Sugar Tech
https://doi.org/10.1007/s12355-026-01744-0

RESEARCH ARTICLE

Artificial Neural Network-Based Prediction of Nipa Sugar Production in Sarawak, Malaysia

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Received: 24 September 2025 / Accepted: 10 February 2026

Abstract

Nipa palm (*Nypa fruticans* Wurmb) plays a vital role in the socioeconomic development of coastal communities in Sarawak, Malaysia, where its sap is traditionally used for sugar production. However, nipa sugar production is highly variable due to fluctuating environmental conditions, making reliable forecasting challenging. Current prediction methods rely on empirical observations and historical trends, which fail to capture the complex, nonlinear interactions between climatic factors and sugar yield. This study addresses the need for a more accurate forecasting model by developing a feedforward artificial neural network (FFANN) to predict nipa sugar production using daily data collected for twelve months from Kampung Tambirat, Sarawak. The FFANN model incorporates key environmental variables, including temperature, humidity, wind speed, atmospheric pressure and sap yield, and is trained using the resilient backpropagation (RPROP+) algorithm. The model's performance was compared to classical time series models (ARIMA and seasonal naïve) and a decision tree regression model. Key results show that the FFANN model outperformed the benchmark models with a coefficient of determination (R^2) of 0.73 and a normalized root mean square error (RMSE) of 0.097. Sensitivity analysis identified temperature, wind speed and humidity as the most influential factors on sugar production. The proposed FFANN model provides a robust decision support tool for nipa sugar producers, offering more accurate predictions for harvest planning and resource allocation. Future research could expand the robustness of the model by integrating multi-year datasets and IoT-based monitoring systems to enhance real-time forecasting capabilities.

Keywords Agro-technology · FFANN · *Nypa fruticans* · Sugar yeild prediction · Environmental factors

Abbreviations

AIC	Akaike information criterion
ANN	Artificial neural network
ARIMA	Autoregressive integrated moving average
FFANN	Feedforward artificial neural network
IoT	Internet of things
MLR	Multiple linear regression
MSE	Mean squared error
PPA	Pusat pemprosesan apong (centralized processing center)
R^2	Coefficient of determination
RMSE	Root mean square error
RPROP+	Resilient backpropagation algorithm
RStudio	A software environment for statistical computing

List of symbols

d_i	Represents the actual values (observed sugar content)
d_{ij}	Actual (desired) value for the *i*th output of the *j*th sample
y_i	Represents the predicted values (ANN predictions)
d^-	The mean of actual value
N	The number of data points
P	Number of output processing elements
y_{ij}	Predicted value for the same

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Introduction

Sarawak, a state in eastern Malaysia, lies in the tropics and is home to a variety of mangrove forests (Abidin et al., 2024). The nipa palm (*Nypa fruticans Wrumb*) is a common species and Sarawak represents the largest nipa population in the country (Athirah and Kho 2024; Okugbo et al. 2012; Tsuji et al. 2011). Nipa palm can be mostly found along the riverbank of Sarawak. Nipa has been utilized in multiple ways to enhance the local livelihoods, in terms of economy, food, medicine, fuel, etc. (Phetrit et al. 2020; Theerawitaya et al. 2014). It is a major income source for communities that live near the nipa palm (Cheablam and Chanklap 2020; Ibrahim et al. 2022). There is a large socioeconomic importance of the nipa palm in Sarawak. Coastal communities in Sarawak have been practicing nipa palm harvesting for generations for their economies (Khair 2018). One of the most traditional products is *gula apong*, which is a rural family practice for sap collection production (Guo et al. 2020; Tamunaidu et al. 2013). In Sarawak, nipa palm sap has been traditionally processed into molasses, and syrup, as a source of income for local communities (Caban et al. 2022; Cheablam and Chanklap 2020).

Nipa is a type of perennial plant that can live up to hundred of years (Matsui et al. 2014a), and it is sustainable resources (Athirah and Kho, 2024; Cheablam and Chanklap 2020). Physiologically, nipa has ability to adapt the saline and brackish conditions (Saelee 2022; Saengkrajang et al. 2021; Tripathi et al. 2012). The nipa palm plant is able to maintain sap production without replanting, fertilizers or pesticides (Tamunaidu et al. 2013). The palm's hypogeal rhizomatous root system permits ongoing recovery and maintenance of extended sap extraction periods, without root damaging the trees regenerative capacity (Tsuji et al. 2011). Nipa palm yields abundant sap from the cut stalks of inflorescences after the floral or fruit heads have been removed (Theerawitaya et al. 2020). Prior to tapping, the stalk of the inflorescence is beaten repeatedly for days to increase the sap (Tsuji et al. 2011). The sap, extracted from the inflorescence, is rich in sucrose, glucose and fructose (Jara'ee et al. 2025).

Nipa palm is an important mangrove in Sarawak, Malaysia, and its sap has a high social–economic potential for communities that produce traditional sweeteners (Alipiah et al. 2025; Jaraee et al. 2023), such as gula apong (Yusoff et al. 2015). Nipa sugar production has low commercial potential due to the wide variation in sap extraction that is greatly affected by climatic factors, for example temperature, humidity and wind speed activities (Matsui et al. 2014a; Sartinah et al. 2022). This variability creates significant production and resource planning challenges (Matsui et al. 2014b).

Currently, there is a lack of efficiency in nipa sugar production forecasting which mainly depend on empirical methods and farmers past qualitative observations and experience toward the issue (Abidin et al. 2024). Despite their potential, these conventional methods are not able to provide a quantitative integration of the complex and nonlinear relationships between various environmental factors on the ultimate sugar output (Santos et al. 2024). For example, it can be seen from the two variables in this study that there is a nonlinear relationship between raw sap volume and final sugar production, such that estimation based on a simple ratio is insufficient for accurate forecasting, thus highlighting a clear gap in the development of a reliable and data-based predictive tool.

The artificial neural networks (ANNs) can address this shortcoming since they provide an ideal approach for modeling complex nonlinear systems that traditional statistical models often fail to capture (Kumar et al. 2015; Taiwo and Musonge 2023). ANNs have been widely used in agricultural forecasting (Amoriello et al. 2022; Chen et al. 2024; da Silva Pereira et al. 2021), e.g., sugar cane yield prediction (Obe and Shangodoyin, 2010) and fruit quality assessment (Lan et al. 2020).

The importance of nipa palm in Sarawak, Malaysia, extends beyond its ecological role, providing a crucial source of income for local coastal communities through the production of traditional sugar. However, the variability in nipa sugar production, largely influenced by unpredictable climatic conditions, presents significant challenges for producers, especially when relying on traditional forecasting methods. These methods, often based on qualitative observations and historical trends, fail to adequately capture the complex, nonlinear relationships between environmental variables and sugar yield. This study, therefore, aims to develop a more reliable and robust forecasting tool through the application of a feedforward artificial neural network (FFANN) model. By integrating key climatic variables, such as temperature, humidity, wind speed and atmospheric pressure, alongside sap yield data, the study seeks to generate accurate predictions for nipa sugar production. The primary objective is to enhance forecasting accuracy and provide a decision support framework that allows producers to optimize harvest schedules and resource allocation. Ultimately, this research endeavors to contribute to the sustainability of nipa sugar production in Sarawak, offering a data-driven approach to address the limitations of traditional methods and ensuring more effective management of this vital resource.

Materials and Methods

Overall Research Workflow

The overall methodology for developing the nipa sugar predictive model is summarized in Fig. 1. The process started with the collection of farm level nipa sap and sugar production data along with corresponding meteorological variables from a nearby weather station. This step was then followed by data preprocessing, where cleaning, scaling and partitioning into training, testing and validation sets took place. The important part of the work was development of FFANN model which focused on the design and implementation of the architecture of the network. Next came the model training and performance evaluation using statistical measures such as R^2 and RMSE. Lastly, statistical and comparative analysis to benchmark the FFANN performance against other models. Further details on each of these phases follow in the next subsections.

Study Area and Data Collection

The study and data were conducted in Kampung Tambirat farm that is located at 1°33′09.8"N 110°30′26.8"E which cover about 50m x 100m area (0.5 ha) along the riverside Batang, located in Kota Samarahan, Sarawak, Malaysia, as shown in Fig. 2a and b. Volume of sap supplied to the Pusat Pemprosesan Apong (PPA) was recorded. The supplied sap was processed to produce syrup at centralized

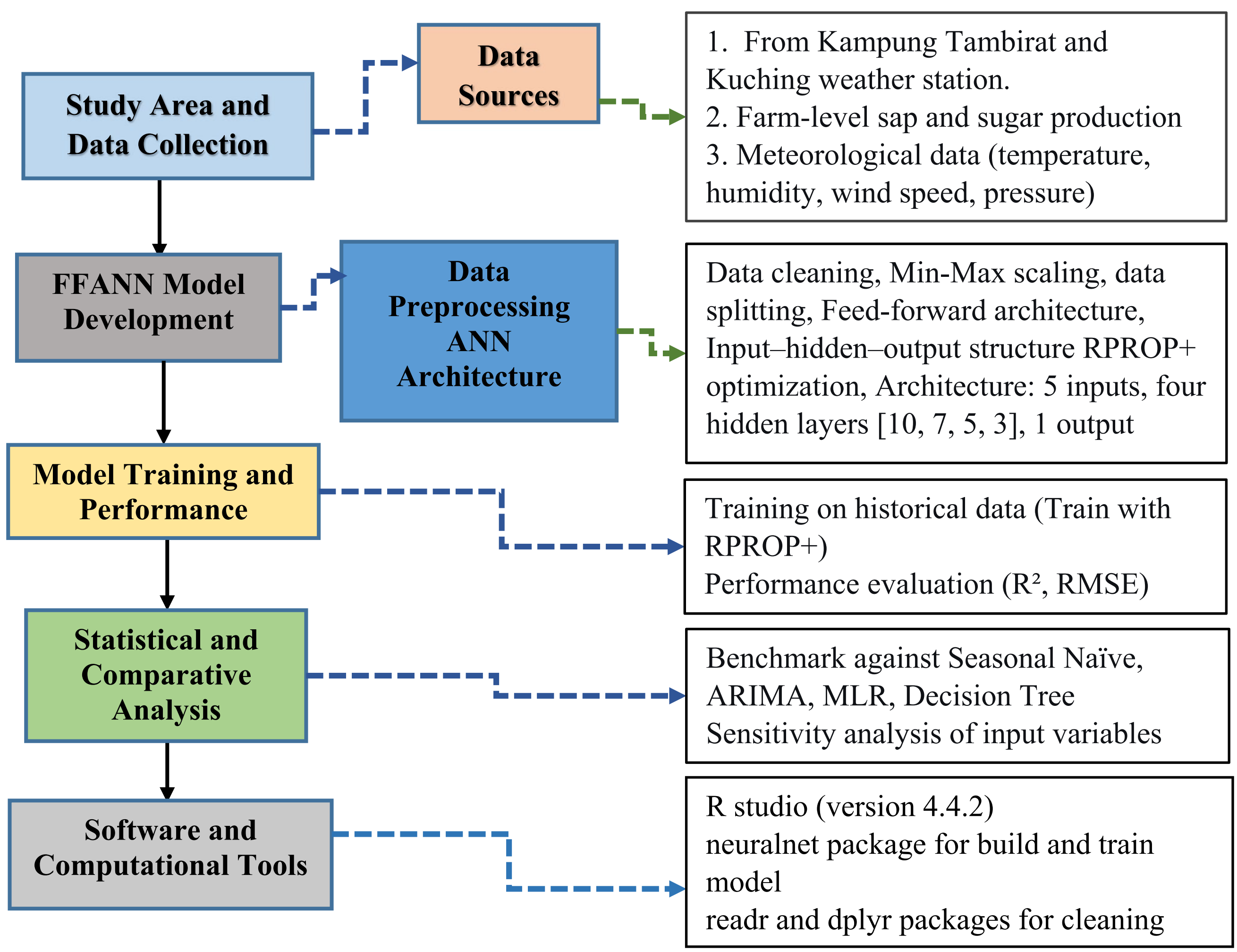

Fig. 1 Methodological workflow for the development of the feedforward artificial neural network (FFANN) model for nipa sugar production prediction, including data collection, preprocessing, model development, training and validation, and benchmarking against conventional forecasting approaches

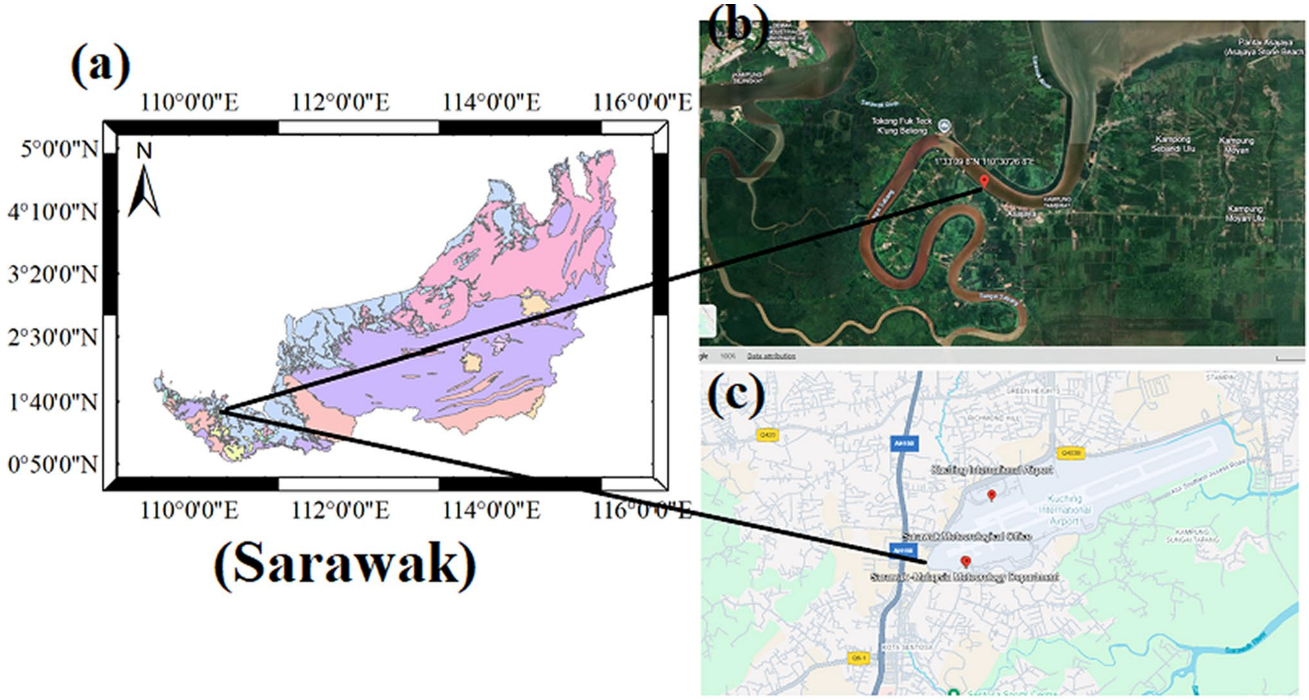

Fig. 2 **a** State of Sarawak, Malaysia. (**b**) Location of Mr Edi's farm located at riverside of Batang. (**c**) Location of weather station (1.47°N, 110.33°E)

Table 1 Data representing monthly sugar and sap production

S. no	Month	Sap (kg)	Sugar (kg)
1	July	1228.2	282.4
2	August	1643	356
3	September	1278	302.2
4	October	1332	304.1
5	November	1612.9	380.2
6	December	2137	448.1
7	January	2472.6	461.1
8	February	1717.65	313.1
9	March	1690.2	320.8
10	April	1591.5	337
11	May	1554.2	311
12	June	1246.2	259.2

processing center. Twelve-month data were obtained daily from July 2023 until July 2024.

The meteorological data were taken from nearby station located at Kuching International Airport (1.47°N, 110.33°E) a reliable authority for regional climate data shown in Fig. 2c. The dataset consisted of temperature (°F) varies from 77.3 to 86.4, humidity (%) varies from 72.7 to 95.7, wind speed (m/s) varies from 1.5 to 5.3, and sap yield (kg) varies from 1228.2kg to 2472.6kg (Table 1).

Table 2 Performance comparison of the proposed FFANN model against benchmark forecasting models

Model	R^2	RMSE
FFANN (proposed)	0.73	0.097
MLR	0.30	1.30
Seasonal naive	– 1.47	1.82
ARIMA	– 1.29	1.75
Decision tree	0.42	1.45

Data Sources

The weather station's data provided a robust foundation for modeling nipa sugar production. While sap yield and sugar content measurements were obtained daily from July 2023 until July 2024. Thus, meteorological data were recorded using automated weather monitoring systems, whereas sap yield and sugar were measured using volumetric analysis, and the obtained data were analyzed using quantitative and qualitative descriptive analysis measuring the volume capacity. In Table 2 and Fig. 3, complete one-year data of sap and sugar production are shown monthly.

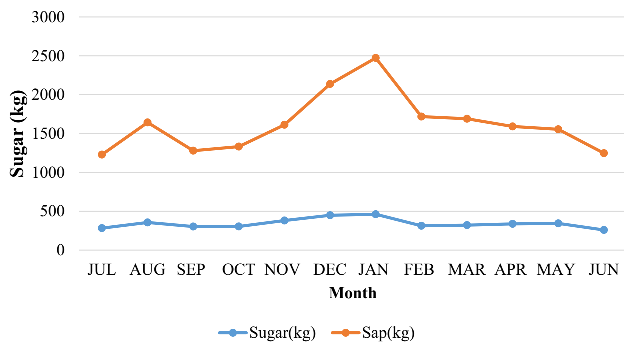

Fig. 3 One-year data of sap and sugar production per month

Model Development

A FFANN was created to estimate sugar content calculated from meteorological parameters and sap yield of one-year data that are presented in appendix table. The model was built using the neural net package in RStudio software, with the input layer containing five neurons for the predictor variables: temperature, humidity, wind speed, pressure and sap. To enable the model to learn intricate associations in the data, four hidden layers with ten, seven, five and three neurons respectively were incorporated. We used a linear activation function in the output layer to produce continuous numerical predictions. The model was trained with a backpropagation with a resilient backpropagation plus (RPROP +) optimization algorithm to minimize the mean squared error (MSE).

Data Preprocessing

The numerical features were all scaled similarly using min–max scaling. The dataset was split to provide stratified sampling to create training (70%), testing (20%) and validation (10%) splits. Zero variance predictors were removed to increase the robustness of the model.

ANN Architecture

A FFANN was built using the R programming language, specifically with the neural net package. This network featured five input neurons and four hidden layers containing 10, 7, 5 and 3 neurons, respectively, culminating in a single output neuron that predicts sugar content. In the hidden layers, the logistic sigmoid function is applied in this model, while the output layer utilized a linear activation function. To train the model, we employed RPROP + optimization to effectively minimize the mean squared error (MSE).

Model Training and Performance Evaluation

The FFANN model was trained on the training dataset, using a fixed random seed (123) to ensure that results could be replicated. The general performance of the models was compared using various measures of forecasting accuracy. In this study, three measures of performance were used.

Mean Squared Error (MSE)

The average cost is equal to twice the average squared error defined by the Equation 1.

$$MSE = \sum_{i=0}^{P} \sum_{j=0}^{N} \frac{(d_{ij} - y_{ij})^2}{NP} \tag{1}$$

where.

P = Number of output processing elements.

N = Number of exemplars in the dataset.

d_{ij} = Actual (desired) value for the ith output of the jth sample.

y_{ij} = Predicted value for the same.

Root Mean Squared Error (RMSE)

RMSE measures the standard deviation of prediction errors, providing an interpretable metric in the same unit as the predicted variable (sugar content in this case). A lower RMSE indicates better model accuracy shown in Equation 2.

$$RSME = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(di - y_i\right)^2} \tag{2}$$

where.

N = the number of data points.

d_i = is the actual value.

y_i = is the predicted value.

R-squared (R.^{2})

R^2 measures the proportion of variance in the observed data explained by the FFANN model. A value closer to 1 indicates better predictive accuracy. The coefficient of determination, R^2, was computed using the Equation 3:

$$R^2 = 1 - \frac{\sum(d_i - y_i)^2}{\sum(d_i - d^-)^2} \tag{3}$$

where.

d_i = Represents the actual values (observed sugar content).

y_i = Represents the predicted values (ANN predictions).

d^{-} = the mean of actual value.

Statistical and Comparative Analysis

In order to evaluate how well the proposed FFANN model predicts outcomes, conventional and machine learning forecasting techniques were used to compare it to several other types of forecasting methods. The conventional methods that were utilized included multiple linear regression (MLR), decision tree regression models and seasonal naïve forecasting, while the machine learning method employed was an autoregressive integrated moving average (ARIMA) model as well as some variant of ARIMA. In order to determine whether or not the ARIMA model was correct, it was important for all series being tested to be stationary. This was accomplished by performing a visual inspection as well as through the process of differencing all series. Additionally, the order of the ARIMA model was determined through the use of the Akaike information criterion (AIC). The seasonal naïve forecasting methodology was used as a baseline for a time series of the historical data and is considered to use a fixed time period for forecasting. All forecast models were assessed within the same testing dataset to facilitate a valid comparison.

A sensitivity analysis based on connection weights was conducted on a trained FFANN to assess the relative influences of input factors on nipa sugar production. This analysis provides estimation of how much each input factor contributed to the production of nipa sugar by calculating the connection weights between the inputs, hidden and output layers of the trained FFANN. The analysis produces a representative value rather than independent or additive contribution for the relative importance of each input factor. As the input variables are not orthogonal and may exhibit interdependencies, cumulative contribution may exceed 100%. Thus, the results of the sensitivity analysis should be viewed as comparative indicator of influence rather than absolute variance partitioning.

Software and Computational Tools

The RStudio programming language (version 4.4.2) was used for data processing, analysis and artificial neural network (ANN) modeling. Several specific packages were used to support model construction and performance evaluation. The neural net package was utilized for building and training the FFANN model, while caret was used data partitioning, normalization and performance evaluation. The readr and dplyr packages were used for data import, cleaning and manipulation. This computational environment provided an effective platforms for reliable modeling and analysis prediction of nipa palm sap sugar content.

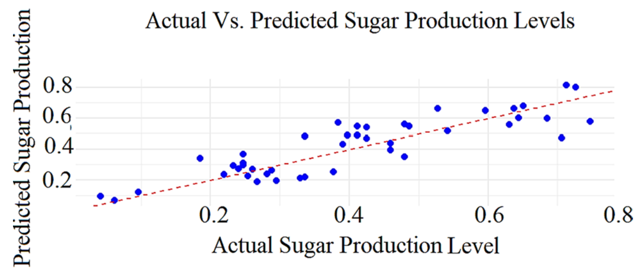

Fig. 4 Actual vs predicted sugar

Results and Discussion

The FFANN model showed an R^2 of 0.73 and an RMSE of 0.097 which demonstrating predictive capabilities. Predictions were close to observed values, especially at mid-sugar content values (0.4–0.6 kg). For extreme values, the model predictions deviated from their observed value. This suggests that data on rare climatic events need to be increased.

The actual and predicted sugar production level aligned closely in the scatter plot (Fig. 4). For mid-range sugar production values (0.4–0.6 units), the model fit particularly well, where the predictions tracked closely the observed data. At low sugar productions (0.2 units), minor deviations occurred, indicating that the model underestimated yields marginally from extreme environments, such as drought or nutrient stress.

Residuals were symmetrical about zero, presenting little bias (Fig. 5). Errors for residuals pertaining to non-normal climatic conditions (e.g., extreme drought) were larger, further demonstrating the value of using multi-year data and additional environmental variables.

According to the results sensitivity analysis as shown in Fig. 6, the relative influence of temperature was the greatest on nipa sugar production, followed by wind speed and

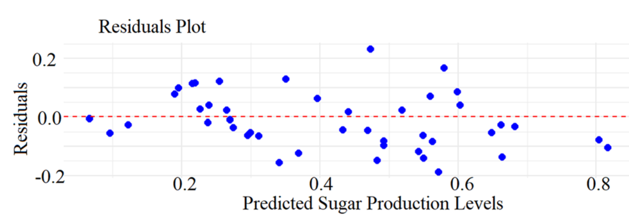

Fig. 5 Residual plot

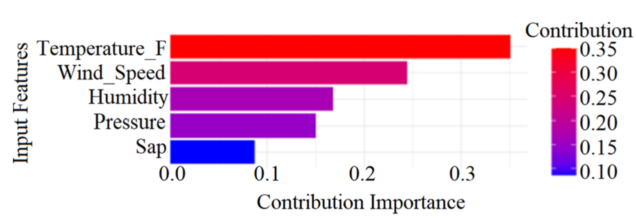

Fig. 6 Relative importance of input variables influencing nipa sugar production as determined by connection weight-based sensitivity analysis of the FFANN model

relative humidity. Atmospheric pressure and sap yield exhibited comparatively lower influence. This indicates that sugar production is governed primarily by environmental conditions affecting physiological processes rather than sap volume alone. In this context, it is important to remember that the reported contribution represents relative influence within the FFANN framework and does not imply independent or additive effects.

The overall performance comparison, as outlined in Table 2, clearly indicates that the proposed FFANN model outperforms the other models. The seasonal naive and ARIMA models as classical time series benchmarking models have shown weak performances with both yielding a negative R^2 and a high RMSE. This finding is critical as it shows that using the historical pattern of sugar production for forecasting is inadequate because it does not capture the core drivers of yield. The system appears to operate from complex, nonlinear relationships with environmental variables in the case study region that require more than univariate model evaluation. Although the FFANN model performed better than the decision tree model which also showed reasonable results ($R^2 = 0.68$), the latter was limited in its predictive capability. The FFANN model achieved the highest R^2 of 0.73 and significantly lower RMSE 0.097, demonstrating that it is the most reliable model evaluated. The FFANN model stands alone in its ability to quantify the dynamic relationships between temperature, humidity, wind speed and sap volume for sugar production estimations.

Previous research has shown that the limitations of traditional time series models used in agro-environmental sciences are similar to those observed in the use of ARIMA for crop yield. In these cases, machine learning techniques have shown to be superior to ARIMA because they can account for the complex, nonlinear relationship between climate factors and crop yield.

Thus, the predictive ability of the FFANN model far exceeded those of all benchmark models that were used for comparison. The FFANN model had the best fit (highest R^2), as well as having the lowest RMSE of any model evaluated. In contrast, both the ARIMA and seasonal naïve models produced the worst fits (negative R^2), which means they were inferior to predicting average values. This finding illustrates that models that are based solely on historical patterns (time series) are not able to model the complex, nonlinear effects of environmental conditions on nipa production. This supports the belief that sugar yield variability does not only vary with time, but also varies according the combination of dynamic environmental interactions captured by the FFANN model.

The FFANN model's ($R^2 = 0.726$) superior performance further confirms the efficacy of artificial neural networks in modeling complex, nonlinear agricultural systems similarly demonstrated by (Obe and Shangodoyin, 2010) in terms of forecasting sugarcane yield. Therefore, this research directly addresses the critical gap arising from the continued reliance on empirical methods for forecasting nipa sugar production (Abidin et al. 2024). The model's sensitivity analysis identified temperature, wind speed and humidity as the three most significant factors influencing factors, providing empirical validation and a quantitative ranking of the qualitative climatic drivers (Matsui et al. 2014a) Sartinah et al. 2022). Furthermore, the complete failure of classical time series approaches (ARIMA and seasonal naïve) is evidenced by the negative values of R^2, suggesting a fundamental mismatch between their linear assumptions and the system's unique complexity. This is consistent with the pattern within the existing literature, whereby machine learning techniques significantly outperform traditional statistical methodologies for nonlinear agro-environmental questions (Chen et al. 2024). Collectively, these results represent a transition in the understanding of nipa sugar production from a qualitatively predictable system.

Conclusions

A FFANN model was successfully developed to predict nipa sugar production in Sarawak, Malaysia, utilizing one year of historical data. The FFANN model demonstrates strong predictive performance with an R^2 of 0.726 and an RMSE of 0.097, indicating its effectiveness in forecasting nipa sugar production. The proposed FFANN model outperformed classical time series models, such as ARIMA and seasonal naïve, which yielded negative R^2 and poor forecasting accuracy. The FFANN model exhibites superior performance compared to decision tree models, highlighting its ability to capture complex, nonlinear relationships between climatic variables and sugar production. Sensitivity analysis revealed that temperature, wind speed and humidity had the most significant influence on nipa sugar production, more so than sap yield, indicating that climatic factors are primary drivers of sugar yield. The model provides a practical decision support tool for nipa sugar producers and stakeholders, assisting the harvest planning and resource allocation, which can improve the sustainability of the nipa sugar industry.

Future studies could include the integration of Internet of Things (IoT)-based sensors for real-time data collection and expand the model using multi-year datasets to improve its robustness, particularly for extreme yield events. This research emphasizes the need for data-driven forecasting methods in agro-environmental sciences, especially for industries like nipa sugar production, which are highly susceptible to environmental variability.

Appendix 1

See Table 3.

Table 3 Detailed one-year data of daily sap and sugar production with weather variables

Temperature (°F)	Humidity (%)	Wind Speed (mph)	Pressure (in)	Sugar (kg)
80.3	83.8	3.1	29.8	10
82.5	80.7	3.6	29.8	12.7
81.2	81.2	3.4	29.7	9.3
80.1	86.2	3	29.7	9.35
81.4	81.5	3.7	29.7	9.4
81.4	83.3	2.8	29.7	9.4
82.2	82.2	3.5	29.7	11.4
82.1	80.1	3.9	29.7	11.2
78.3	91.8	2.5	29.7	9.9
81.3	79.7	2.3	29.7	12.9
81.3	80.6	3.4	29.7	10.85
78.4	89.2	2.9	29.7	8.8
79.1	88.4	1.8	29.7	13.7
80.6	87.1	3.3	29.7	12.4
81.6	85.2	2.5	29.7	11.7
80.6	88.1	3.6	29.8	12.5
80.4	86.5	2.8	29.8	13.2
80.5	87.4	2.8	29.8	14.5
79.3	89.2	2.8	29.8	15.8
81.5	82.5	2.4	29.7	15.8
80.3	87.7	3.7	29.7	16.6
80.4	86.8	3	29.8	17.3
80.7	83.1	3.2	29.8	14.8
81.3	84.9	3	29.7	15
80.9	86.1	3.3	29.7	15.7
80.2	87.5	3.5	29.7	16.4
81.7	85.8	2.6	29.7	17.3
79.7	90.5	3.6	29.7	19.5
78.5	90.2	2.9	29.7	17.7
79.7	85.8	2.7	29.7	15.8
81.7	82.4	3.7	29.7	15.5
79.2	87	5.3	29.7	16.6
81	83.9	3.8	29.7	17.7
80.8	85.7	3.4	29.7	15.3
81.7	83.4	3.1	29.7	15.1
80.3	88	3.4	29.7	16.9
81.3	84.6	3.8	29.7	18.1
81.2	84.8	2.6	29.7	15.6
81.5	84.6	3.7	29.7	16.55
80.4	85.3	4.2	29.7	17.5
80.3	85.2	3	29.7	20.1
83.5	78.8	3.6	29.7	18.6
80.6	89.8	3.7	29.7	17.8
81.7	83.1	2.8	29.7	18.4
79.7	91.3	2.8	29.7	18.6
79.2	87.2	3.5	29.7	18.4
79	90.6	2.5	29.7	18.2
79.5	90.1	2.8	29.7	18.4
80.1	88.8	2.7	29.7	16.7
80.5	86.7	3.4	29.7	15.1
82	82.4	3	29.7	11

Table 3 (continued)

Temperature (°F)	Humidity (%)	Wind Speed (mph)	Pressure (in)	Sugar (kg)
81.3	87.3	2.1	29.7	13.5
80.7	91.3	1.5	29.7	15.75
81.3	87.8	2.7	29.7	18
78.5	92.3	2.8	29.7	16.3
80	88.5	3.4	29.7	17.5
82	83.7	3.6	29.7	12.5
81.7	85.4	4.1	29.7	13.4
82	86.5	3.6	29.8	14.8
81.3	87.4	4.3	29.8	18.25
79.6	90.7	3.1	29.8	21.7
81.7	86.9	3	29.8	22.5
81.2	87.2	2.3	29.8	18.8
82.1	83.4	3.4	29.8	18.9
82	84.2	4.1	29.7	18.3
83	84.9	3.1	29.7	17.8
79	92.3	3.3	29.7	15.1
81.1	85.9	2.6	29.7	18.1
81	89.2	3	29.7	16.5
80.4	87.2	3.1	29.8	16.4
81.3	85.7	2.9	29.7	18.3
79	90.2	1.7	29.8	14.5
81.2	86.4	3	29.7	16.3
79.9	89.9	3.5	29.7	16.5
79.7	90.8	2.7	29.7	18.4
79.7	89.3	2.7	29.7	18.6
80.3	88.5	3.6	29.7	17.5
80.8	89.1	1.5	29.7	16.5
79.8	90.4	2.1	29.7	18
79.5	89.6	3.1	29.7	17.4
78.5	94.8	2.6	29.7	17.7
80.1	88.1	4.4	29.7	16.1
78.4	92.7	2.6	29.7	15.8
82.2	85.5	3.2	29.8	20.1
80.6	88.7	2.4	29.8	23.4
79.1	89.5	3.3	29.8	19.4
81.3	85.1	3.8	29.8	21.2
82.5	80.1	3.8	29.9	18.3
81.1	83.2	4	29.8	17.9
81.3	80.5	4.1	29.8	17.4
78	90.9	2.9	29.8	16.5
80.5	87.2	3	29.8	19.2
77.3	95.7	1.9	29.8	15.5
80.9	86.3	3.7	29.8	14.4
81.5	87.8	1.6	29.8	15.9
82.2	86.6	2.4	29.8	17.8
80.8	88.3	2.3	29.8	17.6
81.6	84.6	2.7	29.8	17.5
82.1	85.2	4	29.8	15.8
80.5	91.6	2.8	29.8	15
79	93.7	4.1	29.8	15.6
79.4	92.6	2.7	29.8	15.8

Table 3 (continued)

Temperature (°F)	Humidity (%)	Wind Speed (mph)	Pressure (in)	Sugar (kg)
80.5	90.4	2.1	29.8	15.1
82.4	86	3.1	29.8	15.9
83.3	83.1	4	29.8	12.4
80.7	87.7	3.5	29.8	16.6
81.3	84.3	3.3	29.8	14.8
81.6	84.8	3.5	29.8	15.8
79.8	89.3	3.1	29.8	15.5
82	86.1	4.5	29.7	14.5
80.4	89.9	4	29.7	16
80	90.5	2.2	29.7	15.6
82.1	87.9	3.5	29.7	15.3
79	91.8	3.8	29.8	13.7
81.2	90.7	2.4	29.7	14.6
80.7	91	2.7	29.7	16.4
80.8	89.9	2.4	29.7	15.9
83.5	84.7	3.2	29.7	14.1
80.1	94.1	1.8	29.7	14.7
79	91.1	3.1	29.7	13.6
81.5	80.9	3.3	29.8	10.1
80.5	85.8	3.9	29.8	12.6
81.9	85.4	3	29.8	15.5
82.8	82.8	3.7	29.7	15.6
81.9	88.1	3.3	29.8	19.7
81.3	90.2	3.5	29.8	16.9
82	83.2	3.3	29.8	17.2
82.9	81.4	2.9	29.7	13.1
80.9	88.8	3.1	29.7	13.8
83	83	3.3	29.7	16.5
84.2	82.3	3.3	29.8	12.7
79.4	93.7	2.6	29.8	12.8
80.9	86.9	2	29.8	14.5
80.3	88.4	3.5	29.8	11.5
81.9	85	4.7	29.8	17.2
82.6	82.8	3.4	29.7	14.1
83.2	82.1	3.5	29.7	14.5
84.2	80.8	3.7	29.7	15.1
84	82.8	3.1	29.7	15.2
83	85.9	2.9	29.7	14.3
84.4	81	3.7	29.7	15
83	85.5	2.8	29.7	14.2
83.5	83	2.9	29.7	10.1
82.4	87	2.3	29.8	12.6
84.2	81.5	3	29.7	15.5
82.3	86.2	3.2	29.7	15.6
83.9	82.1	3	29.7	19.7
84.9	81	3.5	29.7	16.9
83.3	87.2	2.2	29.7	17.2
84.2	83.9	2.7	29.7	13.1
81.6	90.7	2.4	29.7	13.8
83.3	81.4	3.1	29.7	16.5
82.2	87.2	2.3	29.7	12.7

Table 3 (continued)

Temperature (°F)	Humidity (%)	Wind Speed (mph)	Pressure (in)	Sugar (kg)
83.5	80.9	2.5	29.7	12.8
82.2	88.5	2.5	29.7	14.5
82.7	84.8	2.6	29.6	11.5
83.1	87.8	2.4	29.7	19.7
81.5	89.1	3	29.7	19.1
83.6	82.6	3.6	29.7	18.2
83.9	80.4	2.2	29.7	13.3
81.4	90.3	2.8	29.7	13.2
80.8	91.5	2.8	29.7	12.6
83.8	80.7	2.8	29.7	14
84.1	86.5	2.6	29.7	12.5
79.8	93.6	2.4	29.8	12.4
81.8	86.6	2.4	29.7	11.6
81	89.6	2.2	29.7	14.2
84.5	82.3	3.6	29.7	13.6
83.5	86.6	2.1	29.7	13.1
82.9	86.8	3.5	29.7	14.3
82.7	88.5	3.5	29.7	13.8
82.2	89.1	3.7	29.6	12.3
82.4	87.8	2.3	29.7	13.7
82.4	87.7	3.1	29.7	13.5
81.4	88.5	2.4	29.7	13.1
80.8	90.9	3.3	29.7	12.7
82.9	85.8	3.8	29.7	12.5
83.3	86.7	2.7	29.7	12.9
80.4	91.5	3.2	29.7	13.4
83.2	84.4	3	29.7	11.9
82.2	86	3.7	29.7	12.4
81.4	84	3.3	29.8	14.3
81.6	85.9	3.1	29.8	13.2
81.2	85.2	2.9	29.8	13.5
82	82.4	1.8	29.7	12.7
80.4	88.7	3.2	29.8	9
82.3	84.5	2.3	29.8	11.4
81.3	87.9	2.5	29.8	11.6
80.5	86.6	2.7	29.8	11.6
82.7	82.7	2.7	29.7	12
81.3	84.4	3.4	29.7	12.3
80.3	89.5	2.1	29.7	12.7
82.6	85.7	2.7	29.7	12.2
80.7	91.1	2.3	29.7	12.3
81.1	86.3	3.3	29.7	14.5
80.3	84.4	4.3	29.7	12.6
82.4	83.5	2.9	29.7	11.9
83	83.7	2.5	29.7	11.6
84.8	78.6	2.5	29.7	11.1
82.9	82.2	3.6	29.7	13.9
83	80.3	3.3	29.7	12.4
81.8	84.5	2.5	29.7	12.4
78.7	90.1	3	29.8	11.4
80	87.5	2.9	29.7	11.5

Table 3 (continued)

Temperature (°F)	Humidity (%)	Wind Speed (mph)	Pressure (in)	Sugar (kg)
80.4	85.1	3.5	29.1	11.4
81.8	83.8	2.6	29.7	11.4
78.4	88.9	2.7	29.7	12.4
81.3	81.8	3.4	29.7	13
81.2	82.3	4.7	29.7	13.7
79.6	84.9	4.1	29.8	12.6
79.8	83.8	5	29.8	13
80.9	83.1	3.5	29.7	12.4
84	79.8	2.6	29.7	11
84.4	78.1	3.8	29.7	11.6
84.7	81.1	3.1	29.7	11.7
83.6	84.2	3.4	29.7	11.5
81.3	84.4	4.7	29.7	11.3
82.5	82.3	3.1	29.7	10.7
84.5	81.6	2.8	29.7	12.5
85.3	76	3.2	29.7	12.8
84.8	72.7	3.6	29.7	9.8
84.8	74.6	3	29.7	10.2
86.4	73.7	2.9	29.7	10
84.1	78.8	3.2	29.7	9.4
79.9	86.5	3.6	29.7	9.7

Golden syrup at 70° Brix

Author Contribution Muzamil, Ana Sakura and Kasumawati: Conceptualization, methodology, experimental work, data analysis, writing–original draft and review. Imtiyaz: Data analysis, writing – original draft and review. Rasli, Mohd and Vannessa: Proofreading.

Funding Open access funding provided by The Ministry of Higher Education Malaysia and Universiti Malaysia Sarawak. This study has been supported by Jabatan Mufti Sarawak, with grant number IRG/F02/JMNS/86638/2025, and Dana Pembangunan Usahawan Bumiputera (DPUB) UHSB/BAM2019/079A and has been highly appreciated.

Declarations

Conflict of interest The authors declare no conflict of interest.

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