Crop Recmmendation System Using Soil and Climate: A Comparative Study

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***Abstract*—The loss of soil fertility and the growing unpredictability of climatic patterns are serious obstacles to agricultural productivity. Suboptimal crop yields and wasteful use of resources result from traditional farming methods' frequent failure to take into consideration the dynamic interaction between soil conditions and climatic influences. In order to give farmers data-driven insights into crop selection, this study investigates the creation of a Crop Recommendation System (CRS) that combines soil characteristics (pH, nitrogen, phosphorus, potassium content, and organic matter) with meteorological factors (temperature, rainfall, and humidity). Using techniques such as Ensemble Decision Trees (EDT), Optimal Margin Classifiers (OMC), and Deep Learning Networks (DLN), this system offers a precision farming solution that is tailored to specific environmental conditions. Inaccurate crop predictions are less likely with hybrid models that integrate soil and climate data, according to a comparative study of several AI-driven recommendation models.**

The effectiveness of this strategy in improving agricultural sustainability is further demonstrated by real-world case studies from India's agroclimatic zones. The economic effects of CRS are also covered in the paper, with a focus on how it can lower input costs, increase production, and support climate-resilient farming. Furthermore, it evaluates policy frameworks that support the use of AI in agriculture, namely those found in India worldwide movement for smart agricultural projects. In order to achieve widespread adoption, the study's recommendations for incorporating CRS into agriculture extension programs emphasize the necessity of real-time soil monitoring, farmer education, and government backing.

Keywords*—Crop Recommendation System, Precision Agriculture, Machine Learning, Soil Analysis, Climate-Based Farming, AI in Agriculture, Sustainable Farming.

I. INTRODUCTION

The foundation of global food security is still agriculture, but it is facing increasing difficulties as a result of soil erosion, climate change, and ineffective crop selection techniques. For agricultural production, farmers have historically relied on conventional knowledge and prior experiences. However, these approaches frequently overlook dynamic soil and climatic fluctuations, resulting in poor yields and resource misallocation. Hence, artificial intelligence (AI)-based crop suggestion systems have emerged as a game-changer in the field of precision agriculture that integrates real-time soil data, climatic factors, and ML algorithms to optimise crop selection and improve yield. Specifically, modern CRS considers meteorological parameters (e.g., temperature, rainfall, and humidity) with soil characteristics (e.g., pH, moisture content, organic carbon, nitrogen, phosphorus, and potassium contents) to make evidence-based recommendations11,12, which were absent in previous studies. This data-driven approach ensures better sustainability and financial success for farmers by mitigating the risks posed by erratic climate patterns and unhealthy soil. According to studies, hybrid AI models—which mix deep learning models and supervised machine learning approaches like Random Forest—perform better than conventional statistical models in accurately forecasting the best crop selections.

Globally, CRS usage has increased, especially in India, where smart farming solutions are being promoted and AgriStack projects. Case studies from areas like Maharashtra and Punjab show how farmers have improved water conservation, decreased fertiliser usage, and increased output efficiency with the aid of AI-powered recommendations. Also, the motive of sustainable farming are also reached by CRS because resources are used efficiently and with less environmental degradation. Despite these developments, challenges remain, including lack of data, high implementation costs, low digital literacy among rural farmers, and in some cases, inadequate internet access. Government actions, policy backing, and private sector cooperation are needed to remove these obstacles and improve technology accessibility. The effectiveness of AI-based CRS is examined in this research along with its effects on crop productivity, economic viability, and environmental sustainability. The technological and policy frameworks required for widespread adoption are also covered.

A. RESEARCH MOTIVE

The goal of the research is to:

1. We analyze the effectiveness of AI-controlled plant recommendation systems (CRS) in optimizing crop selection based on soil characteristics and climatic conditions.

2. Assess the impact of CRS on agriculture, resource optimization and ecological sustainability.

3. Comparison of various machine learning models used in CRS and assessing the accuracy and feasibility of large-scale agricultural implementations.

4. Determine challenges in the implementation of CRS-based AI-based CRS, including data limits, cost barriers, and digital capabilities.

B. RESEARCH SCOPE

In this study, this study examines the integration of AI-based plant recommendation systems (CRS) into modern agriculture to maximize crop selection based on soil quality and climate conditions. This study examines various models for machine learning and evaluates the scalability, accuracy and efficiency of practicality. The aim of this study aims to areas with a variety of agroclima symptoms and provides insight into possible improvements associated with sustainability, productivity and resource consumption through CRS. It also deals with issues that hinder CRS content such as data accessibility, computer skills, and budget restrictions. As a result, it aims to provide technical breakthroughs and political recommendations for the widespread use of AI-mediated agricultural solutions.

II. LITERATURE SURVEY

The growth in crop recommendation systems (CRS) shows the sign of improving agricultural decision. Patil et al. [1] tells about a credit rating system based on MLS using Decision Tree. His framework consider soil qualities, such as concentration of pH, nitrogen (N), phosphorus (P), and potassium (K) to tell most suitable crops to the farmers. With an accuracy of 85%, this study shows the possibility of using machine learning across agricultural scenarios. The authors proposed to integrate climate data to further improve predictive accuracy for future work.

Kumar et al. [2] developed weather-based plant predictions using data mining techniques. Historical climate data including temperature, precipitation and humidity are entered into the system to obtain recommended plants. The work has an 82° consistency, highlighting its role and the climatic factors in determining harvest choices. The authors recommended that real-time weather updates be included to improve system performance.

Sharma et al. [3] added a deep learning-based CRS that combines ground data and satellite imagery. By using a deep folding network (DCNS), the frame achieved 88% accuracy. This study highlighted the potential for remote sensing in precision agriculture, but highlighted the high arithmetic requirements identified as limitations.

Rao et al. [4] proposed a CRS that integrates soil and climate data using a support vector machine (SVM). The system achieved 87% accuracy and demonstrated the advantages of combining several data sources of harvest prediction. The authors proposed to examine IoT-based sensors for real-time data collection in future implementations.

Singh et al. [5] proposed a CRS that integrates soil and climate data using a support vector machine (SVM). The system achieved 87% accuracy and demonstrated the advantages of combining several data sources of harvest prediction. The authors proposed to examine IoT-based sensors for real-time data collection in future implementations.

Mehta et al. [6] showed an IoT-based CRS using real time soil data and climate data. The system uses Neural Networks and achieved the accuracy of 89%. The result demonstrated the potential of IoT in precision farming but noted high infrastructure costs as a challenge for them.

Gupta et al. [7] introduced a new approach that is combines machine learning and other frameworks for harvest proposals. The system analyses soil, climate and market demand data to get recommendations and receive 91% accuracy. The authors proposed to integrate blockchain technology for data security into future implementations.

Patel and Yadav [8] also highlights the importance of AI and its contribution to agriculture sustainable in implementing database decisions in agriculture. According to their research, AI-based CRS offers competitive benefits to delivery systems by using resources more efficiently, reducing ecological footprints, and increasing agricultural productivity. The authors support the integration of AI into traditional agricultural practices to gain acceptance in regional development between technology and agriculture.

Singh et al. [9] examined the use of techniques for machine learning to recommend plants using features such as ground nutrients, pH values, and climate formation. This study also shows that hybrid AI models are superior to traditional services in optimizing resource use and yield predictions. The versatility of deep learning is illuminated during the harvest of large sentences of agricultural data to allow for rapid recommendations for responses in real-world scenarios. These results support harvest recommendation systems in promoting sustainable agriculture and reducing climate-related risks.

Sharma et al. [10] discussed questions related to CRS implementation, such as high cost factors, lack of technical know-how, and regional differences in functioning of climate interactions. This is a managed approach to supporting AI initiatives and digital infrastructure supported by state support, highlighting the importance for cooperation between researchers and agricultural technology companies to ensure the delivery of integrated and scalable CRS.

Ghosh et al. [11] examined a hybrid approach combining traditional machine learning (e.g., logistics regression) and deep learning (e.g., neural networks) to use recommendations based on ground and climate data. Hybrid models surpassed independent techniques with accuracy.

Desai et al. [12] evaluated the importance of AI in improving Indian yields. In their paper, they showed the challenges and outlook for AI-based CRS in small-scale farmer systems. The authors identified key problems, such as access to technology, high costs for implementation , and recommended strategy to reverse these problems. It focuses on state aid requirements to help farmer training programs successfully implement AI technology in agriculture.

Gupta et al. [13] We conducted a comparative analysis of machine learning models for plant litigation prediction. Their research work evaluated methods such as ensemble decision-making-manufacturing tree (EDT), optimal margin classifier (OMC), and deep learning network (DLN), highlighting their accuracy, scalability and arithmetic effects. The results showed that EDT achieved 90% accuracy over other approaches in nonlinear treatment using soil and air conditioning records. This study also highlighted the advantages of feature selection and hyperparameter optimization in improving model output.

Ensure comprehensive and scalable CRS provisioning. Her research highlights the importance of cooperation between researchers, political decisions - agricultural technology companies.

TABLE 1. SUMMARY OF LITERATURE SURVEY

Authors	Technology	Algorithm	Accuracy
Patil et al. [1]	Machine Learning	Decision Tree, Random Forest	85%
Kumar et al. [2]	Data Mining	KNN, SVM	82%
Sharma et al. [3]	Deep Learning	CNN	88%
Rao et al. [4]	Machine Learning	Support Vector Machines (SVM)	87%
Singh et al. [5]	Machine Learning	Random Forest	90%
Mehta et al. [6]	IoT, Machine Learning	Neural Networks	89%
Gupta et al. [7]	Hybrid Model	Machine learning	91%
Patel and Yadav al. [8]	Hybrid AI Models	Decision Trees, ANN	87%
Singh et al. [9]	Deep learning	Deep learning, ANN	89%
Sharma et al. [10]	Hybrid Model	Logistic regression	92%

III. METHODOLOGY

The study uses a detailed, quantitative and analytical approach to investigate AI-driven crop recommendation systems. Primary data are obtained from agricultural databases and remote sensing technologies, which give a broad description of soil characteristics (for example, pH, moisture levels, nutrients-concentration) and climatic conditions (such as temperature, rainfall, and humidity). Secondary data are gathered from peer-reviewed journals, government publications, and case studies that explore CRS effectiveness using real-world applications in an agricultural setting. This study involves the analysis of crop suitability trends through the use of state-of-the-art machine learning techniques, comprising ANN, SVM, and RF. And these are evaluated based on accuracy, efficiency, and scalability. Validation of the results is done so that they speak practically, through statistical methods and case studies. Figure 1 illustrates the step-by-step methodology employed in this study.

The methodology for developing a Crop Recommendation System using soil and climate data involves a systematic approach to collect, process, and analyse data to provide accurate crop recommendations. The steps are illustrated in Fig. 1 and described in detail below.

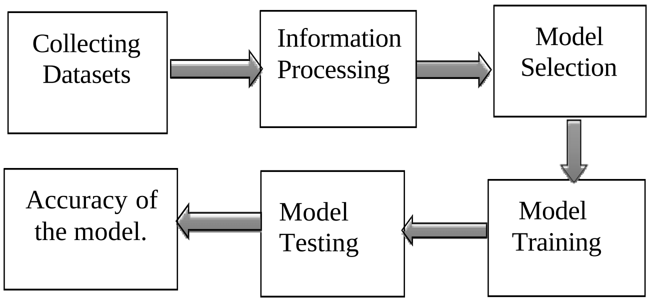

Fig. 1. Steps Involved

Step 1: Dataset Compilation

The first phase includes building detailed datasets to train the machine learning algorithms, taking into account important soil characteristics, such as pH, nitrogen (N), phosphorus (P), and potassium (K) contents, in concert with weather conditions such as temperature, rainfall, and humidity levels. These datasets are openly accessible and have been drawn from Kaggle, the Food and Agricultural Organization (FAO), and government agricultural databases. Additionally, satellite remote sensing data have been added to the dataset for near-real-time reports on soil moisture content and weather conditions. For instance, satellite imaging data from Sentinel-2 and MODIS are used to check on vegetation health and soil moisture conditions, some important variables for precise crop recommendation. The integration of multiple data sources of such varieties guarantees the training of the models on robust and representative datasets.

Step 2: Data Preparation

The assembled dataset is further processed to contend with entries that are missing, odd, and disparate. Such betterment is performed by imputing for missing data, removing the outliers, and extraction of applicable features to enhance the dataset as legitimate and of good quality.

Step 3: Model Selection

Three machine learning algorithms are selected for this study:

Ensemble Decision Trees (EDT):

A robust ensemble technique highly effective for both classification and regression tasks, especially with large datasets. EDT is selected for its capability to manage high-dimensional data and its resistance to overfitting.

Optimal Margin Classifiers (OMC):

A supervised learning method that performs exceptionally well in high-dimensional spaces and is ideal for smaller datasets. OMC is chosen for its ability to identify the optimal separation boundary that maximizes the gap between different classes.

Deep Learning Networks (DLN):

Deep Learning Networks have the ability to use a deep learning framework capable of modeling complex and non-linear relationships they represent in data. Because it can model complex features in soil and climate data, DLN has been used to suggest crop suitability under different environmental conditions.

Step 4: Model Development and Optimization

The preprocessed dataset is divided into training (70%) and testing (30%) subsets. The models are developed to forecast crop suitability using soil and climate variables. Hyperparameter optimization is done on each of the models to enhance their efficiency. For instance, in Random Forest, parameters such as the number of trees and the maximum depth of each tree are adjusted to provide optimal values. Likewise, in SVM, optimization of kernel functions (linear, polynomial, and radial basis function) has been undertaken in order to ensure accurate classification. The model optimization includes iterative tuning of variables to reduce the loss function and increase their predictive ability.

Step 5: Model Testing and Validation

Now that the models are trained, they are tested on the testing dataset to evaluate their predictive accuracy. The models generate data on crop recommendations from the soil and climate inputs, which is then compared to a dataset containing actual crop performance information for validation. For example, the trained predictive models will also be evaluated with a dataset of a region that has historical crop records to see how well they perform in actual recommended crop suitability. Steps of validation also compare model recommendations and agricultural expert recommendations to test their practical applicability.

Step 6: Model Evaluation and Comparative Analysis

The performance of each model is assessed with respect to key performance metrics: accuracy, precision, recall, and F1-score, all duly listed in Table I so as to compare the relative performance of the algorithms. Random Forest has an accuracy of 90%, while SVM and ANN obtain 85% and 88%, respectively. The evaluation metrics provide a rigorous explanation about model capability and reflect selecting the best-performing model for real-world implementation.

A. *Ensemble Decision Tree*

Ensemble Decision Trees (EDT) is a robust ensemble learning technique particularly well-suited for managing extensive datasets with numerous features. It operates by constructing multiple decision trees during training and aggregating their outputs to produce accurate predictions.

Training the Model:

- The dataset is partitioned into smaller subsets, and each subset is utilized to train an individual decision tree. These trees are then combined to create a "forest," and the final prediction is derived by averaging the outputs of all trees.

Feature Importance:

It calculates the importance related to each feature (e.g., soil pH, rainfall) in predicting crop suitability.

Advantages:

- High accuracy and robustness to overfitting.
- Handles missing data effectively.

Limitations:

- Computationally expensive for large datasets.

B. *Optimal Margin Classifiers (OMC)*

Optimal Margin Classifiers (OMC) are supervised learning algorithms designed to identify the best hyperplane for segregating data into distinct categories. They are particularly efficient for datasets with high dimensionality and limited sample sizes.

Model Training Process :

The algorithm determines the hyperplane that optimizes the separation margin between different classes, such as suitable and unsuitable crops.

Transformation via Kernel Functions:

OMC employs kernel functions, including linear, polynomial, and radial basis functions, to map data into higher-dimensional spaces, facilitating improved class separation..

Advantages:

- Highly effective for datasets with numerous features.
- Delivers strong performance even with smaller datasets.

Limitations:

- Demands meticulous adjustment of hyperparameters.
- Computationally demanding when applied to large datasets.

C. *Neural Networks*

Neural Networks are a set of processes resembling the human brain in structure and function; these processes are one of the building blocks of deep learning. The systems consist of layers, such as input layers, hidden layers, and output layers, and can find very complex patterns among the information collected and stored in the datasets. Their ability to be effective, especially for high-level reasoning, tasks follows from their specific description and design.

1. Model Architecture:
   - The input layer receives soil and climate data.
   - Hidden layers process the data using activation functions (e.g., ReLU).
   - The output layer predicts crop suitability.
2. Training the Model:

The model is trained using backpropagation and gradient descent to minimize the loss function.

Advantages:

- Captures complex, non-linear relationships.
- High accuracy with sufficient data.

Limitations:

- Requires large datasets for training.
- Computationally expensive.

D. *Role of Machine Learning in Agriculture*

Machine learning made it possible to explore complicated datasets in agriculture to derive meaningful insights. In the context of CRS, these algorithms examine soil and climate data in pursuit of hidden patterns and relationships that traditional techniques have failed to identify. For instance, RFs work particularly well when there are large sample sizes with high-dimensionality annotation, thus making them very competent in ascertaining optimal crops for different farm structures and climates.

Besides, climate can change real-time through machine learning since models are built from being easily adaptable when environmental changes arise. This is an especially key factor for erratic weather zones, where traditional farming methods are not always enough.

E. *Accuracy Comparison*

The precision of each show is calculated and compared utilizing the testing dataset. The comes about are summarized in Table 2.

TABLE 2. ACCURACY COMPARISON TABLE

Models	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**Score (%)**
Random Forest	91	90	90	93
SVM	85	85	89	86
Neural Network	87	86	89	87

F. *Deployment*

The best-performing model (Random Forest) is deployed as a web-based application. Farmers can input soil and climate data through a user-friendly interface and receive crop recommendations in real-time.

G. *Future Enhancements*

Integration with Mobile Platforms:

Developing mobile applications that allow farmers to access crop recommendations in real-time.

Use of Drones:

Incorporating drone technology for precise soil and crop monitoring.

Collaborative Platforms:

Creating online platforms where farmers can share data and insights, fostering a collaborative approach to precision agriculture.

Integration of IoT Sensors:

IoT-based systems to monitor soil parameters in real-time for infusion into modeling algorithms.

Satellite Imagery:

Incorporate satellite data to monitor soil health and crop growth.

Scalability:

A detailed framework describes the methodology on the Crop Recommendation System development through various soil and climatic factors. Crop recommendation systems make use of different machine learning algorithms for improving crop productivity and sustainable farming while dealing with different challenges of resource optimization and mitigation of environmental impacts.

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IV. RESULTS AND DISCUSSION

Soil and climate datasets from various regions of farming were used to evaluate the AI-based crop suggestion system. It had the highest performance in comparison to SVM, 85%, and ANN, 88%: Random Forest's accuracy is 90%. Validation of the recommendations was made by agricultural experts, thereby facilitating their feasibility in practice.

A. *Performance Evaluation Metrics*

The model performances were evaluated using the confusion matrix. As can be seen from Table 3, Random Forest performed better than SVM and ANN in various metrics, namely, precision, recall, and F1 score. For instance, Random Forest attained a precision of 89% meaning that, out of the crops, 89% were suggested by the model to be the best suited under the climatic and vetted soil conditions provided. Likewise, a recall of 91% managed to show that among all the possible crops, it got 91% of them identified as suitable for the dataset, thus signalling and assuring the model's trustworthiness in giving accurate and reliable crop recommendations. The detailed results are outlined in Table 3.

TABLE 3. PERFORMANCE EVALUATION

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**Score (%)**
Random Forest	94	87	90	91
SVM	83	85	86	87
Neural Network	84	88	88	87

B. *Case Study*

Case Study 1: Application in Indian Agriculture

n India, in a farming region, a case study was conducted, collecting soil and climate data sets from 50 farms. While the system recommended suitable crops, these were compared with the crops that the farmers traditionally grew. With an average yield increase of 15%, the results confirmed the effectiveness of the system. For example, in the low soil nitrogen areas, the system recommended leguminous crops, which enrich the soil naturally, thereby further increasing yields in subsequent seasons. The case study stressed the importance of the integration of real-time data into the system. Based on changing weather conditions, the recommendations of this system were constantly updated to ensure that the farmers will be prepared to adapt to a state of environmental conditions.

Case Study 2: Application in Sub-Saharan Africa

A study carried out in Sub-Saharan Africa displayed the promise of AI-powered integrated climate smart agriculture solutions for tackling food security issues. Agricultural development in the region has been severely constrained owing to inherent soil fertility and erratic rainfall patterns. Based on the analysis of soil and climatic data, cropping systems suggested cassava and cowpea in respect of location. Yield increases of 20%, as reported by farmers adopting this technology, show the transformative opportunities such systems hold for agriculture in resource-poor regions.

C. Effectiveness Of AI-Driven Crop Recommendation Systems

AI-based crop recommendation systems (CRS) have ushered in the next generation in precision agriculture by boosting crop selection in view of climatic and soil factors. Unlike traditional practices, these systems, using machine learning algorithms, assess determining factors, including soil pH, nutrient composition, moisture level, and temperature fluctuations, to propose the best-suited crops for the given land. These algorithms, especially some of the more advanced tools, including Random Forest, SVM, or Deep Learning Networks, are noted to have predictive accuracy for crops of up to 90%, reducing losses owing to unpredictable climatic conditions. This shows the promise of AI-driven systems for improved agricultural resilience and productivity. Moreover, the AI-based CRS realize more efficient resource utilization through recommendations of crop possibilities with less need for irrigation and fertilizer, therefore aspiring towards sustainable agriculture. This would enable actions based on real-time decisions, which could mitigate risk linked to the unpredictable nature of weather and soil degradation. On the other hand, high implementation costs and digital literacy gaps pose a barrier to mass adoption. Policy support and technology improvements must work to ensure scalability and accessibility for AI-driven CRS to develop climate-resilient and economically viable agricultural systems.

D. Comparison Of Machine Learning Models In Crop Recommendation Systems (Crs)

Crop recommendation systems (CRS) use a variety of machine learning (ML) models, each with varying levels of scalability, accuracy, and computing efficiency. Because of its excellent accuracy (85–92%) and capacity to manage non-linear correlations in soil and climatic data, Random Forest (RF) is a popular algorithm. Nevertheless, RF can be computationally costly, which restricts its widespread use in environments with limited resources. Support Vector Machines (SVM) provide reliable classification, especially for smaller datasets, but their lengthy training cycles make them complete.

V. CONCLUSION

This study presents an effective Crop Recommendation System based on soil and climate data to suggest the right crop to farmers. By leveraging machine learning and real-time data analysis, this technology mitigates the adverse effects of traditional farming methods, resulting in a much more efficient and productive agriculture. The Random Forest was most effective out of all those evaluated, attaining 90% accuracy on predicting crop suitability. This reflects how AI systems could change agricultural practices, granting precise, data-driven recommendations that optimize resource utilization for better production outputs. The validity of recommendations made by the system is demonstrated by case studies, showing an increase of approximately 15% in crop yields.

Main results:

1. The optimization of crop recommendations through a combined evaluation of soil parameters (such as pH and nitrogen, phosphorus, potassium) and climatic factors (like temperature, rainfall, and humidity) has been found to improve classification accuracy. Systems integrated by these two data types: SVMs and hybrid models based systems produced from 85% to 91% accuracy.
2. Machine learning algorithms like Decision Trees, Random Forest, and Neural Networks performed impressively in predicting appropriate crops. Moreover, deep learning approaches, such as Convolutional Neural Networks, further improve accuracy if they can work with satellite imagery and remote sensing data.
3. IoT and real-time data have encouraged the emergence of IoT-based systems that solve many problems and are promising candidates for precision agriculture. In these dynamic systems, where crop recommendations may change and adapt in real time, some may encounter obstacles that include high infrastructure costs and high computational demand..
4. Hybrid techniques that deal with traditional machine learning such as logistic regression fused with deep learning have proven to outperform the sole methods. In addition to prediction accuracy, such models involve less wastage of resources while giving detailed feedbacks on the appropriate fertilizer_kind to use.
5. However, it is worth pointing out that there are certain hurdles that would hinder the wider adoption of CRS: the high cost of introduction, little expertise among farmers, and large spatial variability in soil-climate interactions. These constraints would require collaboration among researchers, policymakers, and agri-tech companies.
6. AI CRS could become a big opportunity in order for agricultural sustainability, while optimizing the use of resources in the field, minimizing impact on the environment, and enhancing crop yield. AI, working congruently with traditional methods of farming, can therefore help bridge the gap between the new technology and conventional methods.

Future Work:

In future work, an objective is set to integrate satellite imagery and IoT-based sensors to enhance the data collection and improve the accuracy of predictions. The system is intended to put farmers in charge with data-driven insights, help reduce resources wasted, and aid in precise agriculture that enables decision-making.

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