guaranteeing that they get enough water without wasting any. Smallholder farmers frequently work in areas with poor infrastructure, such as spotty internet access and restricted electrical availability. These limitations may make it more difficult for IoT-based systems to be deployed and operate. In order to facilitate the broad use of precision agriculture technologies, experts stress the necessity of enhanced digital infrastructure. This lowers irrigation system energy costs in addition to conserving water, a vital resource. Because soil types, crop varieties, and climatic variables vary from one place to another, models created in one setting might not be readily transferable to another. For wider use, it is crucial to guarantee these systems' scalability and adaptability. According to studies, system designs that are flexible and modular can make it easier to adapt to a variety of agricultural environments. It takes a shift in behavior to incorporate ML recommendations into conventional farming methods. Cultural norms and prior experiences have an impact on farmers' ability to embrace new practices and their level of trust in technology. According to research, new technologies can be more widely accepted if local settings are understood and farmers are included in the development process. Conversely, Smallholder farmers will be significantly impacted economically by the adoption of precision agriculture (PA) in global farming systems, especially in emerging nations like South Asia and Sub-Saharan Africa. Smallholder farmers are increasingly impacted by the rapid digital innovation that is changing the global agriculture sector, both favorably and unfavorably. The use of technology (such as sensors, GPS, drones, and machine learning) to maximize the use of labor, fertilizer, and water resources in order to increase yields and decrease waste is known as precision agriculture. The global trend toward these breakthroughs offers smallholders a mixed economic picture. Input cost reduction is one of PA's main economic advantages (Aroba, 2024; Oluwasegun Julius Aroba & Michael Rudolph, 2025; Bugwandin, Anwana, & Aroba, 2025; Gao, Li, & Zhang, 2023; M. U. Khan & Sarwar, 2023; Sizan et al., 2025; Wilberforce & Mwebaze, 2025).

Small-scale tomato farm saw a 25% boost in crop output and a 35% decrease in water consumption when IoT sensors and machine learning models were integrated for smart irrigation. Farmers benefit from these advancements because they can produce more with fewer resources, which increases their profitability (Boateng, Aroba, & Patel, 2024; Monchusi, Kgopa, & Mokwana, 2024). Initial implementation expenses are high and include training and hardware. Smallholder farmers might not have the funds to purchase these systems (seed and soil) in the absence of donor programs or government subsidies. Recurring expenses like cloud subscriptions or battery replacements also need to be taken into account. Traditional farming methods frequently need to change in order to implement ML-based technologies. Uptake is further constrained by social factors including women's restricted decision-making authority or their fear of digital platforms, as they are frequently the main agricultural workers. Farmers can access markets and enhance pricing negotiations by using verified production data (from machine learning systems) through systems that link with cooperative or e-commerce platforms. Agribusiness investors are drawn to blockchain-backed records because of the transparency they provide, which connects smallholders to wider value chains (AUDA-NEPAD, 2025; Reuters, 2025; Sharma et al., 2025; Sizan et al., 2025; Zondo et al., 2024). Particularly in export-focused markets, traceability and quality control are becoming more and more important in global agriculture. Smallholders can satisfy these criteria with the aid of precision agriculture technologies, which record input usage and growing conditions. Farmers may reach a wider audience, fetch higher prices, and establish enduring connections with consumers by using digital channels. The economic resilience of smallholders is being further strengthened by the adoption of blockchain-backed precision agricultural platforms to facilitate their access to digital payments, insurance, and finance. Global agricultural policy is rapidly encouraging digital innovation, but for smallholders to reap the full benefits, they require training, equitable financing, and tailored subsidies. Governments, IT firms, and local cooperatives must work together to make sure that the financial gains from precision agriculture are shared fairly and do not accrue to the wealthiest farmers.

3.7. Cost-Benefit Analysis and Return on Investment

IoT sensors and machine learning software are examples of precision agriculture technology that can need a significant upfront investment. But these expenses are frequently outweighed by the long-term advantages. Farmers can get a faster return on investment by increasing crop yields and using less water. Additionally, these systems' data-driven insights empower farmers to make well-informed decisions, which improve crop management and lower losses. Depending on the crop variety and local conditions, economic models indicate that farmers might anticipate a return of up to three dollars for every dollar invested in precision agriculture technologies. For smallholder farmers, this makes precision agriculture not only a financially sensible option but also an environmentally responsible one (Aroba, 2024; Oluwasegun Julius Aroba & Michael Rudolph, 2025; Bugwandin et al., 2025; Gao et al., 2023). Optimizing water use lowers input costs and boosts yield per drop, which directly supports economic agriculture. According to studies conducted in Ethiopia and Kenya, ML-guided irrigation scheduling can increase yields by 15–20% while reducing water use by 30–40% (AUDA-NEPAD, 2025). Furthermore, smartphone dashboards with real-time economic feedback tools (such as water usage graphs and profit forecasts) assist farmers in making financially and agronomically effective decisions. By using predictive analytics, machine learning systems improve financial resiliency. For example, ML models can alert farmers to possible droughts or floods by combining weather data with patterns of water use, enabling them to make appropriate plans (Adebayo et al., 2025; O.J. Aroba & M. Rudolph, 2025; Mortazavizadeh et al., 2025; Reuters, 2025; Sharma et al., 2025).

4. Methodology

4.1. Data Collection

Data Collection Data were collected in Tafelkop, Limpopo (February 2018–April 2019) using a data acquisition (DAQ) system logging hourly measurements of soil moisture, soil temperature, atmospheric temperature, relative humidity, and dew point. Rainfall data were sourced from the Climate Hazards Centre InfraRed Precipitation with Station data (CHIRPS) database and downscaled to hourly resolution. Figure 1 provides an overview of the complete workflow, from data acquisition through model implementation.

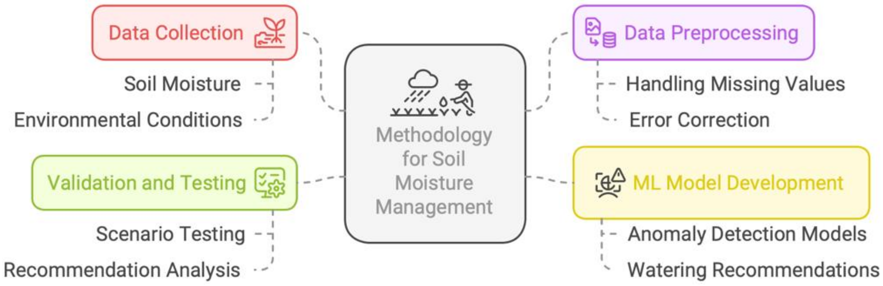

Figure 1.
Framework of the ML-based watering recommendation model.

4.2. Data Preprocessing

Handling missing values and erroneous readings was the first critical step. Missing or negative values were identified and corrected using interpolation techniques and a Bayesian-based chained equations method. In this method, for a set of N independent variables; if one variable (e.g., x_1) had a missing value, it was regressed against the other variables $(x_2, x_3, \ldots, x_N)$ using only observed cases. The predicted values were then used to fill in the missing data. This process was repeated iteratively until a complete dataset was 8 obtained. The consistency between the treated and untreated values was verified to ensure the precision of the imputation. Outliers exceeding ±4 standard deviations from a 30-day rolling mean were replaced through interpolation. Finally, features were scaled using min-max normalization.

4.3. Model Development for Anomaly Detection

To detect low soil moisture anomalies, thresholds based on agronomic guidelines were established. Four machine learning models were developed: Logistic Regression, Random Forest, Support Vector Machine (SVM), and XGBoost. Each model was selected based on specific strengths:

i. Logistic Regression: A statistical model ideal for binary classification, offering interpretability through odds ratios and straightforward probability estimation.
ii. Random Forest: An ensemble model consisting of multiple decision trees, known for robustness against noise and providing implicit feature importance.
iii. SVM: An algorithm effective in handling high-dimensional data by maximizing the decision margin between classes, reducing overfitting.
iv. XGBoost: A high-performance gradient boosting framework using decision trees sequentially built to minimize prediction errors, effective in managing imbalanced datasets.

The dataset was partitioned into training (80%) and testing (20%) subsets, maintaining class stratification. Given class imbalance (with anomalies being rare), the minority class was oversampled using Synthetic Minority Oversampling Technique (SMOTE). Hyperparameter optimization for each model was conducted through grid search coupled with five-fold cross-validation, tuning parameters such as regularization strength, number of trees, tree depth, kernel type, and learning rate. Model performance was evaluated using accuracy, precision, recall, and F1-score. The best-performing model based on F1-score, with particular emphasis on high recall to minimize missed anomalies, was selected for further integration into the mechanistic watering recommendation system.

4.3.1. Mechanistic Model for Optimal Watering

A rule-based mechanistic model was developed to translate the output of the ML anomaly detection into actionable watering recommendations. The logic was as follows: If an anomaly was detected, and the soil moisture was below a predefined threshold, the model calculated the required watering quantity proportional to the moisture deficit. Algorithm 1 below presents the pseudocode for this process.

Algorithm 1 Watering Recommendation

```
Input: soil Moisture Data, low Moisture Threshold,  severity Factor,  ML Model
Output: watering Recommendations
 for each record in soil Moisture Data do
        if record has missing or erroneous values then
        Impute values using chained equations
        end if
        Calculate soil moisture anomaly as deviation from the mean
end for
 Split soil moisture data into training and testing sets
Train ML Model on the training set
for each record in the testing set do
        anomaly Detected ← MLModel.predict(record)
        Set record.anomaly accordingly
end for
for each record in the testing set do
        if record.anomaly and record.soilMoisture < lowMoistureThreshold then
        wateringQuantity ← (lowMoistureThreshold − record.soilMoisture) × severityFactor
        else
        wateringQuantity ← 0
        end if
        Set record.wateringRecommendation to wateringQuantity
end for
return the testing set with watering recommendations
```

A simplified model was developed to simulate crop yield based on soil moisture levels. An optimal moisture range of 60%–80% was defined (Al-Kaisi & Yin, 2003). When soil moisture was within thisoptimal range, the yield was maximized; if moisture levels were below or above the optimal range, yield decreased linearly with the moisture showing a deficit or an excess (Bhattarai & Midmore, 2004; Haddock, 1961).

4.4. System Validation and Testing

The complete system was validated, comprising the machine learning anomaly detection model and the mechanistic watering recommendation model. The predictions of the system and the watering recommendations were compared with the actual conditions observed within the data set to assess accuracy and reliability. Furthermore, the system was subjected to a range of testing scenarios, including varying soil moisture levels, diverse environmental conditions, and different crop types, to evaluate its robustness and general usability. In addition to the accuracy metrics, we used the precision, recall, and F1 score metrics to evaluate the model.

5. Result and Discussion

The machine learning-based decision-making system effectively identified low soil moisture anomalies and provided actionable watering recommendations to maintain optimal moisture levels. Figure 1 shows the distribution of the variables.

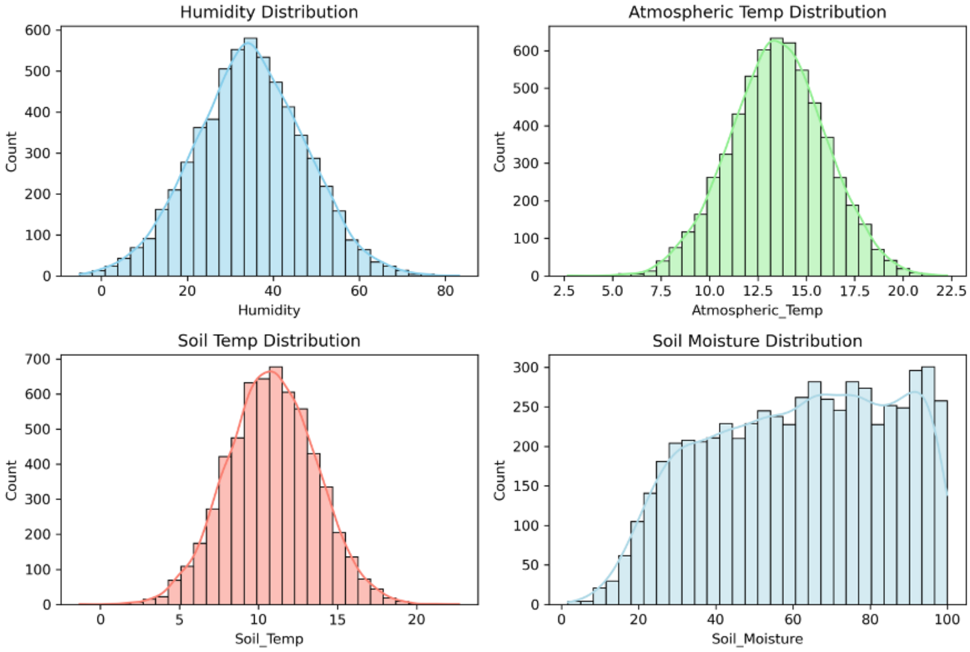

Figure 2.
Distribution of the variables.

We also showed the distribution of the anomalies (see Figure 3) where the soil anomalies over time were highlighted.

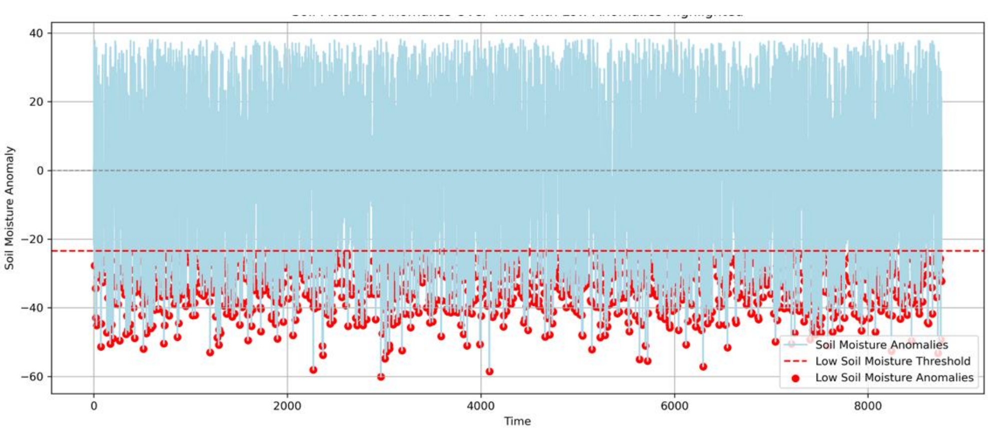

Figure 3.
Identification of soil moisture anomalies. Points in the figure indicate anomalies corresponding to extremely low soil moisture levels.

Table 1 provides a comprehensive summary of the performance of various machine learning models in predicting soil moisture anomalies. The evaluation metrics include accuracy, precision, recall, and F1 score, where recall is particularly important because of its effectiveness in detecting anomalies.

Table 1.
Performance of ML Models for Predicting Soil Moisture Anomalies.

Model	Accuracy	Precision	Recall	F1 Score
XGBoost	0.87	0.89	0.87	0.86
SGDClassifier	0.73	0.53	0.73	0.62
Logistic Regression	0.73	0.53	0.73	0.62
CatBoost	0.70	0.76	0.70	0.71
Gradient Boosting	0.88	0.90	0.88	0.87

Detecting these anomalies is crucial for timely interventions in irrigation, which ultimately supports the goal of recommending optimal water usage. Notably, the XGBoost model achieves an accuracy of 0.87, a precision of 0.89, a recall of 0.87, and an F1 score of 0.86. This balanced performance across all metrics, especially its strong recall, positions XGBoost as the most suitable model for further analysis and implementation in our water management strategy. Figures 3 and 4 also show the performance of the models, with XGBoost having an overall best performance for both ROC and recall values. Using random testing and cross-validation, we also observe XGBoost to perform better than other models (see Figure 5).

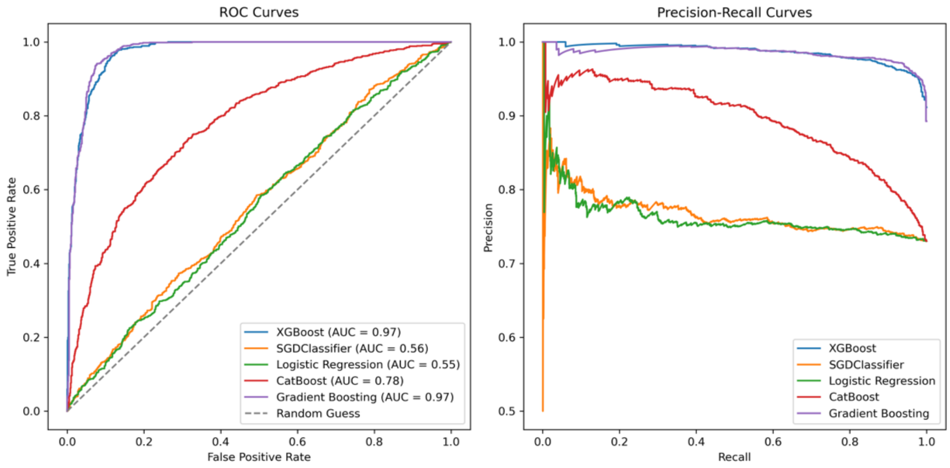

Figure 4.
Receiver operating characteristic and precision-recall curves for the ML models.

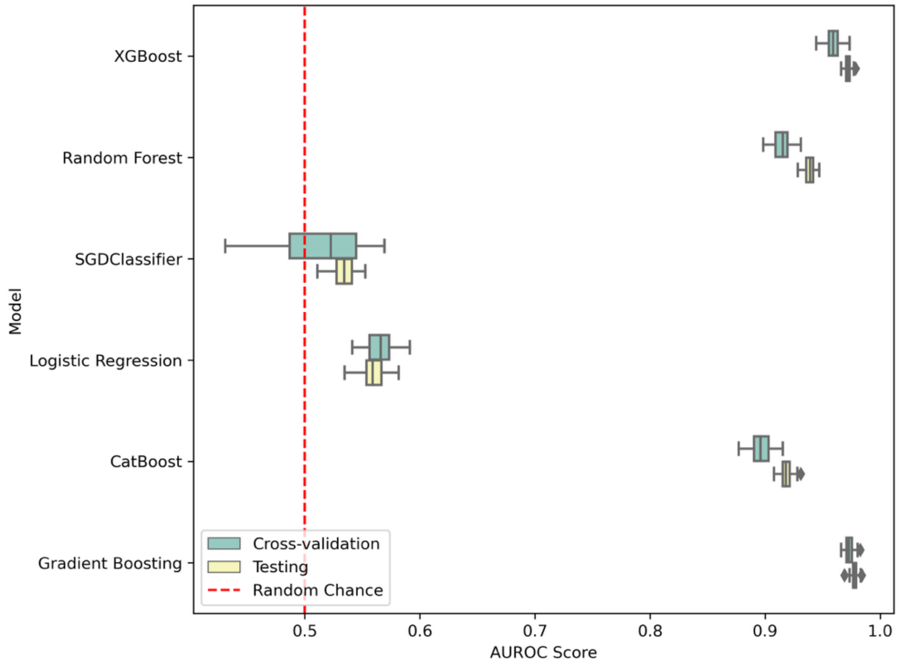

Figure 5.
AUROC Comparison of Models Across Cross-Validation and Testing. XGBoost and Gradient Boosting show the highest scores with minimal variance.

Table 2 presents the soil moisture readings (in percentage), the corresponding anomaly predictions, and the watering recommendations derived from these measurements. In the table, an anomaly prediction of 1 indicates that the observed soil moisture level deviates from the optimal range, which typically suggests a dry condition, while a prediction of 0 denotes normal moisture levels.

Table 2.
Soil Moisture Levels, Anomaly Predictions, and Corresponding Watering Recommendations.

Soil Moisture (%)	Anomaly Prediction	Watering Recommendation
28.10	1	24.4
55.6	0	0.00
12.9	1	47.2
74.4	0	0.00
36.1	1	12.5
40.8	1	5.3
55.7	0	0.00
22.5	1	32.8
138.3	0	0.00
46.7	0	0.00

We see that the moisture readings of 28.1%, 12.9%, 36.1%, 40.8% and 22.5% are flagged as anomalies, triggering watering recommendations of 24.4, 47.2, 12.5, 5.3 and 32.8, respectively. This implies that when soil moisture is low, additional water is advised to restore optimal conditions. In contrast, higher moisture levels, such as 55.6%, 74.4%, 55.7%, 138.3%, and 46.7%, do not require watering (as indicated by a recommendation of 0.00), which helps prevent overirrigation. In general, the Table provides insights into how the model associates low soil moisture with the need for irrigation, supporting a targeted approach to water management by recommending precise amounts of water based on the severity of the anomaly.

Figure 6 demonstrates a clear inverse relationship between soil moisture levels and recommended watering amounts, with critical thresholds highlighted to guide immediate visual assessments for action. Figure 7 further integrates soil moisture data with rainfall and irrigation recommendations, clearly showing instances when rainfall alone could not maintain optimal moisture levels, necessitating supplemental watering. These visual insights align with previous findings by Inyang, Essien, and Mpamugo (2025) highlighting ensemble model effectiveness in practical agritech applications.

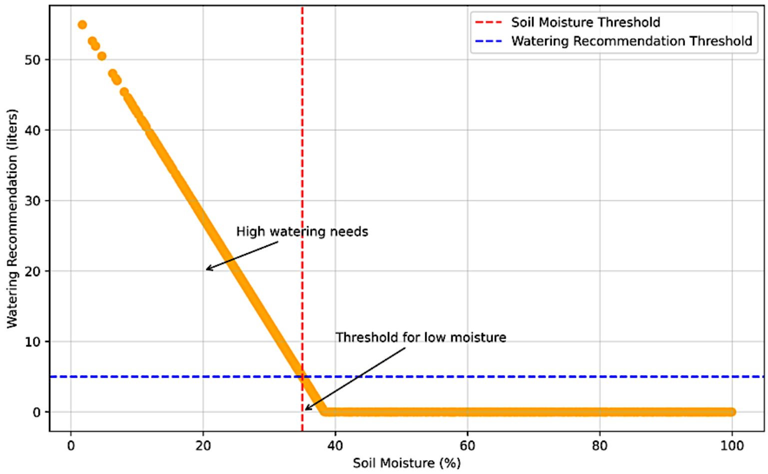

Figure 6.
The relationship between soil moisture levels (%) and watering recommendations (litres) with key thresholds indicated (red dashed line for low soil moisture, blue dashed line for high watering needs).

Contrarily, some literature cautions against uncritical reliance on models like XGBoost due to potential overfitting risks, particularly in varying environmental contexts (Inyang et al., 2025). Indeed, alternative models such as Random Forest have been suggested to offer superior generalization capabilities, especially in more diverse or heterogeneous environments (Li & Yan, 2024). Our study acknowledges these perspectives, emphasizing the importance of continual validation and adaptability of ML models when applied across different ecological zones.

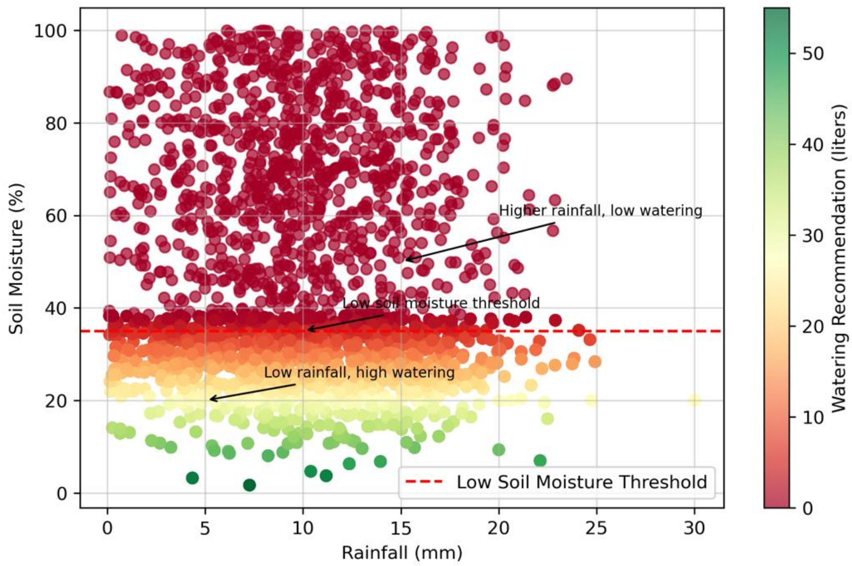

Figure 7.
The relationship between rainfall (mm), soil moisture levels (\%), and watering recommendations (litres), with color coding to represent different watering levels. The red dashed line marks the threshold for low soil moisture.

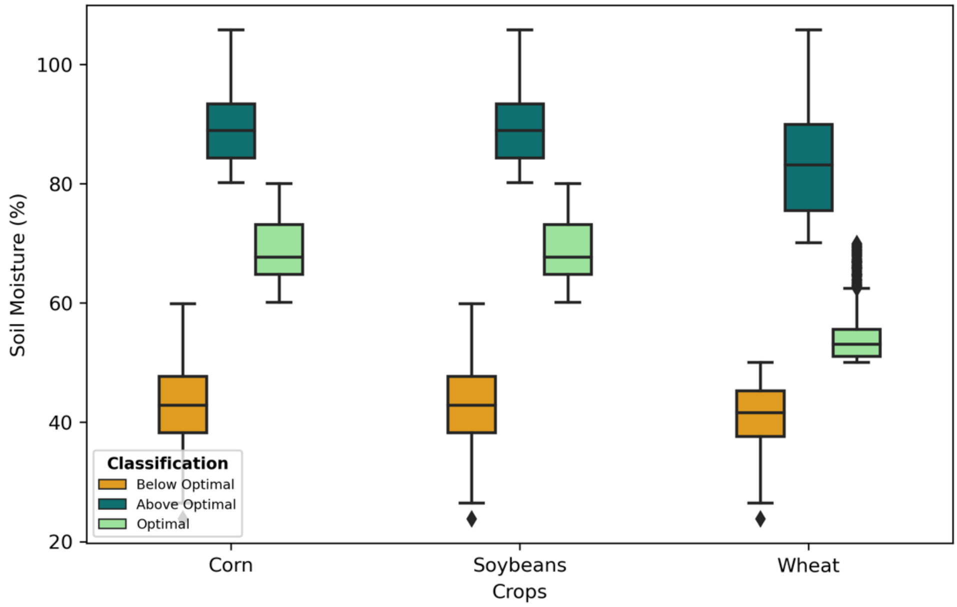

Figure 8.
Distribution of soil moisture and potential yields across crop types.

Figure 8 shows that most soil moisture values fall within the optimal ranges for crops such as Corn (60% – 80%), Soybeans (60% – 80%), and Wheat (50% –70%). Areas outside these ranges indicate potential yield risks that could be addressed by targeted irrigation and drainage improvements (Benti, Chaka, Semie, Warkineh, & Soromessa, 2024).

6. Conclusions and Recommendation

Smallholder farmers have a revolutionary chance with precision agriculture, especially in areas with water constraint and climate change issues. Farmers may increase output, reduce costs, and strengthen their economy by utilizing AI-driven water guidance systems and other PA technologies. However, achieving these advantages calls for coordinated efforts in infrastructure development, capacity building, and policy support. PA has the potential to significantly influence the development of a sustainable and profitable agricultural future for smallholder farmers with the correct investments.The XGBoost model demonstrated high accuracy in anomaly detection, making it suitable for implementation in real-world scenarios. The rule-based mechanistic model provided practical irrigation recommendations that can help improve crop yield for small-holder farmers in rural South Africa. Water recommendation systems based on machine learning have a great deal of promise to improve Sub-Saharan African smallholder farmers' water use efficiency. Even though the techniques used are improving, the effective deployment and uptake of these technologies depend on resolving criticisms about infrastructure, data quality, financial limitations, cultural considerations, and scalability. In order to overcome current obstacles, future research should concentrate on creating context-specific models, enhancing data collection techniques, and cultivating collaborations.

This case study of precision agriculture regarding irrigation holds significant potential to enhance productivity, connectivity, and efficiency among smallholder farmers. Despite current challenges in adoption, strategic investments, capacity building, and continuous technological innovation are essential for realizing a more inclusive and sustainable agricultural future.Localized Algorithm. To guarantee contextual accuracy, machine learning models ought to be trained on hyperlocal data. Localized datasets can be produced through partnerships with national agricultural research centers. To supply infrastructure, funding, and digital literacy initiatives, governments, non-profits, and commercial IT companies should collaborate. Open-Source Platforms: Stakeholders should spend money on open-source machine learning models and tools to cut expenses and promote innovation. Inclusivity and Gender Focus: Systems ought to be built with a variety of user demands in mind, such as those of women and underrepresented groups.

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