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ASI (Agriculture Smart Irrigation) Multiparameter Optimization System for Precision Agriculture

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Abstract: Irrigation is a significant process in smart precision agriculture to manage the water utilization of crop demand. The water required for irrigation is remarkably inconsistent, and the farmer's decision is final regarding when and how much to irrigate. The accurate decision of irrigation process occurrence in the farm field is an important cause to scale and improve the water management procedure, accordingly, the sustainability of smart irrigation. In this proposed research work, a heuristic methodology that combines an Artificial Neural Network and the Genetic Algorithm had developed to predict the optimal water demand of the crop. The proposed methodology tested with real-time agricultural data showed that developed models have been well-suitable for optimal irrigation in precision agriculture contexts.

***Keywords*:** *Artificial Neural Network, Genetic Algorithm, Multiparameter Optimization, Precision Agriculture, Heuristic approach*

1. Introduction

The primary objective of the proposed module, "AMOS System: ASI Multiparameter Optimization System for Precision Agriculture" is to optimize the water resource level for farmers in order to facilitate future precision farming decisions. The module developed to ensure the efficiency of the proposed research " ASI: An (Agriculture cultivation recommender and Smart Irrigation System)" for its usage in larger area crop fields for sustainable water management and high yield harvest. In the year 2050, there will be a great demand for water globally due to climate change and population growth. There exists a challenge to identify a specific measure for optimizing water usage in agriculture to meet the food and water demand.

Agriculture plays a vital role in many country's economies, and it is necessary to implement a fulfilling cultivation technique. Improper irrigation and water management will affect both the crops and increase water wastage. The important cultivation parameters are soil moisture, soil Ph, soil temperature, and humidity. The soil properties vary with sunlight and climate changes. Therefore real-time soil characteristics are required for crop production measurement (Pawan and Reddy 2016). In addition to this, previous crop characteristics are essential for future decision-making. Precision agriculture yields the best results for monitoring these multi-parameters (Unduche et al., 2018).

The crop growth-related parameters considered to optimize precision farming decision-making (Partarini et al., 2019). For the existence of humankind, it is necessary to serve quality food. In countries like Africa, food and water scarcity are the major life issues. Traditional agriculture techniques require more labour and time, which gives less production due to unpredictable environmental scenarios (Ding et al., 2018). Existing solutions for precision agriculture exploit specific parameters, and range limitation is still a challenge (Denis Illie et al. 2016). For optimum yield, it is necessary to understand the ecosystem of the cultivation field and plan water resource utilization. Usually, the soil testing recommendations get delayed (Pawan and Reddy 2016).

The proposed system AMOP aims at optimizing the water resource considering the crop growth characteristics such as rainfall, evapotranspiration, and moisture for precision agriculture. The results of the previous chapter confirm that AISM System is efficient for irrigation planning. Optimization of the system is necessary as the moisture influenced by evaporation and precipitation (Amarendra Goap et al. 2018 and Wu et al., 2020).

The rudimentary objective of this module in this research is to optimize the ASI System utilizing the machine learning algorithm and suitable future decision-making to

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farmers on sustainable cultivation, as shown in Figure 1. The proposed system takes crop growth characteristics as input datasets, the dataset measured from the cultivation field after the entire plant growth gets completed. The AMOP utilizes the novel AAGA (Agro ANN_Genetic Algorithm) for analysis and decision-making. The original scheme of the ANN(Artificial Neural Network) and Genetic Algorithm(GA) hybridized to develop the Agro ANN_ Genetic Algorithm to suit the optimization needs of the agriculture domain. In particular, the developed novel Agro ANN_ Genetic Algorithm compared with the best achievement shown Artificial Neural Network (ANN) algorithm for its validation, fulfilling the objective of the research described. To sustain good crop growth and water stability in precision agriculture, the suggested model offers future irrigation decision-making system.

2. Amop System:

ASI Multiparameter Optimization System for Precision Agriculture

The suggested "AMOP System: ASI Multiparameter Optimization System for Precision Agriculture" framework is presented in Figure 1. The AMOP system gives farmers the opportunity to evaluate the current irrigation schedule being used for the full crop growth before making irrigation-based decisions.

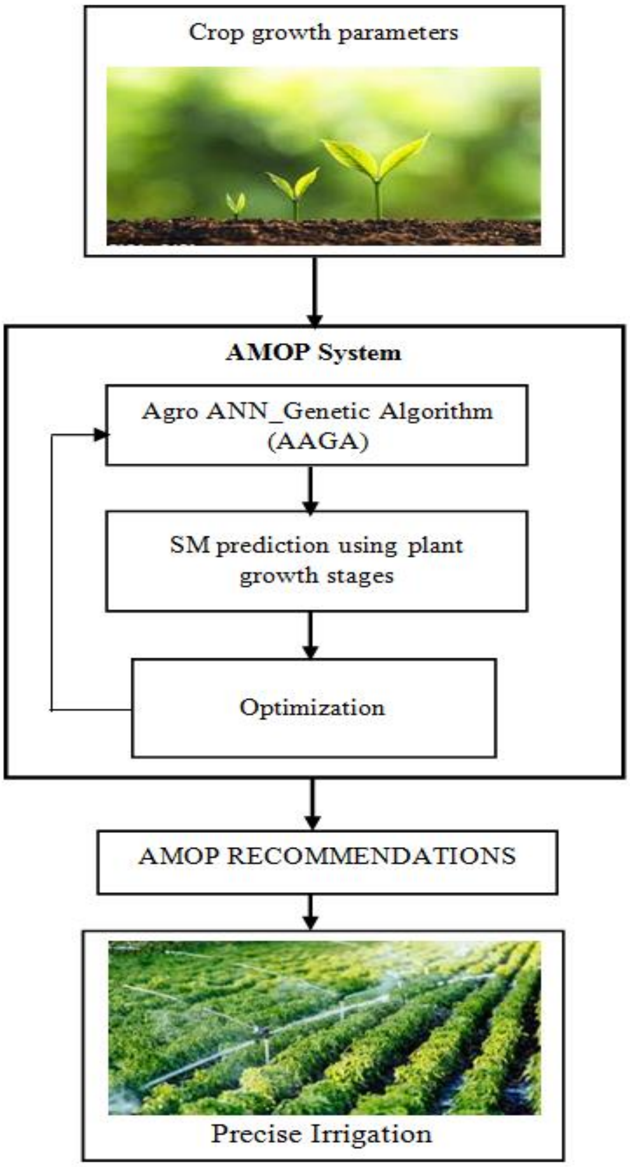

Fig 1 Framework of the Proposed AMOP System

To plan and schedule irrigation, the module uses crop growth characteristics as input information to estimate the ranges of precipitation, rainfall, and evapotranspiration that can support crop yield with future soil water stability requirements (Sorensen et al. 2010 and Togneri et al. 2019). The innovative AAGA (Agro ANN_ Genetic

Algorithm), a hybrid of the Artificial Neural Network (ANN) and the Genetic Algorithm, was used to create the AMOP System (GA).

Algorithm 5 – Agro ANN_ Genetic Algorithm(AAGA)

Input: Crop Growth Parameters(Soil Temperature, Relative Humidity, Soil Moisture, Soil pH, ETo, Plant Growth Stages)

Output: Sustainable Precision Agriculture Decision-Making

Begin

Read Input

Train ANN

Test ANN

Compute MSE

Else

Begin

Create intermediate_population()

Begin

Read random population

While(new population size (n) < population size (N))

Begin

  Select two members at random

  Perform Pc

  Perform Pm

  Add new member in new population

  GOTO While

End

End

GOTO ANN

End

The MSE based Accuracy expressed in Equation (1)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (1)$$

The coefficient of determination R, soil parameters exploit by the rainfall and runoff expressed as R factor. R factor changes based on daily precipitation. The methods are available for R factor calculation on a monthly basis as expressed in Equations (2) to (4)

$$R^2 = 1 - \frac{\sum (Y - Y_m{}^2)}{\sum (Y - Y_o{}^2)} \quad (2)$$

Where Y-observed data; Y_m-modelled value and Y_0-mean of the observed value

$$RMSE = [\sum_{i=1}^{N}(Z_{fi} - Z_{oi}{}^2)/N]^{1/2} \quad (3)$$

where f-forecasts, o-observed value, N-sample size, $(Z_{fi} - Z_{oi}{}^2)$ is the difference squared

$$VIF_i = \frac{1}{1 - R_i^2} \quad (4)$$

where R_i^2 the coefficient of determination 4

3. Experimental Results and Observations

a) Data Collection and Experimental Setup

The crop growth parameters such as soil temperature, soil humidity, soil moisture, and soil pH observed from the field are collected as a dataset and considered the training samples. The three subareas irrigated with sprinkler gadgets, and the other two subareas used drip irrigation. The datasets were collected in the cotton cultivation field in Southern tamilnadu, having various irrigation treatment sub-plots. Further, the precipitation statistical downscaling considered for predicting the accurate measurements providing decision-making support for optimizing water resource usage for irrigation (Nizar Ahmed et al., 2019).

The AMOP system deployed in the agriculture field and the different soil parameters measured by the sensors. The sensors directly connected to the Arduino UNO transmits the measured observations to the server. The simulations performed using the Matlab 2018(a) run on Windows 10 operating system. Under these circumstances, it is by far taken into account that an average cultivation land uses about 55% of the water needed for crop growth for irrigation. In this, 12% of water loss happen on transferring the water to the field. Another showing a utility of 25% in concern to the loss of water due to floor runoff and evapotranspiration. The proposed AMOP system improves the water productivity usage by providing suitable irrigation plans to carry out irrigation in a country like India, where sprinkler and drip irrigation methods widely utilized to water the fields. The results and their analysis are discussed in detail, substantially increasing water productivity - the types of irrigation not considered in the study. The central objective was to measure the soil moisture content during the crop growth stages and control the irrigation level.

b) Observations and Results

The AMOP technology increases water stability by simulating crop growth for a specific crop's soil profile. The daylong process began at 6:00 AM and prepared the server to inspect the crop as depicted in the aforementioned algorithm 1. When assessing the technique for hourly monitoring soil water content levels and imminent precipitation fluctuations, the crop growth stages are taken into account. The aforementioned field data is used to determine the irrigation schedule and consistency of the crop marinating water, which improves the overall performance of the created system's AAGA version.

The optimization of irrigation through the proposed AMOP system assessed for its R2, and RMSE. Table 1 presents the various stages of crop growth. Around 170 days pass during the crop growth development stage, which is divided into four stages: emergence, rapid growth, lag, and senescence. The irrigation constraints identified are herewith defined in Table 1. The performance of the proposed approach assessed for its R2 of (0.974), and low RMSE of (0.039). Thus the AMOP system evaluation for the considered performance metrics was better than the existing system Artificial Neural Network (ANN) shown in Figure 2.

Table 1 Stages of Crop Growth and their constraints

Duration of Crop Growth(days)	**Stages of Crop Growth Development**	**Crop Irrigation Constraints**
1-14	**Emergence –** 90% of the crop seed emerged from the ground.	Upper soil layer content retained close to FC levels.
15-70	**Rapid Growing Stage-**Green stems with an increasing green canopy.	Root zone the soil water content level reaches the maximum canopy growth.
71-113	**Lag Growing Stage-** Triggering of flowers.	Root zone the content retained at lower than the maximum canopy growth.
114-170	**Senescence (Maturity)-**Maximum height of the plant.	The water level should be less than the maximum canopy growth.

AAGA simulates the water level in the crop growing fields. The daily transpiration T_s expressed in Equation (5).

$$T_s = S_k x MA x k_m T_{s,x} x ET_0 \quad (5)$$

where ET_0, the evapotranspiration, $K_m T_{s,x}$ crop coefficient of midseason, S_k, crop coefficient and MA is a micro-advective adjustments

The MA is represented in Equation (6)

$$MA = 1.72MA - MA^2 + 0.30CC^3 \quad (6)$$

ET_0 the Water productivity (W_P) , the biomass calculation expressed in (7)

$$B = W_p x \sum \frac{T_r}{ET_0} \quad (7)$$

Finally, yield of the crop is computed using Equation (8)

$$Y = B \times H_I \quad (8)$$

where, H_I is the percentage ratio of crop yield to the above-ground dry biomass.

Table 2 presents the evapotranspiration measures, rainfall, and prediction to the soil level moisture considering the stages of a plant. The proposed AAGA shows a better measure of 96.32% when compared with the existing ANN.

Table 2 Comparison of ANN Predictions with Proposed AAGA

Stages - Plant Growth	**Evapotranspiration (ET_0) in cm**	**Crop growth (Cg) in cm**	**Soil Moisture Predicted by sensor**	**Soil Moisture Predicted by ANN**	**Soil Moisture Predicted by AAGA**
1-14 days	35	9	25.75	24.20	25.64
15-70 days	40	75	28.08	27.01	28.22
71-113 days	65	113	30.87	29.85	30.68
114-170 days	83	180	33.05	32.17	33.23

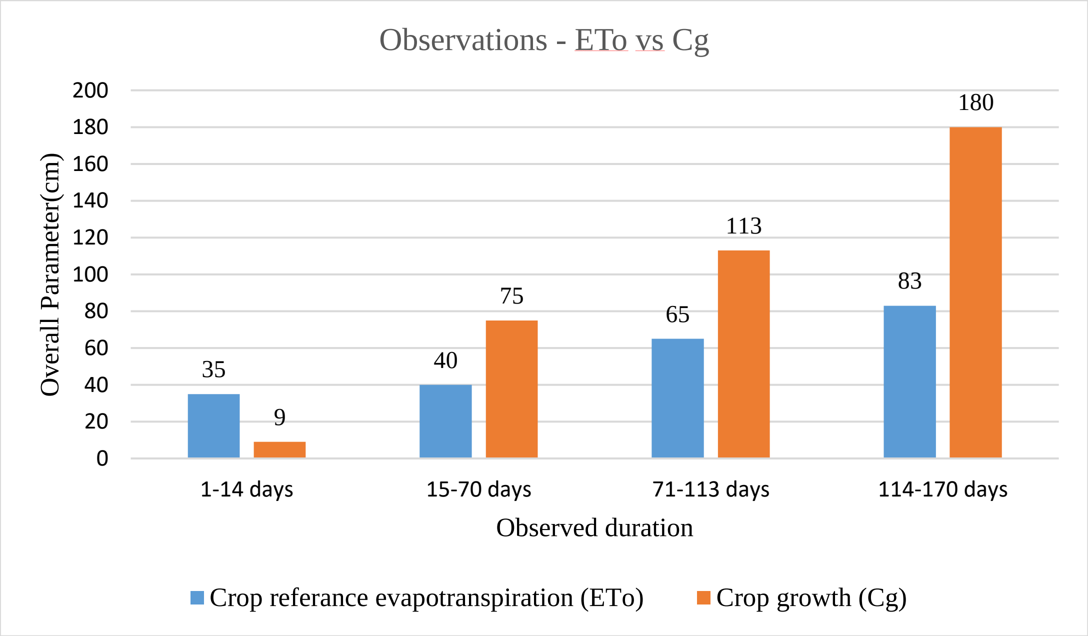

Fig 2 Observations - ET_0 VS R

The results compared with measures ET0 and R observed that the ET0 shows high results on all the stages of plant growth than the R as shown in Figure 2. Usually, evaporation from the open surface is more when compared to the soil surface. The figure shows that instead of plant roots sucking the water, more water evaporated during less rainfall. Then it is necessary for a proper irrigation plan during the third and fourth stages of plant growth.

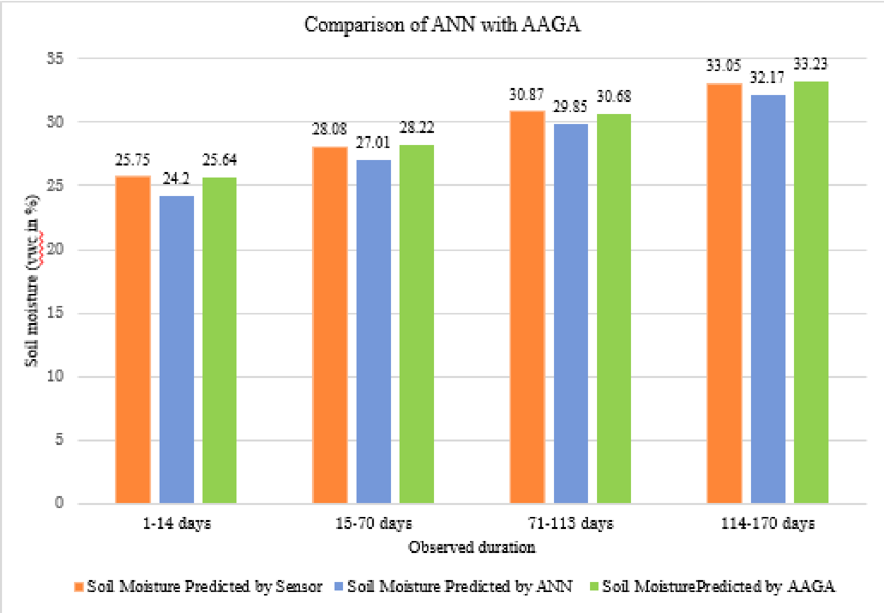

Fig 3 Comparison of ANN with AAGA

Compared with the existing ANN model, the results showed that the proposed AAGA technique shows better results on all the stages of plant growth, proving it to be better than the other, as shown in Figure 3. Here are the predicted values for soil moisture for the days (1 to 14, the moisture level is 25.64), (15–70,the moisture level is 28.22), (71–113, the moisture level is 30–68), and (114–170, the moisture level is 33.33). Based on Figure 3, the proposed AAGA predictions are much better than the existing ANN to plan better irrigation, especially on the last two stages of plant growth, providing a better yield.

Table 3 Comparison of the Proposed AAGA with the Existing ANN with Key Performance Metrics

Stage - Plant growth	Mean Absolute Deviation Threshold	Prediction of Existing ANN model		Prediction of Proposed AAGA model	
		R^2	RMSE	R^2	RMSE
1-14 days	0.121	0.897	0.067	0.961	0.042
15-70 days	0.371	0.891	0.046	0.969	0.038
71-113 days	0.314	0.897	0.057	0.962	0.035
114-170 days	0.423	0.970	0.051	0.974	0.039

The performance indices for the entire dataset are observed. The ratings of the performance indices for both training and testing datasets are carried out by R^2, and RMSE. The relationships among the AAGA and ANN were measured with the testing and training datasets. Table 3 presents the performance evaluation comparison of the proposed AAGA with the existing ANN model considering the stages of plant growth towards the measurement metrics R^2, and RMSE. When predicting the daily irrigation water demand, the suggested AAGA system outperforms the existing method even with a massive amount of records being developed. The AAGA shows better representability and Accuracy than the existing ANN model with very low MSE.

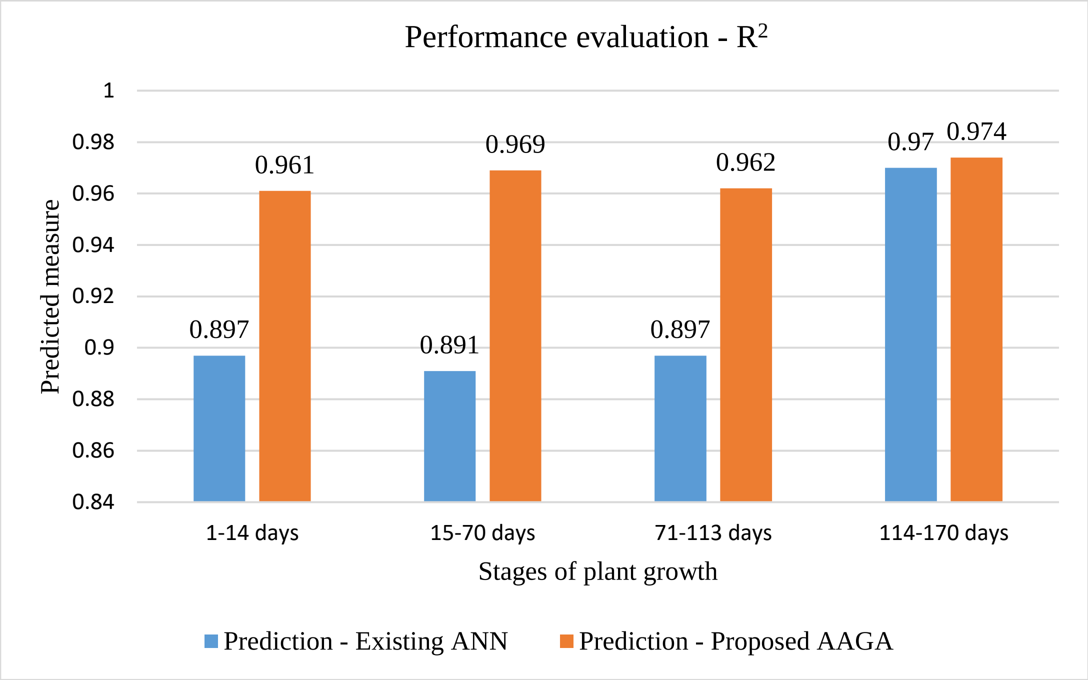

Fig 4 Performance evaluation R^2

The suggested AAGA technique has high R^2 on all stages of plant growth, proving it to be better than the other, as shown in Figure 4. The findings were compared with the current ANN model.Here the R^2 for the days (1-14) - 0.961, (15-70) -0.969, (71-113) - 0.962, (114-170) - 0.974. In order to sustain good crop growth and water stability in precision agriculture, the AMOP system effectively optimises the water level for subsequent irrigation decision-making.

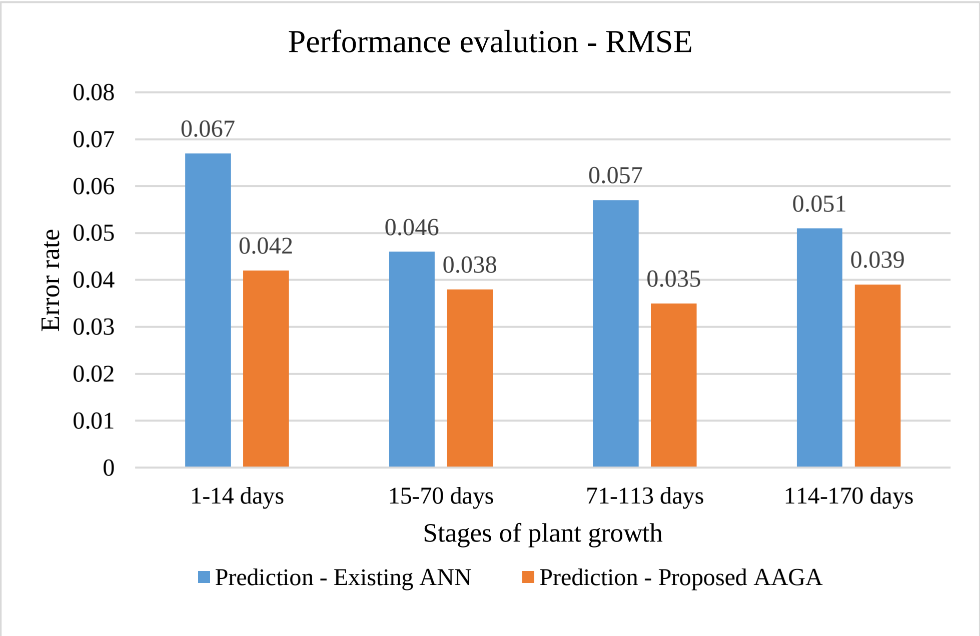

Fig 5 Performance evaluation - RMSE

The results showed that the suggested AAGA technique has a low RMSE error rate on the first three phases of plant growth in comparison to the existing ANN model, indicating it to be superior to the other as shown in Figure 5.Here the RMSE for the days (1-14) - 0.042, (15-70) - 0.038, (71-113) - 0.035 and (114 – 170) - 0.039 is presented. Thus, it is possible to schedule a well-timed and effective watering during the early stages of plant growth.

4. Conclusion

The optimal prediction of soil moisture plays a vital role in predicting irrigation occurrence events in precision agriculture. Additionally, predicting the crop's growth helps optimize irrigation and mitigates water wastage. The developed heuristic methodology combined an Artificial Neural Network and the Genetic Algorithm and proposed an Agro ANN_ Genetic Algorithm (AAGA). This proposed work is carried out to predict soil moister and plant growth stage by stage to optimize the irrigation system. The results show that the proposed research work is suitable for optimal soil moister and crop growth prediction, which leads to the development of an optimized irrigation system suitable for precision agriculture.

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