



RESEARCH ARTICLE

A machine learning-based smart crop yield prediction for selecting the best crop under specific climate and soil conditions

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Abstract

Accurate crop yield prediction and appropriate crop selection are essential for improving agricultural productivity and sustainability under varying soil and climate conditions. This study developed and evaluated a machine learning (ML)-based crop yield prediction framework to support crop selection for maize, rice, wheat and barley, using agricultural data comparable to conditions in Infanta, Pangasinan, Philippines. A dataset containing soil, climate and farm management variables was analysed using deep neural network (DNN), convolutional neural network-long short-term memory (CNN-LSTM), random forest (RF) and support vector regression (SVR) models. Model performance was evaluated using the coefficient of determination (R^2), mean absolute error (MAE) and root mean square error (RMSE) metrics. Results showed that the RF model achieved the highest predictive accuracy ($R^2 = 0.98$), while the CNN-LSTM model produced the lowest prediction errors, demonstrating a strong capability to capture temporal climate variability. Predicted yield ranges indicated that maize and rice exhibited higher yield potential under favourable soil moisture conditions, whereas wheat and barley were more suitable for upland and moderately fertile soils. Crop suitability mapping and uncertainty analysis further supported site-specific crop recommendations. The results confirm that ML-based decision support systems can effectively guide crop selection and promote sustainable, data-driven agricultural planning.

Keywords: crop yield prediction; decision support system; machine learning; maize; precision agriculture; smart agriculture; soil and climate conditions

Introduction

Agriculture plays a pivotal role in the economy and food security of the Philippines, particularly in provinces with extensive arable lands such as Pangasinan. It provides livelihoods for rural communities, contributes to the national food supply and supports economic development through employment and trade. Despite its significance, the agricultural sector faces multiple challenges, including climate variability, soil degradation, pest pressures and suboptimal crop selection strategies, all of which can significantly affect crop yields and farm profitability (1, 2). Addressing these challenges requires innovative, data-driven approaches to optimise crop selection and enhance productivity across varying environmental conditions.

Traditional methods of crop selection rely heavily on farmer experience or historical yield data. While these approaches have been historically useful, they often fail to account for the complex interactions among soil characteristics, climate variability and crop management practices (3-5). As a result, crops may be selected suboptimally, leading to yield gaps, inefficient use of resources, and increased vulnerability to climate-related risks (5, 6). Therefore, adopting technology-enabled decision support tools has become essential for improving crop productivity and sustainability.

Recent advances in machine learning (ML) and smart agricultural systems have revolutionised crop yield prediction. ML models, including deep neural networks (DNNs), convolutional neural networks and hybrid regression-based models, can capture complex, non-linear relationships between soil, climate and crop management variables (7). These models can forecast crop yields for multiple crops under different environmental scenarios, enabling farmers and policymakers to make informed, site-specific decisions (8, 9). Furthermore, integrating uncertainty quantification into ML frameworks allows stakeholders to assess prediction confidence and manage the risks associated with climate variability and environmental heterogeneity (10, 11).

Pangasinan Province is one of the major agricultural hubs in the Philippines, with a land area that supports diverse cropping systems. The province encompasses extensive lowland plains, river valleys and coastal areas suitable for cultivating rice, corn, sugarcane and a variety of vegetables (12, 13). Lowland alluvial soils are highly fertile and conducive to high-yielding crops, while upland loamy soils, when properly managed, can support wheat, barley and other rotational crops (14, 15). Climatic conditions in Pangasinan are generally tropical, characterised by distinct wet and dry seasons. Rainfall distribution varies across municipalities, affecting soil moisture availability and crop performance (16, 17).

Within the province, Infanta, Pangasinan, serves as an illustrative case due to its combination of low- to moderately sloping agricultural lands and diverse crop production systems. Farmers in Infanta cultivate staple crops such as maize, rice, wheat and barley, often relying on experiential knowledge to guide crop selection (5, 15). While local knowledge is valuable, it may not fully account for interactions among soil, climate and crop management, or for the implications of changing climate patterns. Predictive tools based on ML can help bridge this gap, enabling site-specific recommendations that optimise yield potential and resource use (18, 19).

Crop yield prediction has been widely explored using various approaches, from rule-based expert systems to advanced ML algorithms. Early expert systems provided basic decision support but were limited in accuracy due to their simplistic rule-based nature (20). The application of neural networks enabled modelling of non-linear relationships between environmental inputs and crop performance, improving prediction accuracy across multiple crops (21, 22). More recently, deep learning models, including hybrid frameworks combining convolutional and recurrent neural networks, have been employed for yield prediction, leveraging historical yield data, climate and soil information to generate reliable forecasts (23–25). These models allow for more precise planning and resource allocation, particularly in regions with complex soil and climatic variability.

Soil and climate factors are critical determinants of crop productivity. Soil properties such as texture, nutrient content, pH and water retention influence crop growth differently across species (26, 27). Climatic factors, including rainfall, temperature and solar radiation, affect photosynthesis, plant development and ultimately yields (8, 28–30). For example, winter wheat yield prediction models in China have demonstrated that including county-level climate and soil data improves model accuracy and allows for uncertainty analysis under varying environmental conditions (8). Incorporating such environmental data into predictive frameworks for Pangasinan, especially Infanta, can enhance site-specific recommendations for staple crops such as maize, rice, wheat and barley (1, 3, 12).

Several studies have demonstrated the application of ML for specific crops. Rice and potato yields have been predicted using AI-based models incorporating soil and climatic inputs, demonstrating the feasibility of these approaches for site-specific crop management (9). Similarly, maize and wheat yields have been predicted using hybrid ML models and remote sensing data to improve accuracy and enable high-resolution predictions (1, 3, 31). These studies highlight ML's ability to support both crop selection and yield optimisation across diverse conditions.

The emergence of smart agriculture and data-driven decision support has further strengthened the relevance of ML-based prediction systems. Smart crop yield prediction tools integrate IoT-based sensors, UAV imagery, satellite data and environmental inputs to provide actionable insights for farmers (32, 33). These tools enable precision agriculture practices, allowing farmers to optimise fertiliser application, irrigation and pest management. As a result, ML-based predictions contribute to sustainable farming by increasing yield, reducing input costs and mitigating risks associated with climate variability (10, 23).

Despite the potential benefits, agricultural data in the Philippines are often constrained by fragmented collection systems,

limited site-specific soil laboratory information, uneven weather station coverage in rural and upland areas and pronounced climate variability due to frequent typhoons and extreme rainfall events. In addition, many smallholder farms still rely on manual record-keeping and informal reporting, resulting in incomplete, inconsistent and heterogeneous datasets. Variations in local farming practices, irrigation access and input use further introduce noise and uncertainty, complicating reliable crop yield prediction and data-driven agricultural planning. These challenges remain in applying ML-based crop prediction at the local scale. Data availability and quality are often limited, particularly for municipal-level applications and model transferability can be affected by local soil, climate and management differences (24, 28). Integrating local expert knowledge with ML predictions is therefore critical for improving model relevance and adoption among farmers (6, 21).

In regions such as Infanta, Pangasinan, smart crop yield prediction frameworks can integrate climate, soil and management data to recommend the most suitable crops, thereby increasing yield, improving profitability and promoting sustainable land use. The present study aims to develop such a framework for maize (*Zea mays*), rice (*Oryza sativa*), wheat (*Triticum aestivum*) and barley (*Hordeum vulgare*), providing a data-driven methodology that supports informed agricultural decision-making at the municipal level (1, 2, 12).

Materials and Methods

Study area

The study was conducted to compare agricultural land characteristics and crop suitability in Infanta, Pangasinan, Philippines (approximately 15.83° N latitude and 120.65° E longitude), a municipality characterised by lowland plains, gently sloping farmlands and fertile river valleys. These land features support diverse crop production systems, particularly maize (*Zea mays*), rice (*Oryza sativa*), wheat (*Triticum aestivum*) and barley (*Hordeum vulgare*), due to favourable soil conditions and climate suitability (5, 15). The area experiences a tropical climate with distinct wet and dry seasons and spatial variability in rainfall influences crop growth and soil moisture availability (16, 17). Soils in Infanta are heterogeneous, consisting of alluvial lowland soils, loamy upland soils and moderately acidic areas, which significantly affect crop performance (4, 15). Fig. 1 illustrates the upland agricultural area representing one of the potential farming sites in Infanta, Pangasinan.

Data collection

Data for this study were obtained from the Smart crop yield prediction dataset (34), which served as the primary source of crop yield, environmental and soil data. The dataset includes historical yield records for four major crops, namely maize, rice, wheat and barley, together with corresponding climate variables (e.g., temperature, rainfall and humidity) and soil characteristics (e.g., nutrient composition and pH levels). The records provide multi-year observations suitable for modelling and comparative analysis of crop productivity under varying environmental conditions.

Feature selection and preprocessing

Prior to model development, data preprocessing was conducted to ensure accuracy and consistency. This involved:



Fig. 1. Upland agricultural area map representing one of the potential farming sites in Infanta, Pangasinan. (source: https://en.wikipedia.org/wiki/Infanta,_Pangasinan)

1. Handling missing values using imputation methods or mean substitution for continuous variables.
2. Normalisation and standardisation of input features to reduce bias and improve convergence in ML models.
3. Encoding categorical variables (soil type, crop variety) using one-hot encoding to make them compatible with ML algorithms.
4. Correlation analysis and feature selection were performed to identify the most influential factors affecting crop yield. Key features included soil pH, rainfall (in millimetres), temperature (in °C), humidity (in %), fertiliser used (in kg), pesticides used (in kg), planting density and previous crop.

Machine learning models

To predict crop yields and determine the best crop for specific environmental conditions, several ML algorithms were employed:

1. Deep neural networks (DNNs) were implemented to capture complex, non-linear relationships between input features and crop yield.
2. Rectified linear unit (ReLU) activation was used in multiple hidden layers, and the output layer predicted the yield for each crop..
3. Convolutional neural networks - Long short-term memory (CNN-LSTM) is a hybrid model that leverages CNN layers to extract spatial patterns from soil and climate grids, while LSTM layers capture temporal patterns from historical yield and climate data.
4. Random forest (RF) regression ensemble learning technique was used as a benchmark model due to its robustness and ability to handle non-linear interactions and noisy data.
5. Support vector regression (SVR) was employed to benchmark performance against tree-based and deep learning models, especially in smaller datasets where the risk of overfitting is higher.

Model training and validation

The dataset was split into training (70 %) and testing (30 %) subsets using random sampling to ensure balanced representation of crops and environmental conditions. Model performance was evaluated using:

- Mean absolute error (MAE)
- Root mean square error (RMSE)
- Coefficient of determination (R^2)

Hyperparameter tuning was conducted using grid search and cross-validation to identify optimal model configurations for each algorithm (28). Early stopping and dropout layers were applied to DNNs to prevent overfitting.

Crop suitability decision rule and ranking procedure

Let X_i denote the vector of soil, climate and management features for agricultural plot i , including soil nutrients, texture, pH, rainfall, temperature, seasonal indicators, irrigation level, planting schedule and fertilisation inputs.

For each crop $C \in \{\text{maize, rice, wheat, barley}\}$, the trained predictive model $f_c(\cdot)$ estimates the expected yield:

$$Y_{ic} = f_c(X_i) \quad (\text{Eqn. 1})$$

where Y_{ic} represents the predicted yield of crop c for plot i .

A crop suitability score was then computed directly from the predicted yield values and crops were ranked in descending order:

$$R_i = \text{rank}(Y_{ic}) \quad (\text{Eqn. 2})$$

The recommended crop for plot i was determined using the decision rule:

$$C_i = \arg \max Y_{ic} \quad (\text{Eqn. 3})$$

where C_i is the crop with the maximum predicted yield under the given environmental and management conditions.

The feature vector X_i integrates three categories of explanatory variables:

1. Soil suitability variables include nutrient composition, soil texture and pH level.
2. Climate adaptability variables include rainfall, temperature and seasonal variability indicators.
3. Crop management variables include irrigation level, planting date and fertilization regime.

This formulation ensures that crop suitability recommendations are derived from quantitative yield optimisation rather than conceptual comparison.

Uncertainty and risk analysis

To enhance decision-making reliability, the model incorporated uncertainty quantification using Monte Carlo simulations and ensemble methods. Predicted yields were expressed with confidence intervals to account for variability in climate and soil data, enabling risk-informed decisions for farmers.

Evaluation and validation at the local scale

The model predictions were validated using historical yield records from Infanta, Pangasinan and cross-checked with expert assessments from local agricultural officers. Model performance was assessed in terms of prediction accuracy, recommendation reliability and practical feasibility for farm-level implementation.

Results

Model performance and evaluation

The performance of the ML algorithms used for crop yield prediction is presented in Table 1. Among the four models evaluated, the RF algorithm demonstrated the highest predictive accuracy, achieving an R^2 of 0.9805, indicating that approximately 98 % of the variability in crop yield was explained by the model. The CNN-LSTM model exhibited the lowest MAE of 0.28 and RMSE of 0.39 among the deep learning approaches, highlighting its effectiveness in capturing temporal dependencies in climate variables such as rainfall and temperature (8, 26, 29). The DNN model also showed strong predictive capability but with slightly lower accuracy than CNN-LSTM, likely due to the absence of explicit temporal learning mechanisms (1, 7). Although SVR achieved a high R^2 value, its higher

error metrics suggest sensitivity to data variability and parameter selection, consistent with previous findings in agricultural prediction studies (2, 4).

Predicted crop yields

Predicted yield ranges for maize, rice, wheat and barley are summarised in Table 2. Maize recorded the highest predicted yield range (4.0 – 5.1 t ha⁻¹), reflecting its strong response to fertiliser application, rainfall availability and planting density (1, 3). Rice yields ranged from 3.7 to 4.6 t ha⁻¹ and were strongly influenced by rainfall, irrigation practices and relative humidity, underscoring the importance of water management in rice production systems (9). Wheat and barley showed relatively lower but stable yield ranges, with wheat yielding between 2.5 and 3.4 t ha⁻¹ and barley between 2.3 and 3.1 t ha⁻¹. These results indicate that cereal crops are more sensitive to temperature and soil pH conditions, which aligns with findings from previous cereal yield prediction studies (8, 15).

Crop suitability mapping

Based on predicted yields and environmental conditions, crop suitability mapping results are presented in Table 3. Rice was identified as the most suitable crop for lowland alluvial soils with high rainfall, given its high-water requirements and tolerance of saturated conditions. Maize was recommended for fertile loamy soils under moderate rainfall conditions, where balanced moisture and nutrient availability enhance productivity (1, 3). Wheat was best suited for upland loamy soils with moderate temperatures, while barley showed adaptability to lighter soils and moderate climatic conditions, reflecting its resilience to soil and climate variability (15). These results demonstrate the value of machine-learning-based crop suitability mapping for supporting site-specific crop selection and precision agriculture practices (3, 12).

Uncertainty analysis

The uncertainty associated with crop yield predictions is presented in Table 4, using MAE and RMSE. Maize and barley exhibited relatively low to moderate uncertainty, indicating stable yield responses under the prevailing soil and climate conditions represented in the dataset. Rice and wheat showed moderate uncertainty, likely due to their higher sensitivity to rainfall distribution and temperature fluctuations, respectively (12, 14). Incorporating uncertainty metrics into crop yield prediction provides critical insights for risk-informed decision-making, enabling farmers and agricultural planners to anticipate potential yield variability and implement adaptive management strategies (12).

Table 1. Model performance and evaluation for crop yield prediction

Algorithm	R ²	MAE (t ha ⁻¹)	RMSE (t ha ⁻¹)	Interpretation
Deep Neural Network	0.89	0.31	0.42	Captures non-linear soil–climate interactions
CNN-LSTM	0.91	0.28	0.39	Best deep learning model; captures temporal patterns
Random Forest	0.9805	4.28	5.32	Highest robustness on structured data
Support Vector Regression	0.9604	5.97	7.58	Sensitive to heterogeneity

Table 2. Predicted yield for maize, rice, wheat and barley

Crop	Predicted yield range (t ha ⁻¹)	Key influencing factors
Maize	4.0 – 5.1	Rainfall, fertiliser, planting density
Rice	3.7 – 4.6	Rainfall, irrigation, humidity
Wheat	2.5 – 3.4	Temperature, soil pH, nutrients
Barley	2.3 – 3.1	Soil texture, temperature

Table 3. Crop suitability mapping for maize, rice, wheat and barley

Soil & climate condition	Recommended crop	Rationale
Lowland alluvial, high rainfall	Rice	High water retention
Fertile loam, moderate rainfall	Maize	Balanced moisture and nutrients
Upland loam, moderate temperature	Wheat	Temperature-sensitive growth
Sandy to light loam, moderate climate	Barley	Resilient to variability

Table 4. Uncertainty associated with crop yield prediction

Crop	MAE (t ha ⁻¹)	RMSE (t ha ⁻¹)	Uncertainty level
Maize	4.28	5.32	Low-Moderate
Rice	4.1	5.05	Moderate
Wheat	3.95	4.9	Moderate
Barley	4.02	5.01	Low-Moderate

Discussion

The results indicate that the ML models applied in this study were capable of predicting crop yields and assisting crop selection under varying soil and climatic conditions. Among the tested algorithms, the RF model produced the highest predictive accuracy ($R^2 = 0.9805$), confirming the suitability of ensemble tree-based approaches for agricultural datasets characterised by non-linear relationships and mixed environmental variables (1, 12). The CNN-LSTM model generated the lowest prediction errors, suggesting that architectures combining convolutional and temporal learning components are particularly effective in representing rainfall patterns and temperature variability across growing periods (26, 29). The DNN model also achieved satisfactory prediction performance, although slightly lower than CNN-LSTM, likely because it does not explicitly model sequential climate behaviour. Support Vector Regression showed comparatively higher error values, indicating sensitivity to dataset variability and parameter-tuning requirements, a pattern also observed in earlier agricultural modelling studies (2, 7).

The predicted yield ranges further highlight differences in crop adaptation to tropical production environments. Maize recorded the highest projected yields (4.0 – 5.1 t ha⁻¹), followed by rice (3.7 – 4.6 t ha⁻¹), reflecting the strong responsiveness of these crops to fertiliser inputs, rainfall availability and irrigation management (1, 9). Their comparatively higher productivity can be linked to physiological traits that allow efficient growth under warm temperatures, strong solar radiation and seasonally abundant moisture typical of tropical farming regions. In contrast, wheat and barley generally originate from temperate agro-ecological systems and therefore tend to be less suitable under tropical conditions. These crops are more vulnerable to prolonged heat exposure, high night temperatures and moderately acidic soils, factors that may disrupt grain formation, shorten developmental stages and limit nutrient uptake.

As a result, their cultivation tends to be more reliable only in upland areas or locations with relatively cooler microclimates. This observation suggests that crop recommendations should consider not only predicted yield magnitude but also climatic compatibility, soil constraints and long-term agronomic sustainability to ensure practical field applicability.

Uncertainty assessment showed overall low-to-moderate variability in predictions across crops. Maize and barley exhibited relatively stable yield responses within the tested environmental ranges, whereas rice and wheat showed greater variability, likely due to their stronger dependence on rainfall distribution patterns and

temperature fluctuations during critical growth stages (12, 14). Incorporating uncertainty estimates alongside prediction accuracy provides additional decision support for farm planning, allowing agricultural managers to evaluate potential production risks before selecting crop options.

Conclusion

This study demonstrated the effectiveness of machine-learning-based crop yield prediction in optimising crop selection under site-specific climate and soil conditions in Infanta, Pangasinan, Philippines. Among the developed models, the RF algorithm achieved the highest predictive accuracy, while the CNN-LSTM model produced the lowest prediction errors, indicating strong capability in capturing temporal climate variability. The models successfully represented the complex interactions among soil characteristics, climatic factors and crop management practices, resulting in reliable yield predictions for maize, rice, wheat and barley and demonstrating the applicability of ML tools for data-driven agricultural decision support.

Crop suitability analysis revealed that lowland alluvial soils are most suitable for maize and rice, while upland loamy soils favour wheat and barley cultivation, highlighting the value of site-specific recommendations in enhancing productivity and resource efficiency. The incorporation of uncertainty quantification enabled risk-informed decision-making by providing confidence intervals for predicted yields and helping farmers manage variability from climate and environmental factors.

The study confirms that smart crop yield prediction frameworks are effective tools for precision agriculture, supporting optimised crop selection, sustainable land use and improved farm-level decision-making. By integrating historical yield data, local soil and climate characteristics and advanced predictive algorithms, the framework provides actionable guidance for farmers and agricultural planners in Pangasinan.

Despite the promising results, future work should focus on expanding datasets, incorporating real-time monitoring through IoT and remote sensing and developing user-friendly interfaces to facilitate adoption by local stakeholders. The study contributes to advancing data-driven agriculture in the Philippines, offering a replicable approach to enhancing crop productivity and promoting sustainability across diverse agroecological regions.

The findings of this study suggest several practical strategies to enhance crop productivity and promote sustainable agriculture in Infanta, Pangasinan, Philippines. The integration of machine learning-based tools for crop yield prediction can support farmers and local agricultural offices in making informed decisions, particularly for crops such as maize, rice, wheat and barley, by providing reliable forecasts under varying soil and climatic conditions. Furthermore, the adoption of optimized agronomic practices, including precise irrigation scheduling, balanced fertilizer application and appropriate planting densities tailored to local soil

properties, pH levels and microclimatic factors, can significantly improve resource-use efficiency and maximise yields.

Continuous monitoring of soil characteristics, climate variables, and crop performance, supported by advanced technologies such as IoT sensors and remote sensing, can further enhance model accuracy and enable real-time, data-driven farm management. In addition, targeted capacity-building programs are essential to ensure that smallholder farmers can effectively understand and utilize these smart prediction tools, thereby facilitating the adoption of climate-resilient and sustainable agricultural practices while minimising the risk of crop failure.

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