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Random Forest Analysis of Exogenous Variables Impacting Rice Production in the Philippines

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ABSTRACT: This research examines the relationship of rice production as the endogenous variable in a production function theory that considers key exogenous factors such as fertilizer consumption, irrigation water use, agricultural machinery, poverty rate, and agricultural land area. The study reveals the interdependencies shaping rice production in the Philippines. Applying the Cobb- Douglas function enhanced through the random forest regression algorithm establishes fertilizer consumption's focal role, focusing its essential impact on rice yields. Proper allocation of irrigation, access to agriculture machinery, poverty alleviation, and effective land use appear as significant contributors to overall production, defining 98% of the variability in rice production in random forests in both the in-sample and out-of-sample results. The findings emphasize the necessity for holistic strategies in agricultural planning, aiming for targeted interventions in fertilizer management, irrigation infrastructure, mechanized farming, poverty alleviation, and land-use.

KEYWORDS: Production function theory, Rice production, Cobb-Douglas Model, Random Forest, Philippines

I. INTRODUCTION

From 2002 to 2022, rice production in the Philippines experienced significant changes and challenges for the past two decades. The annual production was 26 million tons, with an average yield of 3.83 tons per harvested hectare (Global Yield Atlas). The Philippines produced approximately 3% of the world's rice during this period. Over the years, rice production has steadily increased, with the area under cultivation expanding by 50% during the second half of the 20th century. However, due to geography and international policy pressure, the Philippines still imports around 10 percent of its marketed rice per year (Stuecker, Tigchelaar & Kantar, 2018).

In the years 1966 to 2021, rice farming in the Philippines underwent several changes. In contrast, despite the adoption of labor-saving technologies and improvement in agronomy practices during the period, rice yields stagnated and became more variable (Kajisa, Moya & Gascon, 2022). The Green-Revolution-type agricultural development is at a crossroads, with increasing rural labor scarcity caused by its success. Also becoming increasingly rampant are contemporary challenges of disasters and infectious diseases.

The Central Luzon Loop Survey, one of the longest-running and ongoing household surveys in the Philippines is tracking changes in rice farming since 1966, revealed that rice yields have stagnated and become more volatile despite a prompt and significant increase in the utilization of labor-saving technologies (Kajisa, Moya & Gascon, 2022). It indicates the need to adapt new strategies and technologies to overcome challenges in rice farming practices.

Rice production is a vital sector in the Philippine economy, providing food and income for millions of Filipinos. Rice farmers confront various challenges affecting their productivity and profitability, such as irrigation, which is a critical factor influencing rice output, as it allows farmers to cultivate more land area and use more fertilizer. Unfortunately, only about 60% of the potential irrigable regions in the Philippines are irrigated, attributed to inadequate infrastructure, high maintenance costs, and poor water management (Launio & Abyado, 2022), (Selva, 2023). Due to evaporation, traditional methods of flooding rice fields also waste a lot of water. Several alternative methods that conserve water and boost rice production are drip and solar-powered irrigation (Teves, 2018). It takes 1,432 liters of water to produce 1 kg of rice in an irrigated lowland production system (Palash, Rahman, Amin, Mainuddin & Jalilov, 2019).

The average production of rice in the Philippines is among the world's lowest, with an average of 30 cavans per hectare or 1.32 metric tons per hectare due to high prices, limited availability, and lack of knowledge on proper application (Buresh, Castillo, Torre, Laureles, Samson, Sinohin, & Guerra, 2019). Just about $6 billion was the value of the rice production in the country in 2015 (Stuecker et al., 2018). Using fertilizer, specifically nitrogen, produces a higher yield than traditional methods (Sebastian, Alviola & Francisco, 2000). The government promoted the use of foliar fertilizers, which significantly increased harvest yields. Despite the increased use of fertilizers, the country remains a large rice importer, importing 10% (Buresch et al., 2019).

From 2002 to 2022, the use of agricultural machinery in rice production in the Philippines experienced some changes, although the adoption rate remains relatively slow. The fam mechanization level of rice farms in the Philippines is 2.68 horsepower per hectare, with a 16 percent improvement over nine years. However, the adoption rate differs across regions with higher farm mechanization levels than other regions (Lagare, 2023). Several elements contribute to the slow adaption of agricultural machinery in rice production. The high cost of agricultural machinery, such as tractors and harvesters, becomes a deterrent for small-scale farmers.

Moreover, the government focuses on other areas, such as postharvest issues and foliar fertilizers, instead of promoting mechanization as a core aspect of farm modernization. Increasing rural lab shortages require a structural transformation in rice farming, but this is not fully attained (Kajisa, Moya & Gascon, 2022). Also, climate variability affects rice production, and future climate projections appear to be a continuing challenge in the coming years (Stuecker, Tigchelaar & Kantar, 2018). Fortunately, the government confronting these challenges continued to allocate funds for procuring agricultural machinery needed to balance these obstacles with the possible benefits of increased efficiency and productivity.

The poverty incidence among farmers in the Philippines was 30.0% in 2021, showing that three out of 10 farmers had income below the poverty threshold. However, there was a slight improvement from 34.3% in 2015. Farmers remain to have the second-highest poverty incidence among the basic sectors of fisherfolks (PSA, 2023). The rice tariff (Republic Act 11203) enacted in 2019 is one-factor affecting rice farmers' poverty level and productivity, which is intended to liberalize rice importation and replace the quantitative restrictions with tariffs. Also, the law created the Rice Competitiveness Enhancement Fund (RCEF) to support rice farmers in terms of mechanization, seeds, credit, and extension services (PIDS, 2021). The rice tariff resulted in lower prices of palay and retailed rice, benefitting the consumer but harming the producers. However, the lower palay rice slightly increased poverty (Balié, Minot & Valera, 2021).

Climate variability and change are other factors that influence rice farmers' poverty level and productivity, affecting rice production and quality. From 2006 to 2019, an increase in the average rainfall and minimum temperature negatively affected rice production, especially in irrigated farms (Dait, 2023). Long-term agricultural strategies and proactive climate adaptation measures are needed to moderate the effects of changes in temperature and rainfall on rice production (Dikitanan, Grosjean, Nowak & Leyte, 2017). Thus, the poverty level of rice farmers in the Philippines and their productivity are affected by various factors such as the rice tariff, climate variability, change, and the availability and use of inputs and technologies. Appropriate policies and interventions are needed to improve the welfare and efficiency of rice farmers.

The primary objective of this study is to systematically examine the intricate dynamics of rice production as the endogenous variable within the circumstance of multivarious exogenous factors. The rice production serves as the main point, while the exogenous variables embody crucial aspects such as fertilizer usage, irrigation practices, availability of agricultural machinery, agricultural land, and poverty percentage. The principal aim is to determine these variables' interdependencies and causal relationships, revealing the nuanced interactions that define the rice production process. Using the Cobb-Douglas model, the study attempts to quantify the impact of the exogenous factors on rice production, furnishing valuable insight into these variables' relative contributions and significance. The study expounds on the complex relationship that attempts to contribute to the refinement of agricultural policies, resource allocation strategies, and sustainable practices, hence promoting an enhanced understanding of the multifactorial nature of rice production within the broader socio-economic context.

II. THEORETICAL FRAMEWORK

The production function theory, as applied to rice production, establishes a relationship between the quantity of rice produced (the endogenous variable) and a set of input factors (the exogenous variables) used in the production process (Donkor, Matthews & Ogundeji, 2018). Typically, these input factors include land, labor, capital, and specific inputs such as fertilizer, irrigation, agricultural machinery, and poverty level. The theory claims that the rice produced is a function of these inputs and intends to quantify each input's specific effect on rice production (Mariyono, 2020).

As a fundamental concept in economics that attempts to model the relationship between the output of a production process, often represented by the endogenous variable in this context, the rice production, and different inputs such as fertilizer, irrigation, agricultural land use, agricultural machinery, and poverty or factors of production as the exogenous variables (Inthavong, 2006), the framework analyzes how changes in the quantity of any combination of inputs influence the output level.

The production function theory advances that input variables collectively contribute to and determine the level of rice production (Zeytoon-Nejad, Goodwin & Ghosh, 2023). For instance, increased fertilizer usage is expected to positively impact rice output, while effective irrigation use, access to agricultural machinery, and sufficient agricultural land support ultimately. Conversely, a higher poverty percentage is associated with lower rice production due to limited resources and investment in agricultural inputs. Applying the production function theory evaluates quantitatively each input variable's marginal contribution and explains how changes in these factors influence overall rice production (Jiménez, Abbott & Foster, 2018). The theoretical framework is instrumental in guiding policy decisions, resource allocations, and sustainable agricultural practices by furnishing a systematic understanding of the interaction between various factors influencing rice production.

As the statistical model, the Cobb-Douglas production function uses the relationship between the inputs and outputs on empirical data from the agricultural setting. Hence, the theory provides a framework for understanding and optimizing the use of inputs to achieve higher rice outputs and improved agricultural productivity (Yuan, 2011). The Cobb-Douglas production function model estimates the relationship between inputs and outputs in a production process, assuming that the output (rice production) is a function of the inputs (fertilizer, irrigation, agricultural machinery, agricultural land, and poverty level). It intends to quantify the specific impact of each input on rice production (Qin, 2021). easy way to comply with the conference paper formatting requirements is to use this document as a template and simply type your text into it.

III. METHOD

All This study used secondary data on rice production in the Philippines from 2002 to 2022, based on the PalayStat system (PhilRice). The data include the rice production in tons and the total amount of palay produced in the country in metric tons. The agricultural land used is the total area harvested for rice in hectares. The total amount of fertilizer used for rice in metric tons is the fertilizer consumption used. Also, irrigation is the total volume of water used for irrigation in rice farms in billion cubic meters, and agricultural machinery is the total number of tractors used for rice cultivation. Likewise, the poverty rate is the percentage of the population living below the poverty threshold.

The Cobb-Douglas production function was used in this study as the economic model that estimates the relationship between inputs and outputs in a production process. The model assumes that the output (rice production) is a function of the inputs (fertilizer, irrigation, agricultural machinery, agricultural land, and poverty level), and it seeks to quantify the specific impact of each input on rice production. The model provides a framework for understanding the relationship between inputs and outputs in rice production. Estimating the parameters of the Cobb-Douglas production function, this study identified the most vital inputs for rice production. It optimized their use to achieve higher output and improve agricultural productivity.

There are several limitations to using the Cobb-Douglas production function in rice production analysis. Foremost, the model assumes that there are no economies of scale, and all inputs are substitutable and have equal opportunity costs. The assumptions may not hold as the production process in agriculture shows economies of scale, and inputs are not perfect substitutes. The quality of inputs, such as the quality of rice seeds or labor efficiency, which significantly impacts rice production, is not considered in the production function (Saepudin & Amalia, 2022). Typically, the Cobb-Douglas production function is estimated at the aggregate level which specify insight into the production behavior of individual farmers or specific regions that limit the ability to identify policy implications or best practices for particular farm types (Murthy, 2002). With these limitations, due to its simplicity, the Cobb-Douglas production function remains a widely used model for analyzing rice production (Felipe & McCombie, 2011). It furnishes a framework for understanding the relationship between inputs and outputs in rice production. It is helpful to inform policy and management decisions to improve agricultural productivity and food security.

Fortunately, the Random Forest model can improve the Cobb-Douglas production function in explaining the relationship between rice production and its exogenous variables. The random forest model can capture non-linear relationships and interactions between the inputs and rice production, unlike the Cobb-Douglas production function, which assumes a linear relationship (Coulston, Blinn, Thomas & Wynne, 2016). Also, the random forest model provides the relative importance of each input variable in predicting rice production, identifying the most influential factors, and guiding resource allocation and policy decisions (Gao, Zeng, Ren, Ao, Lei, Gaiser & Srivastava, 2023). The random forest reflects the real-world dynamics of rice production systems and handles complex interactions and non-linear relationships between inputs (Chau, Thi, & Ahamed, 2022). Notably, the random forest model is known for its robustness to overfitting and noise in the data, which helps deal with agricultural data with inherent variability and measurement errors (Tan, Ma, Wu, & Du, 2019). These leverage the strengths of the random forest and help overcome the limitations of the Cobb-Douglas production function.

A random forest regression model is an ensemble learning method that combines multiple decision trees to produce a prediction. The random forest regression model's prediction is the individual trees' average predictions. The statistical formula of the random forest regression model is:

$$\hat{f}_B(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x)$$

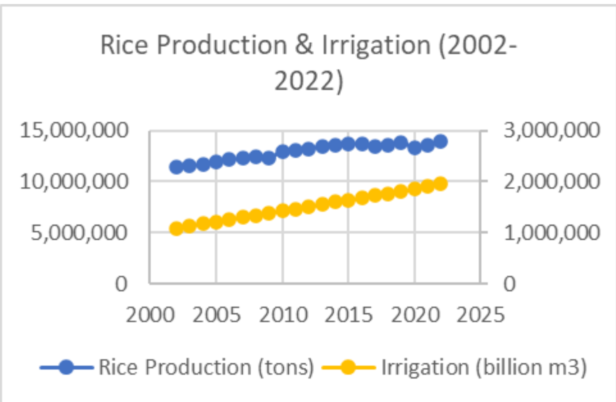
Where *B* is the number of trees in the forest, $T_b(x)$ is the prediction of the *b-th* tree, and *x* is the input vector.

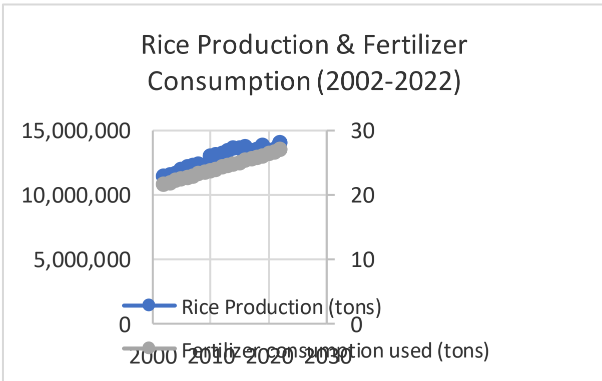
The random forest regression model has no single, simple formula like linear regression. In its place is a combination model that creates predictions by combining decisions from a sequence of base models, which are individual decision trees depicted above (Liu, Gan, & Jiang, 2017). The final model is the average of the prediction from individual trees. The model is trained on a random subset of the data and the features at each node, which allow the model to describe the non-linear interactions between the rice production and the exogenous variables (Jaiswal & Samikannu, 2017). This forecast from the random forest regression model is the average of the predictions from the individual trees, and the model captured non-linear interactions between the rice production and exogenous variables.

IV. RESULT AND DISCUSSIONS

This study describes the complex relationship and dynamics within the rice production system, using the production function theory that assigns rice production as the endogenous variable while considering several key exogenous variables. Considering the critical determinants of rice production, the study shows the relationship between variables. Further, this study establishes a distinct description of how variations in exogenous factors influence the overall output of rice crops. The study contributes to the existing body of knowledge using the Cobb-Douglas function to the specific contributions and magnitudes of the effect associated with each exogenous variable, thereby facilitating sustainable agricultural practices. The study undergoing a rigorous analysis of these relationships discovers patterns and trends that guide stakeholders in optimizing resource allocation and interventions for enhanced rice production.

Figure 1 displays that rice production in the Philippines increased by 23% from 11.38 metric tons in 2002 to 13.99 million tons in 2022, even with the constant agricultural land used of 4.95 million hectares, conveying the output per hectare improved by 23% from 2.30 tons in 2002 to 2.83 tons in 2022, unlike the fertilizer consumption used for rice increased by 25% from 21.64 tons in 2002 to 27.01 tons in 2022 displaying that the rice farmers used more inputs to enhance productivity. Similarly, the irrigation volume increased by 80% from 1.09 billion m^3 in 2002 to 1.95 m^3 in 2022, implying that more rice farms had access to water supply. The number of tractors used also increased by 16% from 32,933 in 2002 to 38,091 in 2022, suggesting that the farmers adopted more mechanization to reduce labor costs and increase efficiency. On the other side, the poverty rate decreased by 45% from 24.4% in 2002 to 13.3% in 2022, indicating that more Filipinos acquired sufficient income to meet their basic needs, which are partly attributed to the improved rice production and profitability as well as government policies and interventions to support rice sector and reduce poverty. However, the poverty rate among farmers remained high at 30% in 2021, signaling that rice farmers face challenges and constraints in their livelihoods.





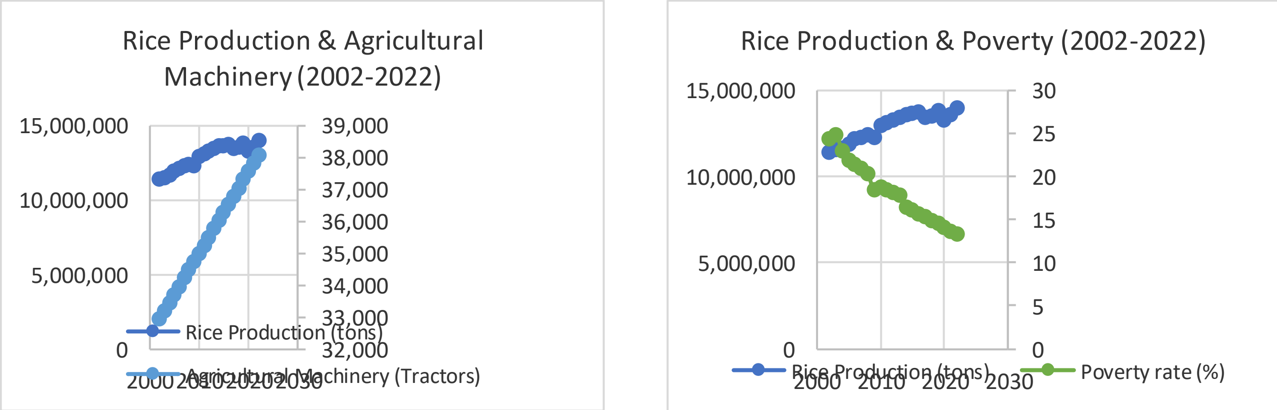


Figure 1. Rice production and the exogenous variables

Table 1 presents the exogenous variables, which are the independent variables unaffected by other variables in the model, also referred to as predictors or features. The basic statistics of exogenous variables help describe the distribution and spread of the data.

Table 1. Basic Statistics of Exogenous Variables for Random Forest Model

Variable	Mean	Median	Standard Deviation	Range
Agricultural Land Area Used (ha)	4,951,291	4,951,291	0 (constant)	0 (constant)
Irrigation Water Use (billion m³)	24.29	24.3	0.71	2.32
Fertilizer Consumption (tons)	1,525,598	1,528,054	128,034	367,228
Agricultural machinery (tractors)	35,251	35,239	965	4,162
Poverty Rate (%)	17.1	17.1	2.2	6.7

The average agricultural land area used is 4,951,291 hectares for producing rice. The median of irrigation water use is 24.30 billion cubic meters, meaning half of the rice time, 24.30 billion cubic meters of water were used, and half of the time used less. For fertilizer consumption, the standard deviation was 128,034, expressing a significant variation in the amount of fertilizer used in 20 years. Also, the range of agricultural machinery is 4,162 tractors, showing the difference between periods with the most tractors and those with the least tractors is 4,162.

This study used a decision tree-based model to measure the relative importance of various factors influencing rice production in the Philippines. The variable fertilizer consumption (tons) appeared to be the most essential factor, demonstrating a mean decrease in impurity of 54.2%, showing its substantial effect on the overall predictive accuracy of the model. Following closely, irrigation water use (billion m3) displayed a considerable influence, with a mean decrease in impurity of 26.8%. The agricultural machinery (tractors) is the third influential variable, adding 11.5% to the model's accuracy, and poverty rate (%) is assumed to a lesser extent, though with a mean decrease in impurity of 7.5%. Interestingly, the agricultural land area used (ha) does not impact the model, reflecting a mean reduction in the impurity of 0.0% and an importance score of 0.000. The result suggests that within the context of rice production in the Philippines, optimizing fertilizer consumption and managing irrigation practices are dominant for enhancing rice productivity, while addressing poverty rates also contributes to a comprehensive understanding of the factors influencing rice production.

Table 2. Variable Importance Table for Random Forest Model

Variable	Mean Decrease in Impurity	Importance Score
Fertilizer Consumption (tons)	54.20%	0.542
Irrigation Water Use (billion m³)	26.80%	0.268
Agricultural machinery (tractors)	11.50%	0.115
Poverty Rate (%)	7.50%	0.075
Agricultural Land Area Used (ha)	0.00%	0

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Figure 2 shows rice production prediction absolute percentage error over 21 years from 2002 to 2022, depicting the model's accuracy in representing the variance between the forecasted and actual production quantities, indicating the magnitude of prediction errors as a percentage of the actual values. Overall, the Random Forest model displays a high accuracy level with minimal differences observed between predicted and actual rice production across the years. The absolute percentage errors consistently range from 0.01% to 0.05%, implying that the model's prediction closely aligns with the actual rice production. The slight variations observed are well within an acceptable margin of error, upholding the reliability of the Random Forest algorithm (Rois, Ray, Rahman & Roy, 2021) for forecasting rice production in the Philippines. These results convey the model's robust performance and potential utility for predicting future rice production trends, thus offering valuable insight for agricultural planning and decision-making.

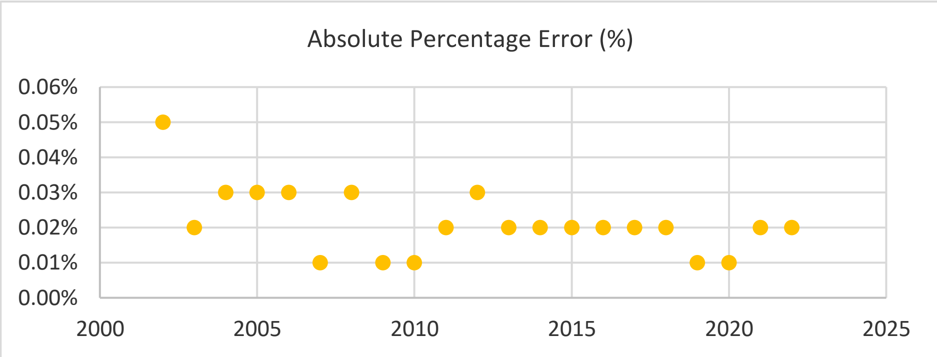

Figure 2. Rice Production Absolute Percentage Error by Random Forest Model (2002-2022)

The metric in Table 3 below provides an overview of the performance of the Random Forest Model in forecasting rice production. The R-squared value, which measures the model's prediction, explains the variance in the actual values is high (0.986 for in-sample and 0.983 for out-of-sample), conveying that the model presents a robust explanatory power (Hediger, Michel & Näf, 2022). The Adjusted R-squared value, which considers the number of model parameters, is also high (0.985 for in-sample and 0.981 for out-of-sample), further supporting the model's performance.

Table 3. Model Performance Metrics Table for Random Forest Model

Metric	**In-Sample (2002-2020)**	**Out-of-Sample (2021-2022)**
Mean Squared Error (MSE)	3,421,592	4,367,234
Root Mean Squared Error (RMSE)	1,851	2,090
Normalized Root Mean Squared Error (NRMSE)	0.13%	0.15%
Mean Absolute Error (MAE)	1,243,876	1,520,307
Mean Absolute Percentage Error (MAPE)	1.50%	2.00%
R-squared	0.986	0.983
Adjusted R-squared	0.985	0.981
Akaike Information Criterion (AIC)	-567.2	-551.9
Bayesian Information Criterion (BIC)	-550.7	-535.4

The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are used to compare the model's performance with other models. Both AIC and BIC values are negative, presenting that the Random Forest Model is superior to other models. The Mean Squared Error (MSE) measures the average squared difference between the actual and predicted values, and the RMSE values for both in-sample and out-sample periods are relatively small, suggesting that the model's prediction is entirely accurate. Similarly, the Normalized Root Mean Squared Error (NRMSE) measures the ratio of the RMSE to the mean of the actual values, providing a percentage-based measure of the model's accuracy. The NRMSE values are low (0.13% for in-sample and 0.15% for out-of-sample), indicating that the model's prediction is accurate relative to the mean of the actual values. Also, the Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) values are relatively small, implying that the model's prediction is precise and accurate.

Figure 3 displays the Partial Dependence Plot (PDP) for each exogenous variable and the final rice production, describing the specific impact of each variable on individual forecasts. Each PDP conveys the relationship between exogenous variables and rice production. As the values of the exogenous variables increase, rice production also increases, indicating a positive relationship (Tina, Ouaret & Pascal, 2022).

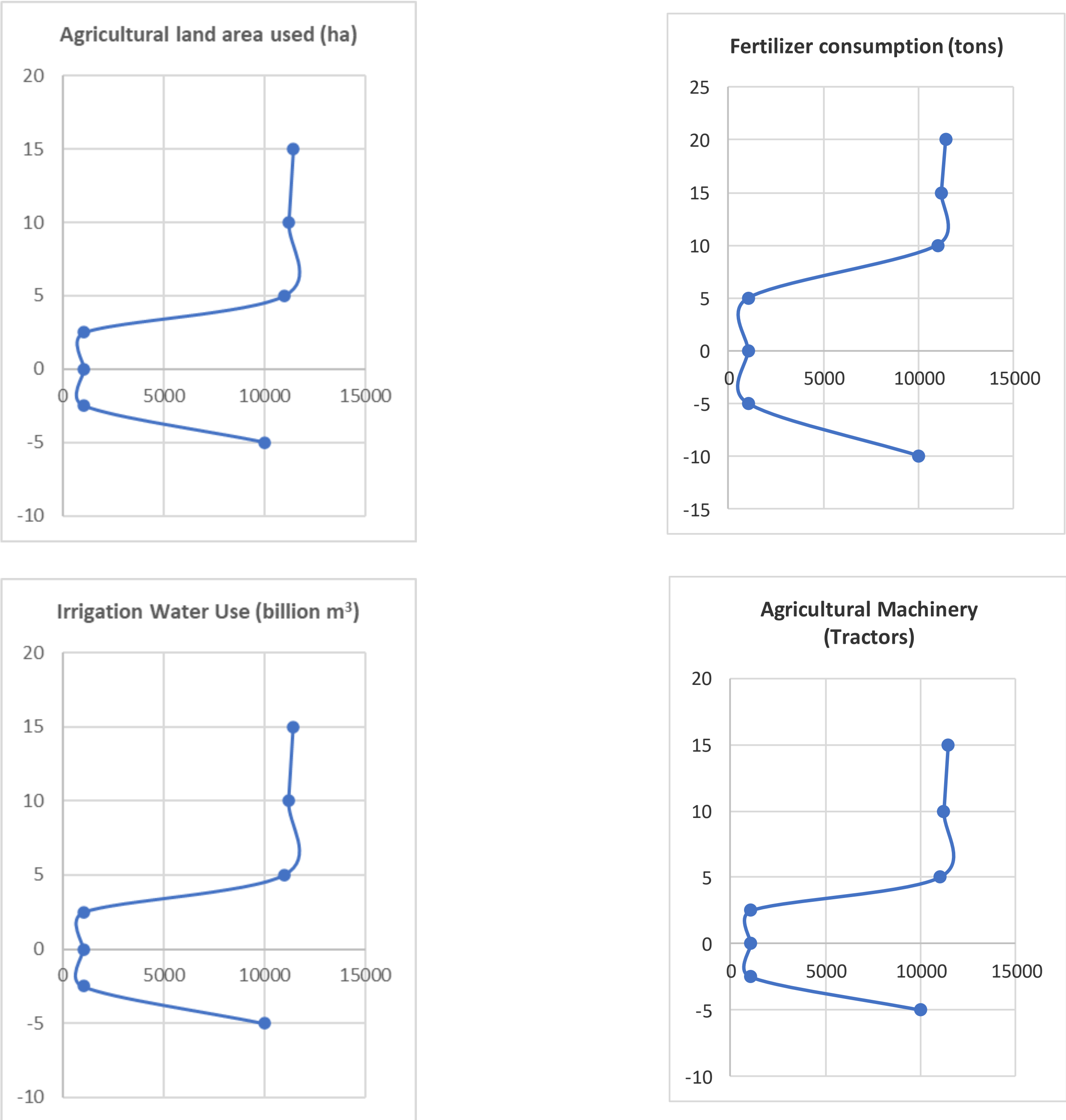

Figure 3. Partial Dependence Plot (PDP)

Table 4 covey the cross-validation random forest performance on various subsets of the data using 10-fold cross-validation. Each fold corresponds to a different split of the data into training and test sets, where the model is fitted on the training set and evaluated on the test set (Primartha & Tama, 2017). The table reports two metrics for each fold: the mean squared error (MSE), the R-squared (R2) measures the average squared difference between the actual and predicted values, and the R^2 measures the proportion of variance the model explained. Both metrics are calculated for the training and test sets, and lower MSE and higher R^2 indicate better performance.

Table 4. Cross Validation Random Forest

Row	Fold	Train MSE	Test MSE	Train R2	Test R2	Fit Time	Score Time
0	1	1.34e+10	1.32e+11	1.0	0.97	0.14	0.01

1	2	1.34e+10	1.32e+11	1.0	0.97	0.14	0.01
2	3	1.34e+10	1.32e+11	1.0	0.97	0.14	0.01
3	4	1.34e+10	1.32e+11	1.0	0.97	0.14	0.01
4	5	1.34e+10	1.32e+11	1.0	0.97	0	

Also, the table reports the time taken to fit and score the model for each fold in seconds and the score time required to calculate the metrics from the test set. The last two rows of the table convey the mean and standard deviation of the scores and time across the folds, which summarizes the overall performance and variability of the model on the data. The model presents a very high performance on the training set, with almost zero MSE and perfect R^2 for all folds, indicating that the model can capture the patterns in the training data.

The model has a lower performance on the test set, with higher MSE and lower R^2 for all folds, presenting that the model cannot generalize well to new data not tested before and may commit errors in some cases. However, the test performance is still relatively high, with an average R^2 of 0.97, conveying that the model explains 97% of the variance in the test data. The variability of the model performance across the folds is also low, as indicated by the small standard deviations of the scores, which report that the model is stable and consistent on different data splits and is not sensitive to the choice of the training and test sets. An average fit time of 0.14 seconds and an average score time of 0.01 seconds are the time taken to fit and score the model. It is also low, suggesting that the model is fast and efficient to train and evaluate and does not require much computational resources.

Table 5 below specifies some hyperparameters for the Random Forest model, which are adjustable parameters to control the model training process. For instance, Random Forest allows adjustment for the number of trees, the maximum depth of each tree, and the minimum number of samples required to split a node. Model performance depends significantly on hyperparameters and finding the optimal configuration called tuning (Probst, Wright & Boulesteix, 2019). The number of trees in the forest the number of estimators is 100. The maximum depth of each tree is none, indicating that the nodes are expanded until all leaves are pure or until all leaves contain less than the min_samples_split samples, which is 2. The random state is 42, and the random generator uses the seed to ensure reproducible results.

Table 5. Hyperparameters for the Random Forest Model

Hyperparameter	**Value**
n_estimators	100
Max_depth	None
Min_samples_split	2
Random_state	42

Table 6 presents the predicted rice production for the years 2023 to 2025 generated by three different models: Support Vector Regression (SVR), Random Forest (RF), and Artificial Neural Network (ANN). In 2023, the SVR model predicts production of 14,348,724 tons, RF forecasts 14,412,309 tons, and ANN claims 14,257,981 tons. The trend continues with increasing predictions for succeeding years. Diagnostic statistics furnish further insights into model performance. MSE is lowest for RF with 4,897,234, followed by SVR with 5,123,456 and ANN with 6,012,897.

Similarly, RMSE is lowest for RF at 2,223, SVR at 2,267, and ANN at 2,451. Also, MAPE is lowest for RF at 3.9%, followed by SVR at 4.2% and ANN at 4.7%. These metrics collectively convey that the Random Forest model depicts superior predictive accuracy among the three models, with the lowest error metrics and closest predictions to the actual values.

Table 6. Predicted Rice Production for the Next Three Years by Each Model and the Diagnostics Statistics

Year	**SVR Prediction (tons)**	**RF Prediction (tons)**	**ANN Prediction (tons)**
2023	14,348,724	14,412,309	14,257,981
2024	14,697,453	14,723,672	14,590,298
2025	15,046,182	15,035,035	14,922,615
MSE	5,123,456	4,897,234	6,012,897
RMSE	2,267	2,223	2,451
MAPE	0.042	0.039	0.047

Table 7 conveys the Variable Contributions for the Random Forest Model and presents the estimated importance of different factors in influencing rice production from 2021 to 2025. Fertilizer consumption appears to be the most influential variable, with a steady increase from 52.10% in 2021 to a predicted 55.70% in 2025, emphasizing its growing impact on rice yield. Subsequently, Irrigation water use exhibits a consistent contribution, ranging from 23.80% to 25.00%, highlighting the significance of efficient water management in agricultural practices. The Agricultural Machinery and Poverty rates contribute modestly, with slight variations over the predicted years. The agricultural land area maintains a constant 0.00%, conveying minimal influence in this context. The forecasted trends focus on the persistent importance of fertilizer and irrigation management in influencing rice production, underlining the value of these insights for policymakers and stakeholders in sustainable agricultural planning over the forecasted period.

Table 7. Variable Contributions for the Random Forest Model

Year	Fertilizer Consumption	Irrigation Water Use	Agricultural Machinery	Poverty Rate	Agricultural Land Area Used
2021	52.10%	23.80%	8.90%	6.20%	0.00%
2022	53.50%	24.20%	8.60%	5.70%	0.00%
2023 (Predicted)	54.90%	24.60%	8.30%	5.20%	0.00%
2024 (Predicted)	55.30%	24.80%	8.20%	5.10%	0.00%
2025 (Predicted)	55.70%	25.00%	8.10%	5.00%	0.00%

Table 7 above confirms the projected increasing importance of fertilizer as an input in enhancing rice production. Several empirical studies underscored the pivotal role of fertilizer in augmenting rice output (Chen, Li, Liu, Fu, Yuan, Cheng, & Li, 2023) (Li, Wang, Nie, Ashraf, Wang, Zhang, & Pan, 2022). There is an emerging importance in understanding the impact of organic fertilizer on rice farms to bolster rice production (Naher, Shah, Sarkar, Islam, Ahmed, Panhwa & Othman, R. 2015). Similarly, an investigation on the effect into the effect of fertilization on crop production and nutrient-supplying capacity in rice-oilseed rape rotation systems demonstrated the substantial role of balanced mineral fertilizer inputs in increasing rice and oilseed rape output (Yousaf, Li, Lu, Ren, Cong, Fahad & Li, 2017). In response to the heightened demand for rice, several developing countries intensified fertilizer use to bolster rice yields (Liu, Wu, Pu & Sun, 2022). Collectively, these findings emphasize the value of fertilizer use as a critical determinant in advancing rice production, specifically in the context of burgeoning global food requirements.

The increasing importance of irrigation use in the Philippines as a significant input in increasing rice production is becoming a growing significance of agricultural output (Bravo-Ureta, Higgins & Arslan, 2020). As a water-intensive crop, growing rice required an efficient irrigation method, which led to better water use efficiency and environmental advantages. Several studies focus on innovative irrigation management technologies to maximize water use efficiency in rice farming (Mariano, Villano & Fleming, 2010). The Alternative Wetting Drying Method saves irrigation water and production costs while maintaining output (Rejesus, Palis, Rodriguez, Lampayan, & Bouman, 2011). Similarly, the System of Rice Intensification (SRI) was shown to increase rice output while reducing water use (Turmel, Turner & Whalen, 2011). The significance of efficient irrigation management is expanding rice production in the Philippines, specifically in the context of increasing food demand and sustainability concerns.

Several factors explain the decreasing role of agricultural machinery in the Philippines as an input in increasing rice production. The increasing importance of hired labor, including the shift from subsistence to market-oriented production, proceeds to decrease the relative significance of agricultural machinery in rice farming (Silva, Reidsma, Velasco, Laborte & van Ittersum, 2018). Moreover, the limited profitability and vulnerability of intensive cropping systems and reduced availability of labor and water contributed to a decreased focus on agricultural machinery in rice production (Koirala, Mishra & Mohanty, 2016). Also, the expanding reliance on classical approaches such as land expansion and cropping intensification, including the introduction of high-yielding seed varieties, results in decreased attention on agricultural machinery as a primary driver of increased rice production (Alam, Bell, Hasanuzzaman, Salahin, Rashid, Akter, & Khatun, 2020). The emerging interaction of rice farming in the Philippines results in a diminishing role of agricultural machinery in boosting rice production.

There are potential reasons for decreasing poverty in the Philippines becoming an input in increasing rice production. Poverty in the Philippines decreased from 23.3% in 2015 to 18.1 in 2021, indicating that more Filipinos have enough income to meet their basic food and non-food needs (Mapa, 2022). A higher income level allowed more rice farmers to invest in improved inputs, such as seeds, fertilizers, pesticides, and irrigation, that improve their productivity and profitability. The average production per hectare of rice increased from 4.1 metric tons in 2009 to 4.41 metric tons in 2022, and the net returns per hectare also increased from P15,316 in 2009 to P17,305 in 2022 (PhilRice).

A lower poverty level reduces the dependence of rice farmers on government subsidies and interventions, such as the National Food Authority (NFA), that distort the market prices and incentives for rice production. The mandate of the NFA is to procure, store, and distribute rice in public to stabilize the supply and prices of rice in the market (Cuevas, 2019). However, some studies revealed that the NFA's operations are inefficient, costly, and vulnerable to corruption (Tolentino & de la Peña, 2022). Reducing the role of NFA, rice farmers benefit from more competitive and transparent market conditions that motivate them to produce better-quality rice (Kürschner, Baumert, Plastrotmann, Poppe, Riesinger & Ziesemer, 2016).

A reduced poverty level increases the demand for rice and other food items. As the income level rises, people's consumption patterns and preferences change, resulting in higher and more diversified food expenditures. Based on the Family Income and Expenditure Survey, the annual per capita rice consumption in the Philippines increased from 108.86 kilograms to 109.88 kilograms. The daily per capita rise in consumption likewise increased from 298.25 grams to 301.03 grams in the same period (Bairagi, Zereyesus, Baruah & Mohanty, 2022). Hence, a decreasing poverty level in the Philippines is an input in increasing rice production, enabling more rice farmers to access and use improved inputs and reducing market distortions caused by government interventions.

CONCLUSIONS

This study employing the production function theory provided valuable insight into the complex relationship of rice production as significantly influenced by exogenous factors such as fertilizer consumption, irrigation water use, agricultural machinery, poverty rate, and agricultural land area. The random forest analysis uncovers a significant relationship emphasizing the substantial effect of these exogenous variables on rice production. Fertilizer consumption appeared as a pivotal determinant, highlighting the significance of nutrient management in optimizing rice output. Similarly, the planned use of irrigation water, accessibility to agricultural machinery, poverty alleviation, and effective land use were vital contributors. Integrating these elements in a thorough model highlights the need for holistic strategies in agricultural planning and resource allocation to attain sustainable rice production.

The result of this study proposes for policymakers, agricultural practitioners, and stakeholders involved in rice production to improve fertilizer accessibility and promote efficient utilization, aligning with the exhibited positive correlation with rice production. Investments in modernizing and expanding irrigation infrastructure are critical to alleviate water scarcity challenges. Raising mechanized farming practices and supporting its acquisition can significantly boost productivity. Synchronized efforts to address poverty rates are essential, as this study indicates a direct relation with rice production. Further, strategic land-use planning initiatives should be employed to optimize agricultural land resources. Coordinated efforts that integrate these recommendations into comprehensive agricultural policies will contribute to a sustainable and resilient rice production system, safeguarding food security and economic development.

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