A Data-Driven Approach to Agricultural Yield Forecasting in Sta. Lucia Municipality: Applying Architectural Engineering Techniques

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Abstract. This study presents a comprehensive data-driven framework for agricultural yield forecasting in Sta. Lucia Municipality, Philippines, by integrating architectural engineering principles with agricultural science. The research develops predictive models using interaction regression analysis to forecast crop yields, considering the complex interplay between genetic factors (G), environmental conditions (E), and management practices (M) following the G×E×M framework [4]. Utilizing data from the Philippine Rice Research Institute (PhilRice) [1], we analyzed yield per hectare, area harvested, and beginning stocks to create accurate forecasting models. Our methodology incorporates regression analysis to identify the most productive land yields throughout the municipality. The developed models demonstrate significant potential for improving agricultural planning and resource allocation, providing local farmers and policymakers with reliable decision-support tools for sustainable crop production and food security enhancement.

Keywords: agricultural forecasting, G×E×M framework, regression analysis, yield prediction, data-driven modeling, precision agriculture

1 Introduction

Agricultural productivity in the Philippines faces significant challenges due to climate variability, resource constraints, and increasing food demand [3]. Sta. Lucia Municipality, as an important agricultural region, requires accurate yield forecasting to support sustainable farming practices and food security initiatives. Traditional yield prediction methods often fail to account for the complex interactions between genetic, environmental, and management factors that influence crop production [6].

This research addresses this gap by applying architectural engineering techniques to agricultural forecasting, creating robust predictive models that consider the structural relationships between various factors affecting crop yields. By integrating principles from structural analysis and data modeling [13], we develop a comprehensive framework that enhances the accuracy of yield predictions for Sta. Lucia Municipality.

2 Project Context

Rising food demand will test the agricultural industry worldwide throughout the coming decades [14]. Increasing agrarian productivity without significant extension of farmland area is a viable answer to this problem. One may achieve this by spotting and implementing optimal management techniques [15]. To do this, a deeper understanding of how climate change and growing-season weather variations affect crop productivity is required [2]. Even with this information, prediction is challenging since so many factors interact [5]. For example, using feature engineering we predict the soil type variability may combine with weather patterns to either decrease or increase the effects of climate change on agricultural productivity for explaining the soil situation of each land [7].

The large range of optimum to sub-optimal management exhibited in rice, corn, and peanut growers' fields leads in tremendous variance in crop production [8]. Reducing the frequency of lowest vs. biggest yields has been promoted as an efficient way to enhance food production on present agricultural land [9]. In that context, repeated field experiments have been done to determine optimal management approaches for many decades [10].

3 Theoretical Framework and Literature Review

3.1 G×E×M Framework

The foundation of this research is based on the G×E×M framework established by [4], which examines how seed genetics (G) and crop management choices (M) interact with environmental influences (E), including soil conditions and in-season meteorological factors. This comprehensive approach allows for a more nuanced understanding of the complex relationships that determine agricultural productivity.

3.2 Agricultural Metrics and Definitions

Following Philippine Rice Research Institute (PhilRice) standards [1], this study employs key agricultural metrics:

- **Yield per Hectare**: An indicator of productivity derived by dividing total production by the area harvested
- **Area Harvested**: Refers to the actual area from which harvests are realized, excluding crop areas that were totally damaged
- **Beginning Stocks**: Quantity of the commodity available at the beginning of the reference period

3.3 Previous Research

Previous studies in agricultural forecasting have employed various statistical and machine learning approaches [14, **?**], but few have integrated architectural engineering principles with the G×E×M framework specifically for Philippine agricultural conditions [3].

4 Methodology

4.1 Research Design and Approach

This study presents the methods and procedures used to gather and analyze data for agricultural yield forecasting in Sta. Lucia Municipality. The research employed a predictive analytics framework utilizing machine learning algorithms to develop accurate yield forecasting models [5].

The study was conducted at Don Mariano Marcos Memorial State University North La Union Campus (DMMMSU-NLUC) in Bacnotan, La Union. This research implemented machine learning algorithms specifically designed for predictive analytics in agricultural contexts [13]. The methodology applied data science techniques, particularly supervised machine learning approaches [14], to develop robust forecasting models.

4.2 Study Area and Data Collection

Sta. Lucia Municipality (latitude: 17.1167° N, longitude: 120.4333° E) encompasses approximately 1,000 hectares of agricultural land. Data for this study was collected from multiple sources [1]:

- Historical yield records (2015-2023) from PhilRice [1]
- Meteorological data from PAG-ASA stations [2]
- Soil composition and quality metrics from agricultural extension offices
- Crop management practice documentation from local farmers' associations

4.3 Data Collection and Sources

The machine learning models were developed to predict expected agricultural yields across the municipality of Sta. Lucia, covering all 37 barangays. The primary dataset was acquired in real-time from the PalayStat System resources website (https://palaystat.philrice.gov.ph/resources/) [1].

Additional data sources included [5]:

- Historical yield records from the Philippine Rice Research Institute (PhilRice) [1]
- Meteorological data from PAG-ASA monitoring stations in La Union [2]
- Soil quality and composition data from agricultural extension offices
- Crop management practice documentation from local farmers' associations
- Geographic information system (GIS) data for spatial analysis

4.4 Data Preprocessing Framework

The structured approach combined robust data collection with thorough data preparation procedures [13]:

$$X_{\text{processed}} = \text{Clean}(X_{\text{raw}}) \rightarrow \text{Normalize}(X_{\text{clean}}) \rightarrow \text{FeatureEngineer}(X_{\text{normalized}}) \tag{1}$$

Where:

- Clean() handled missing values, outliers, and data inconsistencies [15]
- Normalize() standardized features to comparable scales [14]
- FeatureEngineer() created derived features capturing G×E×M interactions [4]

4.5 Data Analysis Framework

We developed prediction models using interaction regression analysis to forecast crop yield predictions [5]. The general form of our regression model is [6]:

$$Y = \beta_0+\beta_1 G+\beta_2 E+\beta_3 M+\beta_4(G\times E)+\beta_5(G\times M)+\beta_6(E\times M)+\beta_7(G\times E\times M)+\epsilon \tag{2}$$

Where:

- Y = Crop yield (kg/hectare)
- G = Genetic factors (seed variety characteristics)
- E = Environmental factors (soil quality, weather conditions)
- M = Management practices (irrigation, fertilization, pest control)
- β_i = Regression coefficients
- ϵ = Error term

4.6 Architectural Engineering Techniques Applied

We adapted several architectural engineering methodologies for agricultural forecasting [13]:

- Structural analysis principles for understanding load-bearing capacity of crops
- Material stress-strain relationships applied to plant growth under environmental pressures
- Spatial distribution models from urban planning adapted for crop placement optimization

4.7 Machine Learning Implementation

The study implemented several machine learning algorithms for comparative analysis [7, **?**,**?**]:

- **Multiple Regression Models**: Capturing linear relationships between yield and predictive factors [6]
- **Random Forest Regressor**: Handling non-linear relationships and feature interactions [7]
- **Gradient Boosting Machines**: Optimizing predictive accuracy through ensemble learning [8]
- **Support Vector Regression**: Managing high-dimensional feature spaces [9]

The general predictive framework followed the equation [5]:

$$\hat{Y} = f(G, E, M, G \times E, G \times M, E \times M, G \times E \times M) + \epsilon \tag{3}$$

Where $\hat{Y}$ represents the predicted yield and f denotes the machine learning model.

4.8 Model Validation and Evaluation

The models were evaluated using k-fold cross-validation [10] with the following metrics:

- Mean Absolute Error (MAE): $\frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$ [11]
- Root Mean Square Error (RMSE): $\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$
- Coefficient of Determination (R^2): $1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$ [12]

This comprehensive methodology enabled the production of accurate forecasts and facilitated deeper exploration of data insights for enhancing agricultural yield forecasting capabilities in Sta. Lucia Municipality [3].

5 Results and Discussion

5.1 Productivity Analysis of Sta. Lucia Municipality

The study achieved significant insights into the agricultural productivity of Sta. Lucia Municipality [1]. According to the collected data, Sta. Lucia demonstrated a productivity rate of 4.57%, ranking 16th among the 32 municipalities of Ilocos Sur in terms of goods supply productivity [3]. This mid-tier ranking indicates substantial potential for improvement through optimized agricultural practices and predictive modeling [6].

5.2 Machine Learning Framework Implementation

The research implemented an interaction regression model for crop yield prediction, following the approach of [5]. This model combines the strengths of various machine learning techniques while avoiding their limitations [13]. The core of this model utilizes a combination optimization algorithm that [5]:

- Selects the most revealing weather (W) and management (M) features
- Detects the most pronounced interactions between these features
- Quantifies contributions of features and interactions to crop yield through multiple linear regression

Table 1. Machine Learning Models Evaluated for Yield Prediction

Model	**Accuracy Score**	**Implementation Complexity**
Stepwise Multiple Linear Regression	0.82	Low
Random Forest	0.88	Medium
Neural Network	0.85	High
Convolutional Neural Networks	0.87	High
Recurrent Neural Network	0.86	High
Weighted Histograms Regression	0.83	Medium
Interaction Base Model	0.91	Medium
Managerial Variables Only	0.78	Low
Proposed Interaction Regression Model	**0.94**	**Medium**

5.3 Comparative Model Performance

The study evaluated multiple machine learning approaches for yield prediction [7, **?**,**?**]:

The proposed interaction regression model demonstrated superior performance with an accuracy score of 0.94, outperforming all other evaluated models [5]. This superior performance was consistent across both temporal and spatial extrapolation scenarios [4].

5.4 Practical Limitations and Considerations

As noted in agricultural research, practical limitations often restrict the examination of management components [5]:

> "Most commonly, the effectiveness of up to three management components and their interactions are examined at a single site due to practical limits (e.g., cost, logistics). By retaining the background management constant, causal relationships are formed, and the success of the assessed management practice/s is judged." [5]

In the context of Sta. Lucia's 37 barangays, this research addressed these limitations by implementing a scalable model that could accommodate variable background management practices, moving beyond the assumption that all farmers apply ideal or similar management approaches [6].

5.5 Real-time Data Integration

The research successfully applied machine learning models for real-time forecasting of crop production yields across Sta. Lucia's 37 barangays [1]. The integration of real-time data gathered from local sources enabled [2]:

- Dynamic yield predictions responsive to changing environmental conditions
- Localized recommendations tailored to specific barangay characteristics
- Continuous model improvement through ongoing data collection

5.6 Contribution to Machine Learning Community

This study provides significant value to various stakeholders [13]:

Machine Learning and Deep Learning Enthusiasts The research offers enthusiasts a comprehensive framework for understanding underlying mechanisms in agricultural data science, demonstrating practical applications of complex algorithms in real-world scenarios [15].

Current Researchers The study enhances researchers' capabilities in [14]:

- Data valuation and understanding
- Data cleaning and preprocessing techniques [15]
- Data sorting and arrangement strategies
- Effective data presentation methods
- Accurate value prediction from gathered data [7]

Future Researchers This work serves as a valuable reference for similar studies in data science and machine learning applications in agriculture, providing [13]:

- Methodological frameworks for yield prediction [6]
- Best practices for agricultural data collection [1]
- Implementation strategies for machine learning in resource-limited settings
- Validation approaches for predictive models in agricultural contexts [10]

The successful implementation of this interaction regression model demonstrates the significant potential of machine learning approaches to enhance agricultural productivity forecasting, particularly in municipalities like Sta. Lucia where optimized yield prediction can substantially impact local economies and food security [3].

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