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RESEARCH ARTICLE

Machine learning approach for crop planning and resource allocation in the Bargarh Canal Command

Priyanka Mohapatra[1], Jagadish Chandra Paul[1], Dwarika Mohan Das[2], Sanjay Kumar Raul[1], Ambika Prasad Sahu[1], Subhashis Saren[3], Bimalendu Mohanty[4], Sefali Rout[4] & Sanghamitra Sahu[4]

[1]Department of Soil and Water Conservation Engineering, College of Agricultural Engineering and Technology, Odisha University of Agriculture and Technology, Bhubaneswar 751 003, Odisha, India
[2]Krishi Vigyan Kendra, Jagatsinghpur, Odisha University of Agriculture and Technology, Bhubaneswar 751 003, Odisha, India
[3]Department of Soil Science and Agricultural Chemistry, College of Agriculture, Odisha University of Agriculture and Technology, Bhubaneswar 751 003, Odisha, India
[4]Krishi Vigyan Kendra, Dhenkanal, Odisha University of Agriculture and Technology, Bhubaneswar 751 003, Odisha, India

*Correspondence email - priyanka.rs21@ouat.ac.in

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Abstract

Agricultural decision-making in the Bargarh Canal Command (BCC) of Eastern India faces challenges due to climate variability and resource limitations. This paper presents an advanced machine learning (ML) framework for optimizing agricultural decision-making by integrating predictive modeling, clustering techniques and genetic algorithms. This framework aims to enhance crop yield and net return predictions while considering environmental factors, resource constraints and market dynamics in the BCC of eastern India. Three state-of-the-art ML algorithms–Random Forest (RF), XGBoost and Long Short-Term Memory (LSTM), were implemented and compared using a comprehensive set of input features, including environmental, agronomic and management factors. The XGBoost model demonstrated superior performance, achieving an average R^2 of 0.87 and RMSE of 0.32 for yield prediction and an R^2 of 0.83 with an RMSE of 0.52 tons/ha for net returns prediction across all crops. Four distinct crop clusters were identified using the k-means analysis method, revealing trade-offs and opportunities for optimization. The framework enables various decision support applications, including crop calendar optimization, risk assessment and resource allocation planning. Recommendations include weather-responsive planning, cluster-based diversification, precision agriculture investments, monitoring system enhancements and policy interventions to promote sustainable agricultural intensification.

Keywords: cluster analysis; command area; crop yield prediction; water-profit optimization; XGBoost

Introduction

Agricultural optimization is a critical challenge in the face of increasing global food demand, climate change and resource constraints. As the world population continues to grow and environmental pressures intensify, the need for innovative approaches to maximize agricultural productivity while minimizing resource usage has become paramount. This study presents a comprehensive ML framework that builds on various algorithm optimization results to enhance agricultural decision-making (1).

By integrating predictive modeling for crop yields and returns with clustering techniques, optimal crop-water-profit relationships can be identified, which can also provide deeper insights into agricultural planning and resource allocation (2, 3). Sophisticated models such as ML algorithms, including RF, XGBoost and LSTM networks incorporate a wide range of input features, including environmental factors such as soil composition, temperature and precipitation patterns; agronomic variables such as crop varieties and planting densities and management practices such as irrigation schedules and fertilizer applications. Predictive models can also be combined with advanced clustering techniques to identify the natural groupings of crops based on their water requirements and profitability. This multifaceted approach allows us to understand the complex interplay between various agricultural factors and their impact on overall farm productivity and sustainability. This approach leverages state-of-the-art methods to predict crop yields and net returns. The integration of these advanced analytics with genetic algorithm optimization results in a dynamic framework that can adapt to changing environmental conditions and market dynamics. This innovative approach enables the development of weather-responsive planning strategies, allowing farmers to adjust their crop selection and management practices in real time, based on forecasted weather patterns (4).

The framework enables cluster-based crop diversification, balancing risks and rewards for farmers (5, 6). It guides precision agriculture investments and identifies areas for optimal technology adoption. This data-driven approach enhances agricultural decision-making, promoting sustainable and profitable farming practices. The framework's ability to analyze diverse data sources offers unprecedented precision and adaptability in agricultural planning (7 -9), leading to efficient water use, reduced environmental impact and improved economic outcomes. Farmers can make informed decisions on crop selection and resource management, while policymakers can develop effective agricultural policies. Researchers can refine predictive models and optimize crop production strategies. This research advances precision agriculture, demonstrating the potential of data analytics and machine learning to revolutionize farming practices (10, 11), addressing challenges of climate change and resource scarcity.

This study develops a comprehensive ML framework for enhanced agricultural decision-making, integrating predictive modeling, clustering analysis and optimization. The framework addresses complex challenges in modern agriculture, potentially impacting global food security, sustainable resource use and environmental adaptation (12, 13). By leveraging advanced models (Random Forest, XGBoost, LSTM) and cluster analysis, it provides data-driven insights to optimize water and land resources, enhance net returns and improve crop yield, while accounting for environmental factors and market dynamics.

Materials and methods

Study area and data sources

The study area selected is the Bargarh Canal Command (BCC), situated in the western part of Odisha and encompassing sections of the Mahanadi River basin (Fig.1). This region spans 11 blocks across the districts of Balangir, Subarnapur, Sambalpur and Bargarh. Geographically, it is positioned between latitudes 20°43' N and 21° 41' N and longitudes 83°39' E and 83°58' E, with an elevation of 185 m above mean sea level. According to the 2011 census, the populations for the districts of Balangir, Bargarh, Sambalpur and Subarnapur are 1648997, 1481225, 1041099 and 610183 respectively, reflecting a high population density. The mean maximum temperature in this area is 33.3 °C, while the mean minimum temperature is 20.6 °C. The BCC is categorized within the Eastern Plateau and Hills Zone of India. The total Culturable Command Area (CCA) measures 115.36 thousand ha, with a cropping intensity of 133 %. Land use data for the study area indicates that 76.74 % is dedicated to cropland, 8.11 % to built-up areas, 5.21 % to flooded vegetation and 5.96 % to tree cover. Soil composition analysis shows that 83.8 % of the area is covered by Inceptisols, 14.11 % by Vertisols, which range from loam to clayey loam and 1.86 % by Alfisols, characterized as red loamy soil. The occurrence and distribution of aquifers are heterogeneous, as are their yield properties. The prevalent methods of groundwater extraction in the district include dug wells, dug-cum-bore wells and shallow tube wells.

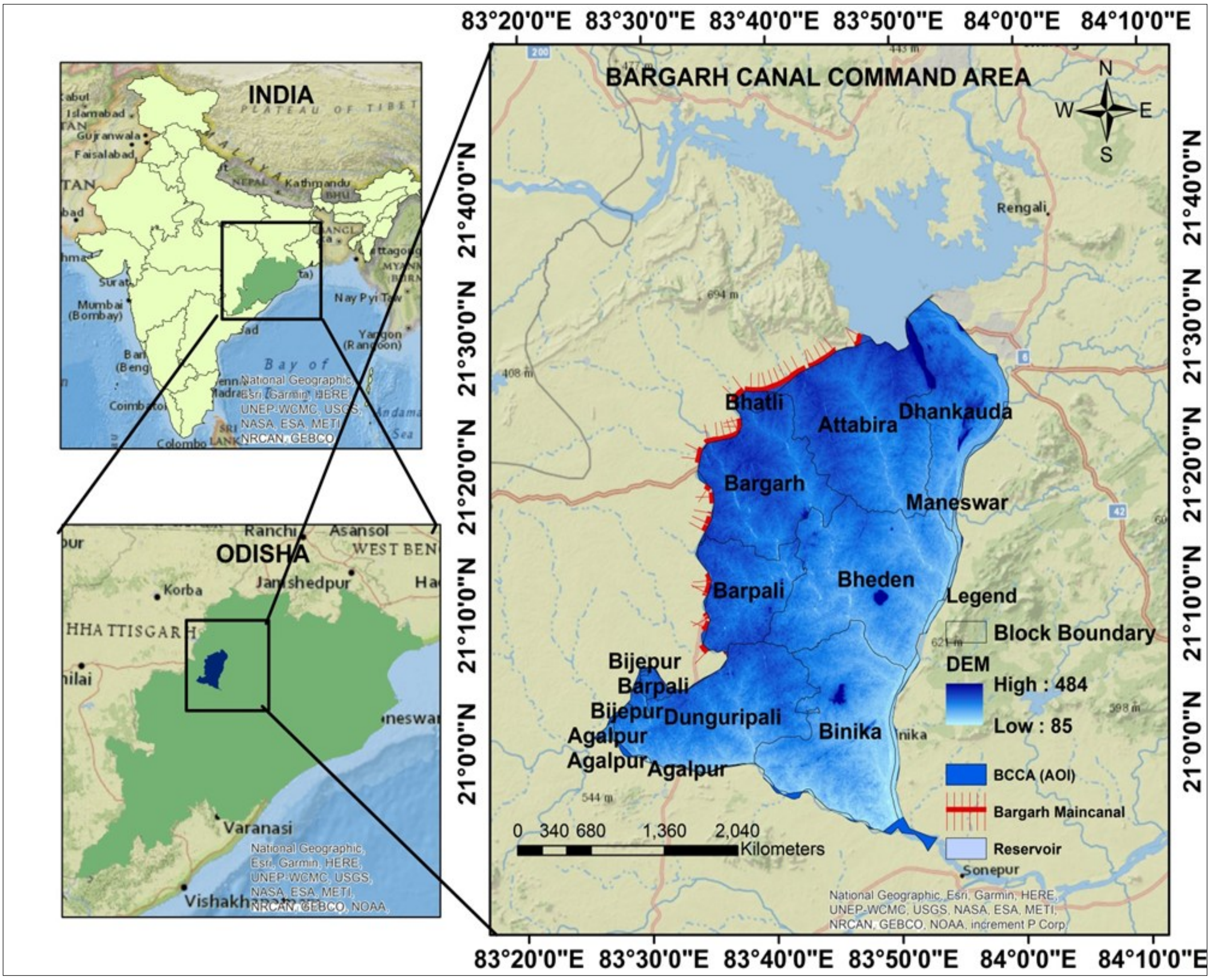

Fig. 1. DEM and study area map.

The data sources mentioned provide a comprehensive foundation for analyzing agricultural trends and factors in India, particularly focusing on the Bargarh Canal Command Area (BCCA). The India Meteorological Department and NASA POWER offer historical weather data spanning from 2010 to 2023. Crop yield records from the Agricultural Research Institute and the College of Agriculture, Odisha University of Agriculture and Technology in Bhubaneswar cover the same period. Soil quality, a crucial factor in agricultural output, is represented by the 2018 soil survey data from the National Bureau of Soil Survey and Land Use Planning (NBSS and LUP). The economic aspects of agriculture are covered by market price data from the Agricultural Market Information System and Agriculture Statistics Book, as well as input cost data from the Farm Economic Survey. These economic indicators, spanning from 2010 to 2023 for market prices and 2015 to 2023 for input costs, provide valuable insights into the financial dynamics of farming in the region, including profitability trends and the impact of various economic factors on agricultural production. The complete methodology is shown in Fig. 2.

Data preparation and model training

Predictive models incorporate a comprehensive set of features such as environmental, agronomic and management factors. The environmental factors included daily temperature metrics (minimum, maximum and average), rainfall characteristics (amount, frequency and intensity), humidity levels (daily average, minimum and maximum), solar radiation and wind speed. Agronomic factors included crop type and variety, growth stage measured in days after planting, soil characteristics (pH, nutrient levels and moisture content), fertilizer application details (type, amount and timing), irrigation scheduling (amount and frequency), pest and disease incidence and the previous crop in rotation. Management factors considered planting density, planting and harvesting dates, labor input and machinery usage. The crop water requirement was calculated using the CROPWAT software and water availability was similarly determined (13, 14). This diverse array of features aim to capture the complex interplay of variables affecting crop growth and yield, enabling the models to make more accurate predictions across various agricultural scenarios.

The crop yield prediction model begins with feature engineering, where new valid data points are created from existing information, such as the number of days or days since the last rainfall. The process then addresses missing data using advanced methods such as the Multivariate Imputation by Chained Equations (MICE) implementation algorithm. Temporal alignment was performed to match weather data with different crop growth stages. Feature normalization adjusts the data to ensure that all features have similar scales, facilitating easier comparison. The dataset was split into training (70 %), validation (15 %) and testing (15 %) sets. Hyperparameter tuning was performed using a grid search with 5-fold cross-validation. Finally, model tuning was conducted using grid search with cross-validation to optimize the model settings. These steps collectively ensure that the data are well prepared for effective ML analysis (15, 16).

Predictive modeling framework

The predictive modeling component of the framework serves as the foundation for informed optimization by providing accurate forecasts of crop yields and economic returns under different scenarios. The integration of multiple ML algorithms provides robustness and allows for comparative analysis of different modeling approaches.

Machine learning algorithms

Three state-of-the-art algorithms were implemented and compared to identify the most effective approach for agricultural prediction. RF represents an ensemble learning method that uses multiple decision trees to capture complex nonlinear relationships between input features and crop yields (17). The ensemble approach provides robustness against overfitting while maintaining interpretability through feature importance analysis (18).

XGBoost represents a gradient boosting framework that has gained prominence for its performance and efficiency in structured data prediction tasks. The algorithm builds models sequentially, with each new model correcting errors from previous models, resulting in highly accurate predictions. XGBoost has proven particularly effective for agricultural applications due to its ability to handle missing values and complex feature interactions (19, 20). Table 1 shows the parameters used in the XGBoost configuration.

Table 1. XGBoost Configuration

Number of estimators	500
Maximum depth	8
Learning rate	0.01
Subsample	0.8
Colsample by tree	0.8
Objective function	‘reg

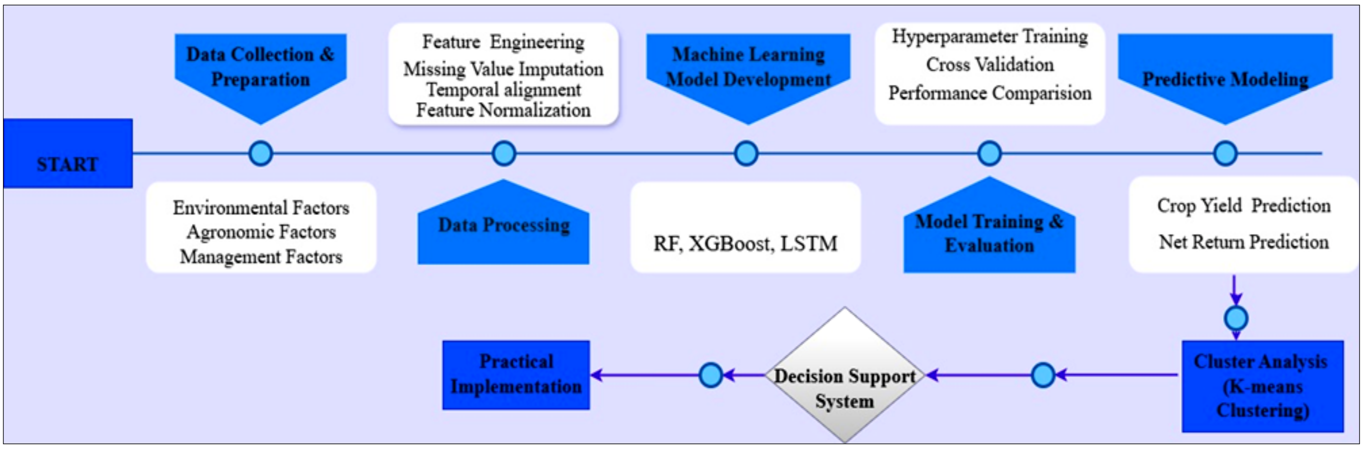

Fig. 2. Flow chart.

LSTM networks represent a specialized recurrent neural network architecture designed to capture temporal dependencies in sequential agricultural data. LSTM models are particularly well-suited for agrarian applications where historical sequences of weather, soil and management data influence current crop outcomes. The architecture addresses the vanishing gradient problem that limits standard recurrent networks in learning long-term dependencies (21, 22).

Cluster analysis of crop characteristics

We employed clustering techniques to identify natural groupings of crops based on their water requirements, profitability and other key characteristics. Two clustering approaches were compared in this study: the K-means clustering approach, a centroid-based algorithm that partitions observations into k clusters. To determine the optimal number of clusters for each method, the researchers employed several techniques, including the elbow method, silhouette analysis and gap statistics (23, 24). These methods helped ensure that the clustering results were robust and accurately represented the underlying structure of the data (25, 26). Table 2 shows the k-means configuration for the study area.

Table 2. K-means configuration

No of clusters	4
Initialization	k-means++
No of initializations	50
Maximum iterations	500

Results

The comparative analysis of ML algorithms reveals significant differences in performance characteristics that influence their suitability for agricultural prediction applications.

Model comparison

The XGBoost model demonstrated superior performance for most crops, achieving an average R^2 of 0.87 and RMSE of 0.32 tons/ha for yield prediction. For net return prediction, the model achieved an R^2 of 0.83 with an RMSE of 0.52 tons/ha. Fig. 3 showed the performance comparison of RF, XGBoost and LSTM models for crop yield prediction. XGBoost exhibited the highest R^2 score (0.87) and lowest RMSE (0.32) across all crops.

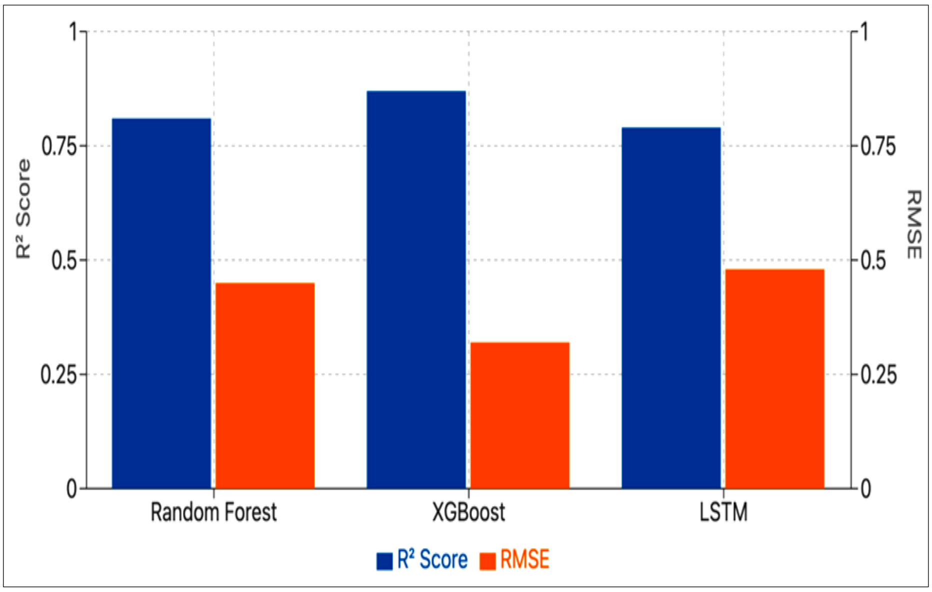

Fig. 3. Performance comparison of Random Forest, XGBoost and LSTM models for crop yield prediction.

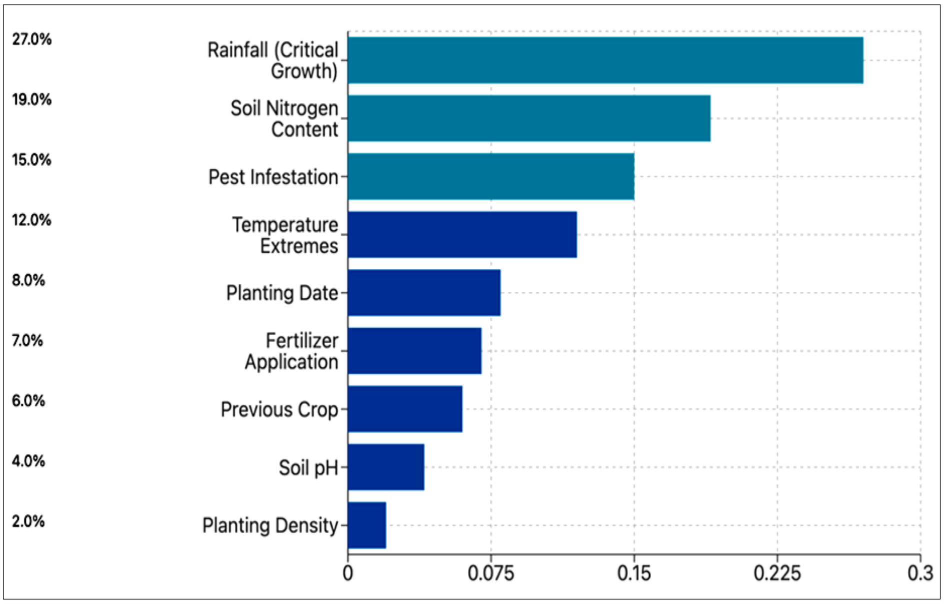

Fig. 4. Feature importance in the XGBoost model for predicting crop yield.

Feature importance analysis

The analysis of factors affecting crop growth revealed several key findings. Rainfall during critical growth periods emerged as the most crucial factor for the majority of crops, highlighting the importance of water availability. Soil nitrogen content was identified as the second most significant factor, underscoring the role of nutrient availability in crop development. For high-value crops, pest impact during the flowering stage proved to be a critical determinant of yield. Temperature extremes at specific growth stages were found to have varying effects across different crop types, emphasizing the need for crop-specific climate considerations. These insights provide valuable guidance for farmers and researchers in understanding and prioritizing the most influential factors impacting crop productivity and yield. Fig. 4 represents feature importance in the XGBoost model for predicting crop yield, showing the relative contribution of each input variable to prediction accuracy.

Crop-specific prediction performance

The model's performance exhibited notable variations across different crop types, with paddy demonstrating the highest prediction accuracy, achieving an R^2 value of 0.92. This indicates that the model was particularly effective in forecasting paddy yields, likely due to the crop's more predictable growth patterns and lower susceptibility to external factors. Fig. 5 illustrates XGBoost model performance by crop type, showing prediction accuracy for both yield and net return. Higher-value crops generally show better prediction accuracy.

Pulses and oilseeds showed moderate accuracy levels, with R^2 values ranging from 0.75 to 0.85, suggesting that while the model performed reasonably well for these crops, there was still room for improvement in capturing all the factors influencing their yields. Crops with higher susceptibility to pest outbreaks presented a greater challenge for the model, resulting in lower accuracy levels with R^2 values between 0.68 and 0.72. This reduced performance can be attributed to the unpredictable nature of pest infestations and their significant impact on crop yields. The model's struggle to accurately predict yields for these pest-prone crops highlights the complexity of accounting for biotic stresses in yield forecasting models. Future improvements to the model may need to incorporate more sophisticated pest prediction algorithms or real-time pest monitoring data to enhance its accuracy for these

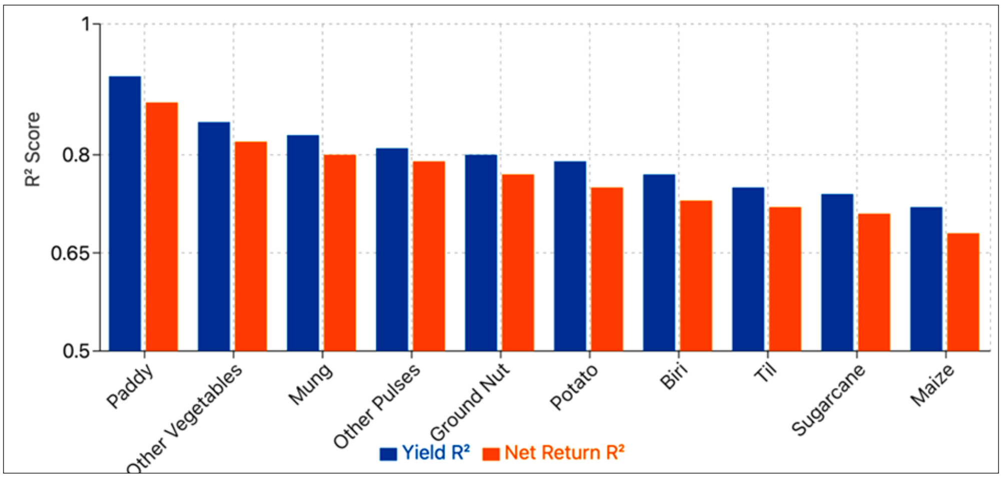

Fig. 5. Crop-specific prediction performance.

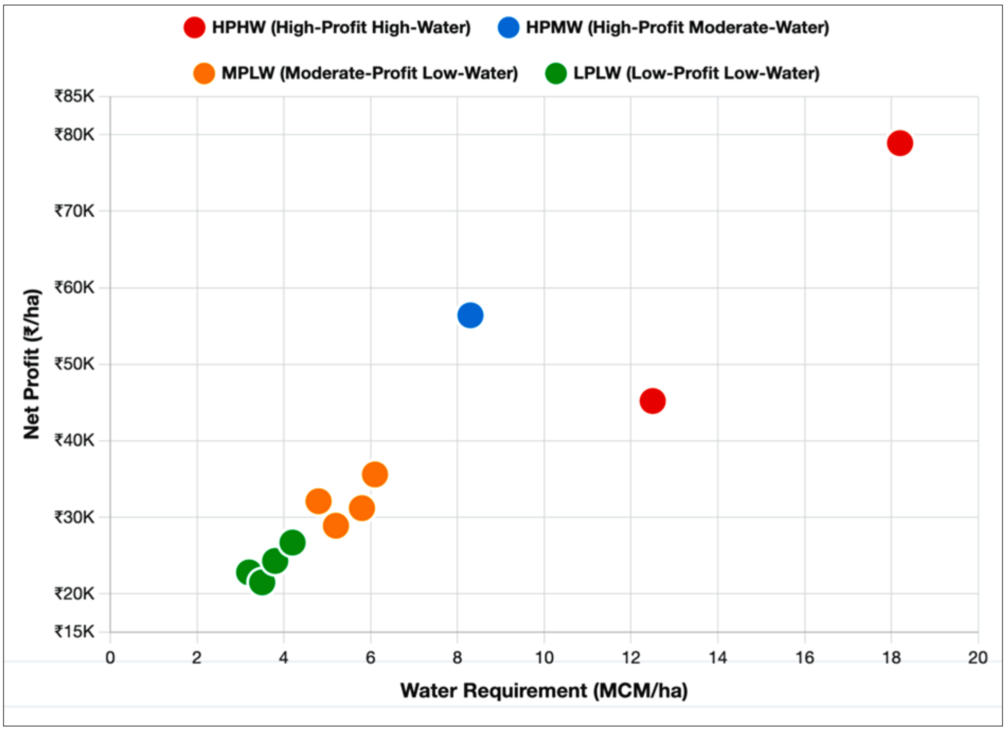

Fig. 6. K-means crop clustering analysis.

vulnerable crops.

Cluster analysis of crop characteristics

Fig. 6 showed K-means clustering of crops based on water requirements vs net return. Four distinct clusters emerged, showing clear trade-offs between water usage and profitability. The clustering solution achieved a high silhouette score of 0.73, indicating well-separated and internally coherent clusters (27). The K-means clustering (with k=4) identified the following crop clusters. The text outlines a K-means clustering analysis that categorizes crops into four distinct groups based on their profit potential and water requirements. The High-Profit, High-Water (HPHW) group includes paddy and sugarcane, which offer high profits but demand substantial water resources. The High-Profit, Moderate-Water (HPMW) group comprises vegetables, presenting an attractive balance of high profits and moderate water usage. The Moderate-Profit, Low-Water (MPLW) group, consisting of wheat, maize, sunflower and til, offers moderate profits with minimal water consumption. Lastly, the Low-Profit, Low-Water (LPLW) group includes mung, biri, other pulses and groundnut, which generate lower profits but require less water. This classification system provides valuable insights for farmers and agricultural planners, enabling them to make informed decisions about crop selection based on profit potential and water availability in their specific contexts.

Impact of weather scenarios on optimal allocation

The analysis of weather scenarios provided valuable insights into crop allocation strategies under varying rainfall conditions. In normal rainfall conditions, the optimal allocation closely mirrored the base genetic algorithm results, suggesting a robust baseline strategy. However, when faced with below-average rainfall, a significant shift in crop allocation was observed. Specifically, there was a 15 % reduction in HPHW crops in favour of MPLW crops. This adaptive strategy, while necessary to mitigate water scarcity, resulted in a 12 % decrease in total net returns, highlighting the economic impact of reduced rainfall on agricultural productivity. Fig. 7 shows the effect of different rainfall scenarios on optimal crop allocation and expected net returns. Lower rainfall scenarios shift allocation towards MPLW and LPLW crop clusters.

Conversely, above-average rainfall scenarios presented opportunities for increased profitability. The analysis revealed an 8 % increase in HPHW crop allocation under these conditions, capitalizing on the abundance of water resources. This shift in strategy led to a 5 % increase in total net returns, demonstrating the potential for higher profits when water availability is not a limiting factor. These findings underscore the importance of flexible crop allocation strategies that can adapt to changing weather patterns, balancing water usage with profit potential to optimize agricultural outcomes across various rainfall scenarios.

Decision support applications

The integrated ML framework enables several practical applications for agricultural decision-making.

Crop calendar optimization

The optimised crop calendar is a comprehensive planning tool that integrates multiple factors to determine the optimal timing for planting, cultivating and harvesting crops. It takes into account weather forecasts and historical patterns, allowing farmers to anticipate and prepare for potential climate-related challenges or opportunities. This data-driven approach enables more precise decision-making regarding seed selection, irrigation scheduling and pest management strategies. Fig. 8 showed an optimized crop calendar based on predictive modelling and genetic algorithm results, showing optimal planting and harvesting windows for various major crops.

Additionally, the optimised crop calendar considers the availability of labour and machinery, ensuring that resources are efficiently allocated throughout the growing season. It also incorporates market timing considerations, helping farmers align their production with periods of peak demand or favourable pricing. Furthermore, the calendar accounts for water availability throughout the growing cycle, enabling farmers to plan irrigation schedules and implement water conservation measures as needed. By synthesising these diverse factors, the optimised crop calendar empowers farmers to maximise yields, minimize risks and enhance overall agricultural productivity.

Resource allocation dashboard

This dynamic research allocation interface allows users to adjust key constraints such as water availability, land use and labour resources, providing real-time visualization of optimal crop allocation and financial projections. This feature enables the exploration of various scenarios and resource trade-offs, demonstrating the sensitivity of

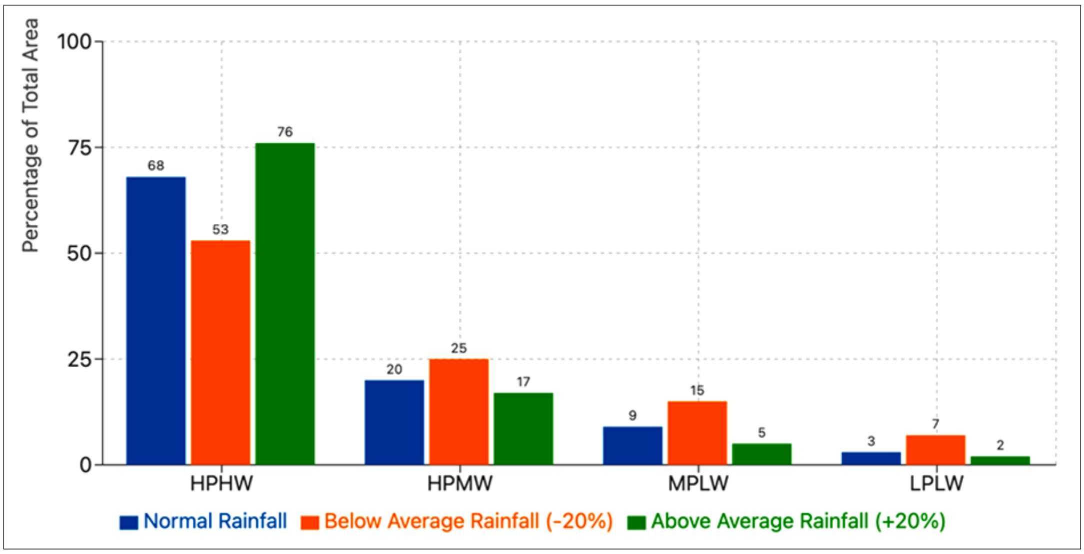

Fig. 7. Weather scenario impact analysis.

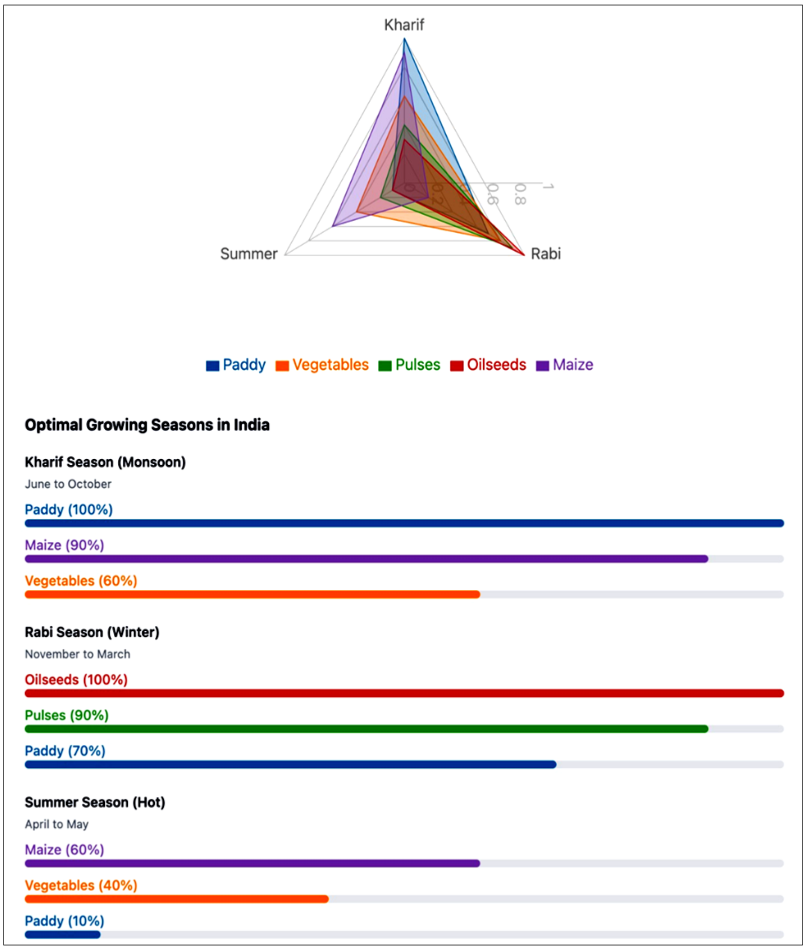

Fig. 8. Optimized crop calendar based on predictive modeling for BCC (India).

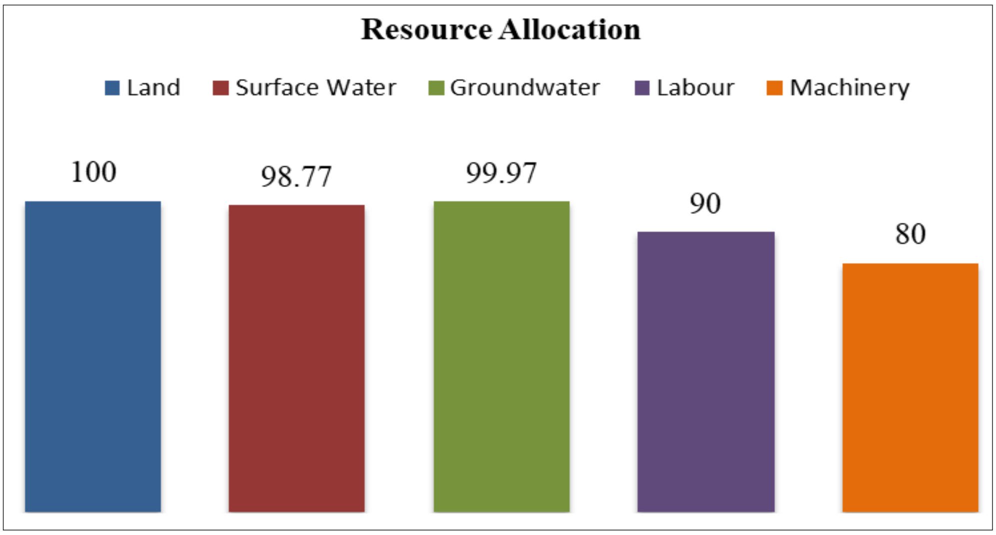

Fig. 9. Resource utilization percentage.

crop choices to different resource constraints. Fig. 9 depicts the interactive resource allocation dashboard that allows users to adjust constraints and visualize impacts on optimal crop allocation and expected returns.

Practical implementations based on ML analysis

The implementation of this advanced ML framework encompasses a comprehensive approach to agricultural management and decision-making. The data collection system forms the foundation, utilising automated weather stations, soil sensors, satellite imagery and farm management software to gather diverse and relevant information. This multi-faceted data collection ensures a holistic view of agricultural conditions, enabling more accurate predictions and insights.

The model update protocol ensures that the ML framework remains current and accurate. Weekly retraining with new weather data allows for rapid adaptation to changing conditions. At the same time, seasonal calibration with yield results and annual feature set expansion contribute to long-term improvement and refinement of the model. The user interface caters to various stakeholders, providing accessible tools for farmers, policymakers and financial institutions to leverage the ML-driven insights effectively. The recommendations based on ML analysis cover a wide range of agricultural strategies, including weather-responsive planning, cluster-based crop diversification, precision agriculture investments, monitoring system enhancements and policy recommendations.

These strategies aim to optimise water usage, balance risk and profit, improve efficiency and support sustainable agricultural practices through data-driven decision-making.

Discussions

A comparison with traditional agricultural planning methods demonstrated substantial improvements across all the performance dimensions. Traditional methods typically rely on historical planting patterns, local knowledge and simple rules of thumb, which may not account for changing conditions or optimising resource allocation effectively. Production improvements of 77.6 % over traditional methods indicate substantial potential for increasing food production through optimized crop allocation. These improvements result from the better matching of crops to suitable conditions, optimal timing of cultivation activities and improved resource allocation that maximizes yield potential.

The results of this comprehensive study demonstrate the significant potential for improving agricultural decision-making through the integration of ML and metaheuristic optimization techniques. The superior performance of XGBoost in predictive modelling, achieving an R^2 score of 0.87, establishes a strong foundation for informed optimization by providing accurate yield and profit forecasts under varying environmental and management conditions. Feature importance analysis reveals critical insights into the factors that most significantly influence agricultural outcomes. The prominence of rainfall timing during critical stages of growth, accounting for 23.4 % of the predictive power, emphasizes the fundamental importance of water availability in determining crop success. This finding aligns with established agricultural science while providing quantitative validation of the relative importance of different factors. The high significance of soil nitrogen content (18.7 %) reinforces the critical role of nutrient management in boosting agricultural productivity and supports the continued emphasis on precision nutrition strategies. Results of this study demonstrate significant potential for enhancing agricultural decision-making through the integration of ML and optimization techniques. Some key practical implications also include precision agriculture implementation, weather-responsive planning, nutrient management strategies, crop diversification guidance, water resource optimization and financial planning tools that could potentially improve access to credit for farmers adopting optimised practices, scalable decision support and providing a framework for continuous improvement of agricultural decision support systems.

Conclusion

An advanced ML framework for the Bargarh Canal Command was developed to enhance agricultural decision-making by integrating predictive modeling for crop yields and returns with clustering techniques. The XGBoost model demonstrated superior performance for yield and net return prediction. Clustering analysis identified four distinct crop clusters based on water requirements and profitability. The framework enables dynamic optimization based on weather scenarios and provides decision support applications such as crop calendar optimization and resource allocation. Recommendations based on the analysis include weather-responsive planning, cluster-based diversification, precision agriculture investment, monitoring system enhancement and policy recommendations. The methodologies and insights presented here constitute a robust framework for sustainable agricultural intensification in the face of climate variability and resource constraints. This approach not only maximizes economic returns but also promotes resilient farming systems that can adapt to changing conditions.

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Authors' contributions

PM conducted the research, acquired the data, performed the statistical analysis and drafted the manuscript, JCP contributed to conceptualization and supervision, DMD carried out data analysis and edited the manuscript, SKR assisted in conducting the research work, APS provided supervision, SS[1] and BM collected data, SR assisted in conducting the research work and SS[2] also contributed to data analysis. All authors read and approved the manuscript. [SS[1] stands for Subasish Saren and SS[2] stands for Sanghamitra Sahu].

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interest to declare.

Ethical issues: None

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Grammarly software for proof reading and grammar check. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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