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MACHINE LEARNING-DRIVEN MATHEMATICAL MODELING FOR CLIMATE-RESILIENT CROP ROTATION AND NUTRIENT MANAGEMENT

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ABSTRACT

The upsurge in global population and the alarming rate of soil degradation due to over-reliance on only one type of crop have called for sustainable agricultural practices. This paper proposes a Machine Learning Approach for Mathematical Model of Climate Adapted Crop Rotation and Nutrient Management using advanced machine-learning skills. The system taps into soil nutrient status, history of farming activities, climatic history, and the enhanced vegetation index to suggest the required crops and the cropping pattern, which is aimed at improving soil health and increasing crop yield. The Bayaesian Ridge Multiple Imputation by Chained Equations (BRMICE) method is used to cope with the missing data, assisting in data improvement and making accurate forecasting to be more viable. The model also uses Recursive Feature Elimination (RFE) for selecting the relevant variables and applies Random Forest (RF) to predicting climate change and its likely effect on crop growth. The proposed system had an R^2 score of 0.92, the RMSE (Root Mean Square Error) was 2.8 and MAE 1.9 all of which demonstrated a very high predictive performance. This performance is much better than the baseline models like Random Forest, Linear Regression, and K-Nearest Neighbors which have higher error rates. Involvement of climate resilient areas and soil nutrient applications in the crop recommendation enables flexibility for regions like Tamil Nadu Delta which have diverse agriculture and changing climatic regimes that require a more systematic sustainability goal in farming practices. As a result, this system also marks a remarkable improvement in precision agriculture, enhancing crop yield and at the same time retaining the soil health and sustainability in the long term. This numerical model involves a systematic, organized and productive means of managing crop rotation systems aimed at enhancing soil health, yields and climate change adaptation.

KEYWORDS: Crop rotation, nutrient analysis, climate resilience, machine learning, sustainable agriculture, crop yield prediction, soil fertility.

INTRODUCTION

Agriculture is one of the most important occupations in India, especially as it accounts for approximately 42.6% of the workforce and is also responsible for about 18% of the country's GDP [1] as in Fig.1.

Fig. 1 India's Agriculture Economy

Tamil Nadu has been productive in the agricultural sector as most of its labour force is rural with over 60% of workers engaging in farming sectors focused on sugarcane, rice, pulses, and cotton[2]. Nonetheless, the state is confronted with several agricultural issues that are detrimental to productivity as well as sustainability. The factors and the reason for such unsustainable practices of agriculture include erosion, soil degradation, and climate change which continues to disturb the weather patterns. The decrease in nutrient levels is attributed to traditional monocropping, while temperature increase, and existing erratic patterns as a result of climate change would require diversification in crop types and varieties for resilience[3]. Crop rotation has emerged to be sustainable and focuses on restoring nutrients in soil but in the absence of climate resilient practices, farmers remain exposed to weather extremes which lead to crop losses (Fig. 2.)

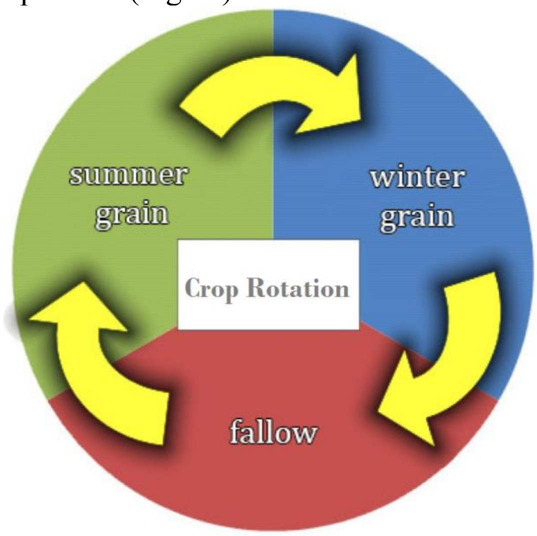

Fig .2 Crop Rotation

Monoculture farming, including rice cultivation which is favored in specific areas like the Cauvery Delta, features on the list of one of the main problems that characterizes agriculture in Tamil Nadu. In a recent study conducted by farmers in the Cauvery Delta area, TN agricultural university, about a shocking 75% of farmers were into monoculture farming as well as rice farming. This practice, however, has some short-term benefits of growing more crops, but it resulted in the depletion of all important nutrients within the soil itself, including Nitrogen, Phosphorus, and Potassium. Rice monoculture rotation has caused adverse effects on the soil because of the imbalance present within the nutrient provision in the soil. Nutrients are being used at a faster rate, and their replenishment is slower, creating a system that cannot be improved. Similarly, the same surveys reported that Tamil Nadu's agricultural landscape has a hunger for nutrients, and a third or more than forty percent of it is already lost. Organic matter content is going out dangerously fast. And if that was not enough drama in the theatre of challenges for agriculture in Tamil Nadu, climate change is bringing more. The state has seen a disruptive trend in rainfall, where over the last decade there has been a 20 percent decrease during the northeast monsoon. For example, districts like Ramanathapuram and Thoothukudi are worst affected, with drought every alternate year. In such areas, in which more than 70 per cent of agriculture is rain-fed, the absence of assured supply of water particularly makes the farmer vulnerable to crop failure[7]. Under these circumstances, monocropping added to the vagaries of the monsoon patterns threaten Tamil Nadu's farmers. Crop rotation has been suggested as an alternative sustainable practice to monocropping. This approach involves alternating crops depending upon the difference in nutrient requirements and characteristics to replenish soil fertility and enhance yields[8]. However, the traditional crop rotation needs optimization with modern data-driven approaches for consideration of soil health and climate resilience. Therefore, to overcome these challenges, this paper introduces a Crop Rotation-based Crop Recommendation System that integrates nutrient analysis and climate resilience using machine learning techniques. The crop recommendation system will be constructed to integrate crop rotation with soil nutrient analysis and climate resilience practices based on machine learning techniques. This data-based approach may yield 15-20% more crops, which was the result of pilot studies in drought-prone areas in Tamil Nadu where drought-tolerant crop varieties were introduced. The system provides solutions that will enhance both the fertility of the soil and the adaptability to changing climate conditions, hence enabling more robust agricultural practices, by incorporating climate predictions into crop recommendations.

LITERATURE REVIEW

Crop rotation remains a key tactic for soil fertility management and nutrient depletion prevention. Studies have shown that crop alternation using crops that typically replenish nitrogen in the soil with nutrient demanding crops can make soils healthy and yield rich. ML algorithms enable farmers to predict the levels of nutrients, pH, and organic matter present in the soil so that farmers can plan ahead for fertilization and crop choice [9]. With ML-based systems, it analyses meteorological and soil data in order to recommend crop selection, which enhances its yield and quality [10]. A prototype combining real-time data and ML techniques has proven more significant improvements in crop selection pertaining to the soil conditions. However, in order for long-term sustainability, climate factors must be included in crop rotation strategies.

In the meantime, through assessing nutrient content in the soil, farmers can efficiently manage their resources. Further recent progresses also point out the centrality of incorporating climate factors since extreme temperatures and drought conditions can make nutrient depletion worse [11]. Climate change resilient crops are important for addressing food and nutrition insecurity in marginal lands. Underutilized and neglected crops offer promise due to a high nutritional profile and tolerance to abiotic stressors [12]. Climate-resilient crop selection research highlights the need for integrated approaches that account for both nutrient and climate variability.

Machine learning approaches are demonstrated to be very efficient tools for processing big data in precision farming. Random Forest, Support Vector Machines, and Neural Networks are all popular techniques used for predicting soil conditions and crop yields

[13]. Machine learning models are also being created to forecast the weather pattern impact on crop health so as to assist in climate-adaptive crop recommendation systems [14]. These improve crop yield prediction models based on historical weather patterns and help in supporting sustainable agriculture and resource optimization. [15].

SYSTEM DESIGN

In the proposed Crop Recommendation System, three main modules crop rotation, nutrient analysis, and climate resilience are included and employed using machine learning algorithms. All these components combine to offer crop recommendations that optimize soil health and improve their resilience towards adverse climatic conditions.

Data Collection The module collects data from government of India Data ports across multiple sources in the form of soil nutrient levels [16], history climate data [17], and real-time environmental conditions NDVI[18] crop history. IoT sensors and remote sensing technologies play a vital role in such data collection in real time.

Nutrient Analysis: This module conducts in-depth analysis of soil nutrient levels and climate trends to predict potential nutrient depletion and the likelihood of climate stressors such as droughts and heat waves. Continuous monocropping, particularly in rice-based farming systems, has depleted the soil nutrients substantially in Tamil Nadu's Cauvery Delta regions. Studies by Tamil Nadu Agricultural University (TNAU) indicate that there is increasing deficiency of organic carbon and other essential nutrients in soils within this region. Without replenishing these, crop yields will continue to decline. In Nagapattinam and Tiruvarur, soil tests have confirmed a substantial drop in potassium levels, which is a critical component in rice cultivation. In such cases, alternative crops that require less potassium, or methods to replenish the soil, can be recommended.

Climate Resilience Analysis: This module prescribes crops based on soil nutrient analysis, climate patterns, and historical cropping sequences. In addition to this, the Cauvery Delta is also vulnerable to climatic stressors like irregular rainfall, droughts, and floods. According to IMD data, northeast monsoon has been declining by 20% for the delta over the last decade. Again, areas such as Nagapattinam have been experiencing recurrent drought, which affects considerably crop cycles and yields. It considers crops' tolerance toward climate factors such as drought and heat stress as well as irregular rainfall patterns. Climate data-both historical and real-time-is used to train machine learning models in predicting the probability of adverse weather events. For example, a periodic cycle of low rainfall in the area will evince water-loving crop suggestions or even timing changes for sowing seasons.

The core of the system will use Random Forest (RF) to predict the impact of certain crops on soil nutrients considering climate variations. Recursive feature elimination, RFE, will be used for feature selection. Models will then undergo cross-validation to ensure the ultimate accuracy of crop recommendation.

METHODOLOGY

The proposed model comprises of different phases from data collection such as soil health data, climate data, previous crop history data and nutrient data to prediction of crop rotation patterns and recommending crop which is high climate resistant. Architecture of the proposed model consists of phases that integrate various components such as soil health data, climate data, and machine learning algorithms which are depicted in Fig. 4.1.The model's architecture can be tailored to the unique challenges of Tamil Nadu’s delta region. By using soil health data from the delta, the system can identify nutrient depletion trends caused by paddy monocropping and suggest leguminous crops to restore fertility. The model can recommend crops based on climate stress data (e.g., drought-resistant crops for regions facing water shortages), helping farmers adapt to changing weather patterns.

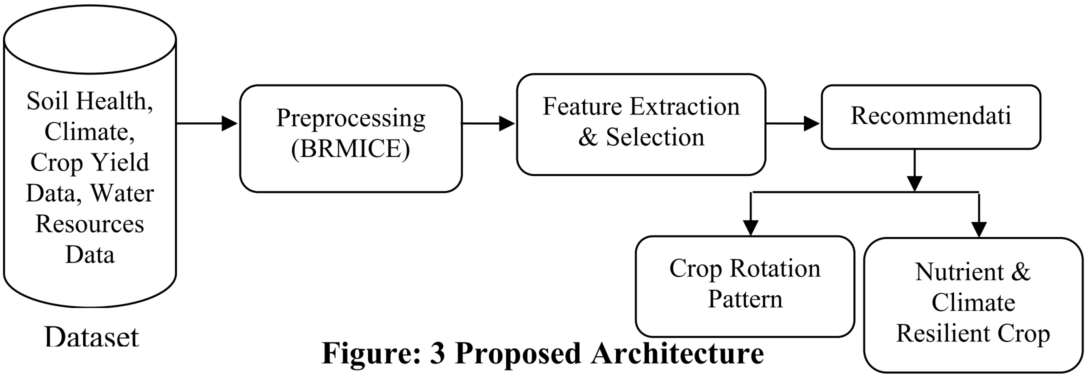

Figure: 3 Proposed Architecture

DATA PREPROCESSING

Many soil health datasets contain missing entries for critical parameters like nitrogen (N), phosphorus (P), potassium (K), or pH levels. Missing values complicate the training of machine learning models, as they lead to biased predictions or inaccurate insights. The SHC Scheme data is usually updated every three years. This low temporal resolution means that significant changes in soil quality or nutrient levels between cycles are not captured. While NDVI is a widely used index, its limitations in regions like the Tamil Nadu delta necessitate the use of alternative indices and technologies. Enhanced Vegetation Index (EVI) improves upon NDVI by correcting for atmospheric conditions and soil background noise, making it more reliable in areas with dense vegetation and high atmospheric aerosols. It is Ideal for monitoring crops like rice and sugarcane in the delta region. It performs better than NDVI in areas with dense vegetation and high humidity. It is mathematically understand through the give Equ. 3.

$$EVI = G \times ((NIR - Red))/((NIR + C1 \times Red - C2 \times Blue + L)) \quad \text{--- Equ. (3.1)}$$

Where, NIR is Near-Infrared reflectance, Red is Red reflectance, Blue is Blue reflectance, G is Gain factor (typically 2.5), C1&C2 are Aerosol resistance coefficients (usually C1=6, C2=7.5), L is Canopy background adjustment factor (usually 1). Dataset are normalized, to handle missing data in the soil health dataset (for example, missing values for nitrogen, phosphorus, potassium, or pH levels), several preprocessing techniques can be applied. One such common method is Data Imputation, where missing values are replaced by plausible estimates based on other data points. It preserves the underlying structure of the data, making it more suitable for predictive modeling in agriculture. In traditional MICE, the imputation method is static. When dealing with high-dimensional data like soil health variables, where multicollinearity between variables may exist, Bayesian Ridge Multiple Imputation by Chained Equations (BRMICE) can improve the robustness of imputations by introducing a prior distribution over the regression coefficients. This allows for flexibility in handling different types of variables (categorical, continuous) and relationships in the dataset. It reduces bias by adapting to different feature relationships. Given that relationships between variables such as soil nutrients and NDVI can be non-linear, traditional MICE using linear regression may not be sufficient.

The imputation is performed by modeling the coefficients with a Gaussian prior as in Equ. (3.2).

$$\hat{\beta} = (X^T X + \lambda I)^{-1} X^T y \quad \text{--- Equ. (3.2)}$$

Where, X is the matrix of input features (e.g., soil nutrients, weather data, crop history), λ is the regularization parameter (controls overfitting), I is the identity matrix, β is the vector of regression coefficients. The posterior distribution is calculated, and missing values are imputed based on Equ. (3.3) updated distribution.

$$P(\beta \mid X) \propto P(X \mid \beta) P(\beta) \quad --- \text{ Equ. (3.3)}$$

This method is especially useful when the soil dataset has a large number of correlated features. Weather data missing values over a time computed using the formula in the Equ. (3.4).

$$X_t = \alpha + \sum_{i=1}^{p} \phi_i X_{t-i} + \sum_{j=1}^{q} \emptyset_j \in_{t-j} + \in_t \qquad \text{--- Equ. (3.4)}$$

Where, Xt is the weather variable (e.g., temperature) at time t and α, ϕi, θj are model parameters. This accounts for the temporal correlation in weather data, ensuring consistent imputation over time.

For the spatial imputation of missing values of EVI, use the following Equ. (3.5).

$$\mathrm{EVI}(s_0) = \sum_{i=1}^{n} \lambda_i \mathrm{EVI}(s_i) \qquad \text{--- Equ. (3.5)}$$

The location with missing EVI is s0, and λi will be a set of weights calculated from variograms that represent spatial correlation.

FEATURE SELECTION AND MODEL TRAINING

The main features are nutrient levels, climate variables (for example, temperature anomalies and precipitation variance), and crop data. The technique of Recursive Feature Elimination (RFE) is applied to optimize feature selection and train machine learning models on datasets made up of parameters of soil and climate [19]. RFE forms the basis of crop recommendation systems by sequentially peeling away irrelevant features to improve prediction accuracy [20]. The system is trained to discern patterns in nutrient depletion and crop resilience to climate extremes. Along with nutrient analysis, the system includes data from climate models, such as projections of future changes in weather variability. These data determine which crops are better suited in the light of changes expected in weather. For example, drought-tolerant varieties can be advised to places that are witnessing decreasing rainfall, while heat-resistant varieties are suggested for areas that are warming up.

CROP RECOMMENDATION ALGORITHM

The recommendation algorithm takes into account: Soil nutrient levels, Predicted weather conditions, previous crop and crop rotation principles and Vegetation health. The system optimizes for yield and sustainability, ensuring that nutrient depletion is minimized and crop rotation principles are followed as in Equ. (3.6).

$$\mathrm{Maximize} \sum_{i=1}^{n} (\mathrm{Yield}_i \times \mathrm{Profit}_i) - \sum_{j=1}^{m} \left(\mathrm{SoilNutrientDepletion}_j\right) \qquad \text{--- Equ. (3.6)}$$

Where, Yield_i is the yield of crop i, Profit_i is the profit per unit of crop i, $\mathrm{SoilNutrientDepletion}_j$ is the nutrient depletion caused by growing crop j. The system optimizes for yield (measured in terms of productivity and profit) while minimizing soil nutrient depletion. The objective function takes into account multiple variables that influence crop selection, such as soil nutrient content, climate conditions, and historical crop data. The optimization is subject to certain constraints related to soil health, weather forecasts, and crop rotation. Crops must be selected such that soil nutrient levels (N, P, K) remain within acceptable ranges. For instance, growing high nitrogen-consuming crops like maize would need to be balanced with nitrogen-fixing crops like legumes in subsequent seasons. Crops must be suitable for the predicted weather patterns (rainfall, temperature). Model helps ensure that the recommended crops are resilient to upcoming climatic conditions. A crop cannot be recommended if it violates crop rotation principles (e.g., planting the same crop consecutively in the same field), to prevent soil degradation and pest buildup.

RESULTS AND DISCUSSION

MODEL ACCURACY AND PERFORMANCE

The integration of nutrient depletion and climate resilience into the crop recommendation system significantly improved model performance. Performance of the proposed model is estimated through the R2, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).

TABLE 1
COMPARISON OF PERFORMANCE OF PROPOSED MODEL WITH BASELINE MODELS

Model	R^2 Score	RMSE	MAE
Proposed Model (Enhanced MICE + RFE+ Random Forest)	0.92	2.8	1.9
Random Forest (RF)	0.88	3.5	2.5
K-Nearest Neighbors (kNN)	0.81	4.7	3.9
Linear Regression (LR)	0.78	5	4.3

The Proposed model achieves a high R^2 of 0.92, low RMSE of 2.8 and MAE of 1.9 which indicates a strong correlation between recommended crops and actual yield outcomes in varied climate scenarios compare to baseline models RF, kNN and LR. The inclusion of climate data improved the system's ability to recommend drought-resistant and heat-tolerant crops, enhancing its utility for climate-impacted regions.

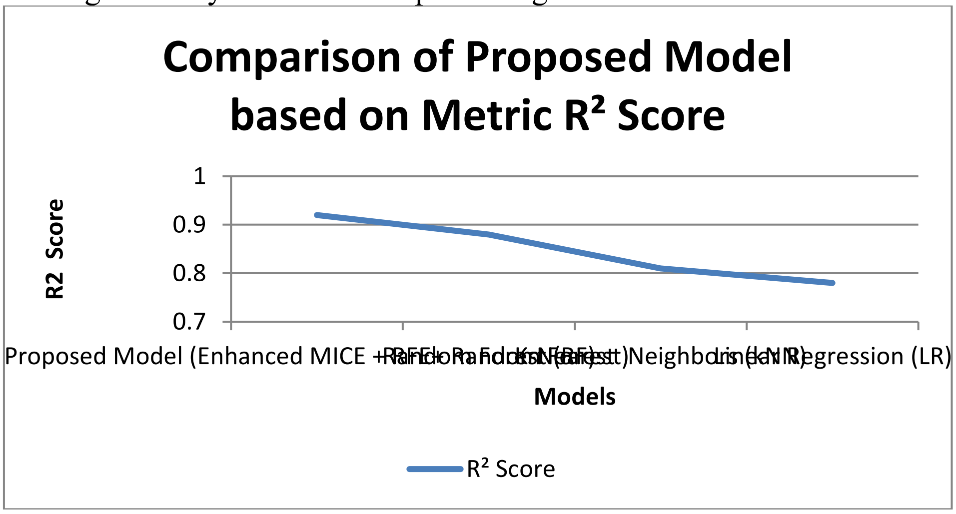

FIG 4 Comparison of Proposed Model based on Metric R^2 Score

Figure 4 shows a pictorial representation of comparison of proposed model based on the metric R2 and it is clear that the proposed model shows a high R2 of 0.92 compare to the baseline model RF, kNN, and LR with the value of 0.88, 0.81, and 0.78 respectively. This difference in R^2 score highlights the proposed model's superior predictive performance and robustness in diverse agricultural environments.

Figure. 5 shows a pictorial representation of comparison of proposed model based on the metric RMSE and MAE, from that it is clear that the proposed model shows a low RMSE of 2.8 and Low MAE of 1.9 respectively compare to the baseline model RF, kNN, and LR with the value of 3.5, 4.7, and 5 of RMSE and 2.5, 3.9, and 4.3 of MAE respectively. This result shows that the proposed model showing the model's ability to minimize average prediction error, making it highly effective and indicating better prediction accuracy, especially in terms of larger errors.

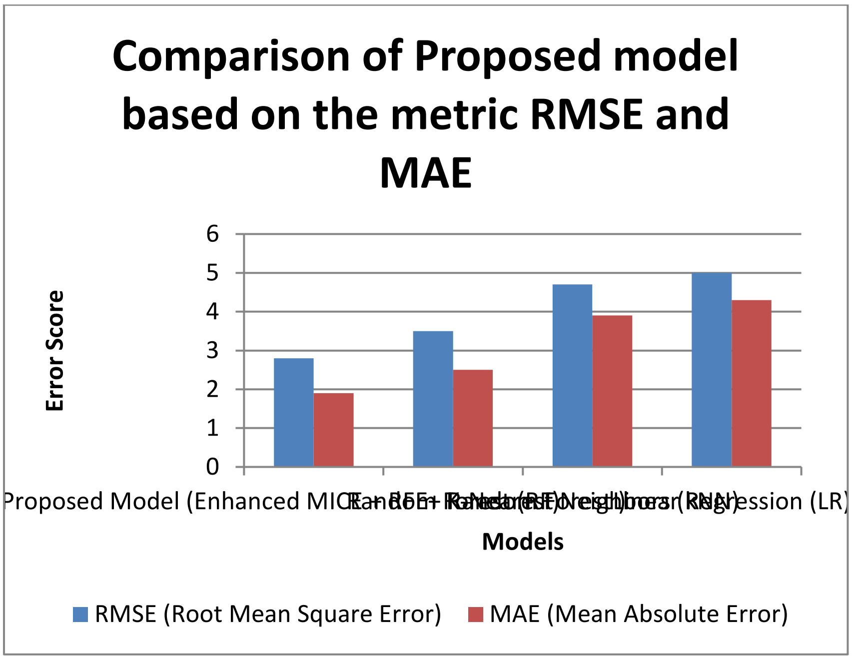

Fig: 5 Comparison of Proposed Model based on Metric RMSE and MAE

IMPACT OF CLIMATE-RESILIENT CROP ROTATION

Fields that implemented the system's recommendations experienced better adaptation to climate stress. Yield improvements of 15-20% were observed in regions prone to drought, where the system recommended drought-tolerant crops. Crop rotation was well implemented as to ensure nutrient balance in the soil and thus prevent further degradation under challenging climate conditions.

LIMITATIONS AND FUTURE WORK

While the system shows promise in integrating climate resilience, its reliance on accurate and localized climate data is a limitation. Variability in climate data quality, especially for smallholder farms, can affect recommendation accuracy. Future enhancements will focus on real-time climate forecasting integration and the inclusion of pest and disease resilience in the recommendation algorithm. This will enhance the capabilities of the model in tracing and forecasting long-term changes in soil health along patterns of crop rotation to encourage sustainable farming practices.

CONCLUSION

The proposed Machine Learning-Driven Mathematical Modeling for Climate-Resilient Crop Rotation and Nutrient Management offers a comprehensive solution towards sustainable agriculture. By benefiting from machine learning, the system provides intelligent crop recommendations balancing the soil nutrient needs and improving adaptability to varied climate conditions. The model achieves superior accuracy with an R^2 score of 0.92 and RMSE and MAE of 2.8 and 1.9, respectively, by combining Recursive Feature Elimination for feature selection, Random Forest for crop recommendation, and BRMICE for handling missing data. These are such results that would sustain the system while handling complex information like agricultural soil health, crop history, weather data, and climate resilience indices, which are still tough to handle in environments like the Tamil Nadu Delta Regions. The potential of this system would prove useful to farmers when they would seek improved yield as well as soil health before the impact of climate change. The model's dual approach of using both RFE and RF ensures that key factors such as nutrient levels, historical cropping data, and climatic conditions are initially prioritized to enable more accurate and sustainable crop rotation planning. Moreover, the introduction of the RF model to predict climate increases the flexibility of the system toward unpredictable weather conditions and is very useful for farmers who seek maximum crop productivity along with soil health. Future versions of the model could include data on pest and disease resistance, which might assist farmers in the selection of crops best suited to soil and climate conditions while also being more resilient against possible biotic threats.

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