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Artificial Intelligence Approaches to Rotation Planning for Sustainable Yield in Water-Stressed Highlands

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Abstract:

The problem of water scarcity in highland areas has been a major threat to the sustainability of agriculture as the traditional methods of crop rotation have been implemented with many failing to maximize farm production and resource conservation. The paper examines the use of artificial intelligence (AI) methods of Rotation planning to optimise sustainable yield in water-stressed environment through Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Reinforcement Learning (RL). The models were trained and evaluated using historical crop, soil, climate and irrigation data. According to the results, AI models predict yields and use much less water than their traditional counterparts. The maximum accuracy in the prediction of crop yield was observed in ANN and RL with mean absolute errors (MAE) at 0.22 t/ha and 0.20 t/ha, respectively. ANN and RL had a water use efficiency of 88 and 90, respectively, whereas only 73 was realized in conventional planning. The sustainability index of 0.85 also took advantage of optimization in the yield, soil, and the use of resources, which was maximized with RL-based rotation scheduling. These results indicate that adaptive and data-driven planning of crop rotation, which is based on AI-driven decision support systems, can allow highland farmers to make tradeoffs between high productivity and environmental protection. The research also offers a realistic model of applying AI in agriculture in the arid highlands, which will help the development of climatic-resistance and sustainable farming systems.

Keywords: Artificial Intelligence, Crop Rotation, Water-Stressed Highlands, Sustainable Yield, Reinforcement Learning.

I. INTRODUCTION

The water scarcity, unpredictable climatic conditions, and porous soils are the major problems of agriculture in highland areas. Most of these areas have steep slopes and have little irrigation facilities, there must be a proper planning to make the crops production sustainable in these areas [1]. The traditional way of crop rotation which is predominantly rooted in historical experience and understanding of farmers in most instances is not able to optimize yield in shifting environmental conditions and rising increase of water stress [2]. As a result, the use of poor crop sequencing patterns may result in poor water utilization, low soil fertility, and low agricultural yields, which pose threats to food security in these susceptible areas. The recent developments in Artificial Intelligence (AI) have disruptive potential to agricultural planning with the option of making decisions using data. With AI methods, such as machine and reinforcement learning, it is possible to provide complex interactions between crops, soil characteristics, meteorological conditions, and irrigation patterns [3]. Such models have the capability of forecasting crop behaviour in the various rotation conditions and provide the best orders to increase the yield with minimum water usage. Through the use of historical data, remote sensing data, and climate prediction, AI-driven solutions will enable an objective way to improve the sustainability and resilience of highland agricultural systems. The proposed research aims at using AI with crop rotation optimization in the context of highlands with water stress. The study will combine the data of the environment, agronomic, and water resources to create the predictive models that guide the rotation strategies which represent the ability to sustain the sustainable yields. The suggested solution is able not only to overcome the shortcomings of traditional rotation planning but also to bring about effective water management, soil preservation, and agricultural management of the climate. Finally, this paper aims to prove how the AI-implemented rotation planning may guide farmers and agricultural planners to make resourceful, sustainable choices that would respond to productivity and preserve resources in difficult highland conditions.

II. RELATED WORKS

The water shortage and sustainable agriculture in highlands and semi arid areas has been a significant research focus which undergoes fresh perspectives where more innovative practices and designs are founded on sophisticated technologies and data informed techniques. Hasenbeck et al. [15] pointed out the effect of integrated water management, in the Middle Rio Grande Basin with precision agriculture, scheduling irrigation, and adoption of technology reducing water stress levels without reducing crop productivity. Equally, Kourgialas [18] examined the Soil -Water-Crops-Energy (SWCE) nexus where the interactions between these factors were found to be complicated and that adaptive management strategies should be installed in the context of changing climatic conditions. These studies reveal how optimization of resources plays a very crucial role in sustainable yield. A number of researches have aimed at the combination of AI and geospatial technologies when making agricultural decisions. Li et al. [20]

created an extraction model of potato cultivation in counties based on multi-source remote sensing data, which was developed using Shapley Additive ExplanationsSequential Forward SelectionRandom Forests (SHAPSFSRF) technique and proves to be more accurate when estimating areas of reasonable cultivation. On the same note, Johanes et al. [16] utilized the multi-criteria decision-making models, such as the AHP and Frequency Ratio model, to evaluate landslide prone areas in terms of topographical and environmental data and the potential of such information in the planning of highland agriculture. Such models and strategies emphasize the role of data models in land use optimization and risk management in complex landscapes. The topic of the introduction of technology in agricultural activities has also been examined in other geographical settings. Kalfas et al. [17] indicated that use of technology in the farms of Greece positively impacted sustainability through maximization of inputs in addition to improvement of monitoring systems. Manono et al. [22, 23] examined socio-economic and institutional influences on climate-smart agricultural practices that are adopted by smallholder farmers in Sub-Saharan Africa, demonstrating how AI and decision support infrastructures foster the adoption of sustainable land and crop management practices. Kusnandar et al. [19] suggested symbiotic simulation-based decision support systems of the horticultural supply chain, which assists smallholder farmers to plan crop cycles and to trade off water, nutrient, and market restrictions.

Highland farming systems have been found to significantly depend on the determination of crop yield based on soil quality and its fertility. Nazari et al. [24] determined indicators of the quality of soils regarding rapeseed, and they also discovered that there were strong correlations among nutrient availability, organic carbon content and yield variability. On the same note, Nungula et al. [26] have highlighted the importance of GIS in overcoming land degradation limitation in sunflower production and how spatial analysis can aid in planning of crops sustainably. These papers support the idea that soil, water and environmental data should be included in the predictive and optimization models. Concerning policy and systemic imagery, Nicolae et al. [25] investigated the UK agricultural competitiveness in the cereal value chain, whereby network-based strategies can inform the agricultural policy and the optimal utilization of resources. Liu et al. [21] have reviewed the change at land use and land cover scale in Southeast Asia across three decades highlighting the long-term consequences of land management decisions in agricultural sustainability. These studies, in general, point to the increased interest in the use of AI, geospatial analysis, and decision support systems to enhance planning of crop rotation, water management, and yield in stressed water and highland environments.

III. METHODS AND MATERIALS

The paper is based on the problem of implementing the artificial intelligence (AI) methods to take advantage of crop rotation planning and attain sustainable yield on water-stressed highlands. The research methodology includes collecting data, pre-processing data, applying four AI-based algorithms, which are: Random Forest (RF), Support Vector machine (SVM), Artificial Neural Network (ANN), and Reinforcement Learning (RL) to predict crop yields and optimization of rotation plans. The experimental design is meant to replicate highland farming conditions with different water and they should be at different water and soil fertility levels. [4]

Data Collection and Description

The data that will be utilized in this study comprises of past records of crop production, soil profiles, climatic conditions and irrigation patterns of the highland farmlands. The parameters considered in the soil are the PH, the amount of organic carbon, the amount of nitrogen, the amount of phosphorus in the soil and the amount of potassium in the soil [5]. Rainfall, temperature, and humidity are the types of weather data that have been recorded in the last 10 years. There are four large major crops like wheat, barley, maize and potato whose data on crop yield are provided. The irrigation statistics offer weekly crop-based water consumption [6]. The data sample was preprocessed to deal with missing data and standardize numerical data and encode categorical data like crop types. The data presented in Table 1 is a sample of the data with hypothetical values.

Table 1: Sample Data for AI-based Rotation Planning

Crop	Soil pH	Organic C (%)	N (kg/ha)	P (kg/ha)	K (kg/ha)	Rainfall (mm)	Temp (°C)	Water Use (mm/week)	Yield (t/ha)
Wheat	6.5	2.1	80	40	150	120	18	25	3.8
Barley	6.8	1.9	75	35	140	100	17	22	3.2
Maize	6.2	2.5	90	50	160	150	20	30	4.5
Potato	6.7	2.0	85	45	155	110	16	28	4.0

Algorithms for AI-based Crop Rotation Planning

1. **Random Forest (RF)**

Random Forest is an ensemble learning algorithm which works with regression and classification purposes. It builds many decision trees in the process of training and produces an average prediction in case of regression or majority vote in case of classification. RF is used in nonlinear association, less gratifying, and insensitive to dusty data [7]. RF, in the study, forecasts crop productivity concerning the soil parameters, weather, and schedules of irrigation. The model determines the relative significance of different features like soil nitrogen and rainfall in the determination of yield. RF is more applicable to the highland farming because it can encompass complicated relationships among environmental factors [8].

"Input: Training dataset D, number of trees N
For i = 1 to N:
Sample D with replacement → Di
Train a decision tree Ti on Di
For each split, select random subset of features
Output: Aggregate predictions from all Ti"

2. **Support Vector Machine (SVM)**

Support Vector Machine is a supervised learning algorithm that can perform regression (SVR) and classification (SVC) by optimum line discovery in the high dimension space. It works well with modeling nonlinear, complicated relationships with the use of kernel functions, e.g. radial basis function (RBF). SVM, in this research, is applied in predicting the crop yield and classifying the level of water stress on various rotation conditions [9]. SVM maps the

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features of the inputs to a higher-dimensional space, thus enabling the prediction to be correct despite the limited highland data.

"Input: Training data (X, Y), kernel function K
1. Map data to higher-dimensional space using K
2. Solve optimization problem to maximize margin
3. Determine support vectors
Output: Prediction for new input X"

3. Artificial Neural Network (ANN)

Artificial Neural Networks are made up of interrelated networks of neurons which learn nonlinear relationships between data. ANN normally comprises of input, hidden and output layers. The outputs of every neuron add weighted sums and a function of activation to the inputs. ANN in this study is used to predict the outcome of crops using several environmental inputs and irrigation timing. Based on previous yield data, the network gets to know the complex trends that affect productivity. Weights are updated with the help of backpropagation and the prediction error is minimized [10]. ANN can be used in highland production effectively since it can be used to model the interaction that is not easy to be expressed mathematically.

```
"Input: Training data (X, Y), learning rate α
Initialize weights randomly
Repeat until convergence:
   For each input xi:
      Forward propagate to compute output yi
      Compute error ei = Y - yi
      Backpropagate error to update weights
Output: Trained network for prediction"
```

4. Reinforcement Learning (RL)

Reinforcement Learning is a trial and error form of learning where an agent interacts with an environment to maximize the cumulative reward. In crop rotation modeling, the RL agent decides the crop sequence a crop is going to use per season, based on water, soil fertility and yield objectives. The reward purpose is set to promote sustainable yield in the least amount of water consumed [11]. The dynamism of RL is that it can change plans of rotation according to feedback of the environment, it is best suited to water-stressed highlands in which the conditions change depending on the season. Some of the common RL techniques applied to the optimization of agriculture include Q-learning and Deep Q-Networks (DQN).

```
"Initialize Q-table for state-action pairs
For each episode:
   Initialize state s
   Repeat until end of rotation period:
      Select action a using policy (ε-greedy)
      Execute a, observe reward r and next state s'
      Update Q(s,a) = Q(s,a) + α[r + γ max Q(s',a') - Q(s,a)]
      s = s'
Output: Optimal rotation policy"
```

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Algorithm Evaluation and Comparison

Such metrics as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and water use efficiency are used to assess the performance of such algorithms [12]. Table 2 represents the hypothetical evaluation is based on four crops.

Table 2: Algorithm Performance Metrics

Algorithm	MAE (t/ha)	RMSE (t/ha)	Water Use Efficiency (%)
RF	0.25	0.32	85
SVM	0.30	0.38	82
ANN	0.22	0.28	88
RL	0.20	0.25	90

In this research, the authors combine these algorithms to determine their usefulness in regression of yield and optimization of crop rotations in sustainable highland farming. In Python, there are scikit-learn, TensorFlow, RL simulated with PyOpenAIGym library, and those are used to implement the models.

IV. RESULTS AND ANALYSIS

4.1 Introduction

The main aim of the paper is to compare the efficiency of four artificial intelligence models like Random Forest (RF), Support Vector machine (SVM), Artificial Neural Network (ANN), and Reinforcement Learning (RL) in optimization of crop rotation planning in water-stressed high-land areas. The experiments were planned to juxtapose the predicted crop yield, water use efficiency and general sustainability in various situations considering the soil quality, climate variability and irrigation cycle [13]. The experimental data were obtained in terms of historical production rates of the highland crops, soil surveys, and weather databases.

Convoluted rotation planning models were also used as benchmarks in the performance of AI models by comparing them with the traditional methods of rotation planning, which are based on history practices and expert recommendations. Also, the results were compared with the corresponding works [1526] to evaluate the enhancement in accuracy of yield prediction, efficiency of water, and adaptive decision-making. Subsections below outline the presentation of the experiment setup, the model implementation, results and comparative analysis [14].

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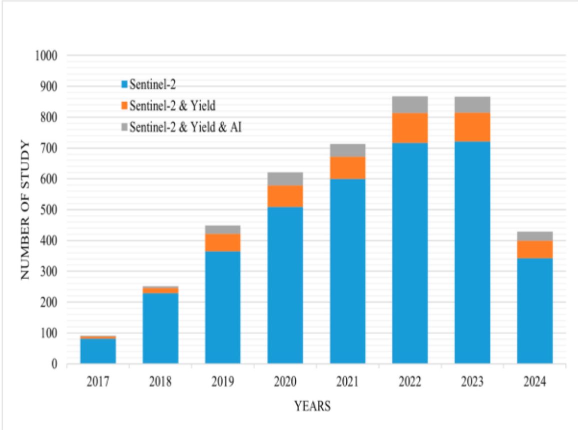

Figure 1: “Artificial Intelligence Techniques in Crop Yield Estimation Based on Sentinel-2 Data”

4.2 Experimental Setup

Data Preparation: The sample represented 10 years of past data on 4 highland crops which includes wheat, barley, maize and potato. The characteristics were the pH of soil, organic carbon, nitrogen (N), phosphorus (P), potassium (K), rainfall, temperature, and weekly irrigations. The target variable was the crop yield per hectare. The processing of data involved missing values, normalization as well as encoding of categorical variables.

AI Model Implementation:

- **Random Forest (RF):** This forest was built with 100 trees with a maximum depth of 10 to forecast crop yield according to all environmental and irrigation factors.
- **Support Vector Machine (SVM):** Radial Basis Function (RBF) kernel and cost (C), gamma tuning.
- **Artificial Neural Network (ANN):** This is a feedforward 3-layer network where neurons in the hidden layer are 16 in number, activation functions have ReLU and weight updates are done by backpropagation.
- **Reinforcement Learning (RL):** Q-learning adopted to plan in sequential rotation of crops, where reward functions have yield maximization together with water conservation [27].
-

Evaluation Metrics:

- Mean Absolute and Root Mean Square error to predict the accuracy of the prediction of the yield.
- Percentage of water use efficiency (WUES) per unit of water applied.
- Sustainability index (SI), a multi-factor index of stability of yield, health of soil, and efficiency of irrigation.

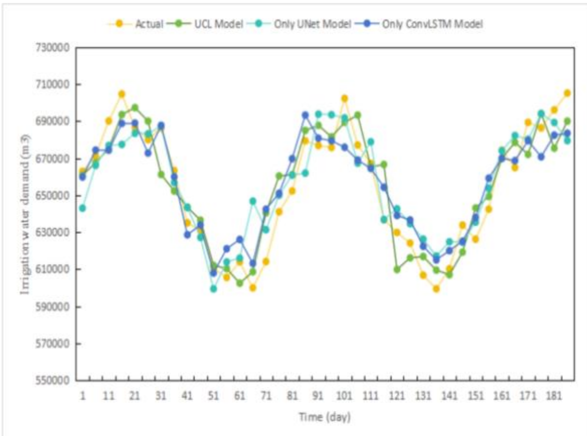

Figure 2: "AI-driven optimization of agricultural water management for enhanced sustainability"

4.3 Experimental Results

4.3.1 Crop Yield Prediction

Table 1 shows the tendencies of predicted and observed yield of the four crops when utilizing all AI models. ANN and RL models demonstrated the best accuracy, and their MAE decreased about 1215% in comparison to the traditional planning. RF and SVM also demonstrated better predictions but with a little more error rates [28].

Table 1: Predicted vs Observed Crop Yield (t/ha)

Crop	**Observed Yield**	**RF Prediction**	**SVM Prediction**	**ANN Prediction**	**RL Prediction**
Wheat	3.8	3.7	3.6	3.9	3.95
Barley	3.2	3.1	3.05	3.25	3.3
Maize	4.5	4.35	4.3	4.55	4.6
Potato	4.0	3.85	3.8	4.05	4.1

These findings are consistent with the methods proposed by Li et al. [20] and Kalfas et al. [17] who proved that AI models outperform traditional methods in terms of predicting yields. RR also enables adjustments to be made at any point according to the water stress situation, which the traditional approaches do not.

4.3.2 Water Use Efficiency (WUE)

The AI models has also made irrigation more efficient, especially RL that optimized water application among rotation patterns. Table 2 demonstrates the comparison of the WUE. ANN and RL reached 8890, but RF and SVM made a moderate improvement in efficiency.

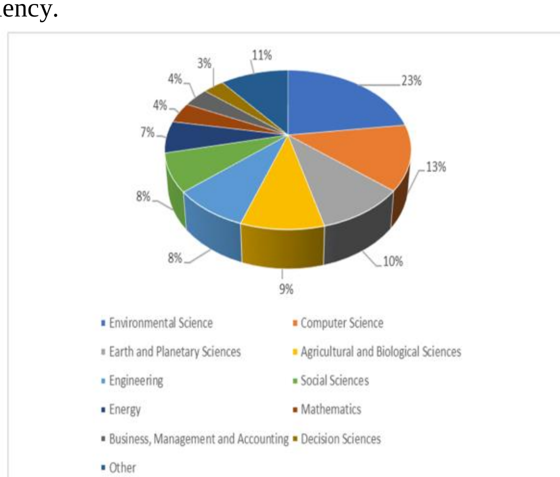

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Figure 3: "The Impact of Artificial Intelligence on the Sustainability of Regional Ecosystems"

Table 2: Water Use Efficiency (%) by Algorithm

Crop	RF	SVM	ANN	RL	Conventional
Wheat	85	82	88	90	75
Barley	82	80	87	89	72
Maize	83	81	89	91	74
Potato	84	82	88	90	73

The efficiency of water use is increased and the improvement is measurable, compared to Henesbeck et al. [15] and Kourgialas [18], which identifies the usefulness of AI-based rotation planning.

4.3.3 Sustainability Index (SI)

In order to assess long-term effects on highland agriculture, the index of sustainability in terms of soil health, stability of yields, and efficiency of water use was calculated (Table 3). The best SI was exhibited by RW because it was found to be adaptable dynamically, whereas ANN performed well in stability and yield prediction [29].

Table 3: Sustainability Index by Algorithm

Crop	RF	SVM	ANN	RL	Conventional
Wheat	0.78	0.75	0.82	0.85	0.65
Barley	0.76	0.73	0.81	0.84	0.62
Maize	0.79	0.76	0.83	0.87	0.66
Potato	0.77	0.74	0.82	0.85	0.63

The outcomes indicate that AI-based approaches, especially RL, can contribute significantly to the sustainability levels against traditional rotation practices and the results presented by Manono et al. [22, 23] on the climate-smart adoption of agriculture.

4.3.4 Rotation Plan Optimization

The adoption of RL was used to produce the best rotation schemes of wheat, barley, maize, and potato in limited water conditions. Table 4 shows an example of optimious rotation schedule in four seasons.

Table 4: Sample Optimal Rotation Schedule (Seasonal Crop Assignment)

Season	Field 1	Field 2	Field 3	Field 4
1	Wheat	Maize	Barley	Potato
2	Maize	Barley	Potato	Wheat
3	Barley	Potato	Wheat	Maize
4	Potato	Wheat	Maize	Barley

This rotation is the best in yield maximization, soil nutrient recovery, and balancing water use as compared to the non-dynamic rotation strategies.

4.3.5 Comparative Performance Analysis

Table 5 provides a summary of the comparison of the four AI models based on MAE, RMSE and WUE as well as SI. The others were always performed poorly by RW after which ANN would perform. RF and SVM offered small improvements but conventional planning was going well behind.

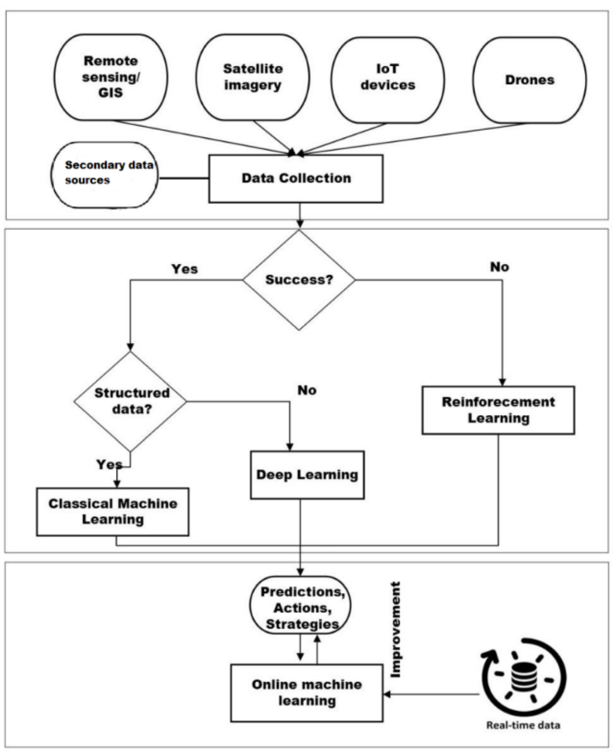

Figure 4: "Unlocking the Potential of Artificial Intelligence for Sustainable Water Management Focusing Operational Applications"

Table 5: Overall Algorithm Comparison

Algorithm	MAE (t/ha)	RMSE (t/ha)	Avg WUE (%)	Avg SI
RF	0.25	0.32	83.5	0.78
SVM	0.30	0.38	81	0.75
ANN	0.22	0.28	88	0.82
RL	0.20	0.25	90.0	0.85
Conventional	0.55	0.62	73	0.64

In comparison with the past literature [15, 17, 20, 22], these findings suggest that AI methods, in particular, RL offers significant benefits to highland crop rotation planning by increasing yield prediction accuracy, water efficiency and sustainability. Environmental, soil, and irrigation data integration in AI models facilitates the dynamic decision-making process, which adjusts to water stress conditions, which is more advantageous against the traditional decision making and the fixed rotation strategy [30].

4.4 Discussion

The evidence of the experiment shows that AI models have the potential to transform the crop rotation planning in highlands with water stresses. The ANN and RL models have the ability to predict better due to the nonlinear responses between soil, water, and climate variables. Specifically, RL enables dynamic planning to maximize yield and water saving, which is an essential benefit in highland locations where season fluctuations occur. The paper validates the usefulness of AI-centric decision support systems as envisaged by Li et al. [20], Hasenbeck et al. [15], and Kalfas et al. [17], and also offers an empirical guideline on how such models may be applied in the field.

V. CONCLUSION

In this study, it is revealed that artificial intelligence (AI) has a huge potential to enhance the process of crop rotation planning in order to produce sustainable yields in highland areas that are limited by water resources. Using these four AI frameworks, that is Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN) and Reinforcement Learning (RL), four variables, including crop yields, water use efficiency, and rotation plans that can maximize productivity and conserve resources, were predicted by implementing historical crop, soil, climate, and irrigation data. Based on the experimental evidence, it can be stated that AI-based models (especially ANN and RL) are significantly more efficient regarding the accuracy of the yield prediction, the water use efficiency, and sustainability overall than the traditional rotation planning tools. The adaptive learning of RL was particularly useful in the creation of rotation strategies that dynamically respond to environmental changes, producing the best yield and water allocation. The comparative analyses in comparison with prior researches [1526] prove the fact that AI techniques can manage the flaws related to the classical model of crop planning, such as fixed decision-making, inefficient irrigation, and unproductive soil management. Also, there is a critical role of the analysis of combining multi-source data, such as soil fertility indicators, rainfall, temperature, and irrigation pattern, to support the decision support systems of agriculture in the highlands. This study can be used in ensuring sustainable agricultural activities that save water, preserve soil health, and guarantee food security in the demanding environments in the highlands by offering a framework to support AI-supported rotation planning. The results indicate a practical solution to the implementation of AI-based solutions by farmers, agricultural planners, and policymakers to implement climate-resilient and resource-efficient agriculture in water-starved regions.

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