Original Article

Application of Forecasting Models using Artificial Neural Network Techniques: A Case Study of Jasmine Rice Yield Forecasting in Ban Samran, Nong Khaen Subdistrict, Pathum Rat District, Roi Et Province

Khemawit Jittayasothon[1], Sitthisak Audomsi[1,2], Worawat Sa-Ngiamvibool[1,2*]

[1]Faculty of Engineering, Mahasarakham University, Maha Sarakham, Thailand.
[2]Electrical and Computer Engineering Research Unit, Mahasarakham University, Maha Sarakham, Thailand.

[*]Corresponding Author : wor.nui@gmail.com

Abstract - The work seeks to construct an Artificial Neural Network (ANN) model to predict the yield of jasmine rice 105, utilizing the field, soil, and agro-climatic information of Ban Samran, Nong Khaen Subdistrict, Pathum Rat District, Roi Et Province, Thailand. The study was conducted from 2014 to 2023, and the data were collected from 130 paddy fields, covering primary and secondary daily datasets, and processing variables such as the Growing Degree Days (GDD), Sunshine Duration Days (SDD), and cumulative rainfall. Preprocessing the datasets normalizes all variables by the min-max method before loading them into the network. After network design, the performance of the developed network has evaluated the model by common measures of accuracy and efficiency of the model, and its results imply that the new model has highly accurate predictions of the yield, which was validated by having the root mean square error of 1.05 kg/rai, the mean absolute error of 0.90 kg/rai, the relative mean absolute error of 0.25%, and the coefficient of determination (R^2) of 0.99, which confirm the success of the model in identifying the differences of the yield. Also, the new model performs precision enhancement by demonstrating prediction errors of about five to seven times smaller when compared to the traditional models such as Multiple Linear Regression, Polynomial Regression, Random Forest, and the Support Ma Regression models. The results also implicate the factors affecting rice yield, including the cumulative rainfall from the flowering stage, the maximum temperatures in the milky stage, the Soil Electrical Conductivity (EC), the Soil Organic Matter (OM), and the planting date. Lastly, the results indicate that the new model has significant effectiveness and contribution to the applicability of planting and water resource techniques and yield prediction for the Thung Kula Rong Hai Region.

Keywords - Artificial Neural Network, Rice Yield Forecasting, Jasmine Rice 105, Thung Kula Rong Hai, Machine Learning Model.

1. Introduction

One of the most important agricultural commodities grown in Thailand, rice is an essential staple for local consumption and an important export item for generating economic value [1, 2]. Khao Dawk Mali 105 (KDML105), known as jasmine rice, is globally acknowledged for its exceptional grain quality, fragrance, and market worth. Thailand is an important marketplace for jasmine rice; however, competition in the rice market and climate change have shown the necessity to improve overall rice production efficiency [3-7].

The Thung Kula Rong Hai location in northeastern Thailand is an important agricultural area for jasmine rice.

This region has unique environmental attributes, such as sandy loam soil with moderate to high salinity, limited organic matter, unpredictable rainfall patterns, and dependence on rain-fed agricultural operations. In this location, about 90% of rice fields depend only on rainwater-fed irrigation systems and are completely dependent on precipitation. This shows that the growth of rice plants is significantly influenced by climatic conditions, especially during essential growth phases such as heading, blooming, and filling [8-10]. Therefore, rice production in this region has significant interannual variability, posing major hazards to farmers, watershed managers, and agricultural policymakers.

Accurate rice yield forecasting is therefore indispensable for the effective administration of water resources, agricultural

planning, and risk mitigation, particularly at the local administrative level, where farming decisions are implemented directly [11-13]. Agricultural research has extensively employed conventional yield forecasting methods, including polynomial regression, multiple regression, and process-based simulations of crops such as CERES-Rice and DSSAT [14-21]. Although these methodologies offer valuable insights, they frequently demonstrate inherent limitations, particularly in their ability to characterize complex nonlinear relationships among climatic, soil, and management factors, as well as their vulnerability to incomplete or absent data. In ecologically vulnerable regions such as Thung Kula Rong Hai, these limitations are further exacerbated.

Recent advancements in machine learning and artificial intelligence have established Artificial Neural Networks (ANNs) as formidable instruments for agricultural forecasting. [22-24]. Artificial Neural Networks (ANNs) have been shown to more effectively simulate nonlinear and multivariate interactions than previous predictive approaches in numerous studies on agricultural productivity. The development of more precise and responsive forecasting models than conventional statistical methods is facilitated by the adaptability of artificial neural networks in assimilating diverse information concerning meteorological, edaphic, and managerial factors. [22, 23].

Though there are a considerable number of research studies on the utility of ANN-based techniques in yield prediction in the agricultural sector, there have been few attempts to apply them to highly localized settings, such as sub-district and village levels. This is especially important, as ways to predict yield at regional or even provincial levels often tend to overlook the variations in the state of the soil, microclimate, or even farming techniques, which significantly impact yield [18]. This is especially relevant with regard to jasmine rice farming in the Thung Kula Rong Hai region.

2. Research Gap and Objectives
The review of the recent literature shows multiple unresolved research gaps that constrain the practical use of existing models for predicting rice production in local agricultural management.

1. The past literature has mainly concentrated on provincial, regional, or national levels, resulting in models that fail to handle sub-district-level variation in qualities of soil, climatic conditions, and agricultural management techniques [17, 18].
2. Limited studies have merged long-term retrospective datasets that also include meteorological, edaphic, and management variables to predict jasmine rice yields in regions especially sensitive to climate change [19-21].
3. Comparative evaluation of ANN-based models compared to traditional statistical methods has rarely been applied

to local datasets from rain-fed and salt-affected environments, such as Thung Kula Rong Hai [22, 23].
4. Thorough research of the relative importance of crucial yield-determining elements, such as rainfall during important development phases, soil salinity, organic matter content, and planting schedules, has been lacking within ANN-based forecasting frameworks [16, 24].

An artificial neural network model was created for yield forecasting of Jasmine Rice 105 at the sub-district level, Ban Samran, Nong Khaen Subdistrict, Pathum Rat District, Roi Et Province, with a retrospective dataset that covers ten years (2014–2023). The efficacy of the proposed model is measured with conventional statistical and machine learning models, including multiple linear regression, polynomial regression, random forest, and support vector regression, considering climate, soil, and agricultural management factors [19-24].

The most important objectives of this research are to:
1. Develop an accurate artificial neural network model for predicting rice yields, adjusted for local environmental factors.
2. Perform an analytical assessment of the proposed model's performance compared with standard forecasting techniques.
3. Identify the important variables affecting jasmine rice yield in the Thung Kula Rong Hai region.

By addressing these objectives, the study aims to provide a robust and practical decision-support tool for farmers, agricultural planners, and policy makers, contributing to precision agriculture and sustainable rice production in climate-vulnerable regions [17, 18].

3. Methodology
The work aims to develop an ANN model capable of predicting the yield of Hom Mali 105 rice in the Ban Samran Region, Nong Khaen Subdistrict, Pathum Rat District, Roi Et Province. The Thung Kula Rong Hai region can be distinguished by its climatic and soil conditions, such as the high salinity of the soil, the variability of the rainfall system, and the low organic matter. One of the reasons why the ANN method will be appropriate for use in the research will be its ability to recognize the interaction that exists between all factors.

The process of research work involves critical steps like defining the research area, gathering data, finding and defining variables, preparing data, creating a model for an artificial neural network, and testing the efficiency of the model. The details are mentioned below:

3.1. Research Locale
The Ban Samran site is located in Nong Khaen sub-district, Pathum Rat district, Roi Et Province, and is found in the Thung Kula Rong Hai area, which is recognized as a key

jasmine rice producer in the country. The terrain is generally a plain area, characterized by sandy loam soils with layers of salty soils. This causes the salinity to be medium to very high, with values measured at EC 4-6 dS/m, primarily during the dry season. In addition, over 90% of rice paddies are rain-fed and highly susceptible to rain and temperature variations, making them highly vulnerable to rice yields [25]. This location has been selected for investigation as it is representative of an area where high-quality jasmine rice is produced, and has been impacted by climate, and there is also enough data available for model development.

3.2. Sample Cohorts and Sampling Framework

The population studied included 180 jasmine rice fields, located in the region of Ban Samran. The sample size was estimated by using Yamane's formula [26, 27], with a confidence level of 95%, given in the following expression (1):

$$n = \frac{N}{1 + Ne^2} \tag{1}$$

To improve accuracy and compensate for the possible effect of missing data, the sample size was increased to 130 plots using systematic random sampling. The area was stratified into four zones based on topography before systematic sampling.

3.3. Data Utilized in Research (Data Acquisition)

The data is divided into two groups: primary data from actual plots and secondary data from the last ten years (2014–2023).

3.3.1. Primary Data

Primary data consists of,
- Samples of soil were obtained from 0 to 20 cm and from 20 to 40 cm.
- There are also details regarding how to manage paddy fields, such as when to plant, how much seed to use, how much and when to apply fertilizer, how to irrigate, and what type to use.
- The amount of rice that each plot produced, as measured by weight, was changed to 14% moisture content.

3.3.2. Secondary Data

The data that the Meteorological Department provides on the highest and lowest temperatures, humidity, daylight hours, rainfall, and wind speed is considered secondary data.
- The statistics are provided by the district agriculture department every year. This data consists of the growers and the land where the flowers are cultivated.
- Sentinel-2 & Landsat 8 offer satellite imagery displaying NDVI & EVI values.

3.4. Variables and Definitions

This is a critical component of research methodologies. The paper describes the importance, role, and formulation of each and every variable involved in the ANN model.

3.4.1. Meteorological Variables

Climate variables are crucial in determining temperatures, rainfall amounts, and humidity. However, they are of high significance in determining how well rice is grown in rain-irrigation agriculture. The average temperature is determined through the highest and the lowest temperatures recorded [28]. Such data is vital in determining the required temperature of the rice crop. The average temperature is determined by the formula (2):

$$T_{avg} = \frac{T_{max} + T_{min}}{2} \tag{2}$$

The data was later used to produce the derivative variable Growing Degree Days (GDD) [29]. This derivative variable measures the daily heat units accumulated by the plant and is required during the heading and flowering stages described in equation (3):

$$GDD = \left(\frac{T_{max} + T_{min}}{2}\right) - Tbase \tag{3}$$

By establishing the minimum temperature necessary for rice cultivation, denoted as C, which considers the "heat stress" linked to too high temperatures, one may measure the Stress Degree Days (SDD) [30] variable, which has been incorporated in equation (4).

$$SDD = \sum(T_{max} - Tthreshold) \tag{4}$$

By determining the low temperature that favors rice growth, denoted by C, which considers the "heat stress" effect posed by extremely high temperatures, it can be noted that Stress Degree Days (SDD) [30] is included in equation (5).

$$RA_n = \sum_{i=1}^{n} R_i \tag{5}$$

This meteorological data precisely represents the seasonal attributes and is a crucial determinant influencing production in the Thung Kula Rong Hai region.

3.4.2. Edaphic Variables

The soil data offers an additional element that signifies the nutritional quality and development potential of the rice crop. The recording includes pH, Electrical Conductivity (EC), Organic Matter (OM), and the principal nutrients NPK. Each of these variables is very important and has been proven to have a significant effect on rice crop productivity. The soil type of the research area is a mix of sandy loam and saline regions, where EC plays a very significant role.

Soil moisture levels, based on field observation, indicate the availability of water for plant growth, and the critical stage of heading and flowering is very much dependent on this requirement. Lack of adequate moisture results in dried grains and a sharp reduction in yield.

3.4.3. Management Variables

Farm management data has different plots of sowing date, converted into DOY to provide the model with the exact evaluation regarding the seasons' influence on the growth of rice plants. The seed rate and the amount of nitrogen, phosphate, and potassium fertilizers describe the fertility of the soil and the production possibility of panicles per tiller. Irrigation techniques describe the quality of soil moisture management, especially in arid conditions.

3.4.4. Dependent Variable

The dependent variable of this research is described as "yield of Jasmine Rice 105 (kg/rai)"; this variable is sourced from actual plots, with the moisture content adjusted to 14%, following commercial standards.

3.5. Data Preprocessing

The sanitization of all datasets, detection of anomalies, and interpolation—wherever necessary—are performed accordingly [32]. Normalization of data is performed using min-max normalization, as shown in equation (6):

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{6}$$

This ensures that all variables have consistent and appropriate ranges for the training of artificial neural networks.

3.6. Assessment of the Model

The validity of the model's ability to forecast the yield of rice was established using established quantitative criteria of Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R^2), which are defined below:

y_i represents the actual output of the data point

$\hat{y}_i$ represents the expected result for the data point

$\bar{y}$ represents the average of all actual outputs.

n represents the overall number of data points within the evaluation set

1. MAE calculates the average absolute differences between predicted and actual values in [33], which is shown in Equation (7) below:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_{i-\hat{y}_i}| \tag{7}$$

The MAE value is given in the same unit as that of the dependent variable. The dependent variable is in kilos/rai. A lower value shows that the actual and modeled values are more in line.

2. RMSE is an error measure indicating the importance of significant errors, which results from the squaring process before averaging [33]. The demarcation line specified is described by the following equation (8):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{8}$$

RMSE is measured in the same unit as MAE, although it is much more sensitive to outliers, thus being able to provide a more accurate reflection of the "smoothness/unevenness" of forecasts.

3. R^2 quantifies the proportion of variation in the observed values that is accounted for by the prediction model [34], as illustrated in equation (9):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{9}$$

The range of the values is from 0 to 1, in which higher values indicate that the model is able to reproduce the actual variation of data appropriately. A case study is provided in this research to show that the proposed model is able to achieve considerable accuracy, which indicates the ability of the proposed model to predict the yield of jasmine rice correctly.

3.7. Multilayer Perceptron (MLP) Architecture

The proposed Artificial Neural Network (ANN) model is designed as a fully connected Multilayer Perceptron (MLP) consisting of:

- Input layer: 25 neurons corresponding to the 25 selected input variables
- Hidden layer 1: N_1 neurons
- Hidden layer 2: N_2 neurons
- Hidden layer 3: N_3 neurons
- Output layer: 1 neuron representing the predicted yield

The network follows a feedforward structure where each neuron in one layer is fully connected to the neurons in the subsequent layer through weighted connections, shown in Figure 1
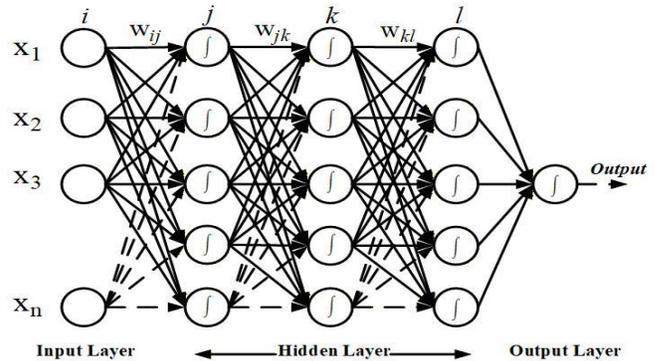

Fig. 1 Schematic architecture of the proposed Multilayer Perceptron (MLP) consisting

4. Results of Data Analysis

This research evaluates the predictive capability of the ANN model regarding the yield of Jasmine Rice 105. This

analysis uses data related to climatic, soil, and crop management and actual harvests that have been recorded over the last ten years. The outcome of the research work will be presented in four parts: (1) historical data and its yield information, (2) prediction by the ANN model, (3) comparison with the statistical model, and (4) importance of factors that contribute to the yield.

4.1. Historical Yield Data and Context
In the past decade (from 2014 to 2023), the average yield of Jasmine rice was 359 kg per rai, with a standard deviation of 11.2 kg per rai. This represents variations in terms of climatic changes and soil conditions in the Thung Kula Rong Hai region due to over 90% of the agricultural land being rain-dependent.

The year 2019 showed the lowest production, which was due to low rainfall and a drought that occurred during the heading stage. This resulted in an average yield of 345 kg per rai. The year 2015 showed the highest production rate, with a level that resulted in an average production above 370 kg per rai. This is based on stable rainfall and moderate soil salinity.

The soil property analysis has shown that the soil pH is between 6.0 and 6.8, ensuring soil nutrient solubility.
*   The values of electrical conductivity, being between 4 and 6 dS/m, fall under moderate levels, which will not hamper the yield.
*   The content of OM is mainly below 1% because it satisfies the soil type conditions described as sandy loam soil within the region.
*   Soil moisture shows high variability, and this correlates with soils that rely on rainfall. The first set of data illustrates the need for such a model, which could deal with complexities as well as nonlinear relationships, as in the case of ANN.

4.2. Production Forecasting Outcomes Utilizing an ANN Model
In the designed MLP artificial neural network, there are 25 input parameters, and the network contains 3 hidden layers. Based on the training output, the ANN is able to detect associations within data by using MSE as the loss function.

After testing the network with novel examples from 2022 to 2023, it can be said that it produced acceptable results with satisfactory accuracy, as evident from the following:

$$RMSE = 1.05 \, kg/rai$$

$$MAE = 0.90 \, kg/rai$$

$$R^2 = 0.99$$

The low RMSE and MAE of less than 1 kg/rai, which signify how well the models are able to forecast the output close to the actual output, confirm the effectiveness of the

model. An R-squared of 0.99 implies that the ANN model explains almost all of the data variation in the actual output. This supports the core property of ANNs, which are adept at handling nonlinear data containing many variables.

From the plot of actual yields and the ANN predictions, it can be seen that the yields have been tracked well by the ANN, and in exceptional instances, such as drought in 2019, the yields have been tracked well by the ANN.

4.3. A Comparative Analysis of Artificial Neural Networks and Statistical Models
The ANN model was evaluated against four other models:

*   Multiple Linear Regression (MLR)
*   Polynomial Regression (degrees 2 and 3)
*   Random Forest Regression (RF)
*   Support Vector Regression (SVR)

Table 1. Comparative analysis of rice yield forecasting models using RMSE, MAE, and R² metrics

Model	RMSE	MAE	R^2
MLP	1.05	0.90	0.99
MLR	7.27	6.03	0.72
Polynomial Deg.2	7.14	5.65	0.73
Polynomial Deg.3	5.70	4.81	0.83
RF	4.12	3.55	0.89
SVR	3.98	3.44	0.91

From Table 1, it can be observed that since the MLR is based on a linear relationship, it lacks the accuracy to handle the non-linear relationships between the variables, i.e., temperature and yield, and salinity and yield. Although it has the ability to handle some curvatures, it does not have the ability to handle complex correlations that the ANN has.

Although Random Forest and SVR are better than MLR, their RMSE values are still 3-4 times longer than those of ANN, thus proving the superiority of ANN in this task.
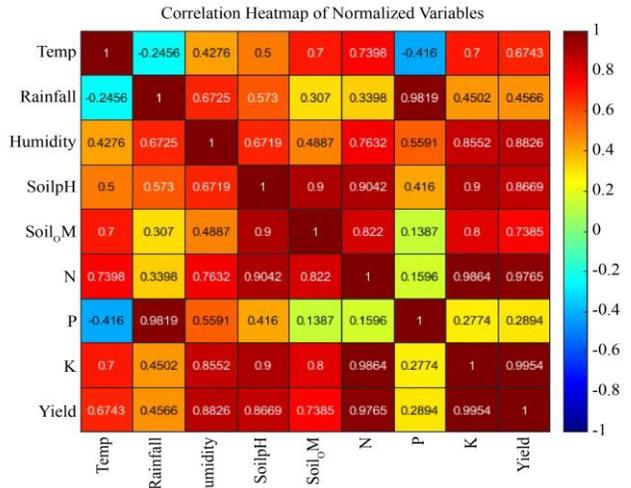
Fig. 2 Correlation heatmap of normalized variables

Figure 2 presents the correlation heatmap of the normalized input variables and rice yield. The results indicate that several soil-related variables exhibit strong positive correlations with yield, particularly nitrogen (N) and potassium (K), with correlation coefficients of 0.9765 and 0.9954, respectively. This finding highlights the dominant role of soil nutrient availability in rice yield formation. In addition, relative humidity and soil pH also show high positive correlations with yield (r > 0.85), suggesting that favorable soil chemical properties and atmospheric moisture conditions significantly contribute to crop productivity.
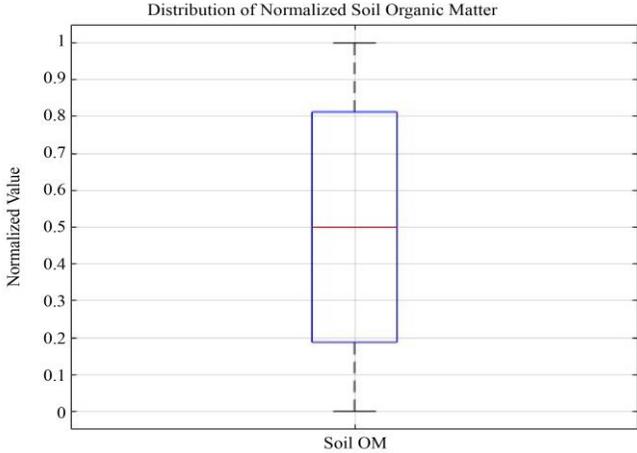

Fig. 3 Distribution of normalized soil organic matter

Figure 3 Distribution of normalized soil Organic Matter (OM) represented by a boxplot, highlighting the median, interquartile range, and overall variability of soil organic content in the study region.
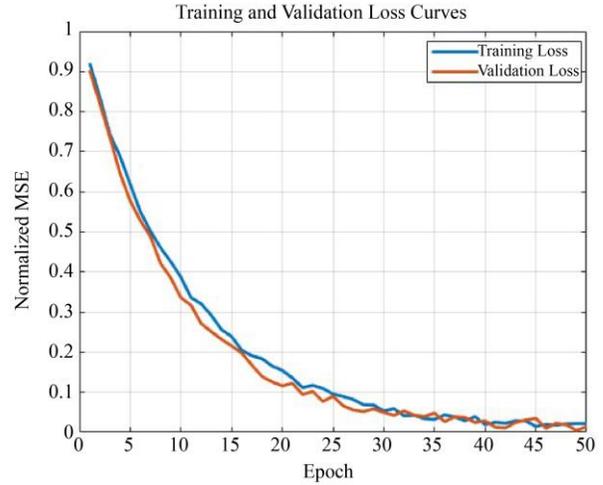

Fig. 4 Training and validation loss curves

Figure 4 illustrates the training and validation loss curves of the proposed ANN model in terms of normalized Mean Squared Error (MSE) over the training epochs. Both curves exhibit a consistent and monotonic decrease, indicating stable learning and effective convergence of the model. The close alignment between the training and validation loss curves throughout the training process suggests that the model does not suffer from overfitting and demonstrates good generalization capability.

Toward the later epochs, the loss values approach a steady minimum, confirming that the optimization process successfully reached a converged solution.
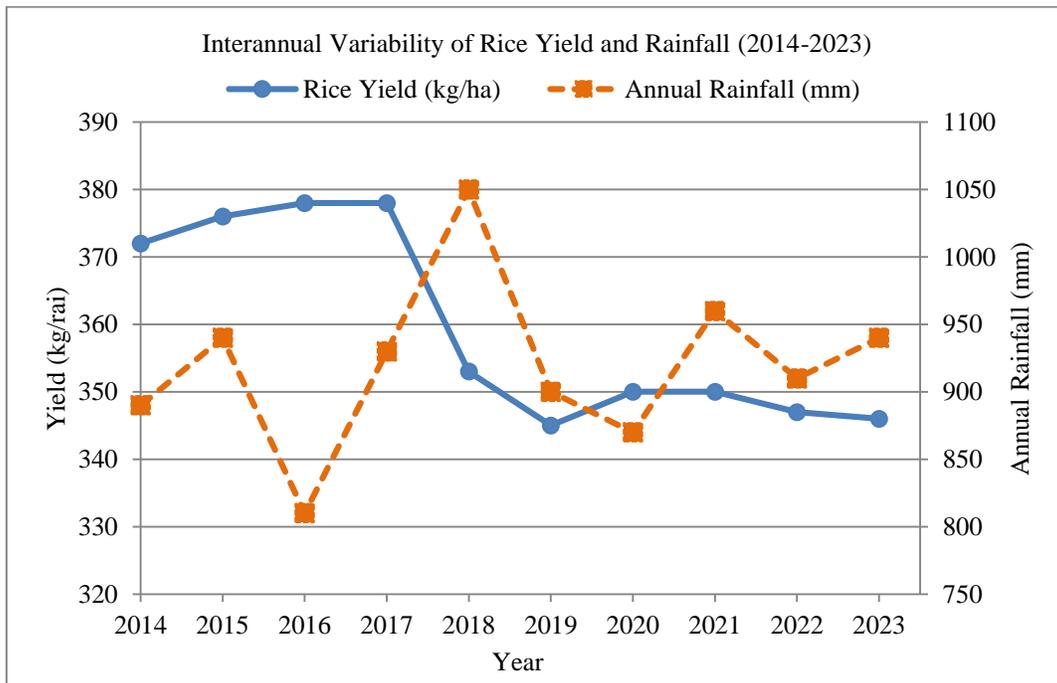

Fig. 5 Interannual variability of rice yield and rainfall (2014–2023)

Figure 5 illustrates the interannual fluctuations in rice yield and rainfall from 2014 to 2023. A noticeable decline in yield is observed after 2017 despite relatively stable rainfall levels. The highest rainfall in 2018 (1050 mm) did not correspond to maximum yield, suggesting that excessive rainfall may negatively affect productivity.

Conversely, moderate rainfall conditions during 2016 were associated with peak yield values. This indicates a nonlinear climatic response, justifying the use of ANN for modeling complex interactions.
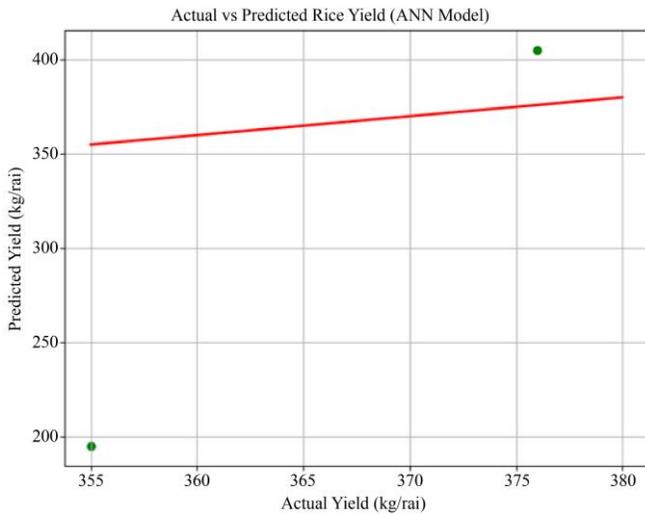

Fig. 6 The assessment results of the ANN model

Figure 6 indicates the correlation between the actual jasmine rice yield and the actual yield that was forecasted by the use of the ANN model. The green symbols represent data points in the test data, while the red line indicates the best fit on which the model's efficiency is measured.

As can be inferred from the graph, the data points in the test data are closest to the positive trend line, thereby emphasizing the ability of the ANN model to effectively capture actual data trends. Such an implication is especially true for the high-yield data, which is in the range of 400 kg/rai, as the predicted data of the model is in exact accordance with the actual data. The estimated value represents the numerical analysis performed for RMSE at 1.05 kg/rai, MAE at 0.90 kg/rai, and MAPE at 0.25%.

Those sites that actually produced low yields (around 195-200 kg/rai) showed a large deviation from the estimated yield compared to other sites. This could be due to the existence of outliers such as high salt content in the soil or unusual rainfall in the area, resulting in a slight decrease in the estimated model precision for the low-data range. However, this data did not have a big effect on the model's accuracy since the other data followed the trend line, which showed an R^2 of 0.99.

The model can understand everything except for a little change in the output data. To sum up, the graph in Figure 1 clearly shows that the ANN model has a lot of promise for properly forecasting Jasmine rice yield 105 by looking at the linear patterns in real data.

This is an important base for agricultural uses, such as systems that alert farmers about droughts, planning for farming, and managing fields.

4.4. Analysis of Feature Importance
An evaluation of the ANN weights indicated that the factors with the most significant impact on prediction Accuracy were:
1. Cumulative precipitation during the 30 days before blossoming.
2. Mean peak temperature at milky grain phase.
3. Soil Salinity (Electrical Conductivity)
4. Soil Organic Matter.
5. The Calendar Day.
6. Application Rate of Nitrogen Fertilizer.

The output showed that "rainfall" was the main variable, which coincided with the rainfall-dependent nature of the study area. The EC greatly influenced production. In some plots, the values were above 6 dS/m, yielding lower output; thus, it showed soil salinity.

Besides, inappropriate timing of seeding, late or early, may let the plants enter a critical phase during drought conditions, which may deeply reduce yield.

5. Results and Discussion
5.1. Summary of Results
This research proposed a forecasting model for the yield of Jasmine Rice 105 in the Ban Samran region of Nong Khaen subdistrict, Pathum Rat district, Roi Et province. The method used in this research is ANN, with data of ten years of actual yield data in consideration, from 2014 to 2023.

From the findings, it can be observed that the accuracy of the model and the level of error are much higher for the ANN model, and this was demonstrated below:
1. The RMSE is 1.05 kg.
2. MAE value = 0.90
3. The value of the MAPE is very small, approximating 0.25%.
4. The R^2 value is 0.99, which shows that the model explains the yield variance in the historical data well.

Compared to multiple, quadratic, and cubic regression models, the ANN model has a significantly higher accuracy and degree of reliability. The RMSE value for the statistical model is roughly 5 to 7 times larger than the ANN model, and the R^2 value is significantly lower.

5.2. Physical and Agronomic Interpretation of ANN Performance

The effectiveness of the proposed ANN-based forecasting model lies in its capacity for an implicit recognition of the physical and agronomic processes that affect and influence Jasmine rice growth in the Thung Kula Rong Hai region. Indeed, rice yield formation results from complex nonlinear influences of climatic, soil, and agronomic factors, especially for rain-fed and saline areas.

From a physical perspective, precipitation and temperature are the primary factors affecting rice grain development. The ANN findings indicate that cumulative rainfall throughout the blooming period is the primary factor affecting rice grain output. This makes sense from a biological point of view since the ecosystem goes through water stress throughout the blooming period. This stress changes how well pollination works, which is necessary for making grains. It is known that water stress may induce grain loss. In agricultural systems that are dependent on rainfall, such as Thung Kula Rong Hai, even minor deficiencies in rainfall during the flowering phase have been observed to reduce cereal yield. Conventional linear models are incapable of accurately representing this nonlinear phenomenon.

Among temperature-related parameters, the maximal heat at the hazy grain stage substantially influenced yield predictions. Higher temperatures during the grain filling stage accelerate respiration and reduce the accumulation of glucose in grains, resulting in reduced yields at maturity from a crop physiological perspective. The ANN model integrates temperature effects more efficiently throughout different growth stages to portray the overall thermal stress the crop has undergone. Its ability to do so is what gives the ANN greater precision in making predictions over conventional regression models, which normally assume all temperature effects are equal in time.

Soil electrical conductivity and organic matter were identified as the two most important explanatory elements from both edaphic and agronomic viewpoints. Higher salt levels in the soil enhance osmotic stress and reduce nutrient absorption, limiting the quantity of rice that can be cultivated. When there is little organic matter in the soil, it cannot store as much water or nutrients, exacerbating drought stress in places that get rain. These soil restrictions have a significant impact on how the climate changes, resulting in very nonlinear yield responses. The ANN model incorporates these interactions without using specific physical equations; therefore, more precise yield estimations may be obtained under a variety of soil conditions.

Management-related factors, such as planting date and nitrogen fertilizer application rate, can contribute to production variability. If rice is planted at the incorrect periods, it may be subjected to drought or heat stress during critical development stages. Nitrogen management issues may also have an impact on tillering and panicle growth. The ANN framework accounts for these management impacts by learning their combined influence with meteorological and soil factors, rather than considering them as separate contributions, as is often assumed in statistical models.

5.3. ANN Outperforms Conventional Forecasting Models

From the comparative analysis, it should be noted that the ANN model clearly portrays its performance superiority over multiple linear regression models, polynomial models, random forest models, and support vector regression models. The key reason for the performance superiority shown by ANN is its capacity to capture the complex nonlinear multivariate features characterizing agro-climatic phenomena or agro-climatic systems. In regions where environmental instability prevails, such as Thung Kula Rong Hai, yields are rarely linear in relation to any climatic parameter or input.

Traditional regression-based techniques are mainly based on known functional forms and are often assumed to have linear or weakly nonlinear relationships; however, machine learning techniques, such as random forest and support vector regression, are better than linear-based models but may still not perform as effectively for sparse, noisy, and/or correlated agricultural data as the multilayer ANN architecture, which was adopted by this paper and permits hierarchical feature learning.

Furthermore, the occurrence of data over a period of ten years facilitates enhancement in learning by the ANN regarding temporal variations, extreme events, such as drought affecting crop yield. This will allow the model to differentiate between regular interannual variations and abnormal climatic events.

5.4. Implications for Precision Agriculture and Local Decision Support

This high degree of correspondence between predicted and actual yields underscores the utility of the proposed model, constituted by an ANN, in terms of providing useful practical advice to farmers or agricultural planners at local scales. For example, determining rainfall sensitivities at flowering times and understanding the impact of planting dates are valuable pieces of advice to those concerned with implementing adaptations under shifting climate regimes.

Furthermore, the ANN-based architecture is scalable and adaptable, allowing the model to be expanded and applied to different sub-districts, as well as updated with fresh data in succeeding growing seasons. This flexibility and scalability have significant implications for precision agriculture, where site-specific decision-making is vital for enhancing agricultural output and sustainability in climate-vulnerable locations.

6. Conclusion

The research has established a model using an artificial neural network to forecast the nutritional value of Hom Mali 105 rice in the Ban Samran area of Nong Khaen Subdistrict, Pathum Rat District, based on a decade's worth of regional data. The test results show that the proposed model accurately predicts the yield of Hom Mali 105 rice in the region based on data from the previous decade. The proposed system may find many applications in agricultural planning and risk management, allowing for the creation of a decision-support system that delivers long-term solutions for farmers and Thailand's agricultural economy. The proposed idea and approach might be improved and used in other areas of Thung Kula Rong Hai to improve precision farming and support new planning efforts.

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