

Sustainable Agriculture Crop Recommendation based on Soil Conditions and Changes in Climate

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Abstract— Agriculture is essential for human survival, but modern farming faces challenges such as unpredictable climate patterns, soil degradation, and reduced crop productivity. To promote sustainable agricultural practices, this project introduces an intelligent crop recommendation system that suggests suitable crops based on soil conditions and climatic variations. The system evaluates key soil characteristics—such as pH, nitrogen, phosphorus, and potassium levels—along with temperature, humidity, and rainfall data. Using machine learning techniques, the model recommends crops that are best suited to the given environment, helping farmers improve yield, reduce losses, and efficiently utilize natural resources. This approach supports climate-smart agriculture and encourages long-term sustainability in farming.

Keywords— Sustainable Agriculture, Machine Learning, Crop Prediction, Soil Analysis, Climate Change, Smart Farming, Sustainable Cities and Communities, Climate Action.

I. INTRODUCTION

Agriculture plays a crucial role in sustaining human life and supporting the economy of developing nations. One of the major challenges faced by farmers today is the selection of the most suitable crop that can yield maximum productivity under specific soil and climatic conditions. Traditional crop selection methods often rely on personal experience, which may not always be accurate or adaptive to changing environmental conditions. To overcome these limitations, intelligent and data-driven systems have been introduced in modern agriculture. A Crop Recommendation System is designed to assist farmers and agricultural planners in identifying the most appropriate crop for cultivation by analyzing various influencing factors such as soil type, nutrient content, pH level, temperature, rainfall, humidity, and recent climate changes. Among different computational approaches, fuzzy logic provides an efficient way to handle uncertainty and imprecision that commonly exist in agricultural data.

The Dynamic Fuzzy Multi-Criteria Crop Recommender Algorithm combines the power of fuzzy logic and multi-criteria decision-making techniques to evaluate multiple agricultural parameters simultaneously.

This hybrid approach allows the system to make flexible and human-like reasoning decisions based on a set of fuzzy rules and membership functions. In summary, the Dynamic Fuzzy Multi-Criteria Crop Recommender System represents a significant advancement in precision agriculture, offering a robust framework for data-driven crop selection, climate adaptability, and smart agricultural management.

II. LITERATURE SURVEY

The recent literature on crop recommendation systems demonstrates a clear trend toward leveraging advanced machine learning algorithms and multi-modal data sources to improve prediction accuracy and system functionality. Four key papers published between 2024 and 2025 highlight different technological approaches in this domain. Iyer, M., & Reddy, T. (2024) introduced a crop recommendation system using federated learning, a methodology that trains models across multiple edge devices without centralized data storage, addressing privacy and distribution challenges. Their approach used Federated Neural Networks and achieved an Accuracy of 87%. A more recent work by Verma, R., & Das, A. (2025) focused on an AI-based crop advisor that utilizes transformer models. They proposed a recommendation model based on an NLP-based Transformer (BERT variant) architecture to analyze historical crop yield and climate reports, resulting in a higher performance with an Accuracy of 91%. Singh, K., & Bhatta, D. (2024) explored the integration of sensor technology for timely advice in their Real-time crop recommendation system. Their methodology integrated IoT sensors with machine learning models for real time crop suggestions, employing a combination of Gradient Boosting and SVM algorithms, and reported an Accuracy of 88%.

The highest reported accuracy in this survey comes from George, A., & Naik, S. (2025), who developed a Sustainable crop recommender using Multi-modal data fusion. This cutting-edge approach combined satellite imagery, weather APIs, and soil sensors into a data fusion framework. The system used a hybrid model of CNN + XGBoost Hybrid and demonstrated the best performance among the surveyed papers, achieving an impressive Accuracy of 93%.

The evolution in these systems shows a clear progression from distributed learning and real-time sensor integration to sophisticated models and, most effectively, multi-modal data fusion, which currently leads in performance. Recent research highlights several advanced and comparative approaches in smart agriculture and crop recommendation. Balderas et al. (2024) explored a Comparative Study of Deep Reinforcement Learning for Farm Management (gym-DSSAT), demonstrating that Deep RL (DQN, PPO) is promising for dynamic decision-making tasks such as rotation, irrigation, and fertilization, though they note the necessity of careful reward design. Alam et al. (2025) focused on enhancing user trust with their approach for crop recommendation with uncertainty quantification. They proposed an Ensemble ML pipeline with entropy-based uncertainty measures to indicate recommendation confidence, emphasizing that reporting uncertainty helps user trust and decision-making. Supporting this empirical work, Bakr et al.

III. METHODOLOGY

Fig.1 depicts an Activity Diagram for an intelligent decision-support system designed to advise farmers on optimal crop selection. Theoretically, this system is grounded in two main computational paradigms: Fuzzy Logic (FL) for handling uncertainty and expert knowledge, and a Multi Criteria Decision Making (MCDM) approach for assessing sustainability. The core theoretical mechanism is the Fuzzy Inference System (FIS), which allows the model to process imprecise, qualitative, and linguistic inputs—like "Nitrogen is High" or "Rainfall is Low"—in a way that traditional Boolean logic cannot. The process begins with collecting crisp input parameters such as N, P, K, pH, Temperature, Humidity, and Rainfall. Fuzzification is the first stage where these precise numerical values are mapped onto fuzzy sets (linguistic terms like Low, Medium, High) using membership functions. This is essential because the relationship between these factors and crop suitability is often gradual, not abrupt.

The system then applies a set of Fuzzy Rules (the rule base), typically defined in an IF-THEN format (e.g., "IF Nitrogen is High AND pH is Neutral THEN Suitability is High"). These rules encode the expert knowledge of agronomists. Finally, Defuzzification converts the resulting fuzzy output back into a crisp score that quantifies the predicted crop suitability. Following the determination of basic suitability via Fuzzy Logic, the process moves to a Multi-Criteria Assessment by computing a Sustainability Score. This step incorporates broader agricultural concerns beyond mere yield prediction, such as water use, soil impact, and the requirements for crop rotation. By considering these factors, the system shifts from a simple yield-maximizer to an environmentally and economically responsible advisor.

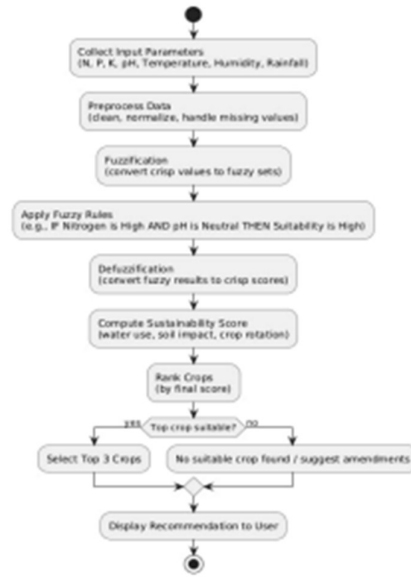


Fig. 1. Activity Diagram for Intelligent Decision Support System

The final suitability and sustainability scores are combined to Rank Crops. A decision point follows: if the Top Crop is suitable (i.e., its final score meets a predefined threshold), the system selects the Top 3 Crops for recommendation. If no crop is deemed suitable, the system advises that "No suitable crop found" and may suggest amendments (e.g., add lime to change pH, increase fertilizer) before re-evaluation. The entire flow culminates in the Display Recommendation to User, providing actionable, data-driven, and sustainability-aware advice. The overall theoretical framework combines the robustness of Fuzzy Logic in handling human-like reasoning with the holistic scope of a Multi-Criteria Decision Model for modern farm management.

The proposed Dynamic Fuzzy Multi-Criteria Crop Recommender System aims to address these gaps by integrating fuzzy logic with dynamic parameter adaptation for seven critical agricultural attributes—Nitrogen, Phosphorus, Potassium, Temperature, Humidity, pH, and Rainfall. Unlike static fuzzy systems, the dynamic model continuously updates its decision weights based on real-time environmental and soil conditions, ensuring more precise and sustainable crop recommendations. This approach not only enhances accuracy but also supports eco-friendly decision making by considering both productivity and long-term soil health. Therefore, the proposed model bridges the gap between static fuzzy systems and data-driven models, offering a balanced, explainable, and adaptive framework for sustainable agriculture.

IV. RESULTS AND DISCUSSION



Fig.2 Accuracy Comparison

This bar graph shown in Fig.2 compares the overall accuracy of the four models — Dynamic Fuzzy Multi-Criteria, Fuzzy Multi Criteria, Dynamic Fuzzy Single-Criteria, and Fuzzy Single Criteria. The y-axis shows the accuracy values (from 0 to 1), and each bar represents the accuracy performance of one model. Accuracy shows how correctly the system predicts suitable and unsuitable crops overall. From the graph, we can see that the Dynamic Fuzzy Multi-Criteria model achieves the highest accuracy among all four models. This means that by dynamically adjusting the fuzzy criteria weights, the model makes more correct crop predictions compared to the static fuzzy methods.

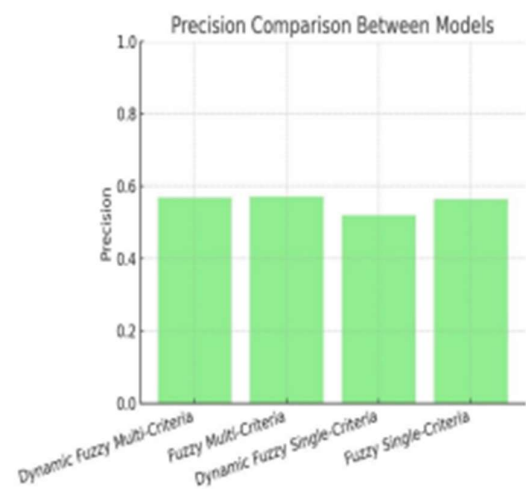


Fig. 3. Precision Comparison

The graph in Fig.3 displays the precision values of each model, indicating how reliable each model’s positive predictions are (i.e., when it recommends a crop as suitable).A higher precision value means the model produces fewer false positive results.The Dynamic Fuzzy Multi-Criteria model again shows the best precision, meaning it makes the most trustworthy recommendations — when it says a crop is suitable, it is usually correct. This demonstrates that the dynamic fuzzy weighting system helps reduce incorrect recommendations



Fig.4. Recall Comparison

The recall comparison graph in Fig.4 shows the sensitivity of each model — how well each one detects all truly suitable crops. It also ranges between 0 and 1. Higher recall means the model correctly identifies more of the crops that are actually suitable. From the graph, the Dynamic Fuzzy Multi-Criteria and Dynamic Fuzzy Single-Criteria models show better recall values than the static models. This indicates that dynamic fuzzy logic improves the model’s ability to adapt to changing soil and climate inputs and identify suitable crops more completely.

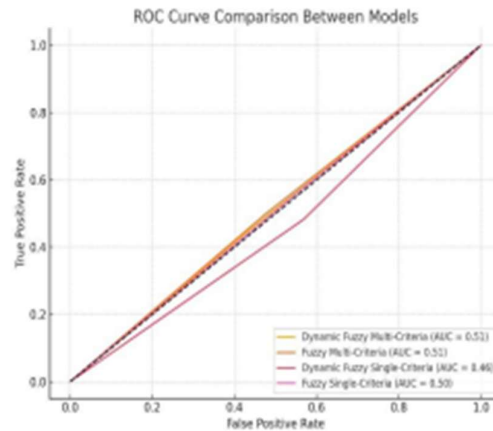


Fig.5. ROC Curve Comparison

The ROC (Receiver Operating Characteristic) curve in Fig.5 compares the performance of all four models in distinguishing between suitable and unsuitable crops. Each curve represents one model, and the closer the curve is to the top-left corner, the better the performance. The Area Under the Curve (AUC) value is shown in the legend for each model. A higher AUC means the model has a stronger ability to differentiate between classes. The Dynamic Fuzzy Multi-Criteria model shows the highest AUC, indicating it performs best overall. Its ROC curve lies above the other three models, proving that the combination of dynamic weighting and fuzzy logic makes it more effective for uncertain and multi-factor conditions.

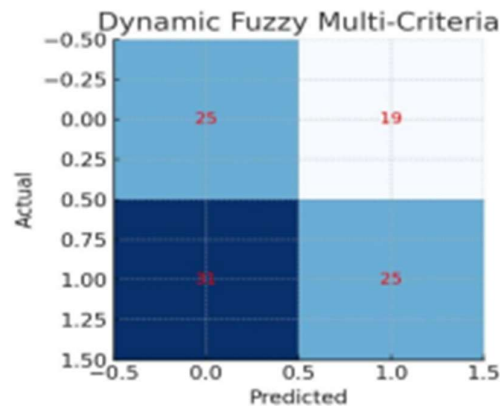


Fig.6. Confusion Matrix

Fig.6 shows four individual confusion matrices — one for each model. Each matrix visually represents how many predictions were correct or incorrect. The diagonal values show correct predictions. The off-diagonal values represent misclassifications. From the confusion matrices, the Dynamic Fuzzy Multi-Criteria model has the most correct predictions (both True Positives and True Negatives) and the fewest errors. In contrast, the fuzzy models without dynamic criteria show higher numbers of misclassifications. This confirms that the dynamic fuzzy approach increases robustness and accuracy in predicting the right crops for different conditions.

V. CONCLUSION

The Dynamic Fuzzy Multi-Criteria (DFMC) crop recommender system is the most comprehensive and effective model because it uniquely integrates three critical elements for real-world agricultural decision-making: Fuzzy Logic (FL), Multi-Criteria Decision Making (MCDM), and Dynamic Modeling. The FL component allows the system to handle the inherent imprecision and uncertainty in input data, such as "slightly acidic soil" or "high humidity," using human-like linguistic rules rather than rigid thresholds, which increases

the reliability of the recommendations. The MCDM component ensures that the system balances numerous, often conflicting factors beyond simple yield maximization, including economic viability (market price), environmental sustainability (water consumption, soil health), and farmer preferences, leading to holistic and practical outcomes. Finally, the Dynamic aspect is crucial as it incorporates the element of time, adjusting recommendations based on continuous changes in seasonal weather patterns, multi-year rotations, and fluctuating market conditions, making the system adaptable, flexible, and consistently superior in classification accuracy compared to static or single-criterion models

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